RELIABLE FOREST FIRE DETECTION SYSTEM USING WIRELESS SENSOR NETWORKS AND INTERNET OF THINGS

Thesis submitted in fulfillment of the requirements for the Degree of

DOCTOR OF PHILOSOPHY

By

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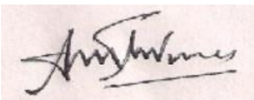
DECLARATION BY THE SCHOLAR

I hereby declare that the work reported in the Ph.D. thesis entitled **"Reliable Forest Fire Detection System using Wireless Sensor Networks and Internet of Things"** submitted at **Jaypee University of Information Technology, Waknaghat, India,** is an authentic record of my work carried out under the supervision of **Dr. Yugal Kumar and Dr. Pradeep Kumar Singh.** I have not submitted this work elsewhere for any other degree or diploma. I am fully responsible for the contents of my Ph.D. Thesis.



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SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the Ph.D. thesis entitled **"Reliable Forest Fire Detection System using Wireless Sensor Networks and Internet of Things"**, submitted by **Amit Sharma** at **Jaypee University of Information Technology, Waknaghat, India,** is a bonafide record of his original work carried out under our supervision. This work has not been submitted elsewhere for any other degree or diploma.

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Thanks to all of you!
Amit Sharma

LIST OF ACRONYMS & ABBREVIATIONS

ABC	Artificial Bee Colony
Acc	Accuracy
ACM	Association for Computing Machinery
ACO	Ant Colony Optimization
AFARP	Anglo French Aerospace Research Programme
ANN	Artificial Neural Network
AODV	Ad-Hoc on-Demand Distance Vector
APIT	Approximate Point-In-Triangulation
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
AWiFS	Advanced Wide Field Sensor
CAGR	Compound Annual Growth Rate
CBD	Convention on Biological Diversity
CCD	Charge-Coupled Device
CFDB	Corsican Fire Database
CNN	Convolution Neural Network
DA	Disaggregation-Aggregation
DL	Deep Learning
DM	Decision Maker
DSR	Dynamic Source Routing
DV-Hop	Distance Vector Hop Localization

FCMCP	Fuzzy C-Means Clustering Process
FDU	Fire Detection Unit
FFD	Forest Fire Detection
FFSS	Forest Fire Surveillance System
FILDA	Firelight Detection Algorithm
FIRMS	Fire Information for Resource Management System
FLIR	Forward Looking Infrared
FN	False Negative
FN	False Negative
FP	False Positive
FP	False Positive
FTCC	Fault-Tolerant Cooperative Control
FWI	Fire Weather Index
GERB	Geostationary Earth Radiation Budget
GIS	Geographic Information System
GOES	Geostationary Operational Environmental Satellite
GPRS	General Packet Radio Service
GPS	Global Positioning System
HSACP	Harmony Search Algorithm Clustering Process
HSI	Hue Saturation Intensity Color Space
HSL	Hue Saturation Lightness
HSV	Hue Saturation Value
HTTP	Hypertext Transfer Protocol
IDS	Intrusion Detection Scheme

IEEE	Institute of Electrical and Electronics Engineers
IF	Intermediate Frequency
IoT	Internet of Things
IP	Internet Protocol
IR camera	Infrared camera
KDD	Knowledge Discovery in Databases
LANDSAT-7ETM	Land Remote Sensing Satellite Enhanced Thermal Mapper
LANDSAT-8	Large Scale Dataset for Active Fire Detection/Segmentation
LEACH-C	Low-energy Adaptive Clustering Hierarchy-Centralized
LST	Land Surface Temperature
MAC	Medium Access Control
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MQ-2	Grove-Gas Sensor
MSG	Meteosat Second Generation
NDVI	Normalized Difference Vegetation Index
NOAA-16	National Oceanic and Atmospheric Administration
OPNET	Optimized Network Evaluation Tool
PFP	Pixel for Pixel
PRR	Packet Reception Ratio
QoS	Quality of Service
RF	Radio Frequency
RGB	Red Green Blue

RM	Random Forest
RPA	Robotics Process Automation
RSSI	Received Signal Strength Indicator
RTLD	Real Time Load Distribution
RTM	Radiative Transfer Model
RTMLD	Real Time Mobility Load Distribution
SeDrip	Secure Data Dissemination Protocol
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SMS	Short Message Service
SQS	Simple Queue Service
SVM	Support Vector Machine
TLPN	Three layer Perceptron Neural Network
TN	True Negative
TP	True Positive
UAV	Unmanned Aerial Vehicle
UCON	Usage Control
VIIRS	Visible Infrared Imaging Radiometer Suite
VSM-SL	Virtual System Module Source Language
WBANs	Wireless Body Area Networks
WSNs	Wireless Sensor Networks
YCbCr	Luminance, Chrominance blue, Chrominance Red
YUV	Luma and Chroma Components

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ABSTRACT

The emergence of Wireless Sensor Networks technology and Internet of Things has an extensive range of applications in category of monitoring the environment. In this thesis, we have studied the problem of monitoring and detecting forest fire as the potential application area of WSNs and IoT. Forest fires are the main reason behind the degradation of environment at present. The present forest fire monitoring system lacks in providing real time monitoring for each point in a target area at all the time and support early detection from threats. Forests fires possesses great deal of threat that disturbs the complete ecosystem and further leads to global warming and ozone layer depletion. Early detection of a potential fire event is the possible solution to reduce the cause or its risk up to 95%. There exist many techniques that can be employed in order to protect forests from fire. Satellite systems and Unmanned Aerial Vehicles are the systems that can be useful for the detection of forest fires. These systems can cover area of any size but not capable of providing real time information of the entire region of interest. Moreover, Satellite and UAVs based systems can only be used for monitoring and firefighting purposes. Therefore, the accurate prediction of forest fire at its early stage is critically important.

On the other hand, WSNs technology is most advantageous among others as it offers real time deployment of sensor nodes which gathers environmental parameters like relative humidity, atmospheric gases, light intensity and ambient temperature values. The other major advantage of using WSNs technology is that their scalable network can cover large hostile areas. The use of WSNs is rapidly increasing for many civil domains which include the coverage, real time monitoring, SAR, security, agriculture, remote sensing and many others. Smart sensors are the next big revolution in the WSNs technology which can provide several opportunities for major applications along with reduced risks and lower costs. In this thesis, we have gone through the various ongoing research trends and future aspects for potential WSNs in the application of forest fire detection. The key challenges of WSNs towards civil applications are also studied, including different sensors, topology, environmental parameters and communication technologies. Based on the survey of recent literature, we analyze the research challenges and present the insights for approaching these challenges in context of forest fire detection. The sensor deployment at region of interest gather useful environmental information continuously at day and night time, providing the recent and accurate information to the control stations. However, these

sensor networks when deployed, faces some serious obstacles like vulnerability to hostile environmental conditions, limited power resources which needs to considered carefully.

In our study we have proposed a framework using Wireless Sensor Networks technology and Internet of Things for monitoring the environment and detection of fire event at the early stage. Our framework includes deployment of specific wireless sensor modules in forest area, localization of faulty, event triggering sensor modules and the verification of fire event through image processing. The sensor modules are deployed deterministically in region of interest where each of the module transfers sensed information directly to sink or coordinator node. The sink node is located centrally at equal distance to each normal node such that the threat of fire can be detected as early as possible with less energy consumptions. To monitor the environment state at any time from remote places, we have integrated ThingSpeak IoT analytics platform. ThinkSpeak cloud platform provides data analytics in real time basis and data storage. The MATLAB interface of ThingSpeak analytics is used for the validation and evaluation of our proposed framework. The sensor network gathers the environmental data which is continuously monitors at ground station for adversaries through cloud platform using Internet. We did extensive experiments by training of sensor network in fire scenarios and normal condition to check the efficiency of proposed WSNs based fire detection system. It is observed from the experimentation that proposed framework using WSNs and IoT can provide immediate reaction for fire events while maintaining network lifetime.

The second aim of this thesis is to identify the faulty nodes in a sensor network. The sensor modules in larger number are deployed in the target area. The dense deployment of sensor modules covers large areas where it is not important that each of the sensor module has the prior knowledge about their location coordinates. The sensor network deals with the issue of node failures that affects the performance of network. Moreover, a fire event can be triggered by any of sensor module in a network. Therefore, it is very essential for the efficient working of a network that central server has the knowledge about location of each sensor module in a network. The second objective is framed to address the issue of node failures and finding the accurate location estimation of unknown sensor nodes in a network. An improved range free location estimation algorithm is proposed for the accurate estimation of location of unspecified sensor nodes. The location of unknown sensor modules is estimated using the information from 1-hop and 2-hop anchor nodes. The anchor nodes have the knowledge about their location coordinates and this information is used by other normal nodes in a network for computing global coordinates. The normal node collects 1-hop and 2-hop anchor's information which is utilized for finding the valid grid points. The proposed location estimation scheme is an improvement of distributed range free localization scheme and achieve better location estimation with minimum estimation error.

The third aim of this thesis is to verify the fire event for the reduction of false alarms. Presently, there are many techniques that have been designed for the detection of fire and apart from them, there are only few techniques that can do the verification as well as monitoring. There are many techniques for the simulation but only few for the implementation. Thereby, the whole idea is to design a system that can not only detect the forest fires but also verify the fire, so that some steps can be employed well before the disaster happens in order to save the environment. An image processing based algorithm is designed for the verification and confirmation of forest fire event. The classification of fire and non-fire event is carried out using rule based color model. The proposed model of fire confirmation uses histogram equalization, RGB and YCbCr color model approaches for the confirmation. The performance of the designed fire confirmation algorithm is validated through two set of images, where one set consists of fire like images and other consists fire images. The confirmation of a possible forest fire event is carried by implementing image processing technique and hence the fire occurrence is validated while achieving 93% of accuracy for true detection.

This research work is focused on designing an efficient framework based on WSNs technology and IoT, that can provide better accuracy for early fire detection system. This is practical application oriented work which is helpful in classifying fire and non-fire pixels for effective and early detection of forest fires.

CHAPTER 1

INTRODUCTION

CHAPTER 1

INRODUCTION

In this thesis we accentuate the importance of Wireless Sensor Networks (WSNs) and Internet of Things (IoT) for the application of forest fire detection. This chapter highlights the importance of forest fire detection and the significance of image processing for the confirmation of fire event. An exhaustive literature review pertaining the corresponding work towards the application of forest fire detection using WSNs and IoT is also presented. Forest fires are the most common peril in forests and it is an uncontrollable event that occurs in nature and poses a great deal of threat to the wildlife as well as for the people who live there. Forest fire causes serious health hazards due to the presence of smoke and other poisonous gases which disturbs and destroys the complete ecosystem. The forest fire event further leads to global warming and depletion of ozone layer. It is reported that each year from last decade, total number of 4 to 6 million wildfire events happened across worldwide [1]. The reported wildfire events across worldwide from year 2004 to 2019 are depicted in Figure 1.1. It is found from the study that from year 2004 to 2019 the noticed forest wildfire events lies in the count between 4 to 6 million every year.

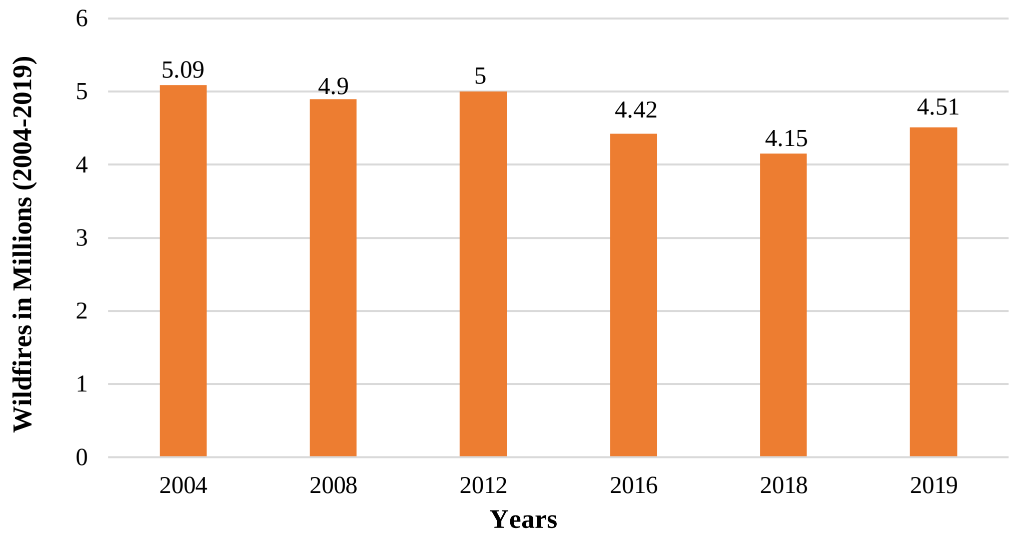


Figure 1.1: Globally reported events of forest fires

The spreading features of forest fires reveals that for fighting the fire event in order to minimize the damage or to prevent the cause, the monitoring center must be aware of threat at most 3 to 5 minutes after the initialization of fire event [2]. Early detection and accurate prediction of fire event is the most effective solution for fighting the trouble against fire. The early detection of fire, behavior of fire in terms of its spreading and speed are critically important for fire extinguishing.

1.1 FOREST FIRES

This section gives an outline of the global scenario for forest fires. It is very essential to study the forest fires to ratiocinate its background and to provide the justification for undertaking of study. The forest fires are the most uncontrollable event causes critical disturbance to complete ecosystem that needs to be tackled implementing WSNs technology. The following reason is the driving force behind for the undertaking of this research in order to prevent forest from fires. Due to the presence of various other problems, human civilization affects biological resources massively and ultimately leads to the degradation of biological diversity. There is a strong requirement of planning forest management with efficient tools for the preservation of biological diversity. India is a country having rich biodiversity of flora and fauna. The degradation of forests due to forest fires and other activities affects wildlife and poses threat to habitat which has been a matter of concern. An act (Wildlife Protection Act, 1972) for protecting wildlife, animals, birds, plants and things that are connected to wildlife has constituted in order to ensure the environmental and biological safety of the country [3]. The establishment and supervision of protected areas considering the optimal use of resources, conservation and rehabilitation of ecosystem are addressed in article 8 of CBD (Convention on biological diversity) [4]. The protected areas of a country are very valuable and of great significance for the preservation of natural and cultural resources. The good conservation of protected areas provides various opportunities and benefits in terms of ecological, educational, economic and social values. However, these protected area in a country are exposed to various threats. The most common hazard that happens in a forest is wildfire that completely disturbs and destroys ecosystem and wildlife. The occurrence of wildfire across the globe in increasing every year that causes a great deal of threat to entire biodiversity.

1.1.1 Terminology of Forest Fires

Ever since the science starts to begin the terms fire risk and fire hazard are related to forest fire management. There found various different expressions and definitions for these two terms. The proper understanding of fire management terms such as fire hazard, danger, risk, vulnerability, etc. is important as wrong interpretation may lead to misunderstanding from their real meanings.

Fire risk is defined as the combination of fire likelihood chances and the consequences of identified fire hazard. It is used for measuring the loss and harm from a fire activity. Fire risk determines as the probability dangerous consequences of fire and expected loss for damage assessment in terms of loss of lives and natural property. The prediction of fire risk is expressed by the equation shown below.

$$Fire\ Risk = Fire\ Hazard\ \times Fire\ Vulnerability$$

Where, fire hazard is the characteristic of fire condition and fire vulnerability is the amount of loss. Fire hazard is a characteristic of fire condition that causes damage to environment, property, wildlife and people. The definition of fire hazard states that it's a phenomena or manmade activity has the potential of physically damaging the environment which results in loss of wildlife, loss of natural property, and leads to the degradation of environment. Fire vulnerability is the amount of loss takes place to a specified portion at risk and fire vulnerability is measured as 0 for zero damage and 1 for overall damage [5]. Fire vulnerability is a combination of conditions and processes which are designed considering various environmental, physical, economic factors for evaluating the impacts of hazard.

1.1.2 Indian Scenario of Forest Fires

The forest cover of India is around 21.6% out of total area cover of India which is approximate 3.3 million Km2. The geometric location of India makes it a country with mega biodiversity. India has different climate regions which includes Himalayan region at its northeast, tropical zone at south and desserts in northwest part of the country. The vegetation in Indian forests varies form evergreen forests of south west region and alpine forests in north region. There exists many semi-green, tropical hill and pine forests in between these two-extreme vegetation of forests [6]. Due to the involvement of humans and their lifestyles the forests in India declining very fast. The vulnerability of fire incidents in Indian forests differs from one place to another based on the kind of climate and vegetation. On the basis of forest records, it is observed that more than 50% of forests in India are vulnerable to fire and Rs. 450 crores are Indian annual loss due to forest fires. Over 10,500 incidents of forest fire have been reported in the year of 2016 which are five times more than the reported events of previous year [7].

1.1.3 Forest Fire Impacts

Most of the reported fire incidents in India caused by human interventions. These fires adversely affect Indian forests in many perspectives such as social, economic and ecological impacts. The adverse impact of forest fires in India includes loss of vegetation such as fuel wood and timber, loss of natural habitat such as microorganisms, wildlife and biodiversity. The average estimated loss due to forest fires is very high which strong demands for such a system that can reduce the cause or stop it. The fire tolerance of trees in thick forests ensures the long-term fire exposure in forest. It is believed that due to human interventions in forest for grazing and triggering intentional fire for clearing field's further leads to the degradation of forest areas. This intervention of human in forests for making goods leads to the conversion of thick forests to dry grasslands and scrublands and becomes highly prone to fires. It is also observed that with the increase in forest utility by humans, the noticed wildfire events also increased [8]. The wildfires are significantly impacting the forest areas. The flames of fire is the reason behind killing of major vegetation. The soil for a short period of time becomes more like a concrete surface after wildfire incidents. The healthy trees and roots usually suck up the moisture when it rains but after wildfire the water has nowhere to go. Overtime the landscape could change entirely, with trees replaced by shrubs and grasses. Wildfires are usually a necessary part of the regeneration cycle but as wildfires become so frequent, it poses a great deal of threat to complete ecosystem. Forests plays a huge critical role in capturing carbon and taking in more greenhouse gases. The more forest fires are burning more carbon gets released and more accelerating of climate changes happening.

1.1.4 Causes Responsible

Forest fire is an uncontrollable fire that happens in nature and causes threat to forest wealth and entire regime. The two major causes responsible for forest fires are environmental and human related forest fires. The natural fire happens due to natural calamities whereas human related fire occurs due to the intervention of human intentionally or unintentionally. Forest fire is one of the major reasons behind forest degradation. At present, there are many agencies working for the conservation of forest wealth. Their efforts can only be successful if the factors causing of deforestation are not taken into account [9].

1.1.5 Natural Forest fires

The event of natural forest fires occurs due to the lightning, striking of rocks and the friction among timbers. The wildfires are entirely dependent on global climate and precipitated by climate conditions. The years of temperate climate allows the growth of vegetation. If the vegetation is followed by the period of strong heat with little moisture the vegetation dries out. This dried out vegetation can act like a giant mass of kindling where a single spark can set fire to whole area. Fires can be started by lightning strike during the storm and it is also possible for a wildfire to begin from a spontaneous combustion. As the massive dead vegetation decomposes, it releases heat. When this is intensified by heat of Sun, the dry outer layer of composting mass ignites. Wind during fire also a particular danger as it sparks fire to travel quickly and blow sparks long distances to initiate more fires. The crawl fire may move along the ground consuming fallen leafs and dry vegetation. The crown fire may move around the tree tops and sucks all the oxygen from the area below and destroys anything underneath [10]. In many forests the most efficient way to prevent forest fires is to undertake controlled burns which diversifies the local species and reduces the amount of fuel available to wildfire.

1.1.6 Manmade Forest Fires

The manmade fires happen due to the involvement of humans knowingly or unknowingly. Humans are the biggest cause of forest fire by some margin as fire may be started accidently or a deliberate action. The manmade fire in forest happens because of the excessive logging operations, burning of wastes, fire caused during cleaning and construction, fire caused form any crashed vehicle or unknown persons. The carelessness of human activities plays major role in starting of a fire. Train wheels on the track, power lines and even shooting the target with a gun can create a spark. The increase in human activity is likely to be increasing the severity and number of wildfires [11].

1.1.7 Damage Assessment

Damage assessment is important while recovering from wildfires. Fire damage assessment addresses the burn severity of land which is essential after the fire event.

The damage assessment of forest fires requires the understanding of consequences of fire for its evaluation and analysis [12]. The assessment of forest fire damage is very complex where the property of forest is managed by multiple authorities for their goods. The fire damage assessment helps in determining the situational awareness of the affected land through remote sensing. The fire fighters and decision makers at remote station can monitors the affected zone remotely and take necessary precautions for future deployments.

1.2 NEED OF FOREST FIRE DETECTION SYSTEM

Forests are one of the most important resources and necessary part of our ecosystem. Humans for their survival are completely dependent on forests from the fresh air we breathe to the use of natural products that we rely on. The forest fire incident happens because of natural causes and manmade activities. Every healthy forest contains some dead plants, trees that are prone to fire easily. Forest fires threatens the wildlife directly and the release of poisonous gases during fire event can affect all lives. Every individual is responsible for protecting the environment from forest fire disaster. Every year from fire million hectares of land are destroyed causing some serious damages to the natural environment. Fire detection system is very important for the detection of fire to stop the cause or to reduce the effect of fires [13]. The continuous monitoring of a fire prone area and predicting fire at its initial stage can significantly reduce the risk of fire as well as firefighting cost.

1.3 FOREST FIRE DETECTION SYSTEMS

For a successful fire management program early detection plays an important role. Fire attack at a very initial stage depends on time, delay, various fuels, weather and the size of fire. Fire detection in its very early stage increases the probability that it can be controlled before it converts to a great damage or an uncontrollable event and early detection also reduces suppression costs and negative environmental impacts. Fire monitoring is the process of characterizing and mapping the parameters of a fire which includes the information of location, fire perimeter, active fronts, size proximity and inhabited areas that helps to know the present status and changes of an active fire [14]. Once the decision has been made to begin the suppression, the importance is then given to fire monitoring which is very important and critical for suppression planning and public warnings. Fire detection systems that have been developed are used for both actions that is detection and monitoring phases. There are four different ways for detecting fire:

1. Smoke
2. Heat
3. Temperature and Gases
4. Flames and Light

Smoke is one of the most reliable parameters for fire detection at daytime because of its spectral signature that is its color and motion features. The characteristic of smoke varies accordance with the burning and the combustion conditions. The fire detection through smoke having major drawback that it gets easily affected by clouds, fog, haze and shadows. Heat also provides a strong measure for the detection of fire which is having maximum possibilities during night time. The emission follows Planck's Law whereas overall energy follows Stefan-Boltzmann's Law. The value of ambient temperature, relative humidity, and other gases present in the atmosphere plays a significant role for the detection of fire event. In any scenario of fire, the value of temperature rises certainly whereas the humidity falls with the rise in temperature, also there exhibits the presence of poisonous gases. An efficient forest fire detection system can be designed considering these parameters for the accurate prediction of forest fire by the continuous monitoring of an area for measuring its state at any time. Similarly, the intensity of light and flames also can be useful for the detection of a possible fire event. On the basis of the review conducted we have identified the various systems for the forest fire detections [15]. There are mainly four type of systems through which forest fire like disasters can be detected and monitored.

1. Human based observations.
2. Satellite based systems.
3. Optical cameras.
4. Unmanned Aerial Vehicle based systems.
5. Wireless sensor network.

1.3.1 Human based observations

In the last decade due to less technological development and less budget the human based observations for the disaster management were prior. Forest fire detection based on human observations and forecast predictions which are not reliable at all that can stop the cause and reduce it. These human based observations cause long delay and many false detections. Generally, humans are involved in every detection method. There will be a direct observation of fire and its smoke which is based on the probability of human detection. Human based observations depend on patrolling, monitoring towers, ground staff and general public is involved for detection purpose. In a study it is found that more than 90% of fires that is reported to New South Wales Rural Fire Service from 2004 till 2009 were estimated by the general public and authorities also from 2001 to 2014, 70% of fires were reported by the general public and 10% of fire reported by the authorities in Portugal [16].

1.3.2 Satellite based systems for Forest Fire Detection

The satellite system having limitations that the system failing for fast effective response. In satellite system the coverage is not continuous with time. In satellite system the images and the data are analyzed through remote sensing. These systems are capable to cover large areas but their response is not effective because the clouds and the reflections causes due to the interference of other particles reduces the spectral resolution. The greatest advantage for those who battle fires is early detection of fire, NASA is working on a system called FireSat that will help providing early detection of fire [17]. Fires can easily and very quickly grow from small areas to area in large size which is hard to contain. Therefore, early detection is one of the major advantages that fire fighters can have. FireSat, the locater is being developed as a cooperative effort between the agency’s Jet Propulsion Lab in Pasadena and Quadra Pi R2E of San Francisco. The team plans to equip satellites with roughly 200 thermal infrared imaging sensors, which will tirelessly search the globe for signs of danger. Fires as small as 35 feet wide can be sensed by the system. Further, they can be found on an average of 15 minutes of igniting and also with in FireSat’s capabilities is spotting oil spills, explosions, and a number of other disasters.

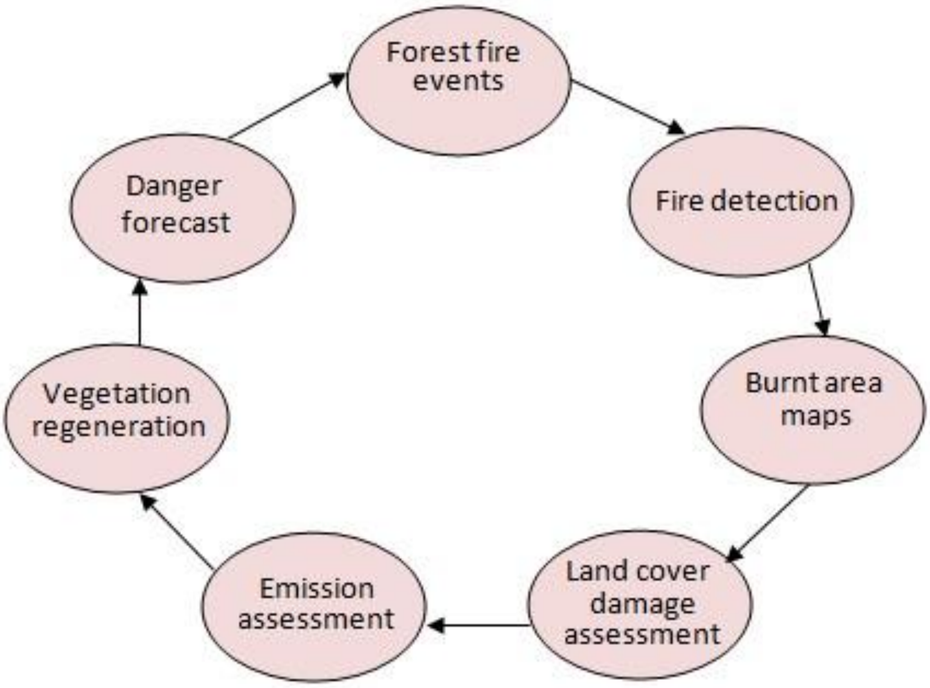


Figure 1.2: Information process of Satellite system for forest fire management cycle

The information from Satellite system can be utilized for monitoring current fires, mapping of burnt areas, damage assessment, emission evaluation, and vegetation assessment and for predicting the likelihood of forest fires. This complete information evaluates the full disaster management cycle as can be seen in Figure 1.2. The information from satellite used to monitor thermal geo-reference information related to area of interest. Sensors present in Satellites measures various parameters that present in land or in atmosphere that may cause forest fires. Thermal sensors measure amount of heat and utilized for detecting fire hotspots [18]. Optical sensor and infrared sensor measure emissions that are visible in near infrared region are utilized for mapping land cover in order to identify burnt areas. The combination of various space-based and in situ sensors are utilized for danger forecasting.

1.3.3 Optical cameras based Forest Fire Detection

In order to reduce the false alarm that caused due to various phenomena like cloud, activities of human and the reflection the optical thermal cameras are used. These systems give a line of sight vision and there will be no vision when there is big tree and mountain. These systems can cover large with less number of camera towers, each tower equipped with thermal camera that detects smoke [19].

1.3.4 Unmanned Aerial Vehicle based systems

Unmanned Aerial Vehicles (UAVs) plays a significant role in the application of forest fire detection. UAVs offers a network of group of vehicles and sensors that are operating in various dynamic and uncertain conditions serving particular applications. The biggest advantage of utilizing UAV is their capability of providing real time situational awareness which is critical component for managing large scale disasters where managers have to make decisions and locate resources [20]. UAV equipped with optical sensors such as vision and infra-red cameras are capable of generating situational awareness in very large scale of wildfires.

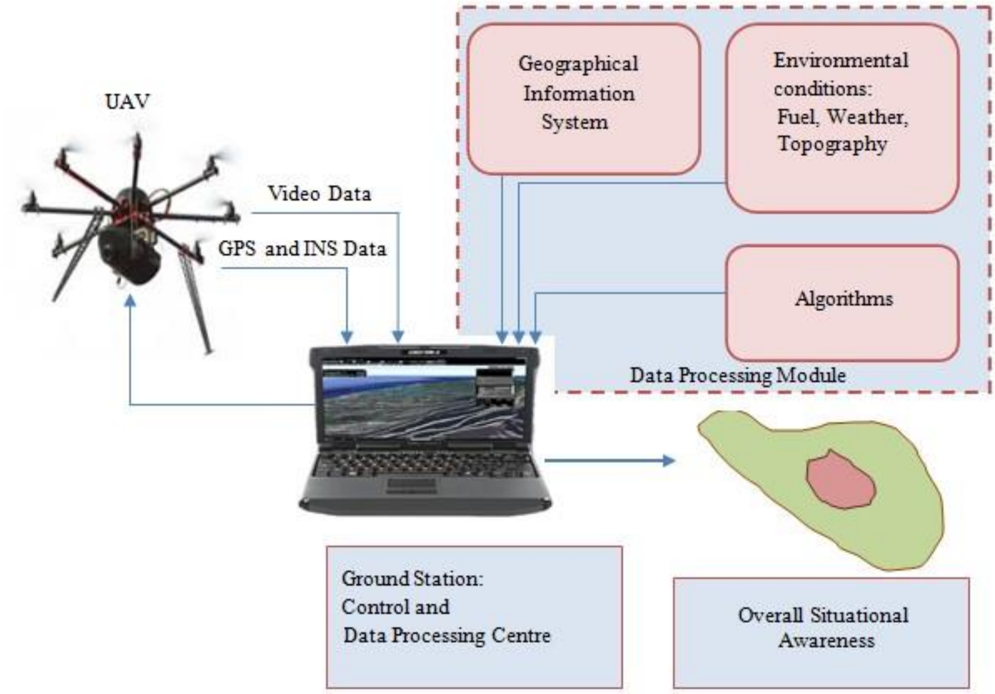


Figure 1.3: Working of UAV based fire monitoring system

The overall concept of using UAVs for monitoring wildfires is depicted in Figure 1.3. Initially a fire fighter launches UAV in region of interest after the detection of smoke. The ground station continuously monitors the area by the data provided by UAVs for the situational awareness. UAV also provides the information about the location that helps firefighters for making operational trajectories. The fire fighters control the operation of UAV by providing coordinates of locations that acts as pathways for UAV. Fire information along with other data like vegetation assessment, topography, and moisture conditions will be forwarded to propagation algorithm in order to generate information for not only current scenario of fire but also for predicting future conditions which ultimately helps in effective decision making [21].

1.3.5 Wireless Sensor Networks based Forest Fire Detection

The advancement in sensors makes WSN the best suitable technique for the detection of forest fires. Sensors provide more accurate data from the zone at any time [22]. The big advantage is their scalable network and their coverage for any size of area. Sensors are able to observe physical parameters around them. We can connect as many as devices to WSN and can add multiple sensors for collecting various parameters. Sensors can be placed anywhere in most typical locations and there is no requirement to build towers.

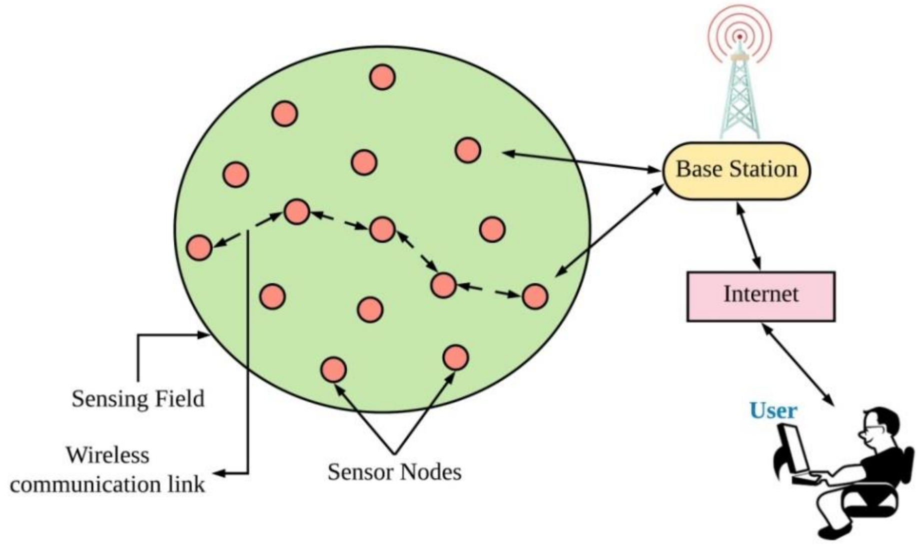


Figure 1.4: Overview of Wireless Sensor Networks architecture

Figure 1.4 presents the system for overview of a fire detection system using sensor network. The system includes sensor nodes, sensing field and base station. The environmental parameters are monitored regularly through the deployed sensors in an area of interest. Every sensed data is transferred through one node to other and further advances to the base station. The base station analyses the monitored information for decision making and provides the data to different user for analysis across the world through internet.

1.4 Wireless Sensor Networks and Inetrnet of Things Overview

A Wireless Sensor Networks (WSNs) is a network that comprises of thousands of application specific sensor device. These sensor devices are deployed in region of interest and capable of measuring at least one parameter from the environment that may be temperature, humidity, instance, smoke, gases, heat, light intensity and many others. Besides of measuring environmental parameters, these sensor nodes also comprise of memory and power unit for processing the information. The sensed information communicates from one sensor node to other via wireless means. The sensor nodes are mostly powered through batteries and predictable for providing long life as sometimes the recharging of a device is difficult because of their deployment in hostile and tough environments. The cost of these sensor nodes is low, hence making it suitable for deployment in large scale [24]. A sensor network consists of different type of application specific sensor nodes which are deployed in forest for measuring the state of region at any time. The positions of these sensor nodes in a network not necessarily known or pre-determined. The biggest advantage of senor network is their scalability, allows the deployment of sensor nodes in most inaccessible environments while providing maximum coverage. Sensor network can efficiently cover area of any size and hence, this network is most suitable for predicting forest fires.

Wireless Sensor Networks are introduced in the application of forest fire detection for protecting the environment from this disaster. With the evolution in integrated circuits designs the computational devices size becomes smaller providing more efficient and fast performances. The growing wireless communication technology together with advanced integrated circuits provides an efficient network paradigm for multiple tasks. With the advancement in technology and large scope of WSNs, it draws attention from various industries and researchers for meeting the challenges. WSNs is an emerging field consisting of large number of small sized, low powered and multi-functional sensor motes that are able to measure, process and communicate the measured data through collaborative process [24]. The advancement of sensor network makes it more suitable for real world applications like in this scenario of monitoring the environment. The evolution of Internet of Things (IoT) provides an efficient deployment paradigm by integrating with sensor network. It allows the connectivity of the deployed sensor devices with internet, which enables smart devices to contribute as

Internet of Things. IoT consists of interconnected networks which provides various facilities for the process of information gathering and its communication by implementing standard communication protocols. IoT enables a network where each device communicates with each other for sharing of information. The integration of WSNs with IoT provides the connectivity of sensor node to the Internet dynamically for collaboration and accomplishment of tasks [25]. The basic architecture of WSNs and IoT serving environmental monitoring for the detection of forest fires is depicted in Figure 1.5.

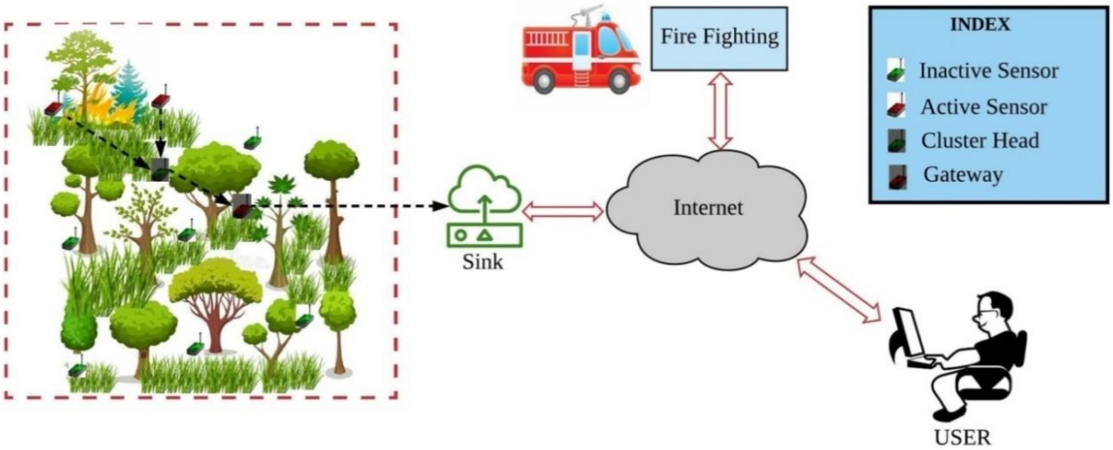


Figure 1.5: General architecture of fire detection system using WSNs and IoT

The sensor devices are distributed in forest area for measuring various environmental parameters such as temperature, light intensity, heat, smoke, humidity, gases, etc. Each of the deployed sensor node communicates with other neighboring nodes for communicating the measured information to the sink node. This sink node servers as a gateway which gathers the field information and transfers it to the ground station through internet for its analysis, decision making and fire-fighting.

1.4.1 Scope of Wireless Sensor Networks

The major advantages of WSNs are their small size, communication at low costs which enables the industries to build sensor capable for monitoring various tasks. The scalable network of WSNs enables their implementation in diverse fields such as forest fire detection and monitoring, agriculture, weather monitoring, hospitals (WBANs), asset tracking, process control and many others [26]. The detailed structure of the current trends in wireless sensor networks for event detection is discussed in Chapter 2. The economic factors, novelty, liability and technical superiority are the driving force behind the adoption of WSNs technology. The recent advances in integrated circuits and communication technology has enabled scope of WSNs for multiple applications. The future advances of WSNs considers the production of more powerful and less costly devices, so that the technology can be implemented for majority of application providing efficient solutions.

1.4.2 Market Opportunity of Wireless Sensor Networks

The market of the wireless sensor network is increasing and expected to reach 93.86 billion USDs by the year 2025. The advancement in the technology of WSNs transforms the way of communication in physical world. To reach high levels of accuracy, efficiency with low costs, the organizations requires more attention, intelligence and real time visibility towards operational data. Wireless Sensor Network is a network of sensor nodes which are deployed in an area of interest for monitoring environmental and physical conditions through wireless means [27].

Figure 1.6: Market of Wireless Sensor Networks (2018-2025)

Figure 1.6 presents the current market state of WSNs from the year 2018 to 2019. The market of wireless sensor network is estimated to reach a compound annual growth rate (CAGR) about 20.5% around the period of 2018-2025. The major applications of WSNs involve robotics which includes sensing through advanced robots, coordination among robots, path planning and its navigation, and localization of robots. The advanced sensors help immediate response from real time conditions and generates an alarm for the system such as forest fire detection, field monitoring, many others. The rapidly growing automation and electronic industries, increases the demand of WSNs for detection, monitoring and security. The increase in reliability along with the better technology of communication acts as the most significant factors in ruling the market for WSNs. Globally, latest trends in WSNs are the future investment in making new technologies and advancing previous infrastructures for supporting IoT and automation industries. Recently, the manufacturers of sensors are investing in technologies for tackling emerging trends and support system like smart cities, vehicle automation that significantly depends on WSNs [28]. The recent innovation in the sensor network like intelligent sensors, expected to support the relative growth for present market of wireless technologies.

1.4.3 Node Failure in Wireless Sensor Networks

Sensor nodes are commonly deployed in forest region for measuring various application specific environmental parameters such as heat, light intensity, temperature, gases, smoke, temperature, etc. for the application of forest fire detection. These deployed sensor nodes collect the environmental data regularly and communicates the monitored information of the field wirelessly to the base station. The sensed information of the field is transferred to the sink node through multiple hops. The sink node is connected to the surrounding network through gateway. The gateway node collects all sensed information of the field and transfers it to the ground station for processing and analysis. In large scale deployment, the sensor nodes may be static or mobile and it is not necessary that each node has the prior knowledge about their location. Each of the sensor node has a computational unit and also equipped with communication device. The coordination among the sensor nodes in a network must provide best performance for the efficient working of a sensor network. There are two main factors that affects the performance of WSNs by causing failure in operation of sensor nodes. The failure of sensor nodes due to environmental factors in forest or because of fabrication issues. Second factor is the draining battery power of any deployed sensor node affects that particular node to drive away from the network [29]. This failure of sensor nodes directly affects the network, hence decreasing the quality of overall WSNs. The transmission of information from source to sink in WSNs should be reliable and temporal constraint for achieving minimum detection to notification delay. In case if there is true fire event and the system detects non fire at its output, then the system is not reliable and depicts false alarm. Therefore, reliability and temporal constraint are the important concerns for an efficient fire detection system.

1.4.4 Energy Consumption in Wireless Sensor Networks

Energy is the most important resource that must be utilized properly. In WSNs, the efficient energy consumption is one of the most interesting design issues. As the size of sensor node is small, it can only be provided with limited power resource. In the real time application scenario of forest fire detection, because of the deployment of sensor nodes in hostile environments it is impossible to charge each node. Also, each sensor node in a network plays dual functioning in terms of data gathering and it’s routing in a multi-hop wireless sensor network. Therefore, draining of any sensor node in a network cause serious issues in networks efficiency. Additionally, the applications that requires continuous monitoring of an area over long period needs to be efficient for energy and utility perspectives. The power is dissipated in sensor network during the data processing, transmission, reception and inactive listening phases [30]. The consumption of power during transmission phase is maximum portion of energy consumed in a network. The energy consumption becomes very significant as most of the sensor nodes remains inactive during the continuous monitoring over long periods.

1.4.5 Delay Constraints in Wireless Sensor Networks

The detection to notification delay is the main factor that governs the efficiency of WSNs. For any application of wireless sensor networks minimum is delay maximum are the chances of accurate estimation. The advancement of WSNs enables remote sensing of an environment for measuring the state of region at any time. In WSNs most of the energy is consumed during the waiting time of active sensor device for a packet to receive [31]. The scheduling of a sensor node from active to inactive and inactive to active mode results in considerable delay as transmitting sensor needs to wait until receiving node turns to active mode. This delay affects the performance of network for sensitive applications such as forest fire detection. Low power processor, limited memory and low power, low data rate radio transceiver are some of hardware constraints of sensor node. Sensor node is designed considering low power processor therefore processing and memory is limited.

1.4.6 Wireless Sensor Network Applications

The development of WSNs originally motivated from defense applications as for the battlefield surveillance some nodes are deployed in order to know enemy movements. However, with the advancement in sensor network technology, WSNs are now implemented for various civilian and industrial applications including military applications, environmental monitoring for the detection of adversaries, healthcare application, agricultural applications and many others [32]. For the application of forest fire detection, large number of sensor nodes are dropped from UAV or an aircraft at forest in order to detect the fire. Once the fire is detected the necessary action and preventions can be taken. For the application of biodiversity mapping, the sensor nodes are deployed in forest to know the biodiversity of wildlife. In recent years majority of the research has been conducted for developing various services in order to make the WSNs reliable for different applications. This research mainly focuses on the localization and event confirmation services that are very essential for application of forest fire detection.

1.5 DATASET DETAILS

Table 1.1 Description of dataset for their usage

Dataset	Number of Images	Image Size	Frame Rate	Format	Usage
Flickr-Fire dataset, 2015 [33]	2000	1024 × 768	1 fps	png	Fire and Non-fire images, fire region classification
Corsican Fire Database (CFDB), 2017 [34]	500	1024 × 768	1 fps	png	Detection and Extraction of fire region
A Large Scale Dataset for Active Fire Detection/ Segmentation (LANDSAT-8), 2020 [35]	31000	7600 × 7600	1 fps	tif	Active Fire Detection/ Segmentation

Table 1.1 presents the description of dataset in terms of their usage. These datasets are used for analyzing the performance of proposed fire detection system.

1.5.1 Flickr-Fire Dataset

Flickr-Fire Dataset contains about 2000 images; and half of the images presents fire flames of different environments such as in thick vegetation, urban area or fire in car, etc. Each of the image has been marked manually as “fire” or “non-fire” by the experts. The Flickr-Fire database guarantees its free public use as it comes under Creative commons license [33]. The sample images of the Flick-Fire database is depicted in Figure 1.7.

(a) (b)

Figure 1.7: Sample images from Flickr-fire dataset

1.5.2 Corsican Fire Database

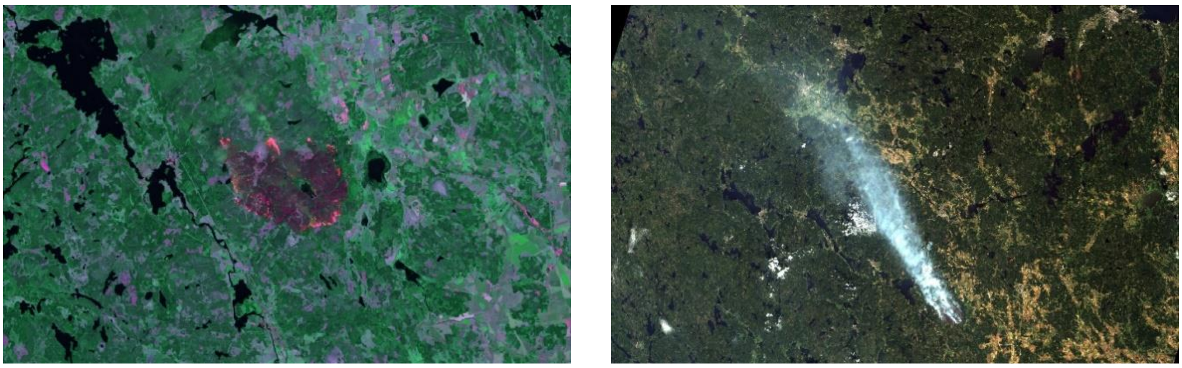
Corsican Fire Dataset contains 500 images that includes images of fires having heterogeneous colors, multiple textures, vegetation, light conditions and different environments. Each of the fire image is manually segmented by building a ground truth through experts. The Corsican fire dataset consists images of both spectrum having size of 1024 × 768 pixels and images are available for free public use in lossless png format [34]. The sample images of the Corsican Fire database is depicted in Figure 1.8.

(a) Red Colored Fire (b) Orange Colored Fire (c) Yellow colored Fire

Figure 1.8: Sample images from Corsican fire dataset having different fire color value

1.5.3 LANDSAT-8 Fire Database

Landsat-8 dataset of forest fire was created from Satellite Landsat-8 images in 2018 from South America. More than 31K of images were managed (15TB of data), with active fire pixels being found on approximately on half of them. The original Landsat-8 scenes (with ~7,600 x 7,600 pixels) were cropped into 128 x 128-pixel image patches. The masks are in binary format where True (1) represents fire and False (0) represents background, and were generated [35]. The sample images of the LANDSAT- 8 Fire database is depicted in Figure 1.9.



(a) (b)

Figure 1.9: Sample images from Landsat-8 dataset

1.6 Performance Indices

To check the validity of the propose techniques and to evaluate the performance of work various indices are considered on the basis of elaborative literature study for state of art approaches. The four possible events are considered for calculating various performance indices. For deriving the classification of fire event True Positive (TP) and True negative (TN) are computed and for the classification of non-fire event False positive (FP) and False Negative (FN) are computed. TP result indicates that the event is accurately identified as the fire event whereas TN indicates that the accurate identification of non-fire event. On the other hand, FP result indicates that image is predicted as fire image but actually it is not a fire image whereas, FN result indicates that the image is identified as non-fire image but it is actually a fire affected image. On the basis of these four predicted events different performance indices are evaluated that are mentioned below:

i) **Precision:** It is the ratio of all positive predictions as it considers only positive predictions. It is measured as the ratio of True Positive to total predictive positives. The percentage range of precision lies in a range between 0 to 100% as it is represented by Eq. (1.1). Precision is used to measure the deviation in input data from its real value and it estimates how precise and accurate model is working.

$$Precision = \frac{TP}{TP+FP} \tag{1.1}$$

ii) **Recall:** It is also known as sensitivity which is used for measuring the capability of model that how many actual positives model can capture. It is measured as the ratio of True Positive to total actual positives as it is represented in Eq. (1.2). The sensitivity result provides the measure of model's capability for correct classification in order to identify true fire pixels. The percentage range of recall lies in between 0 to 100% and more is the recall closer to 100% more becomes system ability for correct detection of fire events.

$$SN = \frac{TP}{TP+FN} \tag{1.2}$$

iii) **F-Score:** F-Score is the function of Precision and Sensitivity which is measured to provide the test performance efficiency. F-Score takes both False Positive and False Negative events into account and finds the balance among Precision and Recall values. It is measured as the weighted sum of precision and recall outcomes and is represented as Eq. (1.3). The percentage range of F-Score lies in between

0 to 100%, and more is the F-Score closer to 100% more becomes system ability for correct prediction of false fire events.

$$F - Measure = \frac{(2 * Recall * Precision)}{(Recall + Precision)} \tag{1.3}$$

iv) Accuracy (Acc): It is measured as the ratio of correctly predicted observations to the total number of observations and expressed as represented in Eq. (1.4). The percentage range of Accuracy lies in between 0 to 100%, and more is the Accuracy closer to 100% more becomes system ability for accurately predicting true fire events.

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \tag{1.4}$$

v) Estimation Error: The estimation error (Δe) is measured for calculating the difference between the actual location of sensor node and the estimated position of sensor node. The estimation error is expressed as Eq. (1.5).

$$\Delta e = \sqrt{(x_r - x_e)^2 + (y_r - y_e)^2} \tag{1.5}$$

where, (x_r, y_r) is real position and (x_e, y_e) is the estimated positions.

vi) Average Error: It is generally referred to as average of all errors. The average error is expressed as Eq. (1.6). The mean and the deviation from mean are calculated for estimating the average error.

$$\Delta E = \frac{1}{n} \sum_{i=m+1}^{n} \Delta e_i \tag{1.6}$$

1.7 SOFTWARE DESCERIPTION

All of the experimentation work that is carried out in this thesis is done by using ThingSpeak IoT Analytics and MATLAB 2018b environment on a machine with configuration Intel Core i3 processor with clock speed of 3 GHz and 8GB RAM.

1.8 MOTIVATION

Forest fires are life-threatening disaster and causes damage to environment that always start either naturally caused or by manmade activity. Forest fires poses a great deal of threat to entire wildlife and human lives and causes some serious health hazard issues due to the release of poisonous gases and smoke. The harmful effects of forest fires disturb and destroys the complete ecosystem. The human interventions in forests for their goods has increased which leads to the deforestation. Some of reckless and careless of human behavior such as smoking of cigarette, electric sparks, or by any source of ignition cause the uncontrolled fire. Recently, it is noticed that with the increase in number of human interventions the incidents of forest fires has increased. According to a survey more than 70% of wildfires are initially ignited through human causes [36].

Forest fires are the most serious issue across worldwide as it leads to global warming and ozone layer depletion. It is observed from the study that the incidents of forest fires across the world lies in between the range of 4 to 6 million every year. It is important to regularly monitor the environment to know the state of any region for its protection and preservation from the disaster of forest fires.

The increased number of forest fire incidents have increased the demand of early forest fire detection systems. The accurate prediction of fire at its initial stage is the only solution that can stop the cause and reduce it to some extent. The early detection of a forest fire is still an open research challenge for meeting the requirement of reliability (reliable transmission of information from source to sink) and temporal resonant (minimum delay of detection to notification). The real time monitoring of an area to measure the state of region at any time equipped with early detection of fire is the possible solution that can reduce the risk upto 95%. On the basis of this motivation and vast literature survey presented in chapter 2, some of the research gaps have been formulated which are discussed in the following section.

1.9 RESEARCH GAPS

On the basis of literature conducted we have found different approaches that can be used for forest fire detection. Wireless sensor networks offer various advantages over other techniques of forest fire detection. The biggest advantage of detecting fires using WSNs is their scalable network and offers more accurate detections at comparatively low cost. Depending upon the elaborative literature survey of various WSNs based forest fire detection techniques some of the research gaps are formulated which lead as the foundation for objective framing of this research work.

1.9.1 Research Gap 1: To achieve the minimum delay and QoS parameters

In order to achieve the real time analysis in Wireless Sensor Networks the efficient deployment of sensor nodes is essential. The efficient fire detection system must support minimum delay and quality of service parameters. Efficient deployment of sensor nodes measures the environmental parameters and communicate the collected information to the ground station for its analysis. For the accurate early detection of what can possibly be a fire event requires reliable transmission of information in network and minimum notification to detection delay. The efficient performance of WSNs based fire detection system relies on these two factors of reliability and temporal constraint. As minimum is the delay between notifications to detection maximum are the chances of early detection.

1.9.2 Research Gap 2: To address the localization and accuracy issue of WSNs

The determination of physical coordinates of sensor nodes in WSNs is a challenging issue. The real-world implementation requires dense deployment of sensor nodes for measuring the state of environment at any time. Since these sensor nodes deployed randomly through airborne devices in hostile environment, it is not necessary that each of the sensor node has the knowledge about its location in a network. An alert can be triggered by any sensor node in a network therefore it is essential that each node has prior knowledge about their location coordinates.

1.9.3 Research Gap 3: To reduce the false alarm rate in case of forest fire detection

The accuracy of forest fire detection system depends on the performance of system in terms of true detection and false detection. For an accurate fire detection system, it is essential to reduce the trigger false alerts. The confirmation of fire event is necessary for the accurate detection of forest fire event.

1.9.4 Research Gap 4: To improve the life span of sensor network and energy issues

Energy is the most important source that must be utilized efficiently because it is impossible to recharge each node in Wireless Sensor Networks. Therefore, designing of an efficient routing algorithm for increasing the lifespan of san network is important concern.

1.10 OBJECTIVES OF RESEARCH WORK

The early detection of forest fire highly relies on continuous monitoring of environment for measuring the state of region at any time. Thus, to predict the fire event at its early stage by analyzing the sensed data in real time an efficient deployment of sensor nodes is required. Additionally, localization and confirmation of fire event are other important services that are required for an accurate detection of fire events. Therefore, the goal of this research lies in designing of Wireless Sensor Networks and Internet of Things assisting early forest fire detection system by aiding real time analysis, localization and confirmation of fire event.

The outline of early fire detection based on real time analysis, and fire confirmation, localization problems are addressed in this research work is based on the objectives listed below:

Objective I

To deploy sensor nodes efficiently for the collection and analysis of environmental data in real time.

Objective II

To design an efficient localization algorithm for estimating the location of sensor nodes and improving accuracy rate.

Objective III

To design a fire detection algorithm for the confirmation of fire event.

1.11 THESIS OUTLINE

This thesis includes six chapter inclusive of this chapter comprising the basic introduction of this research work, highlighting preliminaries associated with this research. Rest of the thesis is oriented as follows:

Chapter 2 presents the detailed discussion of the literature survey done on various Forest fire detection approaches proposed in the past highlighting the state of the art work done in this field. It also discusses the details of identified research gaps in the current literature and objectives formulated for our research work.

Chapter 3 deals with the objective 1 proposed in this research work. An early forest fire detection system is proposed using WSNs and IoT. This chapter deals with the real-world deployment of smart sensor devices in region of interest for monitoring the state of environment at any time to detect the adversaries at their initial stage.

Chapter 4 addresses the localization problem in WSNs by designing and implementing an improved localization scheme for the accurate estimation of location of unknown sensor nodes in a network.

Chapter 5 deals with the implementation of image processing algorithm for the confirmation of fire detection. This chapter highlights the proposed image processing algorithm to classify fire and non-fire images.

Chapter 6 concludes the research outcome of this thesis along with the major contributions and provides the future scope for the extension of this research work to make it robust for the real-time accurate detection of forest fires.

CHAPTER 2

LITERATURE REVIEW

CHAPTER 2
LITERATURE REVIEW

A numerous amount of research is going on in this particular field, "How to Protect our Environment from degradation". The main reason behind the bad environment is forest and rural area fires. There are lot of reasons that cause forest fires, and how long we can only watch the disastrous things happening by reading them in newspapers, magazines or through internet means.The objective of this literature is to study various forest fire detection approaches to identify the most efficient approach for real time application. Due to the variety of research articles in the area of forest fire detection, several of the research databases are extracted for the existing work. In this study we have explored six different databases to study the recent advances in the application of fire detection. The following databases explored are mentioned below:

- IEEE (www.ieee.org)
- Springer (www.sprigerlink.com)
- ACM digital library (dl.acm.org)
- Google scholar (scholar.google.com)
- Science direct (www.sciencedirect.com)
- Hindawi (www.hindawi.com)

This Chapter shows various systems based on different technologies like IR cameras, Wireless cameras, Satellite and UAVs network for the application of forest fire detection. Few of them are deployed alone but there are few that mix multiple technologies. More likely, there is one equivalent technology that can be used for improving the accuracy of performance like GPS system. Figure 2.1 shows the process diagram based on our study that includes the planning, analysis and designing with implementation of system. In this section the planning and the analysis is carried out based on the different researches taken as reference that this study follows. After the investigation of the present techniques and analyzing the requirements, design of the system and its implementation is being done and discussed in following Chapters (3, 4 and 5).

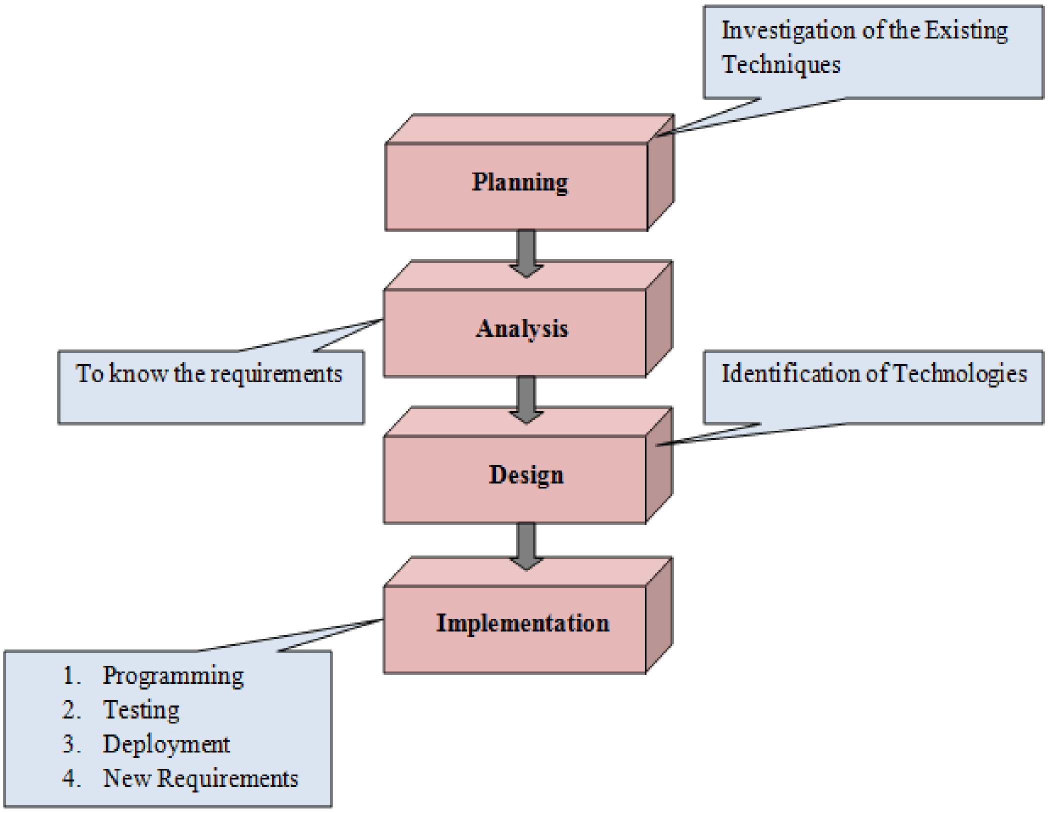


Figure 2.1: Process flow diagram

The brief explanation about existing work in the application of forest fire detection which inspired us to develop an accurate early fire detection system, solution to aid the false alarms and localization issue is presented in this chapter. An extensive literature survey is carried out to outline the importance of forest fire detection system and evaluate the performance of various approaches in terms of accurate and early detection of forest fires. Initiatives taken by several researchers in this application for monitoring, burnt area mapping, early detection of fire is detailed in this chapter. Based on the literature survey conducted some of the research gaps are identified in this chapter which resulted in the commencement of objective framing for the thesis research work. The contributions of proposed work in this thesis are also discussed in the end of this chapter. A sequential overview in the form of block diagram in which review of literature process is conducted represented in Figure 2.2.

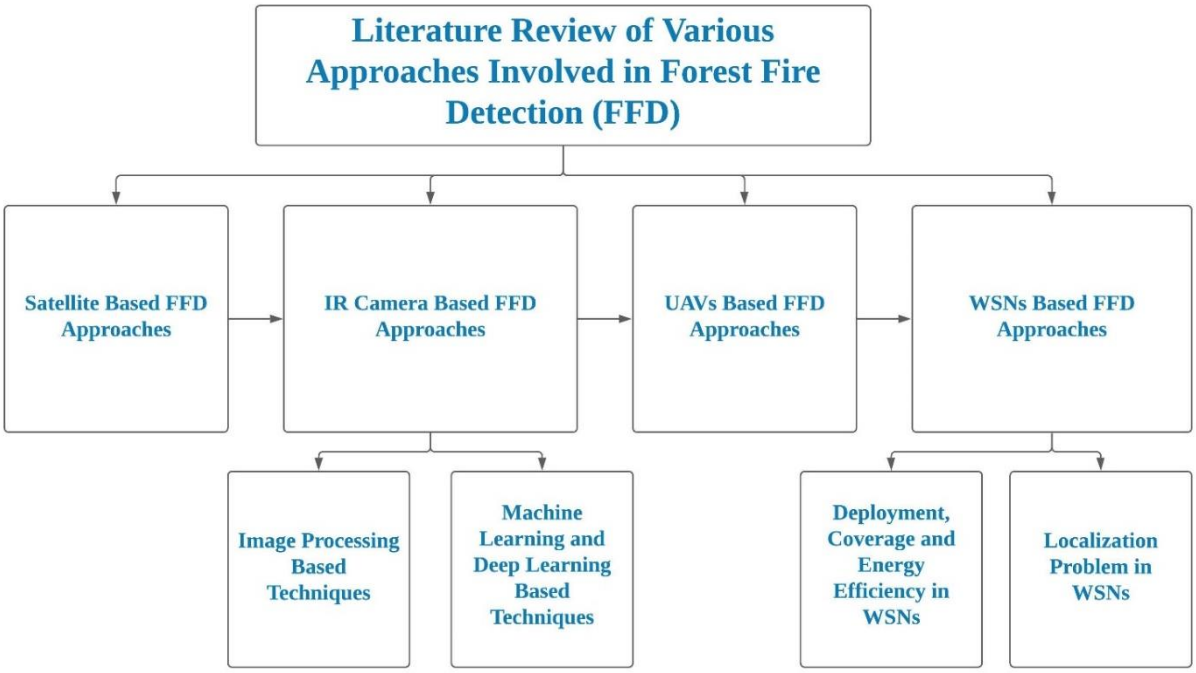


Figure 2.2: Sequential overview of review of literature process

2.1 Literature Review of Satellite Based Forest Fire Detection Approaches

Since, late 1990s there are many available Satellite systems that are used for providing data and other various operational capabilities that can be utilized for the aspects of forest fire application. There found many attempts by various researchers towards monitoring of forest fires using Satellite systems in the literature. Satellite based system can be used for the detection of fires, its monitoring and area assessment. The advantage of using Satellite based system is that, it covers area of any size. Majority of the Satellite based system are used for monitoring the forest fire events and burnt area assessments. There exist many Satellite based approaches which are suitable for fire detection through remote sensing. These approaches are reported in literature and discussed in this section of the chapter.

Forest fire monitoring and danger forecasting approach based on remote sensing is reported in [37]. Monitoring of forest fires through remote sensing in an act of describing the conditions at current time. The remote sensing based monitoring consists of four states, the first one is the accession of the data that is of interest, the second is calculating resultant variables those are equal to danger conditions, third is the formation of relation in between the resultant variables and risk indicators and finally there is the making of risk map. The vegetation condition, meteorological variables and the surface conditions comes in as the remote sensing derived variables. Their research addresses the limitations of system utilizing remote sensing for monitoring environmental adversaries and forecasting risk conditions. The remote sensing based techniques serves the priority of calculating the indicators of fire occurrence and comparing the calculations with actual fire. Though the system is having certain limitations the area is vast and many steps can be employed for making it reliable and acceptable. Another approach for detection of fire using remote sensing is reported in [38] that address the issue of reliable detection and high computation time. Their architecture for the detection collects images for analysis from advanced very high-resolution radiometer (AVHRR). The architecture having several advantages like the operation is fully automatic, the quality of the data is very consistent, cost effective but despite of one thing that the results are not in real time. The system presents false detection and not tested for real time implications.

A forest fire investigation system on real time basis using GIS and remote sensing is reported in [39]. In the first step the digital numbers are converted into spectral radiance for the estimation of land surface temperature (LST). The second step is the processing for fire description, for this purpose they have used thresholding for the separation of the hot spots from the background through image stacking. In the last step the analysis is done in which all the layers are combined in GIS environment. The experimental results present the importance of remote sensing for mapping fires in wild, hostile environments and address the importance of image stacking for the reduction of false alarms. The enhanced spatial resolution of future infrared sensors can even detect small fire and better-quality of temporal resolution can accurately detect the heating signals at early stage. The design is inefficient for detecting small fires and it requires accurate management for planning the control and estimate mapping risk. Guettouche et al. [40] have proposed enhancement of environmental vulnerability assessment model to forest fires by joining human vulnerability issues. Their proposed model for forest land uses remote sensing and GIS techniques that help to plan the environmental vulnerability towards forest fire by combination of multiple information that has been collected from the land. Initially in their system there is a process of defining boundaries for study area in which the targeted area is delimitated for investigation. In the next step the satellite images were analyzed by remote sensing technique in which the data collected by the forests is analyzed. In the last step the whole sum of data produced through image processing is further compiled and implemented by using MapInfo-8 for carrying out the vulnerability. The experimental result shows that system helps the management for planning and adequate control whereas less practical implementation makes the approach not reliable for efficient monitoring. Gandhi et al. [41] proposed geospatial technique for the automatic operation of forest fire detection. They have developed a python program to take real time data from MODIS that makes their system an automatic. In their system the automatic operation is to download MODIS fire information from resource management system and after its analysis the final output is sent by text, emails and the results can also be available in the website. They made a python code which is for downloading and processing the information that is set accordingly system time so that the processing of the system starts automatically. In the very next step, the system will download the latest shapes from FIRMS website and after the filtration the file is added to the database with current date and time. Their research focuses on designing a Satellite based system for monitoring and detecting forest fire which is capable of triggering an alert through SMS and emails which carries the exact location with latitude and longitude information. The response time is reduced and the same information is delivered to all people that are in charge at the same time. The operation of the system requires regular internet connection and manual input of location values making the system not suitable for real time operations. The early detection system of forest fire requires real time monitoring of environment. The implementation of sensor network for monitoring forest fire and detection using MSG-SEVIRI is addressed in [42]. The improved MSG SEVIRI system having much better spatial resolution. SEVIRI sensor characteristics allows climate studies along with these Satellites also carries GERB instrument that provides data through reflected radiations which are emitted by earth, atmosphere. Their architecture having the advantage of highly scalable fire detection and more accurate satellite images. For the future work the different fire regions could be compared with other network performances.

Fan et al. [43] presents design of effective fire tower planning based on MapGIS for forest fire prevention. Their research also analyzes the functions of geographic information system to build prevention system for forest fire. Their research gives various technical ways for fire tower planning to make a capable fire prevention management system. There are two types of data which is required for an efficient tower planning is digital elevation model and 3D drawing of the tower. The two main concepts for tower planning on the basis of GIS are productive planning to define analysis area and the second is productive resolution range. Their system functions have four major aspects, the first is single visible point analysis, second is simple analysis of the visible area and next is optimizing analysis of visible area for checking the resolution range and the final aspect is layout program which predicts multiple towers. It also displays the overlapped area in visible range. Their system not only helps the forest management in terms of technically planning the fire tower locations but also provides a new tower location that reduces the operational cost and results an increment in computation time. MSG-SEVIRI and MODIS Sensor based forest fire detection system that presents better computational time is presented in [44]. The detection is further enhanced by radiative transfer model approach. The limitations of using MSG-SEVIRI that it has a low spatial resolution that are overcome with the help of radiative transfer model (RTM). The experimental results show that the technique is having less false alarm rate which is decreased by 10% of previous MSG-SEVIRI based approach and same system having much better performance for large size fire. The characterization of fire for identifying different region of fire are addressed in [45]. The authors used free space method for characterization of litter fire with the help of transmission phase propagating signal frequency range from 5 to 40 GHz. Cameras used for detection of fire. Propagation of electromagnetic waves determined by the dielectric function in dielectric medium. Temperature measured by the thermocouples at different places at specific duration. The experiments conducted states that their method is suitable for detection with less errors and having high efficiency but system present detection only during day time. Another system for day/night monitoring of fire is presented in [46] with high response time. The authors have introduced a light detection algorithm on the basis of day night band by making use of visible infrared imaging radiometer suite. Their algorithm helps finding fire at both visible light as well as infrared signals at night. VIIR is having much success over MODIS for the fire detection. Their approach lies on VIIRS known as AFARP having the objective for improving the accuracy of detection at low temperature hotspots. FILDA is capable of identifying fire during night time also, whereas AFARP needs another day for the received signals to reach the thresholds. Their approach is having a broader concern in the fire response and the management prospective because at the early stage the fire is still manageable. Further improvements could be done by making use of GOES in order to improve its accuracy for both clear and cloudy conditions and reduce the detection time. The system lacks in terms of detecting small fires accurately, hence increasing false alarms for small fires. An approach for monitoring forest fire and logging activities in forest presented in [47]. The choice of efficient Satellite sensor is very crucial for monitoring fires and the major factor that comes under consideration when executing data requirements for monitoring disturbances in forest is forest disturbance intensity. The RapidEye Satellite system is used because of their capability of pointing in various angles and system having high resolution images. Landsat 7ETM and image from RapidEye were utilized for the evaluation of spatial characteristics to detect fires of low intensity and then image processing is done because multi-temporal RapidEye data needs consistent preprocessing. Initially object based classifications carried out for classifying clouds, water bodies from each image by utilizing eCognition software. The experimental result shows that system is capable for monitoring the fire and logging events but the response in not continuous with time.

Kushida et al. [48] suggested a technique for monitoring of active forest fires using multi-temporal MODIS images. Multi-temporal active fire detection was applied to data that is evaluated from MOD14. Linear regression equations were calculated for getting the radiances by making use of all the pixels. The pixel those were detected as a fire candidate were separated or completely removed from data set and the regression equation were evaluated until there were no pixel to remove. The images from ASTER were overlaid in MODIS data for the evaluation of active fires. The active fire was detected in the ASTER image and MODIS pixels that include these fires are treated as true pixel of fire. If it’s a true fire pixel then it is treated as active fire otherwise as an omission error. The experimental result shows that the system is having eighty percent of accuracy in detection of fire with fewer false alarms. This technique is having less number of errors compared to MOD14.

Laneve et al. [49] presented a global technique for continuous monitoring of forest fire using MSG. They have presented a new processing approach utilizing spatial and temporal resolution in respect of Meteosat system. The main idea is to enhance the detection capability inspite of limited spatial resolution. In their technique the two images were compared in a span of 15 minutes for computing the temperature difference and sudden change in temperature is attributed as fire. The rapid response system of MODIS is not efficient in detecting same fire. The experimental results show the advantage of their approach over MODIS rapid response system providing real continuous monitoring with better accuracy of fire detection. A reliable agent based forest fire detection system using remote sensing is presented in [50]. The system they have designed system is very consistent and self-adaptive such that the same could be applied to any of the images that had been taken from the same Satellite at the same day. Their article presents a solution for fixed threshold values that causes omission errors by implementing self-adaptive agent based approach for detecting small and cool events of fire. According to their research the solution of PFP's is done by using temporal and the spatial information from the pixel alternate to the fixed threshold values. The performance evaluation of their system is carried out by comparing results with MODIS contextual fire detection system. The comparison result shows that their proposed system is having less omission errors and which is due to the fact that the brightness level of detected fire spots temperature values is lower compared to the fixed threshold values.

Ying et al. [51] have developed a distance metric based detection system that recognizes forest changes using MODIS. Their method involves pre-processing in which spatial and temporal approach is used for evaluating the fire candidate pixels in order to provide gap-free data. In the next method the detection in change is calculated by using distance metrics. Their approach explores two features of change, first is pixel's deviation from its own previous behavior and the second is deviation from the neighboring pixels. The distance threshold is then applied to both feature values to recognize the change in the temperature. Their method showed excellent agreement results but also having high commission errors. They have not tested their system for the large areas and the result shows that the system is effective for small areas. Their system suggests that the feature varies for different lands. Therefore, the selection of feature may remarkably impact the change detection performance. The system is not tested for large areas and presents high omission errors. To address the issue of omission errors an approach for the analysis of spatial and temporal feature is presented in [52]. Based on MODIS images they have analyzed the detected fires and they gave investigated the fire frequencies and their relations with like rainfall and fire frequencies, wind and the fire frequency, NDVI and the fire frequency and land cover and fire frequency. The result of their analysis shows that the majority fire happened in low precipitation areas because of the presence of the grass lands and crop lands. They have also identified the fire occurrence in the month of June and July were more because of the high NVDI values. Their research focuses on the analysis of land cover and fire occurrence locations also it is found that more than 80 percent of the fire happened in crop and grass land, also it shows that the fire occurred at elevation lower than 500 meters. Diagne et al. [53] have proposed an algorithm which used for detection of fire using geostationary and polar orbiting satellites. They used generation 9 satellite for their research work. One issue that is measuring globosity is dependent upon local parameters. The advantage of their approach is that the algorithm does not require long time data series in its beginning. Maeda et al. [54] is one very effective system that is particularly designed considering application of disaster management such as fire detection that depends on MODIS Satellite imagery for their operation. It actually collects the images from the satellite and studies these collected information. Satellites covers much area, comparatively others satellite can monitor large distance. But there is typically one problem that occurs with satellite imagery that is weather conditions. Whenever there is a Cloudy or Rainy weather, the resolution of satellite imagery is very low because part of frequency spectrum is absorbed by the clouds and rain that reduces its spectral resolution and very importantly these systems are very expensive.

In this section we have studied various forest fires detection systems based on Satellite imagery. Apart from this, the performance comparison of Satellite based fire detection approaches is presented in Table 2.1 detailing the Satellite sensors, Spatial and Temporal resolution, and methods employed. The biggest advantage of using Satellite system for disaster management is their capability of covering area of any size. These systems are beneficial for monitoring fire event, analyzing the behavior of fire and its direction, burnt area mapping and each of this information can be assessed by the user from remote locations. However, Satellite system offers large benefits but their use for detection of forest fires is not reliable. Satellite responses are not continuous with time moreover low temporal and spatial resolution give rise to majority of false detections.

Table 2.1: Comparison of various Satellite system based forest fire detection techniques

Study	Satellite Sensor	Spatial Resolution	Temporal Resolution (sec per slice)	Methods Employed	Purpose	Drawback
Chowdhury *et al.* [37]	MODIS Data	250 m	20	Remote Sensing	Danger forecasting system	Not Reliable for vast areas, Response is not continuous with time
Li *et al.* [38]	AVHRR Data	1 Km	24.25	Remote Sensing	Automatic operation of detection	Results are not in real time
Prakash *et al.* [39]	Landsat Data	50 m	12.3	GIS and Remote Sensing, Image stacking	Mapping fires in wild, hostile environments	Inefficient for small fires, False alarms
Guettouche *et al.* [40]	Not Specified			Remote Sensing and GIS, MapInfo	Management of planning and adequate control, Mapping risk	Less practical implementations
Gandhi *et al*. [41]	MODIS Data	1 km	15.2	Geospatial Technique	Forest fires prediction and its monitoring	Manual input of locations, Continuous internet is required
Vennila *et al.* [42]	MSG-SEVIRI	500 m	8.21	Sensor network, Fire weather index	Forest fire sensing	Not efficient for detecting different fire regions
Fan *et al.* [43]	WebGIS Data	1 Km	23	MapGIS and 3D platform	GIS and 3D visualization, Fire tower planning	High computation time
Calle *et al.* [44]	MSG-SEVIRI, AWiFS Data	100 m	7.69	Radiative transfer model	Forest fires prediction and its monitoring	False detection for small fires
Masoumi *et al.* [45]	Not Specified			Synchronized image characterization	Characteristics of fire	Future implementations of Radar systems
Polivka *et al*. [46]	VIIRS Data	1 km	21.36	VIIRS fire detection algorithm	Detecting fire at Day/Night	Inefficient for small fires, False alarms
Farnke *et al.* [47]	RapidEye Data	200 m	24.04	eCognition Software	Forest fires prediction and its monitoring	Response time is high
Kushida *et al.* [48]	MODIS Data	1 Km	20.17	Biband threshold method	Active forest fires detection	False detection, High computational cost
Laneve *et al*. [49]	MODIS Data	500 m- Km	13-21	Contextual and threshold technique	Global technique for monitoring fire	Not continuous with time
Movaghati *et al.* [50]	MODIS Data	200 m	18	Self-adapting routing algorithm	MODIS contextual fire detection system	High computational time, Post fire assessments
Ying *et al.* [51]	MODIS Data	250 m	14	Kernel detection estimation	Evaluate fire candidate pixels	High omission errors, Not tested for large areas
Ardakani *et al.* [52]	MODIS Data	500 m	13	Kernel detection estimation	Fire frequencies and their relation	Not continuous with time
Diagne *et al*. [53]	MODIS Data	500 m	16.23	Kalman filter recursive algorithm	Fire detection	Operational cost is high
Maeda *et al.* [54]	MODIS Data	250 m	16	Artificial neural network	Disaster management	Expensive, Area assessment

2.2 Literature Review of IR Camera Based Forest Fire Detection Approaches

IR Camera and image processing based forest fire detection techniques are useful for the verification of fire incident. In this section image processing based fires detection systems for meeting the requirement of fire event confirmation to reduce the false alarms are studied. The remarkable efforts from several researchers have been noticed towards development efficient system for fire confirmation. Researchers have presented lots of efforts in designing fire confirmation approaches and some of potential work done in this field is highlighted in this following section.

2.2.1 Literature Review of Image Processing Based Fire Detection Approaches

Prema et al. [55] have presented a multi feature analysis of smoke particles for the verification of forest fire. An image processing approach is proposed for smoke detection from a video signal. The smoke detection using video according to their system is having serious advantage over previous smoke detection techniques that it covers large area and having fast response time. In their research for the false alarm reduction they have used three different features. Firstly, the filtration of color is done in YUV color space to find or to characterize the smoke region termed as candidate and after that the spatial and the temporal features are extracted from the smoke candidates utilizing spatio-temporal analysis and dynamic texture analysis which are further subjected to SVM for its classification. The experiments based on their research shows that their approach is having high detection rate, and quick processing in comparison to other existing techniques.

Stula et al. [56] have presented an intelligent forest fire monitoring system. They have proposed an architecture that is iForesrFire system based on image processing. Their aim is to design an automatic fire detection system. iForestfire is an intelligent system based on the monitoring through remotely controlled video cameras and the integrations of metrological stations with geo-location information system. This information is processed in real time to detect fire initially. The system is highly accurate capable of working with different equipment’s like Sony, Samsung cameras.

Bao et al. [57] presents an article for optimizing locations for watch towers in forest fire monitoring. The placement of these watchtowers in proper efficient way is very important in terms to decrease the cost and also to cover the large area with immediate response. Location allocation models are utilized for the evaluation of tower locations. Their article concludes three optimization models for the satisfaction of three major requirements that are minimization of cost, coverage, and maximum coverage at minimum cost. The experimental results shows that the visibility analysis and the integrating location models can help more efficiently for placing watch towers in order for fire monitoring in a particular area.

SongLu et al. [58] have designed an algorithm for video analysis that detects flame and smoke using VS2010, Open CV2.1. Authors extract the region through background modeling, after that in order to detect the flame they have used mixed color space feature and smoke detection is done through threshold segmentation. The result shows accuracy of proposed system in terms of accurate detection. Barmpoutis et al. [59] have proposed a detection system on real time basis implementing Spatio-Temporal analysis of video. The methodology of the proposed architecture is having several steps. In the first stage background subtraction is done and after that fire classification is carried out using color analysis. Whenever fire is detected then few of the features are computed and at last the classification process takes place. To differentiate real fire pixels from fire like pixels the authors have used novel features as a result of that number of detection error decreases and also system is having improved performance.

Dimitropouls et al. [60] proposed an automatic fire detection approach through video analysis using Spatio-Temporal modeling and texture analysis. The first step is to filter out the regions which are non-fire moving colored regions. Background subtraction is the first step that is done through the adaptive median algorithm to extract the features because of its efficiency and speed. Then in the next step the color analysis is done through RGB color distribution. The six different features are computed for every detected fire candidate. The first feature is to detect the fire color probability which follows by the spatial wavelet energy analysis, in next the spatio-temporal energy is detected and the remaining three steps features are computed. At last the classification is carried out for decision making. The observed results reveal the performance of approach for accurate detection.

Zanotta et al. [61] proposed a reliable change detection technique from a series of image that are collected from same area at different times. Change vector analysis computes spectral change vectors by multi-temporal spectral images and performing analysis for spectral change vectors in order to extract the change. Their technique is based on three methods. Initially 3D representation of spectral change vectors is computed and then change is detected based on decision rule. The third step is the adoption of the decision rule for automatic detection. Bayesian rule is applied for decision making to identify unchanged features and remove them from analysis. The results pointed out excellent capabilities in automatic detection.

Toulouse et al. [62] presented a wildfire color segmentation algorithm. They have compared eleven algorithms for fire color segmentation. The proposed algorithm uses YCbCr model for reducing illumination effects. The experimental result claims that segmentation can detect fire at day time without smoke. Qiu et al. [63] have designed an edge detection approach for the detection of flame edges using image processing. They have presented a computing algorithm that can define flame and fire edges very clearly and continuously. In their first step the histogram is normalized for adjusting the gray scale and then background noise is removed for the smoothing of image. After the removal of background noise, a sobel operator is used to find out the basic edges which are followed by the adjustment of higher and lower value of thresholds. They have implemented a least mean square algorithm for the identification of preliminary image with edges from the real image and in the last step the unwanted edges were removed. The experimental result shows that their algorithm is very effective and robust for the detection of different color fire flames. The major advantage of their method is the fire edges that are detected are clear and continuous.

Bedo et al. [64] used RGB information and design and design set of rules for classifying fire pixels. In one more study author has used Gaussian model with RGB extractor for the classification of fire region [65]. In recent study authors have employed RGB space for the classification along with Markov modelling for extracting motion features of flicker fire [66]. Dzigal et al. [67] implemented background subtraction for the segmentation of background non-fire objects and the classification of true fire is carried out by implementing three RGB rules. The system presents drawback in terms of high false detection when the value of intensity varies, which is actually a sensitive for the parameters utilized for the extraction of background. The author in [68] designed fire confirmation system using normalized RGB color values. The changing effect of illumination is addressed by proposed normalized RGB approach. The statistical analysis for the three planes of RGB is carried for obtaining a generic model. The sample fire image is distributed in each plane and triangular region is computed drawing three lines which represents the specified region as fire region.

Yuan et al. [69] have designed a fire detection system using CCD cameras. The designed system predicts the fire pixels from grayscale frame of videos by utilizing the statistical features such as standard deviation, mean values for the verification of fire pixels. The designed system is practically used for the detection of smoke along with the real time visuals for the confirmation of fire and non-fire events. Celik et al. [70] have presented a system that uses YUV space model for the detection of fire. The design computes the luminance Y for the declaration of candidate region whereas chrominance U, V are computer for the classification of fire and non-fire pixels. Their proposed work also computes motion vectors for knowing the behavior. The reported experimental results show that the system achieves reduction in false alarm rate, but there exists no tests for the performance validation. The system presents high false alarms because of background noise.

The background noise is further addressed by a study that uses RGB values and YCbCr color model for the detection of fire [71]. Vipin et al. [72] designed an algorithm for fire detection in dark and bright environment that segments fire region using HSI color space model. In the initial stage the pixels with low intensity and low saturation values are filtered for the removal of fire like regions. The authors have introduced a metric-based approach to measure the percentage of burning. The proposed system presents high percentage of false positive and false negatives and there found no attempt for the reduction of false positives. Krstinić et al. [73] presented a fire verification system by recognizing fire regions from video sequences. The system requires a look up table for at the start which shows its drawback in terms of depending on other operator for the detection of fire from video. The experimental results present that the approach is complicated for detecting fire in real time.

Table 2.2: Comparison of Image Processing based forest fire detection approaches

Year	Study	Purpose	Methods Employed	Dataset Utilized	Performance Indices
2016	Prema *et al.* [55]	Smoke feature analysis	YUV color space model, SVM	VisiFire	Accuracy, Sensitivity, Precision, F-Score
2012	Stula *et al.* [56]	Automatic fire detection and alarming	Computational, Artificial Intelligence	iForestFire Database	Sensitivity, Precision
2013	Barmpoutis *et al.* [59]	Discriminate actual fire from fire like objects	RGB, 2D wavelet analysis	Firesense	Accuracy, Sensitivity, Precision, F-Score
2014	Dimitropoulos *et al.* [60]	Fire flame detection for early monitoring	Spatial wavelet analysis, RGB, SVM	Firesense	Precision, Recall
2015	Zanotta *et al.* [61]	Provide change detection	Bayesian decision rule	Landsat	Non Specified
2015	Toulouse *et al.* [62]	Wildfire color segmentation	Bayesian segmentation, YCbCr	UMR CNRS 6134 SPE dataset	Accuracy, F-Score
2011	Qiu *et al.* [63]	Identification of flame edges	Edge-detection methods and Laplacian method	Not Specified	Perimeter
2015	Bedo *et al.* [64]	Detection based on instant learning	RGB color model	Flick-Fire Dataset	Accuracy, Sensitivity
2017	Han *et al.* [65]	Accurate classification of fire region	Gaussian model, YCbCr, RGB	VisiFire	Precision, Recall
2010	Teng *et al.* [66]	To reduce data redundancy and detect hidden fires	Markov modelling, RGB space model	Flick-Fire Dataset	Sensitivity, Precision
2019	Dzigal *et al.* [67]	Accurate classification of fire region	RGB, HSV, HSL	Corsican Fire dataset	Accuracy, Sensitivity, Precision
2011	Toulouse *et al.* [68]	To reduce the changing effect of illumination	RGB color space, Machine Learning	Corsican Fire dataset	Precision, Recall
2010	Yuan *et al.* [69]	To predict fire pixels from gray scale	Gaussian mixture model, RGB	Not Specified	Accuracy, Precision
2015	Zaidi *et al.* [71]	To achieve high true detection rate	YCbCr, RGB color space	Not Specified	Accuracy, Sensitivity, Precision
2013	Vipin *et al.* [72]	To accurately detect active fire hotspots	HIS, YCbCr, RGB color model	LANDSAT	Precision, Recall

In this section several image processing algorithms are exploited for the confirmation of fire events. Apart from this, the performance comparison of Image Processing based fire detection approaches are tabulated in Table 2.2 detailing the methods employed, dataset utilized, and performance indices. Majority of this IR cameras technology requires image processing for extracting the information and analysis. These systems are beneficial for confirming fire event, analyzing the fire behavior. Moreover, these system provides a line of sight vision which sometimes cannot detect the event outside LOS, and are not suitable for detecting fire at its initial stage.

2.2.2 Literature Review of Machine Learning and Deep Learning Based Forest Fire Detection Approaches

In this section Machine learning and Deep learning based fires detection systems for meeting the requirement of high computation speed, energy efficiency and accuracy are explored. The remarkable efforts from several researchers have been found towards development various efficient fire detection system using ML and DL techniques. Researchers have presented lots of efforts in designing fire confirmation approaches and some of the work done in this field is highlighted in this following section.

Author presents a fire detection using support vector machine. The approach is efficient in terms of accurate detection but the computation time is high [74]. Fire weather index is a key aspect for modeling fire events [75]. The FWI is a comprehensive system and it is backed for several decades in North America. On the basis of FWI system, data aggregation scheme is presented and tested for wildfire detection application. The main advantage of using their data aggregation scheme is that it only forwards data that is of interest to application. The experiment result shows that the system is performing reliable coverage.

Soliman et al. [76] designed an algorithm based on ANN for early prediction of fire event. Artificial neural networks are employed so that the system could make automated decisions. Initially the data is collected through sensors (Micaz mote) and the collected information is transferred to already trained ANN and the running ANN system will test if there exists any fire or not. The results show the significance of their design for detecting fire along with the knowledge of direction growth of fire. The system monitors the forest fire constantly without any human supervision.

The scope for future work in this is the same model could be extended to pinpoint the exact the fire point location. Russo et al. [77] proposed an algorithm for forest fires that is based upon cellular automata that will simulate the fire occurrences and it's spreading in zone. In their article the authors have gone through computer algorithm and an improved forest fire model, they have implemented dynamic updating of tree clusters, working on breadth first algorithm and through the optimization of internal memory the time is reduced. The result shows that the design is very effective and feasible. Their article can practically use for majority of application of fire prediction and its management. The importance of statistical data modelling for accurate detection of fire is discussed in [78]. The model is designed considering both indoor and outdoor environments. The design is tested for various environmental conditions and resolves the energy and delay issues. The consumption of energy is critical issue in sensor network. The optimization issue in a network reduces the performance and increases energy consumption. A harmony search algorithm is useful for reducing intra-cluster distance to address the issue of optimization [79]. The experimental result shows that using HSACP the network lifetime is extended in comparison to LEACH-C and FCMCP. The optimization issue and in WSNs during routing is addressed by Kumar et al. [80]. The authors have designed a routing algorithm for WSNs utilizing swarm intelligence technique. Artificial bee colony algorithm is implemented for collecting environmental data periodically. To increase the lifespan of network Ant colony optimization algorithm is implemented. In their research they combine both of these algorithms that are ABC and ACO and proposed ABCACO algorithm for solving an optimization and finite problem in WSN. Their algorithm is characterized is three main parts. The result shows that their technique is efficient for monitoring and detecting fire. Their system increases the stability and also increases the goodput compared to Leache.

Hasan et al. [81] develops intrusion detection scheme implementing SVM and random forest approaches. The success of any of the intrusion detection scheme is a critical issue because of its nonlinearity and network traffic. To find more accurate solution for these problems there are many systems that have been developed which shows level of accuracy. For this purpose, to make the most robust and effective method for IDS the authors build two models for the classification one is based on SVM whereas other is RM. They have used KDD'99 dataset in order to find best intrusion detector among these two. The result shows that the SVM generate much accurate results as compared to RF whereas RF requires less time than SVM. Zhao et al. [82] have presented the use of CS Adaboost algorithm for early smoke detection in order to prevent forest fires. Smoke is the initial stage of what is going to be a large fire. Their paper presents an algorithm for smoke detection which can differentiate fire smoke from other smoke like particles. According to their work initially motion regions are being extracted which will help in order to avoid false distractions. Thereafter, adaboost algorithm is implemented for the reorganization of smoke regions by using smoke flutter and estimating image energy by evaluating wavelet transform coefficients. The experimental result shows that their system not only capable of detecting smoke from image abut also capable of differentiating dense fog from smoke. The designed model lacks in providing the information about fire behavior.

The issue of retransmissions during the routing of information from source to sink consumes energy. Yasin et al. [83] presented a fire detection model using Gossip routing protocol. Their approach offers only selected information towards sink node thereby reducing the retransmission during data routing. The result presents better performance of Gossip routing technique in comparison with other routing approaches. Iorshase et al. [84] designed an ANN based framework for detection of fire. Their proposed research made through artificial neural network with back propagation technique which will detect the fire events. Their method has taken smoke, temperature and gas concentration as the inputs. The implementations are carried out in Java and simulation results shows that the system is much accurate. In their system initially the creation of three-layer perceptron neural network takes place, in the next step system acquire the fire event based on the smoke, temperature and the gas concentration. The third step is to normalize the fire information into a homogenous form and the followed step is to configure the TLPN for detection with the testing data. The next step is to set data for real detection if the vale is 1 means there is fire and if the value is 0 means no fire. In the final step an alert in the form of text is sent to fire-fighting team. The testing results of their approach shows that the system is reasonable accurate. To address the issue of high computation time, Authors in [85] presented an effective solution for fire detection. A regression method is employed for the analysis the results shows the effectiveness of their approach for detecting fire with high accuracy. Initially a dataset that is based on collective parameters obtained from sensors in order to get maximum sensor accuracy. The computational time of the proposed model is very less as their design does not require the computation of whole dataset for the analysis. The designed model is versatile in terms of its applicability for various other disaster management applications. Authors in [86] implemented deep convolutional neural network model for fire detection in real time scenario. The input images and videos are computed for the segmentation of dynamic characteristics of fire color pixels. Authors have done fire segmentation by HSV Color space, after segmentation from video images the features like area, roundness are calculated and based on them further decisions take place. The system is having high computational speed and the architecture is even able to detect fire with heavy smoke. Authors in [87] proposed on board fuzzy logic for the detection of active fires. A fuzzy logic is a probabilistic robust technique. The proposed approach is tested for AVHRR dataset of fire images from NOAA-16 Satellite. In their system they have considered two input variables, pixel value representing original pixel and Housing keeping diagnostic parameter that represents the estimated condition of complete system. The result of the proposed system shows that their approach is suitable for the identification of the active fires. There is an improvement in the hit rates in comparison to the Setzer’s algorithm. Another approach for fire detection implementing CNN is presented in [88]. The designed model accurately detects the fire from smoke in day and night.

This section presents the study of various deep and machine learning approaches for the application of forest fire detection. Apart from this, the performance comparison of machine and deep learning-based fire detection approaches are tabulated in Table 2.3 detailing the methods employed, dataset utilized, and performance indices. The overall cost of these system is low comparatively Satellite and Camera based fire detection techniques. The study reveals some drawback of these approaches as low practicality and limited region of interest capabilities.

Table 2.3: Comparison of Machine and Deep Learning based approaches for forest fire detection

Year	Study	Purpose	Methods Employed	Dataset Utilized	Performance Indices
2009	Gubbi *et al.* [74]	To reduce false alarms	Support Vector Machine	Flickr-Fire Dataset	Precision, Recall
2009	Hefeeda *et al.* [75]	To achieve reliable coverage	Data aggregation scheme	Not Specified	Accuracy, Temporal Constraint
2010	Soliman *et al*. [76]	Early and accurate detection of event	Artificial neural network	Flickr-Fire Dataset	TP, TN, FP, FN
2011	Russo *et al*. [77]	To simulate fire occurrence and its spreading	Cellular automata	LANDSAT-8	Accuracy
2015	Zhao *et al.* [82]	To detect fire from smoke	Machine Learning, Adaboost Algorithm	AImageLab Dataset	R-square, RMSE
2016	Iorshase *et al*. [84]	To estimate the fire accurately and behaviour of fire	ANN, Back propagation	Not Specified	Accuracy, Precision
2015	Kansal *et al.* [85]	To address high computation time and achieve maximum accuracy	Regression Method	Not Specified	R-square, RMSE, Analysis time
2016	Zhang *et al.* [86]	Detection of fire in real time scenario	Deep Convolutional neural network	ImageNet Dataset	Accuracy, Precision, F-score
2016	Leal *et al*. [87]	To identify active fires accurately	Fuzzy logic	AVHRR Dataset	Accuracy, Precision
2018	Muhammad *et al.* [88]	To detect and localize fire	Convolution Neural Network	LANDSAT	Precision, Recall, F-score, Accuracy

2.3 Literature Review of UAV based Forest Fire Detection Approaches

Satellite based system for fire detection requires high professional skills and are tedious as well as time consuming. In this section Unmanned Aerial Vehicles (UAVs) based fires detection systems for meeting the requirement of real time and less false detection are studied. The remarkable efforts from several researchers have been found towards towards development and enhancement of UAVs fire monitoring and verification system. Researchers have presented lots of efforts in designing new topologies for area mapping and some of the work done in this field is highlighted in this following section.

An aerial image-based Fire Detection system using Unmanned Aerial Vehicles is presented in [89]. Their system is well suited for the monitoring and the detection of the forest fires because of its fast response capabilities, low cost and personnel safety. For their implementation they have used two algorithms that include the color and the motion features which are applied to the processing images that are captured by using camera that is mounted on a UAV's. Fire color pixels are extracted using color-based fire detection algorithm and combination of two algorithms classical flow algorithm and optical mass transport algorithm computes the motion vectors. The performance of the system is analyzed for both indoor and outdoor experimentations and it reveals that system achieves better performance in terms of reliability and better accuracy. The system lacks to meet the requirement of its response time and this issue is addressed in [90].

The system is suitable for monitoring and verification of forest fires because of its fast response capabilities, low cost and personnel safety. For their implementation they have used two algorithms that include the color and the motion features which are applied to the processing images that are captured by using camera mounted on a UAV. The authors have used Horn and Schunck algorithms for the computation of motion vectors. These algorithms also distinguish fire from other fire analogues. Various experiments are conducted using this architecture and the results shows that this system is very effective for extracting fire pixels. Their system can detect fire more effectively along with the analogues as well, like some non-firing objects present in the zone which actually looks like the color of fire. The system is having great reliability and accuracy but lacks for detecting fire in smoke. An approach for the accurate detection in smoke environment is presented in [91]. YUV color model is implemented for detection of fire in smoke and the results present accurate detection but observes high computational time during operation.

Christensen et al. [92] has presented the use of UAV network for the evaluation of wildfires implementing simple analysis to achieve computation time and accuracy parameters. The use of UAV's or Radio-controlled aircrafts and remotely controlled/piloted aircraft is a current trend and also a rapidly developing area having various advantages in the field of fire management. Their research shows the significance of UAV's over other means of fire-fighting techniques in terms of safety, cost and flexibility. The author has mainly focused for the cost effectiveness of the system, therefore cost benefit analysis approach is considered. The forward looking infrared (FLIR) technology is used for the hotspot detection and their research shows that the use of RPA and FLIR may have faster response times, less repeated work, faster resource demobilization and less suppression costs. The result shows that the benefits of using UAV and FLIR in terms of reduction in cost of use of the helicopter and also the conclusion shows that if this approach is implemented appropriately, the system could improve the cost effectiveness in comparison of the current techniques. The design achieves high accuracy but observes loss in packet data. This issue of packet loss is addressed by the application of Drone for disaster management [93].

The Drone used is having fixed wings and also equipped with chemical sensors and the flying results of Drone are the 3D model of the captured data. The author has shown various application of using Drone for the disaster management like earthquake, floods and the forest fires. For the forest fire application, drone is capable enough of sensing hot spots before fire which and helps management by providing real time field information. The result based on Drone surveillance shows that it gives very quick hot spot detection with location coordinates to the management which reduces the delay time but the study also clears that their application can be effective only for some special scenarios and extreme high fire weather index. The system achieves quick detection but the deployment cost is high. The solution to achieve less cost deployment highlighting the use of UAV technology for SAR operations of forest fires [94]. Their research shows the advantages of using UAV in searching and rescuing operations. The parameters that authors have considered for on field trial are planning for safety and logistics, timing and other ethical issues. The major advantage of using UAV is the significant increase in personnel safety through air monitoring and best for searching dangerous areas. Their research also shows the limitation of using UAV is its minimum capability in very strong windy areas and high turbulence but apart from all these limitations the UAV can be adopted in many complex conditions where the fast response is required and the personnel safety is necessary. The conclusion tells that using UAV one can achieve quality surveillance, finding correct locations, distributing first aid kits, helping people towards safe areas, and better evacuation of the area but the response is not continuous with time.

Ahmed et al. [95] presented architecture for detection of fire and extinguishing based on Robots. Authors have used temperature sensors for the detection purpose and Robots as actors for extinguishing task. In order to validate the correctness of the system the authors have used VSM-SL because of its relationship with the graph theory. The experimental result shows the system’s correctness for fire detection. The positive thing with their system is that they have designed the system that is capable of extinguishing the fire, which is highly recommendable because previous designs are only doing the detection. The drawback with the design is that it is expensive.

The estimation of UAV location in a network is a critical issue for the efficient working of network. A vision-based UAV position estimation approach is presented in [96]. Blob feature extraction and matching technique is employed for the determination of displacement in UAVs network. Feature matching algorithm is implemented for the computation of homography between continuous images and this homography is composed with previous values for aligning the current processing image in frame. If in any case the aligned image overlap with mosaic value then global alignment error reduction identifies the irregularities among positions by making use of composition of relative motion and location of image in mosaic. The homography estimation is further refined for the reduction in drift errors for motion estimation by utilizing mosaic that can store previous values. The experimental analysis reveals the reliable operation of UAVs network which can also be implemented for avoiding GPS failures.

Ghamry et al. [97] presents forest fire monitoring-based fault tolerant cooperative strategy with cooperative UAV’s. Their algorithm can detect and monitor fire even when fault occurs to one or other UAV’s. They have made four assumptions based on

FTCC. Every UAV has its own sensor for fire detection that cooperatively confirms fire and reduces false alarm rate. The sensor radius will cover the distance assigned for each UAV and there will be no loss of any communication in between UAVs.

According to their architecture number of UAV's moves by following leader follower method for the identification, monitoring and tracking. UAV's network takes off and begins with the mission of tracking and covering. When any fire event is identified by UAV, it alerts the UAVs network, ground station and in charge through phone and then the team will start to track the trajectory. The UAV team again reconfigure their formation as per the situation near the fire spot and tracks the perimeter of fire and provides updated information. Their result shows that the model is stable and having the ability to achieve the formation configuration in case of any faults. With the advancement is technology IoT is everywhere providing the capability to analyze data in real time [98]. In this section we have studied various forest fires detection systems based on Unmanned Aerial Vehicles. Apart from this, the performance comparison of UAVs fire detection approaches are tabulated in Table 2.4 detailing the class and type, camera resolution, capacity and algorithms employed.

Majority of this UAV technology is an optimal solution for real time monitoring to confirm the fire event. These systems are beneficial for monitoring fire event, analyzing the behavior of fire and fire-fighting operations. Moreover, these systems utilized for area mapping, fire-fighting, and fire extinguishing operations. The UAVs based detection lacks in early detection as their response is not continuous with time.

Table 2.4: Comparison of UAVs based forest fire detection systems

Study	**Class and Type**	**Cameras (Resolution)**	**Engine Type**	**Capacity**	**Algorithms/Tools**	**Purpose**	**Limitation**
Yuan *et al.* [89]	Near operational, 1-Fixed wing	IR, Visual-1	Fuel	Less than 2 Kgs	Optical mass transport	To achieve better performance with great reliability and better accuracy	High Response Time
Yuan *et al.* [90]	Near operational, 1-Fixed wing, 2-Rotary	IR, Visual-1	Fuel, Electric	3-5 Kgs	Lab Color Model, Horn and Schunck Optical Flow Algorithm, Blob Counter	High accuracy and Fast response	False detection in smoke environment
Sun *et al.* [91]	Operational, Fixed wing	Thermal- 1	Fuel	5-8 Kgs	YUV color space model	To achieve accurate detection during smoke	High Response Time
Christensen *et al.* [92]	Operational, Fixed wing	IR-4 (720×640)	Fuel	Less than 1000 Kgs	Forward Looking Infrared technology	UAV in terms of reduction in cost of use of the helicopter	Loss of data packet
Restas *et al.* [93]	Near operational, 2-Fixed wing	1-IR, 1-Visual (1920×1080)	Electric	20-250 Kgs	Regression Algorithm	3D model of capture data, and quick hotspot detection	Deployment cost is high
Karma *et al.* [94]	Near operational, 2-Fixed wing	Thermal-1 (160×120)	Gas	2-5 Kgs	Artificial intelligence algorithm	For search and rescue operations	Not continuous with time
Ahmed *et al.* [95]	Operational, 1-Fixed wing, 1-Rotary	IR, Visual-1 (160×120) (320×240)	Fuel	Not specified	Adaboost algorithm	To achieve less delays	High cost
Merino *et al.* [96]	Near operational, 1-Fixed wing	Visual-1	Electric	Not specified	Feature matching algorithm, Blob feature extraction	To estimate the position UAV, Network failures	Less experimental validations
Ghamry *et al.* [97]	Near operational, Fixed wing	Thermal-1 (720×640)	Fuel	Less than 350 Kgs	Neural Network	To achieve the formation configuration in case of any faults.	High computational time, Less accuracy
Kalatzis *et al.* [98]	Near operational, 1-Fixed wing	IR, Visual-1	Fuel, Electric	Less than 10 Kgs	Edge computing, IoT	To achieve high detection rate, very few false smoke detection	High computational time

2.4 Literature Review of Wireless Sensor Networks Based Forest Fire Detection Approaches

This section highlights the literature review of several research articles that are related to the fire detection system utilizing WSNs. We have gone through various articles at Sensors, Springer, IEEE, and Science Direct in order to know the latest advancement in the field of Sensor networks. The objective of this study is to know the recent advancement in the field of sensor network also to study and compare various technologies that has been designed and implemented for forest fire detection application. The literature survey based on the ability of sensor networks for the detection of fire is categorized in three stages. These three stages are:

1. Deployment of senor nodes for real time monitoring of environment.
2. Localization in WSNs
3. Coverage and Energy efficiency in WSNs.

There are several issues that can be considered while designing a reliable forest fire detection system. The literature focuses on identifying efficient approaches with hardware infrastructure description, communication network and processing of information in WSNs.

Lloret et al. [99] presents a WSN based forest fire detection technique which is capable for monitoring both forest and rural environments. Their system also integrates IR cameras for the verification of fire event. In their architecture they have used a multisensor in order to detect fire and for the verification purpose they applied IP Cameras. Based on their implementations they have identified the advantage of implementing WSN is that their Scalability and Connection Strategy using HTTP protocol. The design is flexible and capable of sensing infrared radiation and smoke particles present in an environment. Further few more input variables may be added like temperature (and the instant changes in temperature), carbon dioxide, humidity and other gases for testing the efficiency of the architecture.

Zhang et al. [100] presented a fire detection approach using ZigBee protocol for communication. The system is capable of measuring humidity and temperature values from the environment precisely. The design is efficient as it takes less time to transmit the field sensed information to monitoring center. ZigBee offers advantages for short range wireless communication with less energy consumption and low data rate. The system achieves reliable transmission of information from source to sink and improved lifespan of the network. The design is not reliable when deployed in harsh environments, the experimentation shows the drawback of system for coverage and robustness.

Berni et al. [101] have presented a vision enabled testbed for detection and verification of fire. Their aim is to present a design which is a combination WSNs testbed and ground analysis system to achieve high reliability and robustness in fire detection. There are many techniques that analyze images coming from the remote cameras and evaluating large areas. These systems have high false alarm rate because such system needs to cope up with cloud motions and dust particles which effects pixel's resolution but compared to these systems their approach is covers only small region providing few false alarms. The design is very effective for monitoring fire in small regions. The classification of fire is carried out implementing RGB color model. The result presents the significance of design in terms for the development of fine spatiotemporal sensing network.

The forest fire can be detected and monitored by human based observations, satellite system, optimal cameras and the wireless sensor network [102]. The result shows that the best available system for early forest fire detection are WSN having medium cost, high efficiency, a smaller number of false alarms, maximum accuracy, less delay and can-do multiple tasks. Whereas the satellite systems are very costly having low efficiency, long delay. The human based observations having low cost but at the same time its efficiency is low and having very low localizing accuracy with long delay for detection. The optimal camera system having high cost, their efficiency is good but system is having long delay for detection. By comparing all of these techniques that can be deployed identification of forest fires, their research tells that the WSN has great advantage over all of the other techniques. WSN can provide any of the required data or information that is affecting environment at any span of time more accurately and can be able to cover large areas. During transmission broken routes degrades the performance of network and lessens network reliability. To deal with the issue of broken routes in a network a sub network-based method fire detection is presented in [103]. Their model provides an efficient coverage method which transforms random distributions of a network to organized deployment. According to their system the working of complete network divides into three part of network which reduces the number of nodes used. Further the experimental results of their system show that operating time reduced to greater extent as compared to earlier which will increase the network life and the overall effect is calculated as the energy performance which increases more than half percent as compared to the normal forest fire detection techniques. The design is efficient in terms of coverage but consumes large amount of energy as by processing large amount of data. Data mining-based fire detection approach utilizing WSNs is introduced that is capable of measuring real time data collected from the sensors [104]. The collected information is further subjected to mining technique that is basically the prediction of reusing classification technique at node level that only collects and process abnormal values and transfers them towards sink. The results present reduction in the amount of information exchange and hence reduction in redundancy. The overall results display the systems improvement in terms of speed and decreases network traffic which impacts better network life and hence making possible to detect early fires.

Tunca et al. [105] presented a research on the performance evaluation of WSN in real wildfire scenarios. They have used an OPNET modeler for the evaluation. An OPNET modeler in combination with realistic fire simulator that gives temperature values of the selected zone at regular timely basis. The performance parameters are examined by the delivery report ratio, notification delay, and consumption of energy. They have deployed various sinks which provides a solution for congestion problem in WSN and gives large benefits as energy efficiency and reliability. Their research also targets for studying the location of sink nodes which is an important factor for its performance.

Kosucu et al. [106] designed a WSN testbed for detection of forest fire. They have also designed FireSense previously which is a fire detection system that has successful results for simulation. Now they have taken their research forward in order to make reliable for outdoor measurements of physical changes, direction of wind, and position of ignition. The data is collected for real time deployments and sensed values are integrated with forest fire simulator and these collective values further given as an input to fire detection process for the analysis and the decision making. The simulation results reveal that the successful detection relies on two factors, first is location of fire point from base station and second is packet reception ratio. The operation of detection depends on PRR as if PRR is low the algorithm will not be able to detect a fire event. PRR hits low because of congestion and failure of nodes.

Somov et al. [107] proposed an automatic fires detection system that predicts fire by measuring the amount of toxic gases present in atmosphere. The designed system is capable of identifying fire before the formation of smoke by evaluating the gases in environment and can monitor for a long span of time. The authors have implemented energy conservation scheme for achieving efficient energy consumption, and conservation.

An efficient method for monitoring environment and detection of fire is studied in [108]. The two salient features of their mechanism are grid-based output and event triggering mechanism and the result provide improvement in terms of accuracy while power consumption is reduced. In grid based, this feature divides the area that is to be monitored into NxN structures and makes the output region that is referred as estimated node location that may have one or more adjacent neighboring grids. The second feature is a mechanism to adopt sleep-wake cycles in terms of localization for saving the battery of the sensors while maintaining its efficiency. These two salient features help their system to reduce the computational complexity and the improvement in terms of efficiency. The simulation results based on computer shows that their proposed algorithm is efficient in terms of monitoring but at the same time the response is not fast making it unreliable. Fire detection system addressing the issue of slow response in introduced that measures the environmental parameters in near real time [109]. The data collected is stored in cloud platform and analyzed by the users for latest entries. Cloud based platform provides the advantage of regularly monitoring the environment and for any adversary, fire alert is transmitted to user in the form of text or email.

WSNs based tested for the detection of fire using distributed clustering scheme, supporting minimum delay and high energy efficiency is studied in [110]. Roberto et al. [111] designed a mobile robot-based system and data fusion algorithm for fire detection. Mobile robot (based on tread mill) is used for the detection of fire afterwards a servo motor is deployed for the movement of platform of sensors. The idea of using data fusion is to test temperature and flame sensors. The author mainly focused on a low-cost project. The test result shows that their mobile robot is capable of sensing occurrence of fire and mainly project is very effective for large area fire detection.

Obregón et al. [112] have designed a system on the basis of sensor network for fire prevention. The sensors capable of measuring following parameters are temperature, humidity, speed of wind and its direction. System design consists of a prototype (a sensor network) that recovers the required information, and transmits this collected data wirelessly (through radiofrequency) and at last stores this data for further study. The next step is data recovery which is used within a system having purpose of analyzing data for further analysis. The data is transferred wirelessly via radiofrequency. The transmission is done with the help of MicaUns that generates messages in text form, therefore the modem that is connected with the system can transfer the information whereas for the reception, modem that is connected with the computer is responsible for processing of data. In the next step when the data from each sensor is available in the system, the information is further analyzed to check possibility of fire and at last the visualization is done. For the experimentation the system is successfully tested in the laboratory.

The intensity of wild fires is very high and sensor nodes must have some protection from self-burn. WSNs based fire detection system that can integrate at any environment and communicate effectively on critical circumstances is an efficient solution for real time environments [113]. The authors have introduced a model that can control or monitor bushfire mainly in the areas where the chances of causalities are expected to happen. Kirubaharan et al. [114] have proposed an intrusion detection system that can generate alerts of warning using WSNs. The authors particularly focused on finding the direction and rate of fire spreading, which is very important in order to restrict further damage. The implementation is done through Zigbee standard. Further the design of their system is such that it also detects interference caused due to human or wild animals. The system is tested with few numbers of sensor nodes and showing comparatively better performance for detection.

Alimenti et al. [115] presented low cost microwave radiometer for the identification of forest fires. Among all of the present techniques for detection the microwave radiometer is considered as the most promising approach which significantly helps in reducing the false alarm rate. A low noise block has used for receiver implementations. A local oscillator built in dielectric resonant oscillator features excellent stability in temperature. Therefore, input RF signal is converted into intermediate frequency output signal. Then the input circuitry is used which is composed of bias tee to set input impedance, a two-stage monolithic amplifier for providing IF gain along with digital attenuator for adjusting system gain and band pass filter to define the bandwidth. A square law detector also integrated at the same board for obtaining detector sensitivity and also noise adding calibration strategy is used for gain variations. The experiments held on the basis of their research proves that radiometer have much sensitivity for the detection of fire and also having high gain stability which results that their instrument can reliably measures values with ambient temperature and saving much power required by thermal control unit.

Tanenbaum et al. [116] presents article on wireless sensor network for its various applications. Their article suggests the advantage of wireless sensor network in terms of its feasibility as early warning systems. Wireless sensor network having capability of responding an intrusion within minutes, it allows fire fighter more time to act activity. They have also focused on carefully placing nodes to a vulnerable area with a smaller number of sensor modules. Their experiment shows that multipath radio signal propagation gives much larger radio hop distance in very dense vegetation compare to open space and its very important aspect is the lifespan of a network.

Mohapatra et al. [117] has presented a fire monitoring system that is also capable of localizing faulty nodes in a network implementing fuzzy logic. At certain instance the sensor node can provide incorrect data because of some faults in it. The prime objective behind their study is to detect faulty nodes to reduce the loss of energy. He et al. [118] presented a framework for smoke detection using WSNs and monitors forest fires. Their hardware system composed of power supply module which is responsible for supplying the necessary power and estimates the lifetime of network. Sensor acquisition module gathers the smoke concentration from monitoring areas and digital to analog conversion of data. The microcontroller gathers the field data and communicates it to monitoring center using internet. They have used MQ-2 for sensor module having high sensitivity for gas and smoke, having low cost and long service, rapid response and fast recovery. For the microprocessor module they have used CC2530 and for GPRS module they have used SIM900 which is having function like text message and data business. In their design the information is accepted by sensor nodes and then sent by router to the coordinator and also in parallel sent to GPRS module through serial port and at last it displayed on computer through internet. Their system satisfies the particular need with low cost and easy to install. A hierarchical WSN testbed is tested for the monitoring of forest fire to detect the event at its initial stage [119]. The fire risk is determined by implementing fire weather index which estimates the content of moisture for three fuel classes utilizing collected weather observations. Each of the node in a network has the record about its location on the basis of GPS information. Their network can easily be deployed in area of high interest. The result based on their research shows the accuracy of system for detection with rare false alarms and also suitable for long range communications. Son et al. [120] has presented the design of forest fire surveillance system based on WSN. They have developed FFSS that consist of WSN, middleware and web application. All of the analysis for the collected data is done on middleware and in the web application. The routing protocol works on the principle of minimum cost path forwarding and transfers the information to sink using shortest path. This way of routing data from through shortest path consumes less energy. Their FFSS observes real time forest state everywhere. When there is a fire, their system sends alarm to fire station which provides early extinguishing of fire therefore damage and other consequences gets reduced. The result shows that any system is energy efficient, but the data can be affected by the intruders as the transmission is not secure.

A framework for the secure transmission of information from source to sink in WSNs is presented [121] The authors have used multihop routing protocol where middleware component finds the escape path when a fire alarm is triggered and it also justifies whether that path is safe or not. Their designed method is efficiently dealing with fire events and offers a secure and reliable transmission of information. Barmpoutis et al. [122] proposed system for accurate and low-cost detection of fire event. Their system provides advantage like network is applicable for difficult and harsh environments. The system possesses safe data transmission and flexible network of low cost and lesser energy requirements. The real time monitoring of the environment is the only solution that can protect the region from fire [123]. The confirmation of presence of smoke is analyzed by using cameras that captures the image. This image is analyzed in base station to know the present state and when fire is detected, an alarm is displayed on the screen. The system can accurately confirm the fire event in real time but increases the cost of deployment. Convolution neural network-based fire monitoring system that provides high energy efficiency is presented in [125]. Their design is efficient and results minimum false alarms with low cost computations.

Table 2.5: Comparison of various Wireless Sensor Networks based forest Fire detection approaches

Study	Purpose	Methods Employed	Density	Performance Comparison					
				Coverage	**Detection to Notification Delay**	**Fire Behaviour**	**Energy Efficiency**	**False Alarms**	**Cost**
Lloret *et al.* [99]	To detect fire at earliest and its verification	HTTP routing protocol	Medium	Medium	Less	No	Low	Less	High
Zhang *et al.* [100]	To accomplish data acquisition and long-distance transmission	ZigBee protocol, Star cluster first route topology	Low	Low	Less	No	High	High	Low
Berni *et al.* [101]	Reliable and early detection of forest fires through vision enabled WSNs	Hierarchical clustering	Low	Not Addressed	Medium	Yes	Low	High	Medium
Alkhatib *et al.* [103]	Efficient coverage of region from few sensor nodes	AODV	Low	High	Less	No	High	Less	Low
Saoudi *et al.* [104]	Integration of data mining for FFD	Data mining, MAC protocol	Not Addressed	Not Addressed	Less	No	High	Less	Low
Tunca *et al.* [105]	To evaluate the performance of heterogeneous WSNs	DSR protocol, OPNET	High	High	Medium	No	Low	High	Medium
Kosucu *et al.* [106]	Real time testbed, node failures	Data aggregation, SQS	High	Low	Less	No	High	Less	Medium
Zhao *et al.* [108]	Monitor environmental parameters in real time	LEACH protocol, Bayes data fusion	Low	Not Addressed	High	No	Low	High	Low
Owayjan *et al.* [109]	Early detection of forest fire	Energy aware routing, Zigbee protocol	Low	Low	Less	No	Low	Less	Low
Aslan *et al.* [110]	To support minimum delay and energy efficiency	Distributed communication protocol	Low	Low	Less	Yes	High	More	Medium
Roberto *et al.* [111]	To minimize false alarm and maximum accurate detection	Data fusion algorithm, ZigBee module	High	Not Addressed	Less	No	High	Less	High
Obregón *et al.* [112]	Fire prevention using Sensor nodes	Directed diffusion	Low	Low	Less	No	High	Less	Low
Mohapatra *et al.* [117]	To detect faulty nodes and probability of fire	Fuzzy logic system	Low	High	Less	No	High	Rare	Medium
He *et al.* [118]	Smoke concentration monitoring system	ZigBee module, MAC protocol	High	Low	Less	Yes	Low	Less	High
Molina-Pico *et al.* [119]	To achieve long range communications	Fire weather index, Fine fuel moisture code, Hierarchical clustering	High	High	Less	Yes	High	Rare	High
Son *et al.* [120]	WSNs, Camera, Satellite based monitoring	Minimum cost path forwarding	Low	High	Less	Yes	High	Less	High
Lim *et al.* [121]	Event detection and rescue operation	Multi-hop routing algorithm	Low	Low	Less	No	High	Less	Medium
Barmpoutis *et al.* [122]	Image based fire verification approach	Region based Convolution neural network	Low	High	Medium	Yes	High	Rare	High
Bahrudin *et al.* [123]	Detection of event and report it to user through SMS	Fuzzy neural network, ZigBee module	Low	Not Addressed	Less	No	High	Less	Low
Singh *et al.* [124]	To achieve minimum computation requirement	Deep learning, CNN	High	High	Less	Yes	Low	Rare	High

In this section we have studied various forest fires detection systems based on Wireless Sensor Networks. Apart from this, the performance comparison of WSNs based fire detection approaches are presented in Table 2.5 detailing the methods employed, density and performance indices. The advancement is the technology of WSNs makes the technology most suitable for the application of early detection of fire event. Some of the QoS (Quality of Service) issues associated with the WSNs are discussed in the following literature.

2.4.1 Deployment, Coverage and Energy Efficiency in Wireless Sensor Networks

The efficient coverage in Wireless Sensor Networks receives attention from various researchers. The studies conduct presents the analysis for providing essential requirements for efficient coverage of area of interest using WSNs [125]. The restriction of size, cost and weight of these sensor nodes directly influence the resource availability. These sensor nodes offer limited capabilities for processing, communication and limited source of battery. The low consumption of power is the foremost requirement of majority of WSNs applications and replacing battery in a network is not a realistic solution as sensor modules are deployed in hostile environments in multiple numbers [126]. The coverage issue is WSNs is to efficiently sensor nodes in an area that minimum numbers of sensors provide maximum coverage and low power consumption. The issue of scheduling sensor activity for increasing network lifespan while guaranteeing the maximum coverage is studied in [127]. Their study tackles the coverage issue but does not considers the issue of connectivity. Authors in [128], presents a scheme that guarantees the connectivity. Their study shows the connectivity of network can only be assured only when coverage is achieved for the entire area, and also when the communication range is twofold of the sensing range. This claim does not stand for the problem of discrete point coverage as studied in [129].

The impact of energy consumed during the communication of sensed information on scheduling activity of sensor has given any consideration in [130]. The design either pays no attention to energy consumption or accepts that each sensor node consumes same energy in a network. However, the energy consumption by each node in a network may differ significantly as it depends upon the amount of sensed information for real time scenario. Wang et al. [131] proposed energy efficient scheme that improves the area and coverage problem. Their design addressed the coverage issue by considering nodes stationary in a network. The optimal deployment of sensor nodes offers maximum coverage and guarantees maximum utilization from sensor [132]. The self-deployment scheme utilizing mobile sensor node can enhance the coverage and improves the lifespan of network through the topologies of uniform distribution [133]. Mini et al. [134] designed an algorithm considering the problem of deployment and location of sensor nodes for coverage point of view. Akshay et al. [135] proposed a model for providing maximum efficient coverage by considering automatic dispersion of mobile sensor nodes where the mobility of sensor node requires for covering the complete region due to absence of wireless connectivity.

In WSNs the energy efficiency is most challenging issue for collection and processing of data in a network. Since the beginning of WSNs the energy efficiency is tackled by various researchers which includes energy conservation through sleep scheduling, mobile collectors, controlling the topology and data aggregation. Sleep scheduling, mobile nodes as data collectors and topology control along with many other are the approaches which focuses on techniques for improving the efficiency of network while transporting sensor data. On the other hand, data aggregation is the technique that primarily focuses on transport data reduction. Therefore, data aggregation scheme compliments other mechanisms and is believed as the most efficient scheme for achieving energy efficient collection of data in WSNs. Although, data aggregation scheme are most efficient, still there present some drawbacks that needs to be improved on. Simple data aggregation schemes such as Min, max and Sum includes only statistical measurements of sensors which makes them unreliable for real time applications [136].

The other lost information may be very useful and hence these approaches are not reliable for the applications that requires particular limited information for their operation. One solution to this aggregation issue is distributed source coding technique that performs non-collaborative compression of data at source [137]. The experimentation is not practically validated due to less knowledge about the structure of data. However, the collaborative compression of data at source makes it possible to get the knowledge about structure of data by exchanging the information. The limitation with the approach is that it either requires simple correlation data otherwise it results in terms of high communication load. Compressed sensing is the promising technique that delivers the signal recovery until and unless the signals are in same domain [138]. The technique is focused on reducing the amount of data traffic in sensor network without depending on correlation of data structure. The complication of compressed sensing approach has delayed the further development of their energy efficient data collection scheme.

The energy is a resource that needs to be utilized efficiently in the operation of WSNs. In WSNs application, it is impossible to recharge each node because of their dense deployments. An energy aware clustering algorithm can improve network performance for better energy consumption [139]. The sensor node in WSN contains limited resources like small communication range, having less bandwidth, small memory. Considering these major factors, to enhance network lifespan energy consumption should be minimum. There are many researches that have been proposed for the improvement of the energy efficiency. In their paper they proposed an algorithm that is capable of responding very often and immediately to all of the unexpected events with high energy efficiency because every sensor collects information individually and makes cluster by using competition scheme. The result shows that the system is having improved performance and better energy efficiency. The cooperative MIMO scheme can improve the energy efficiency in WSNs [140]. According to the study MIMO technique can enhance energy efficiency in network but for the application of WSNs this technique is not feasible because of the limitation of size of sensors. To address this issue a CMIMO scheme is introduced and the experimental results presents better performances. The experimental of simulation and the graphical behavior shows that proposed system is having a significant saving of the total energy. The protocol for efficient energy consumption based on cluster head selection in WSNs is studied in [141]. Their protocol enhances network lifespan and provides information to next hop with in a limited time. They worked for the analysis of energy delay trade off by taking consideration the neighboring to sinks distance. The protocol is capable of consuming less energy and small delays.

2.4.2 Localization Problem of Wireless Sensor Networks

The location and position of each node in a network is difficult to know when sensor nodes are deployed densely for real time scenario. The position estimation of unspecified sensor node in a network is termed as localization. Event monitoring through WSNs suffers from dead nodes, faulty nodes and an event of fire can be anywhere in a region of interest. For dealing with faulty nodes, dead nodes the knowledge about location coordinates is prior concern. The authors in [142] proposed routing protocol which gives load distribution that is RTMLD for mobile wireless sensor network. For the sensor location management their approach in RTMLD uses corona mechanism as compared to previous RTLD in which the location is calculated by calculating the location of the three adjacent nodes that leads poor performance. For the optimal neighbor selection RTMLD uses RSSI that saves the calculation time as compared to the RTLD in which it is done by PRR. The PRR demands spare time, much energy and having complex calculations. The major advantage of using corona mechanism is if in any case the mobile sensor node fails to advance the data packet to the towards neighbor node, the same packet will be reversed to any node that is high corona level and also informs the system to stop sending further data packets which makes it flexible. The simulation results of their system based on corona mechanism shows that the system is having high reliability and high flexibility.

Spyridakos et al. [143] proposed a multicriteria disaggregation-aggregation approach for the forest fire detection systems. Their proposed system mainly focuses on using fire detection units with thermal cameras, internet or mobile because of the reliability with less cost. Their research briefs about the decision problem of finding the location for fire detection units. The major conflicting factors are the cost of installation and its operation, screening of the zone, the easiness of maintaining and management and the reliability of the system. In their proposed approach FDU are composed of three parts. In the first part FDU are deployed in forest area along with the power units. The second part is a communication system which acts as a link between unit and the control system and in the third part there is a control system which consists of a server with appropriate software for the management of the system devices and the communication purpose, one other server with appropriate software for image processing which also includes alarm system, display unit, storing and GIS. Their proposed system results a very effective solution for the early detection. The other problem is decision maker, multicriteria DA technique helps greater interactively for DM. The results show that their approach provides flexibility and is well established criteria for DM's to make their decision. The position estimation of every sensor node in a network is very challenging issue. Various solutions have been found in the literature still there is no clear knowledge about its practical and economical deployment. A GPS enabled sensor node is one of the solutions for the problem of localization [144]. The power consumption and cost of deployment for GPS enabled sensor network excludes it as a feasible solution. There exist many techniques for computing the distance in range-based localization scheme. Awad et al. [145] utilizes RSSI (received signal strength indicator) model for the estimation of distance of unspecified sensor node in a network. The signal power is known initially and based on the power dissipation the distance is computed using some geometrical functions. Lee et al. [146] proposed a localization algorithm that measure the distance by evaluation the angle of arrival. One more study is found that calculates the distance of unspecified node in a network by measuring the time difference of arrival. A novel approach for the estimation of location of sensor node in a network is Monte Carlo method which has the advantage over other range-based algorithms for accurate location estimation [147].

Range-free localization algorithm is advantageous over range-based when there is requirement of low cost and low power dissipation. In range-free techniques the location of unspecified sensor nodes is obtained through inter-connectivity among nodes in a sensor network. Thus, reducing the cost of deployment as there is no external hardware is required for the location estimation. Wang et al. [148] proposed a range-free localization scheme known as APIT, in which the possible seed points are computed using neighboring sensor nodes and then triangles are formed on these seed points. The intersection region of all triangles is the estimated location of unspecified sensor node. A distance vector routing-based location estimation scheme known as gradient algorithm is presented in [149]. The proposed scheme allows each node to compute number of hops for the seed point and range-free technique is employed for the computation of average distance, also transmitting this estimated information to the nodes. Kumar et al. [150] suggested a DV-Hop localization scheme which is equivalent to gradient scheme but their method of computing average distance is different. Zhang et al. [151] proposed a location estimation scheme that computes the location of unknown node by using location of neighbor known node. Takashima et al. [152] have proposed a new approach for the location estimation of mobile sensor nodes in a network. The proposed scheme is a tarde-off among accuracy and energy. Almuzaini et al. [153] proposed a range-based localization scheme for knowing the location of mobile sensor node in a network. The problem associated with their design is that when the radio range of sensor node is not perfect then the location estimation is not accurate.

Some other critical challenges of WSNs are security and the privacy issues as the communication process is wireless and its broadcasting nature, the information must be secure. Yu et al. [154] investigated the performance of distributed estimation scheme for a WSN with in the presence of eavesdropper. The authors have investigated notion of perfect secrecy and wiretap channel for the data confidentiality. Multiple antennas can reduce the risk of information loss and enhances the security of complete network. Hu et al. [155] presented a stochastic geometry approach providing security to three tier WSNs. The authors mainly focused on the secure transmission of the information in two processes. The transmission of information through active sensors to the coordinators and the active coordinators that forwards the information to sink. Their design considers multiple antennas at coordinator and utilizes low complexity maximal ratio for receiving the information and information transmission with maxima ratio. The analysis results the performance of their approach and achieves highly secure data transmission. The evaluation of ongoing attack network is also important concern data transmission in WSNs. Further to enhance the security and to know about the ongoing attacks, a chance discovery and usage control based hierarchical framework is studied in [156]. The continuous discovery and other attributes can evaluate the ongoing attack and also discovers unknown new attacks. The two-defense approach that exists to protect WSN are detection based like intrusion detection and preservation based like access control. They have proposed an approach which is a combination of both intrusion detection and access control that employs UCON with continuous decision making and dynamic attribute. UCON performs data control not only at the time of access but also during and after use. Castelluccia et al. [157] identified the security vulnerability and solution corresponds to this issue. Small data dissemination protocols in WSN are used for adjusting configuration parameter of sensor and for the distribution of management commands and queries to sensor. When WSN is deployed some of variables for each sensor node needs to be updated regularly. A small dissemination in network by requesting nodes to exchange information can modify, change or delete variables and hence become consistent in network. The authors have implemented SeDrip protocol and ensures the authenticity and integrity of data and provides enhanced efficiency in security functions which makes it more suitable.

Islam et al. [158] examined the reliability and security aspects of WSNs technology. The reliability, accuracy and time of data generated and transmitted in WSN are the most critical factors. They have explained various ways to make the network reliable such as multipath technique, synchronization and identification and redundancy. They have also identified various security aspects for a WSN that are confidentiality, integrity, authenticity, freshness, availability and non-reputability. They have also provided characteristics of attack in WSN and their prevention. Based on their research they have identified that the public key cryptography which is a traditional cryptographic algorithm is very effective in handling most of the security issues.

2.5 CONTRIBUTION

Early detection of forest fires prevents loss from the disaster by enabling deployment of specific sensor nodes in real time environment. The proposed methodology of this entire study is depicted in Figure 2.3.

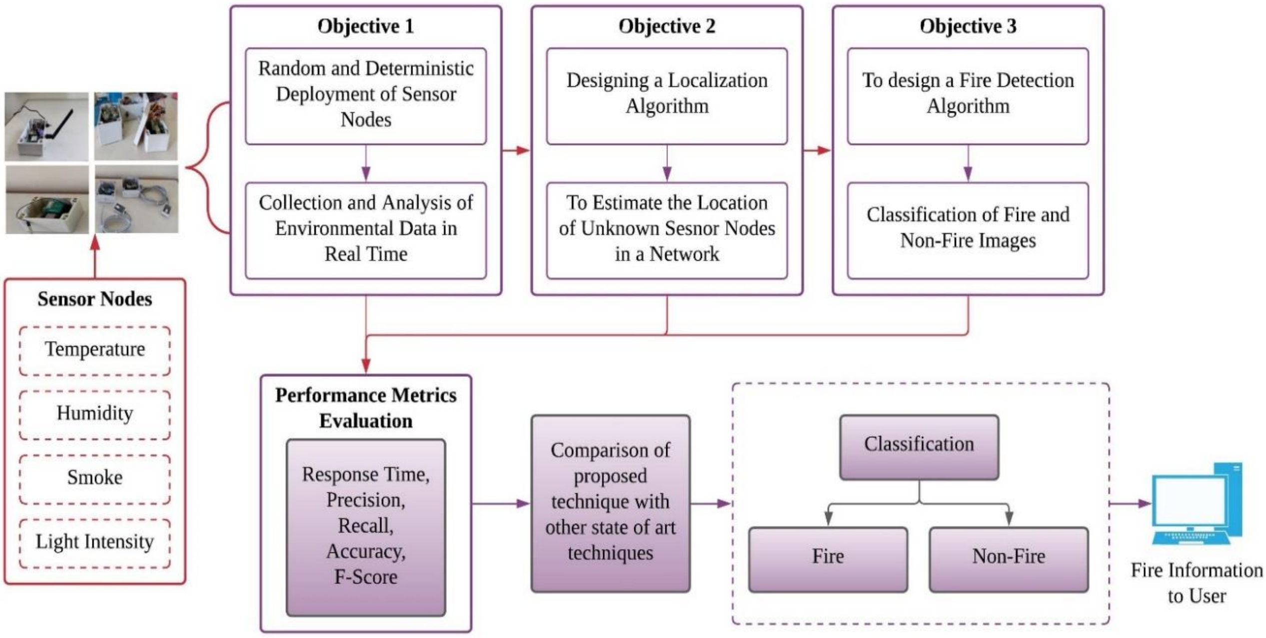


Figure 2.3: The proposed methodology of the entire framework

The designed methodology of this thesis is categorized into three phases based on three objective frames for the research work. Different fire image datasets are utilized for this research work and a comparative analysis is carried out with existing state of art techniques on the basis of several performance indices.

The first phase is the deployment of application specific sensor nodes in an environment for the collection of data on real time basis. The deployed sensor modules measure the state of environment at any time. The proposed design is integrated with

ThingSpeak cloud analytics platform for the storing and analysis of data in real time. Sensor modules collects humidity, atmospheric gases, light intensity and temperature parameters and transfers the sensed data to the cloud in every 2 to 5 minutes. The collected data from region of interest is transferred to ThingSpeak IoT analytics for its storing and analysis. ThingSpeak provides the platform for real time analysis of data in graphical representation with each entry of data. The observation from the analysis of normal condition dataset and fire condition dataset leads to the defining of certain threshold values for each individual sensor. Whenever the measured data exceeds threshold value, system triggers an alert in the form of text and email to the user. The performance of the system based on ThingSpeak analytics compared with other state of art techniques for the parameters of average response time and standard deviation.

The second stage of this research work is designing of a localization algorithm for the identification of unknown location of sensor nodes in a network. Typically, sensor nodes for real time applications are deployed in large numbers at harsh environments. Due to the small size, low power and coverage limitation of sensor nodes, it is not possible to recharge each node in sensor network. Whenever any sensor node fails to communicate the information calls as dead or faulty node, it effects the overall network performance in terms of high-power consumption. Moreover, a fire event can be detected or triggered by any sensor node in a network. Therefore, the location coordinates of each sensor node should be known to the central server or sink node. The problem of identifying the location of unspecified sensor node in a network is termed as Localization. The performance of the proposed algorithm is compared with existing state of art approaches in terms of accuracy and estimation error.

Fire detection algorithm based on image processing is proposed in third stage of this research work to confirm the existence of fire. Images of fire from various datasets are taken considering different color of fire, types of fire and size of fire. The proposed fire detection algorithm works in four stages; image pre-processing, extraction of features, conversion and classification for the confirmation of fire event. The design implements Histogram equalization, RGB and YCbCr model for the verification of fires. The system performance is validated and analyzed with sequence of images consisting of fire and non-fire and fire detection and non-fire detection at its output. The final phase of our research work deals with classification of fire and non-fire images for the confirmation of event.

CHAPTER 3

SENSOR NODE DEPLOYMENT FOR THE DETECTION OF FOREST FIRE

CHAPTER 3

SENSOR NODE DEPLOYMENT FOR THE DETECTION OF FOREST FIRE

3.1 INTRODUCTION

Wireless Sensor Networks presents exceptional features which offers various advantages and multiple challenges for the application of fire monitoring system. The challenges such as limited power, vulnerable senor nodes, and the hostile environmental conditions must be considered before constructing a solution for early detection of fire event using WSNs. This section explains about sensor nodes, various applications and its deployment for forest fire detection and data acquisition. The recent advancements made in wireless technologies has gained attention in different fields of real-time applications. The unique features offered by the wireless networks have developed several wireless communication models to support the real-time environment from different aspects like data delivery, data availability, network security and so forth. Wireless Sensor Network is a type of networking module that has been introduced with the embedding of integrated circuits in advanced technologies [159]. In alignment with the communication technologies, the sensor devices are manufactured in the compact size which assures fast and reliable information delivery modules. In the angle of computational costs, the smaller the devices, the cheaper the expenses. Owing to these features, Wireless Sensor Networks has gained much attention among the industrial and researchers. It supports a wide scope of applications and challenges for the researchers. Concurrently, the enhancement in the hardware is also growing that makes easier deployment of sensor networks in the real-time environment. Much research efforts have been taken to support and explore the capability of sensor networks in different forms of networks modelling such as routing, data analytics, tasks scheduling, network localization, key management and cryptography. These forms of sensor network applications demand for the development of low-expenses, reduced power usage, multi-functionality support and efficient communication ability. It has influenced the development of a collaborative environment with different sensor networks.

A sensor network is a kind of ad-hoc network that contains a huge volume of sensor nodes according to the application requirements. These sensor nodes are holding the potentialities of sensing the environment using its abilities like temperature, humidity, light variations and so on. Despite its sensing the environment, the deployed sensor node has the proficiency of computational power and data processing. It is noticed that the sensing nature of the nodes varied as per the range of the wireless communication links. Since the sensors are powered through batteries, it is hoped for a long lifespan, however, it behaves anonymously in the hostile environment. The sensor nodes are disposable and offers low-cost deployment in large number for monitoring an area [160]. Thus, by abiding with these features, it fits for large-scale applications. As presented earlier, a sensor network is a collection of several sensor nodes which are greatly useful to be deployed inside the forest. The position of the sensor nodes has not been modulated (or) pre-estimated. The sensor modules are placed in an arbitrary manner at the interior region of forest. Wireless Sensor Network (WSNs) is introduced to detect the forest fire at an early phase, in order to preserve the environment [161].

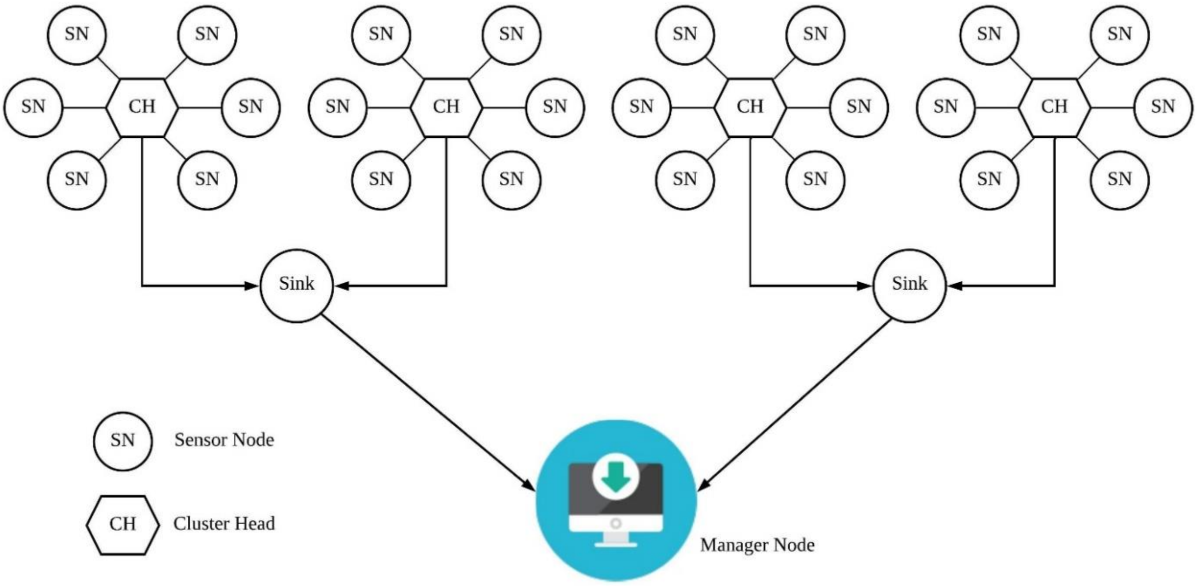


Figure 3.1: Architecture of the WSNs deployment in forest environment

Figure 3.1 depicts the topology of WSNs deployment in forest environment. It represents the hierarchical topology where all of the sensor nodes are joined at lowest level in a Wireless Sensor Networks. The sensor nodes forms cluster by utilizing the information of their respective neighborhood sensor nodes and selects a cluster head (CH). Cluster head election depends upon the important parameters such as limited energy resources, number of local nodes and closeness to base station. Each of the sensor node at lowest level collects the field information and transfer it to their respective cluster heads. The cluster heads carry sensed information and forwards it to the sink node. The same process of data collection is repeated in hierarchy for every level. The coordinator node is accountable for gathering the relevant information and transferring it to the manager node or base station for analysis. The limited resources of energy and harsh environment of forest complicates the deployment of sensor network. Following are some of the design goals that needs to be satisfy for the successful deployment of sensor node in context of early fire detection system:

- **i.** Failure of Wireless Sensor Networks Nodes.
- **ii.** Energy consumption of WSNs.
- **iii.** Detecting fire as its initial stage as early as possible.
- **iv.** Making of a network that is adaptive to all environmental conditions and forecasting the field information.

3.1.1 Node Failure in WSNs

The main responsibility of deploying sensor networks is to monitor the environment, if any abnormal occurrence of events. In the angle of forest applications, it is deployed to monitor the areas of the forest, if any sudden fires (or) disasters occur in the environment. It reports to the concerned entities by collecting the temperature (or) the humidity of the area in the forest. The sensor node communicates with the forest fields using wireless links, so as to collect the information about the forests. The collected data from any forest area is forwarded to the sink node by taking multiple hops. All sensor nodes are connected to the other networks via gateway. The deployed sensor nodes in the forest are unaware about the location of its placement, and thus, it is equipped with the wireless communication devices. The chance of failure [162] of the nodes is high due to the environmental faults presented in the forest. The reasons behind the failures of the nodes are presented as below:

- **i.** The sensor modules are fabricated and thus, the fabrication process might bring issues and also environmental causes sink in the forest, could be a major issue.
- **ii.** The draining of sensor modules battery in the forest might vary with the range the communication. The wider the communication distance, the wider the battery power depletes.

The presence of faulty nodes may affect the quality of the service. Therefore, it is to be understood that the transmission capabilities of the sensor nodes under the forest scenario must be reliable and flexible. In case of any fire event occurrence, the system detects with no fire, then the costs of the environmental security will go beyond our levels. In comparison with the wired environment, it is crucial to suspect the link and the faulty nodes in the forests. The below Figure 3.2 presents the architecture of the WSNs with the faulty nodes (or) link.

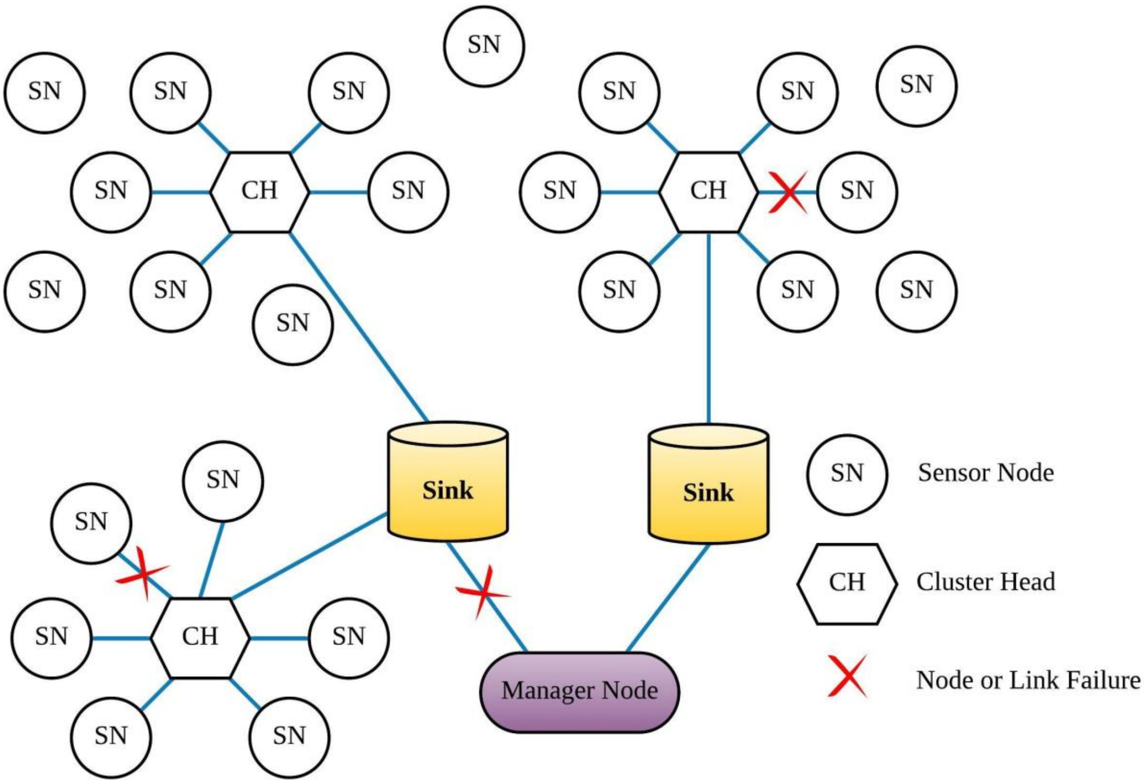


Figure 3.2: Architecture of the WSNs with the faulty nodes (or) link

The above figure indicates the significance of localizing the faulty nodes (or) links in the forest. The affected link will negatively influence the natural environments of the forest. Though it is tough to localize the faulty nodes, still it is of prime importance in forest fire detection systems.

3.1.2 Energy Consumption of WSNs

Energy consumption [163] is one of the ongoing challenges in the WSNs. Since the designed sensor node is a tiny electronic device, it is charged with a restricted power source that normally ranges as, (<0.5 Ah, 1.2 V). The renewing of power sources might be infeasible on the application scenarios. Generally, the responsibility of the sensor node is to accomplish two tasks, namely, data originator and data router that performs multi-hop fashion. Henceforth, the chance of faulty nodes might bring a negative impact on the sensor networks. In addition to that, the applications engaged in the long-term monitoring process have also affected the flexibility and efficacy of the network systems. The surveys state that the most of the power dissipation prevails in the processing, transmission, reception and listening towards the data. The power taken by the sensor nodes during transmission purpose is of great proportionate. While considering the restricted capabilities of a sensor node, a wireless environment has to come up with so many tiny sensor nodes deployed in high density. Since the sensor nodes operate in an ad-hoc fashion, the chance of idle nodes is also high and it also encounters power consumption during the listening process.

3.1.3 Early Detection of Forest Fires

The detection of fire at its initial stage is very important for an efficient forest fire detection system. Forest fire is an uncontrollable event as it spreads aggressively and therefore it is foremost requirement that event of fire should be identified in its early stage at time duration of 2 to 5 minutes. Forest fire detection system can only be called as successful system when it efficiently detects the fire with minimum of detection to notification delay [164]. Also, in case of dense deployment of sensor nodes, localization of ignition point with minimum error is important so that the fire fighter can take necessary preventions. In this work, various sensor modules are deployed in real time environment for the measurement of environmental data and further integrated with cloud platform for the examination of data in real time. The ThingSpeak IoT analytics platform is used, where the field data is stored at every 2-3 minutes of time.

3.1.4 Adaptability to Hostile Environments

Wireless Sensor Networks system robustness depends upon the capability of sensor network to recover from the node failures and communication errors that caused due to hostile environments. There are several challenges that come when a wireless network is designed for sensing parameters from the environments [165]. We must have to keep these things for building a wireless network.

i. Avoid electric wires because wires could hurt people, animals. Therefore the power needs to be generated from batteries and solar panels which states that the system has to be of low power consumption for minimizing the costs.
ii. Visual impact is an important factor in rural places, we should avoid the use of data wires to reduce the visibility of them.
iii. The cameras need to be small so that they are not visible to animals and at the same time they have to be of good quality to get quality images.
iv. The rural areas have many distortions in the form of animals, trees and vegetation that cause reduction in received power. So in wireless network it must be sure that received signal is of enough power.

Additionally, the sensor nodes should be provided with some insulation as high temperature values can destroy them. During fire event the value of temperature is extremely high, thereby causing the node failures and malfunctioning of sensor network. Therefore, considering these challenges an efficient sensor network must be adaptable for node failures in a network such that these failures cannot harm the overall functioning of network.

3.1.5 Scope of WSNs in Forest Fire Detection

The research in forest fire applications, it is mandatory to know about the background of forest fire systems. It is one of the applications related to environmental security that needs to be tackled using WSNs. Nowadays, the world is engulfed with plenty of natural disaster problems and thus, biological resources are getting wasted. An increased awareness arises in the preservation of biodiversity, and thus, planning strategies are innovated in forest fire management. Recently, WSNs has been emerging with new features by aligning with the new communication technologies. Thus, the scientific community has decided to explore the WSNs in the forest monitoring services. The sensor nodes deployed in this environment are low-cost networks and thus, monitoring service will take a limited time and space. These networks are projected as critical elements in the evolution of ubiquitous computing. An intelligent way of acquisitioning the data to track the area of the forest is one of the recent past processes [166]. The idea of incorporating technological advancements towards the pre-defined infrastructure brings a variety of innovation in this study. Whenever the conditions of the social environment changes over time and space, the deployed WSNs assist to collect the real-time data at the least expenses.

3.2 PROPOSED FOREST FIRE DETECTION SYSTEM

Our study aims for proposing a framework that considers three basic goals of forest fire detection 1) Real time monitoring of environmental state at any time, 2) Less power consumption, 3) Adaptability to hostile environments, and 4) Early detection of fire events. Detecting the forest fire at an earlier phase is significant to preserve the environment. There is a strong literature survey on predicting the forest fire using Image processing (or) any other techniques. Some studies have made use of satellite systems for fire monitoring purposes, however, the utilization of these techniques are still in unfavorable part because of high-expenses, low-resolution and heavy time consuming processes [47]. As far as, the execution of these systems in real-time is not possible to detect the forest fire at the earliest [37, 167]. To the deep analysis, IR cameras and Unmanned Aerial Vehicles (UAVs) [58, 168] were employed for the detection process. Regardless, the IR cameras initiate line of sight vision that deteriorates the collection of fire events which are not included in the LOS area [57, 61, 169]. Likewise, the deployment of UAVs adoption is also higher [92, 97]. Therefore, the sensor measurement process plays a crucial role in the forest fire detection process. Owing to it, this section presents the deployment of sensor nodes efficiently to acquire the sensor data.

Generally, there are two types of sensor nodes in the WSNs, namely, Mobile and Stationary nodes. The careful placement of sensor nodes in the forest coverage area becomes a major key factor with respect to size of sensor node. The deployed sensor module gathers the data and then exchange data with base station through the assistance of sink nodes. The below Figure 3.3 presents the adopted methodology of the forest fire detection process.

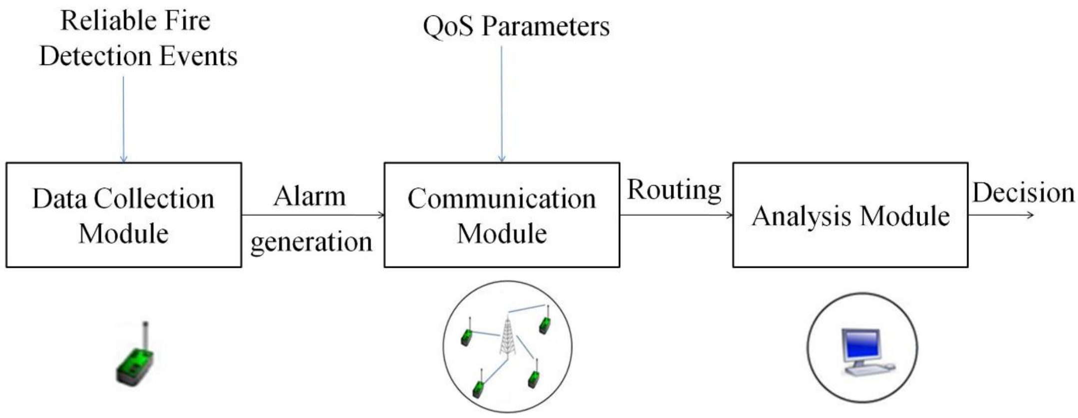


Figure 3.3: Adopted methodology of the forest fire detection process

The above figure depicts the methodology adopted for the forest fire systems using WSNs. The working of the system is divided into three different phases. In the first phase sensor modules are placed in the area of interest for measuring the state of environment at any time. The sensor will work regularly until the event of occurrence of fire happens. The sensor nodes measure variables like humidity, light intensity, gases and temperature. The second phase is the communication module, which is responsible for routing the important information that may be alarms, events or any sensed data to the analysis module while considering certain quality of service parameters. The QoS parameters are taken into consideration like reliability (an event must reach to coordinate node safely), temporal constraint (an event must take reasonable time to reach towards destination) and security (the path must be secure from any attack). The third phase of working is the analysis module which is responsible for examining the received alarms. Then sensed information is processed by the decision-making center that judges if an alarm is false or not. The sensor node has the ability of detecting the local forests by eliminating the overhead prevailing during the communication process. The sensor node which could sense the fire events, will act as active sensors. This tries to send the information using cluster head and gateway to reach the sink node. It consists of three modules, namely,

a) **Data Collection Module:** It is the first module that conjoins with reliable fire detecting events. Based on the collected data, an alarm will be generated.
b) **Communication Module:** This is the second module that deals with Quality of Service (QoS) parameters. Based on the generated alarms, the functioning of the

communication module aligns with the routing protocols.

c) **Analysis Module:** This is the third module that acts as a decision-making system.

Each proposed module is explained as follows:

3.2.1 Deployment Phase

The sensor nodes for measuring the state of environment at any time is deployed in forest area. The parameters such as humidity, light value, ambient temperature and atmospheric gases are monitored through real time deployment of sensor modules. The hardware description of deployed sensor modules is presented below:

3.2.1.1 Hardware Platform: Sensor Modules

Light sensor module captures the light intensity for observing the environment. The Light sensor are often known as photodetector depicted in Figure. The light sensor are used for measuring the intensity of light present in atmosphere. The photodiodes and photo resistors light dependent resistors (LDR) are commonly used light sensors. These light sensors convert the measured light value to voltage or current.

Figure 3.4: Light sensor module

Figure 3.5 depicts the humidity, temperature sensor nodes (HTS-220) which offers low cost measurement of relative humidity and ambient temperature. This sensor utilizes thermistor and capacitive humidity for measuring the temperature and humidity in air and generates a digital signal as its output. This sensor node east to use but at the same time requires careful scheduling for grabbing data. This sensor node provides new sensed data once in every 2-3 seconds. The HTS-220 sensor node is easy to deploy and comes with multicore PVC cable of 2 meter long.

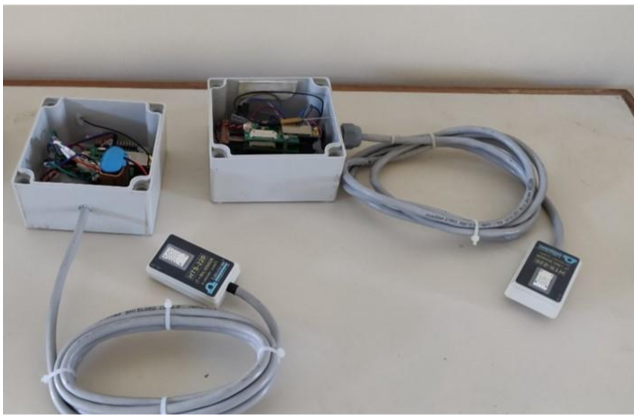


Figure 3.5: Temperature and Humidity sensor

Figure 3.6 presents the smoke (MQ2) sensor that measures the presence of gases in the atmosphere. This sensor node is capable for monitoring the concentrations of flammable gases and presents an analog voltage at its output. MQ2 sensor can measure the presence of gases in a range between 200 to 10,000 PPM and capable of operating at -20°C to 50°C temperature while consuming less than 150 mA.

Figure 3.6: Smoke sensors

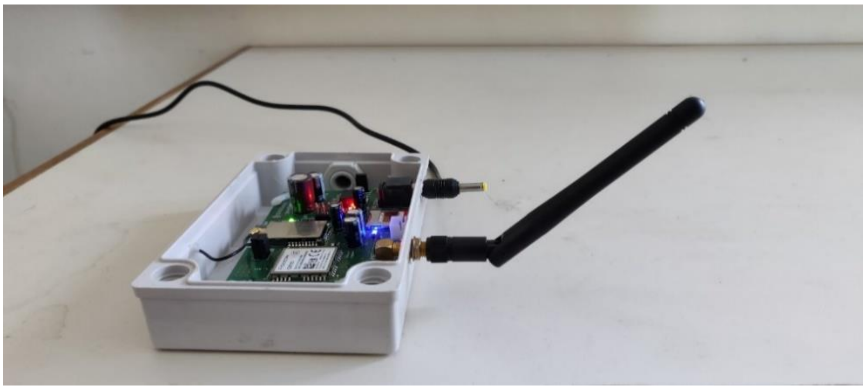


Figure 3.7: Coordinator node

Figure 3.7 shows the sink or coordinator node which is GSM enabled sensor node. This module gathers all the field information and further transfers it towards base station for its storing and analysis. The placement of sink node is critically important for achieving minimum energy consumption and better lifespan of network. The power consumption and lifespan of network are the most essential issues in WSNs based applications. Each sensor node measures field environmental data and transfer its sensed information to cluster head. This process of collection is repeated hierarchically at each sensor level. The collected information from cluster heads is further routed to sink module. The sink module collects all sensed information and further forwards information to base station. Therefore, sink module acts as a gateway among network and base station.

The deployment of the sensor node plays a crucial role in developing efficient design and decision-making systems. It takes the responsibility of enhancing the performance of the detection process. While performing deployment operations of the sensor nodes, it has to encounter two main factors.

- **i.** Finding the average distance between the neighbouring sensor modules.
- **ii.** Formulating the pattern (or) distribution of sensor nodes under a forest area.

Along with these two factors, the functional requirements such as energy consumption capability, detection ability, aligning with the public channels, sensing ability towards coverage area, exploitation ability towards terrain are to be taken before proceeding with the deployment process. The estimation of the average distance among neighboring sensor modules is one of the core parameters which deals with the performance of the abilities of the data collection module. The larger the distance, the detection ability will be affected. In case of fire events, the time taken by the sensor node to collect the temperature data gets inclined, which is also related to average distance sensor modules. Henceforth, the expected fire detection time is achieved by reducing the distance between the neighboring sensor nodes. While in the other angle, the reduced distance among neighboring sensor modules will lead to collision, since the node deployment becomes denser. Thus, the negotiation between the expected time in fire detection and the probability of the collision needs to be balanced.

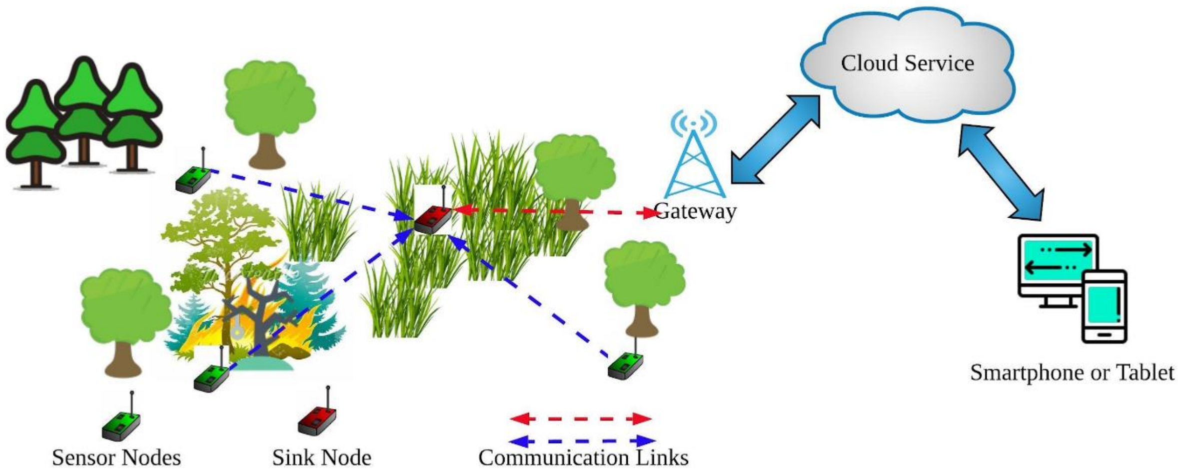


Figure 3.8: Sensor deployment and information transmission

The above Figure 3.8 presents the Sensor Deployment and information transmission process. It consists of sensor nodes, sink nodes, gateway and the smartphone with cloud-assisted services. The sensing field of the forest is determined and the number of sensor modules are placed randomly. The hardware details of the sensor node are given in the next section. The deployed sensor node senses the data and communicates with the sink nodes using a gateway. Then, with the help of cloud-assisted devices, the events occurring in the forest are monitored. The formula to estimate the average distance among neighboring sensor modules is expressed as follows:

$$d = \alpha \frac{ET}{NI^2} \tag{3.1}$$

Where, d is given as average distance which is measured in meters (m); the initial energy of the sensor nodes is given as E and measured in joules (J); The maximum time taken to detect the fire events is given as T, and measured in seconds (s); The lifespan of the sensor nodes is given as N, and measured in seconds (s). An empirical value is α which acts as normalization factor; Symbol, I, is an Important value which is a unit-less parameter.

The important value I is a parameter that defines the forest. It indicates the importance of protecting the forest from the fire. Consider an instance, a forest is located in a cultural heritage site, then, it is considered more for protection. The value of I determines the scope of the protection. It holds the value in a range between 1 to 10, where 1 indicates “not important”, and 10 indicates “highly important”.

3.2.1.2 Coverage and Connectivity

Sensor nodes are placed in target area for monitoring state of environment at any time. A point in region is called covered when the distance among the sensor and point is less than the sensing range(r_s). Any point t in a region is covered from with sensor s_n when,

$$D(s_n, t) \leq r_c \tag{3.2}$$

Where, D is the Euclidean distance among point t and sensor node s_n and r_c is the communication range. As discussed earlier, a simple random pattern and deterministic approach is followed for the deployment process. In deterministic approach the sensor nodes are deployed deliberately and in planned manner at region of interest. For covering the continuous region, most popular deployment patterns of square and triangle are adopted in practice. The main focus behind adopting these two patterns is to assure full area coverage with connectivity.

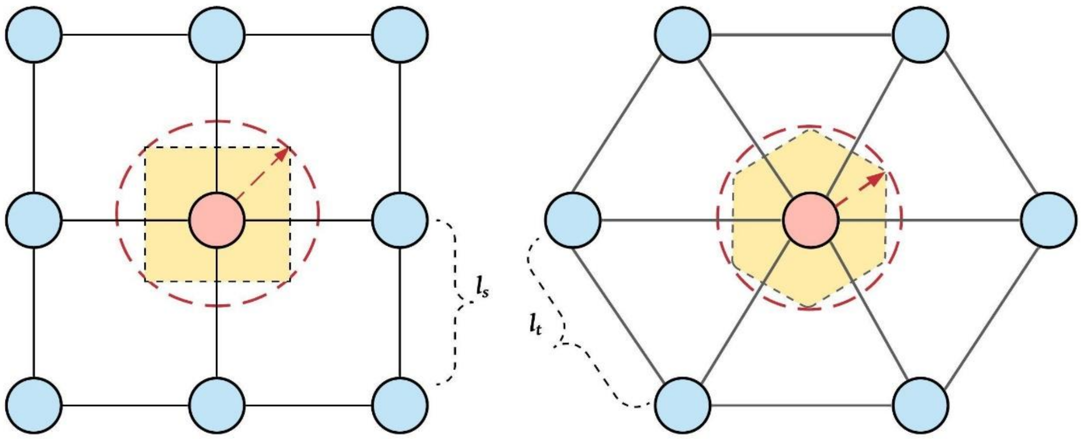


Figure 3.9: Voronoi polygon for deterministic approach of sensor deployment following square and triangular pattern

The deterministic approach also identifies the required number of sensor modules. The number of sensor nodes (N_s) deployed can be determined as:

$$N_s = \frac{T_A}{A_S} \tag{3.3}$$

Where, T_A is the target area and A_S is expressed as an area of Voronoi polygon for sensor node in deterministic approach. The area of Voronoi polygon is estimated by deployment length that is deployment distance l_d. The distance of deployment can be measured by the sensing range (r_s) and communication range (r_c) capabilities of sensor node. For maximum connectivity in deterministic approach the deployment length should always be less than communication range that is $l_d \leq r_c$. The complete coverage and connectivity in deterministic approach can be achieved when each point in region of interest is covered and also each sensor node in a network is connected. The maximum connectivity and coverage in deterministic approach can be achieved for region of interest as given in the Eq. (3.4).

$$A_S(Coverage, Connectivity) = \begin{cases} \min\left(2{r_s}^2, {r_c}^2\right), & Square \\ \min\left(\frac{3\sqrt{3}}{2}{r_s}^2, \frac{\sqrt{3}}{2}{r_c}^2\right), & Triangular \end{cases} \tag{3.4}$$

The ratio of communication range to the sensing range is an important parameter for evaluating the unit area for each sensor node and efficiency of deployment. In random deployment the sensor nodes typically deployed by dropping them through aircrafts or Unmanned aerial vehicles. The random deployment of sensor nodes is considered for hostile environments and provides a scalable network. The random deployment is classified in two patterns that are shown below:

i. Random pattern with homogenous sensor nodes: Here, the nodes are placed at similar distances. It helps to achieve a balanced energy consumption and fair transmission process.

ii. Random pattern with non-homogenous sensor nodes: Here, the nodes are randomly distributed and follow random distance values. It leads to an unbalanced communication process.

In random scattering, large amount of sensor nodes N_s are dropped in targeted area (A). The node density $\rho = \frac{N_S}{A}$, where each of the deployed sensor node is capable of monitoring any point in target area whose distance is less than sensing range (r_s) of the sensor node. The sensing coverage for random deployment is expressed as Eq. (3.5).

$$P_{Coverage} = 1 - e^{-\rho\pi r_s^2} \tag{3.5}$$

The Poisson distribution is derived as for any random point p in a region, the probability of having n number of sensor nodes in a circular covering area S_p which is centered at p along with radius r_s and expressed as Eq. (3.6).

$$P(n,p) = \frac{\left(\rho S_p\right)^n}{n!} e^{-\rho S_p} \tag{3.6}$$

Where, $S_p = \pi r_s^2$. The probability of having no sensor node in region S_p is expressed as Eq. (3.7).

$$P(0,p) = e^{-\rho \pi r_s^2} \tag{3.7}$$

Therefore, the probability of having at least one sensor node in region is estimated as expressed in Eq. (3.8).

$$P_{Coverage}(p) = 1 - e^{-\rho \pi r_s^2} \tag{3.8}$$

As in random scattering, each of the node is uniformly and independently dropped over the target region, each point in target area have identical probability of coverage. Therefore, the sensing coverage of network is expressed as Eq. (3.9).

$$P_{Coverage} = P_{Cv}(p) = 1 - e^{-\rho \pi r_s^2} \tag{3.9}$$

By increasing the sensing range and node density the overall coverage of sensing network increases.

3.2.1.3 Average Event Response Time and Standard Deviation

The average response time is measured as the average of all durations of detection to notification delays in a time interval. The average processing time of an event is computed through detection to notification delay. The average of event response time can be computed as the sum of time intervals of all events divided by the total number of events.

$$T_a = \sum_{i=0}^{\infty} \frac{T_e}{n} \tag{3.10}$$

Where, T_a represents the average processing time of event, T_e represents time interval of all events and n represents total number of events.

The standard deviation is one of the measures of spread of data set. It is the measure that tells the deviation in data set from its mean value. The maximum is the value of standard deviation, more spread out of the data. The smaller is the standard deviation means most of the data close to the value mean. Standard deviation is the square root of variance, and it is found by first figuring out the difference between all of the data points (x) and the population mean (μ), squaring and then taking the sum of these values and at last dividing by (n) which is the number of data points. The standard deviation can be expressed as Eq. (3.11).

$$\sigma = \sqrt{\frac{\sum(x-\mu)^2}{n}} \tag{3.11}$$

Where, x is actual data or data values, μ is the population mean and n is the number of data points.

3.2.2 Data Collection and Communication Module

Once the sensor nodes are deployed, the parameters like humidity, light intensity, gases and ambient temperature of the forest area is sensed by the deployed sensor node. It is assisted by Thinkspeak, an IoT based cloud analytics system that aims to store the sensed data under cloud channels. Figure 3.10 represents the data collection phase where the field data is communicated through sink node to the cloud server for its storage and real time analysis. ThingSpeak cloud analytics platform is used for collecting, monitoring and storing the field data in real time. The data can be fetched at any time for any purposes. The entries of environmental sensed values at every 2 to 3 minutes are stored in ThingSpeak cloud analytics platform. The user at control station visualize the recent entries in graphical representation and can apply algorithms for establishing a connection between sensor network and controller. The channel ID represents various field parameters and each of the measured data is stored in particular fields. The real time information from the environment is monitored through

ThingSpeak channel by using Internet. The field data and status based on the analysis can be updated by user at any time.

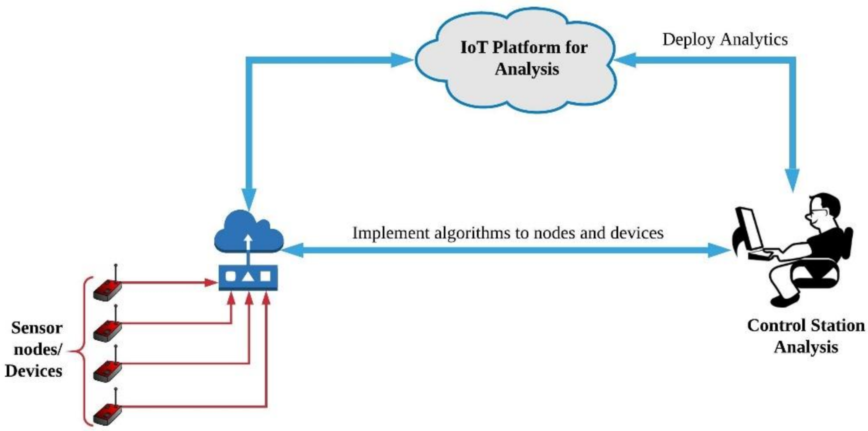


Figure 3.10: Data collection and storing using ThingSpeak cloud analytics platform

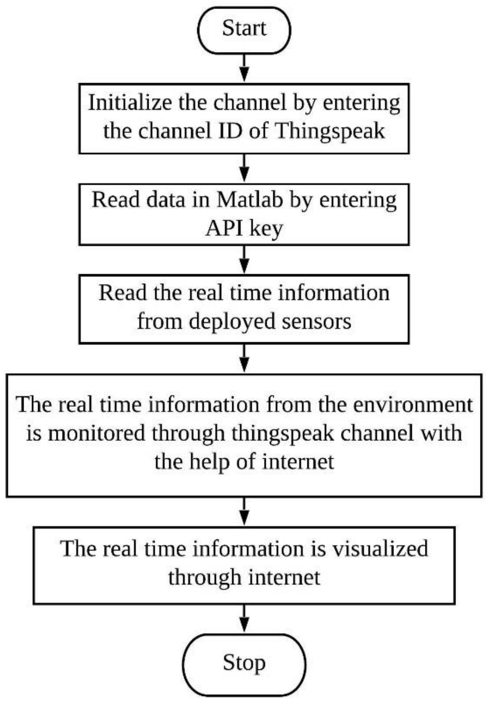


Figure 3.11: Flowchart of data collection and communication module

Figure 3.11 depicts the flowchart of process of data collection using ThingSpeak analytics. The first step is the channel initialization where the channel is created followed by the reading of sensed environmental parameters. The MATLAB interface of ThingSpeak platform provides the reading and monitoring of data using Channel ID and API keys in real time.

Working Flow of Data Collection Module

Input: Input environmental sensed parameters [Tem, Hum, Light, Smoke]

Output: Output Real Time Visualization

START

Step 1: Channel initialization by adding channel ID of ThingSpeak.

Read channel ID = 611406

Key = [read API key] OV1O3FVCFM98WTH2

Step 2: Read data locally with MATLAB interface. It includes read API key. It allows to read the environmental data from the API keys.

Run MATLAB code and system begins to read channel and API and the sensed data begins to port.

Step 3: Environmental scan. Read the real time information of humidity, light intensity, gases and ambient temperature from deployed sensors in every two, three minutes.

Establish connection between sensor network and controller.

Upload data on cloud.

Step 4: Monitoring of real time environmental data through API channel with the help of internet.

Computation of average response time, mean and standard deviations from the observed data set.

Step 5: Visualization of real time data for forest fire prediction.

Generating plots for each entry of data and data variations.

Step 6: Channel updation.

Key = [write API key]

Field parameter updation.

Field 1 to n = [Field 1 to n data]

Status updation.

Status = [Status update]

END

The MATLAB code reads the channel ID and update the cloud with the latest entries. The real time data is visualized in graphical plots by running a MATLAB code. In the last step the channel is updated with the field parameters and current status. The configurability on the collected dataset needs to be followed which focus on reducing the expected fire detection time. There are two conditions, namely, normal conditions and abnormal conditions. The normal conditions deal with the absence of deviated values from the default values, which represents the environment is safe. While the other one, is abnormal conditions which dictates the presence of deviated values from the default values, which represents the environment is not safe. If any deviated values are found, then immediate action is taken by the Monitoring Centers based on the Important value (I). To perform so, the sensor nodes support the adaptive (or) external configurations. Depending on the conditions of the environment, the sampling rate of the sensing parameters are adjusted to increase the fidelity of the system. If any event is detected, then an alarm is generated and communicated via gateway to the monitoring module. The generated alarm is then validated by the analysis phase.

3.2.3 Data Analysis Phase

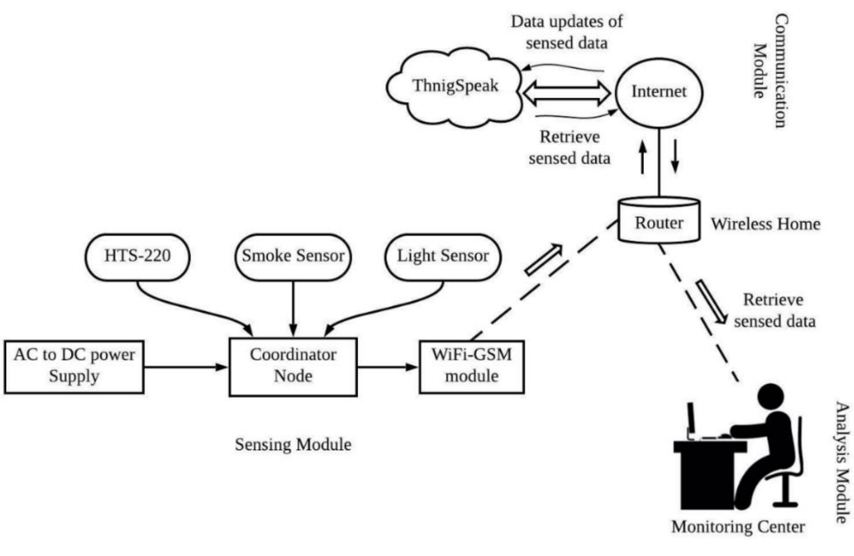


Figure 3.12: Workflow of the proposed data analysis process

Figure 3.12, presents the workflow of the proposed data analysis process for the forest fire detection systems. The process comprises three modules, namely, sensing module, communication module and the analysis module. Each has its own unique purposes to serve in the forest environment. The behavior of the sensor nodes are presented in the sensing module. Here, each sensor node has a proper AC to DC power supply, Wi-Fi GSM module, HTS-220, smoke sensor and the light sensor. Coordinator node is abided with AC to DC power supply and Wi-Fi GSM module. With the help of HTS-220, smoke sensor and the light sensor, the temperature and humidity of the forest area is measured. The measured data is communicated under the entities of communication modules. Thinkspeak, a cloud analytics, is employed to store, manage and communicate the data on the demand basis. The reliability and the temporal constraints are the QoS parameters explored in this study. The reliability metrics focus on the safety of the coordinator node and the temporal constraints focus on the time taken to assist the MCs for taking decisions. In the analysis module, a Monitoring Center (MC) is maintained which continuously monitors the surroundings of the forest environment. In case of any fire events, the MCs begin to perform actively based on the generated alarms. Then, it senses the processed information by the decision making centre that judges if an alarm is false or not.

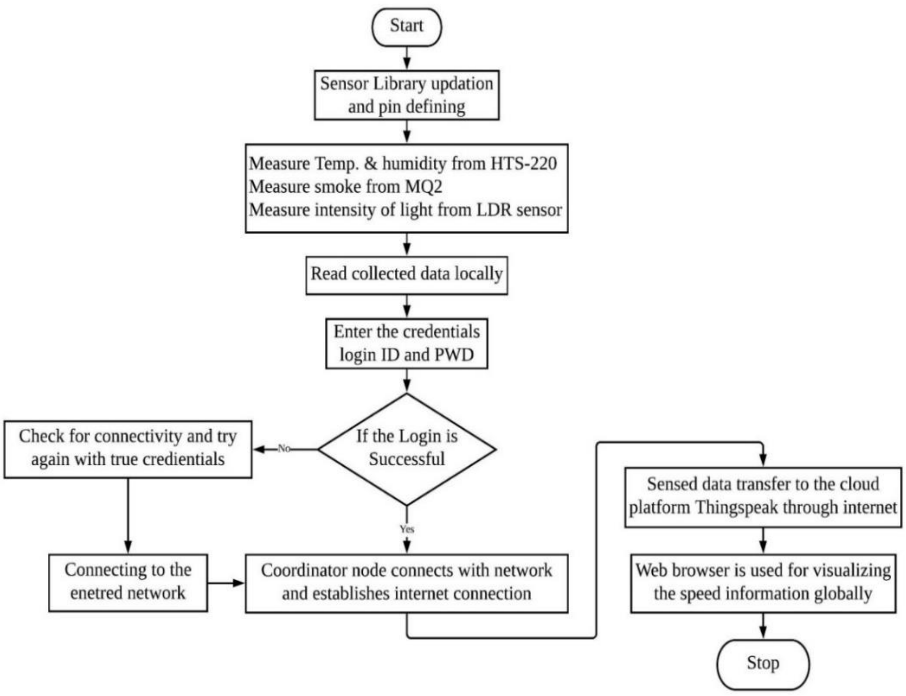


Figure 3.13: Flowchart of ThingSpeak based data analysis and monitoring system

Working Flow of ThingSpeak Analysis Module

Input: Load sensor libraries [Temp, Hum, Light, Smoke]

Output: Visualization of sensor data

START

Step 1: Load sensor libraries and pin defining.

Step 2: Measure environmental data.

Measure temperature and humidity from HTS-220 sensor, measure light intensity from TL sensor, measure atmospheric gases from MQ-2 sensor.

Step 3: Read the measured data locally in monitoring station.

Step 4: Enter the login credentials of ThingSpeak cloud.

Define SSID “Enter the name of network”.

Define Passkey “Enter the Password”.

Step 5: Check for condition.

If the credentials are correct then Fibocom G510 GPRS module connects to “Entered Network” and establishes an Internet connection.

If the credentials are not correct system check for Internet connectivity and again makes an attempt of login.

Step 6: Data transfer to cloud.

The sensed environmental data is transferred to ThingSpeak cloud via Internet.

Step 7: Visualization of sensor data.

Web browser is used for the visualization of measured environmental data globally in ThingSpeak.com.

END

3.3 RESULTS AND EXPERIMENTAL ANALYSIS

This section presents the performance analysis of the proposed model by comparing it with some existing models in terms of response time and standard deviation of the collected data. To begin with this, the hardware details of the sensor nodes are presented as follows:

1. HTS-220: To accomplished the sensing of temperature and relative humidity.
2. TL Sensor: It measures light intensity from environmental monitoring.
3. MQ2 Smoke Sensor: Smoke sensor detects the amount of smoke level present in the air.
4. 2G/3G Gateway Module: Fibocom G510 GPRS module is used which acts as an gateway among sensor network and application.

Table 3.1: Features of the deployed sensors

Sensor	Voltage	Range
MQ2	3-4.5 V	200-10,000 ppm
HTS-220	3-4.5 V	Temp: 0-60C Hum: 0-100%
TL	3-4.5 V	0-4k lux
Fibocom G510	3-4.5 V	2400 bps to 460800 bps

The experiments are carried out for normal conditions and fire conditions through sensor node deployment in real time scenario. The setup is trained for the fire conditions by triggering fire events for defining the threshold values. The results from the deployment of sensor nodes at normal conditions and fire conditions of environment are discussed below:

3.3.1 Results for Normal Conditions of Environment

To test the efficiency of the proposed model of forest fire detection, sensor nodes are deployed in forest area both randomly and deterministically. For the early prediction of fire event it is necessary to monitor environment regularly to measure the state of region at any time. The deployed sensor modules collect humidity, light intensity, atmospheric gases and ambient temperature from the field of interest and transfers the collected values towards control station for analysis. The early prediction of fire event is the only solution to stop the cause and reducing effects of wildfires. WSNs provides the efficiency for the accurate prediction of fire event at its initial stage by continuous measuring of environment. The timely alerts can be generated and forwarded to the ground staff for the necessary preventions and fire-fighting.

Figure 3.14 (a, b, c, d, e): Deployment of sensor nodes for collection of environmental parameters (a) Temperature & Humidity, (b) Smoke 1, (c) Light Intensity, (d) Smoke 2 and (e) Sink node

Figure 3.14 depicts the deployment of sensor modules to measure the environmental data for the normal conditions of atmosphere. In this Figure 3.14, (a) represents the HTS-220 sensor node which measures humidity and temperature values, (b and d) represents MQ-2 sensor which measures smoke particles from environment, (c) represents TL sensor which measure the intensity of light and (e) represents sink node which gathers all sensed information. Each of these sensor nodes are deployed at different location within transmission range of sink node and transfers measured data directly to coordinator node wirelessly. Sink node is Fibocom G510 GPRS modules which transfers each of sensed information towards cloud platform for analysis and storing. The adopted sensor deployment collects the parameter details from the environment for detecting the adversaries. Light sensor which measures the intensity of light, HTS-220, a basic sensor that is deployed at the low cost. The sink node is placed at the centre of the region of interest and has a significant impact over the analysis of energy consumption and lifespan of WSNs. Sink node is programmed for providing the most recent entries of the field data to the cloud server with in every two to five minutes.

Table 3.2: Collected entries of sensed data at normal condition

Instances	Entry Number	Hum 1 (%)	Hum 2 (%)	Smoke 1 (ppm)	Smoke 2 (ppm)	Temp 1 (°C)	Light 1 (lux)
2019-10-15 12:15:23 +0530	401	43.45	50.20	465	245	21.02	153
2019-10-15 12:20:00 +0530	402	44.23	51.47	584	234	21.07	165.22
2019-10-15 12:24:41 +0530	403	45.63	54.31	589	274	21.7	192.39
2019-10-15 12:27:10 +0530	404	47.2	50.03	592	265	21.18	180
2019-10-15 12:31:30 +0530	405	46.32	50.27	590	284	21.23	186.36
2019-10-15 12:34:20 +0530	406	44.82	52.63	560	247	21.03	167.41
2019-10-15 12:38:03 +0530	407	47.61	54.24	570	246	21.72	191
2019-10-15 12:41:28 +0530	408	49.34	55.21	554	269	21.76	175.23
2019-10-15 12:43:35 +0530	409	48.62	50.35	521	236	22.21	185.34
2019-10-15 12:46:03 +0530	410	48.62	50.27	521	238	21.25	167.47
2019-10-15 12:49:29 +0530	411	48.54	51.32	518	241	21.57	185.28
2019-10-15 12:53:01 +0530	412	48.62	51.36	516	268	22.10	176.65
2019-10-15 12:56:10 +0530	413	48.69	51.35	516	257	21.50	169.30

Sensor along with intelligent sensor gateway module is deployed in the field to monitor the various parameters like humidity, light intensity, gases and ambient temperature. The data is gathered using the Sensor nodes deployed and same was stored at cloud for analysis. Data collected from these sensors is stored on cloud using the ThingSpeak IoT Application. The sample of the observed dataset for normal condition of environment is presented in Table 3.2. In this table first column represents date and time of created instance along with their entry numbers. For every time instance the measured values of humidity, light intensity, gases and ambient temperature are presented in the table. The simulation is carried for collecting the data during the experiment in real time outdoor environment. The ThingSpeak IoT analytics is used for collection and storing data in real time environment and related challenges are identified. On the basis of observed dataset several graphical plots have been formed using the ThingSpeak IoT analytics for humidity, light intensity, gases and ambient temperature. With the base of sample data from Table 3.2, the analysis and verification process of the sensor values in ThingSpeak is shown in Figure 3.15.

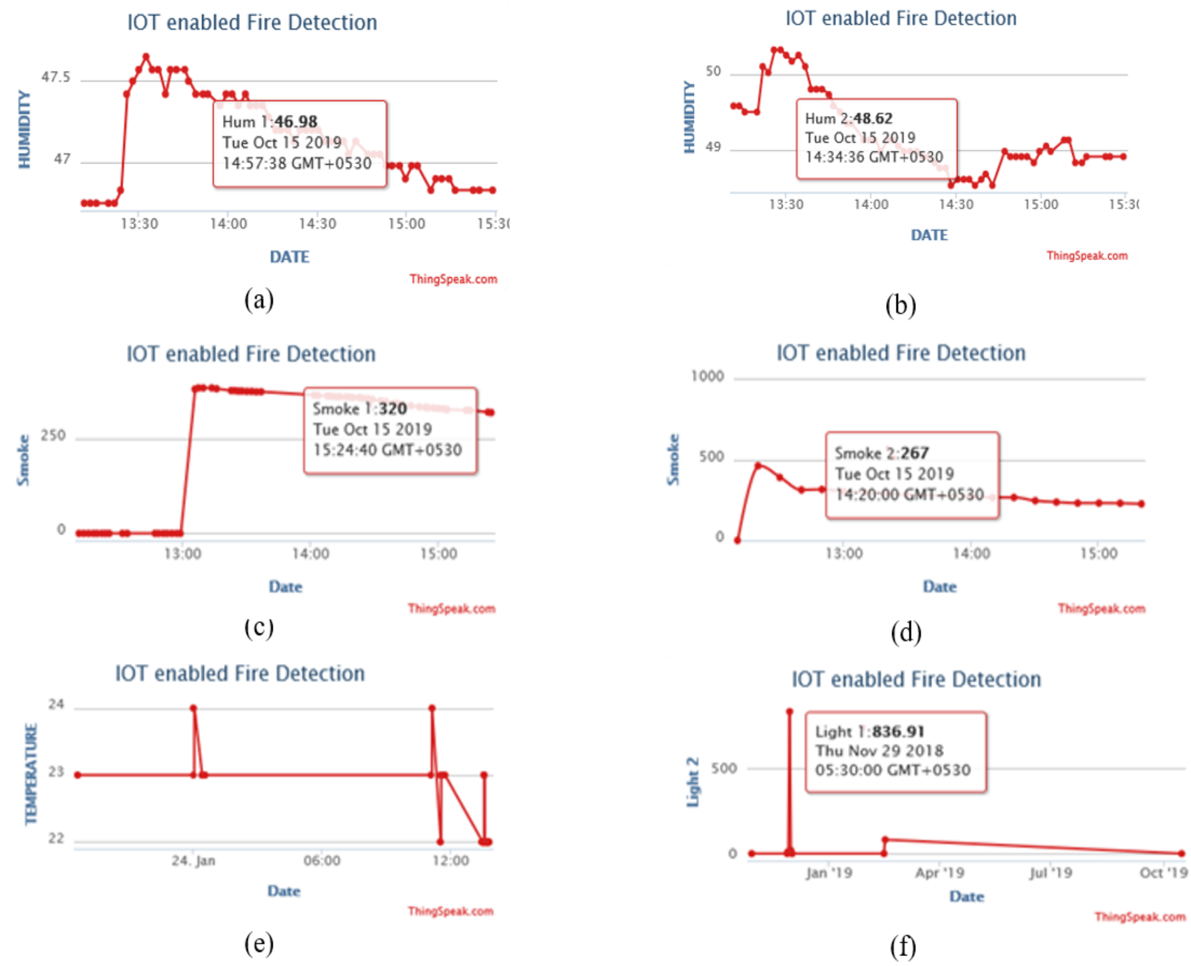


Figure 3.15: Obtained results from Thingspeak IoT analytics for various field set as (a & b): Humidity (in %), (c & d): Smoke (in ppm), (e): Temperature (in °C), (f): Light (in lux)

The above figure depicts the graphical representation of various recorded environmental parameters. It presents the output results of the data collected from ThingSpeak cloud and shows the variations of the parameters like humidity, light intensity, gases and ambient temperature. It senses in near real time basis, as there is a few second delay for data being updated on Think speak. In Figure 3.15, (a & b) represents the plot of recorded humidity values at two different locations, (c & d) represents the plot of recorded smoke values at different locations, and (e & f) represents the plot of temperature and light intensity from different locations. The cloud platform provides the clear verification and analysis of all sensor values for measuring the state of environment. MATLAB interface of cloud platforms allows real time monitoring along with the display of various sensor values in graphical representation by creating channel field sets. The deployed sensors senses in real time and there exists delay of few seconds for the updating of data on Think speak cloud platform.

3.3.2 Results for Fire Conditions of Environment

The proposed model is trained for testing its efficiency in case of fire event. A fire event is triggered intentionally for evaluating the response time of detection to notification delay. The deployed sensor nodes capture the real time environmental feed during the fire event and transfers information to ground station for examination. The study of the real time feeds at ground station confirms the detection and sends an alert in terms of email for fire-fighting team.

(a) (b) (c)

Figure 3.16 (a, b, c): Observation of data in case of fire event (a) Temperature & Humidity, (b) Smoke and (c) Sink node

Figure 3.16 depicts the deployment of sensor modules for the collection of environmental data for abnormal conditions where a fire event is triggered. In this Figure 3.16, (a) represents the HTS-220 sensor node which measures humidity and temperature values, (b) represents MQ-2 sensor which measures smoke particles from environment, and (c) represents sink node which gathers all sensed information and forwards it to the control station for its storing and analysis through Internet. Every sensor module connects directly to the centrally located sink node wirelessly. The adopted sensor deployment collects the parameter of temperature, humidity, light and gases during fire scenario for measuring the capabilities of sensor network.

Table 3.3: Collected entries of sensed data of a fire event

Instances	Entry Number	Temp (°C)	Hum (%)	Smoke (ppm)	Light (Klux)
2019-11-25 14:41:06 +0530	601	60	6	657	3.9
2019-11-25 14:42:32 +0530	602	60	5	653	3.9
2019-11-25 14:43:06 +0530	603	60	5	654	3.9
2019-11-25 14:45:23 +0530	604	61	5	680	3.9
2019-11-25 14:48:03 +0530	605	61	5	684	3.9
2019-11-25 14:51:26 +0530	606	60	5	654	3.9
2019-11-25 14:54:10 +0530	607	61	5	680	3.9
2019-11-25 14:57:30 +0530	608	63	7	500	4
2019-11-25 14:59:45 +0530	609	64	7	506	4
2019-11-25 15:02:16 +0530	610	63	7	508	3.9
2019-11-25 15:05:07 +0530	611	64	7	506	3.8
2019-11-25 15:08:47 +0530	612	60	5	653	3.9

The sample of the observed dataset for abnormal condition of environment for forest fires is presented in Table 3.3. In this table first column represents date and time of created instance along with their entry numbers. For each time instance the measured values of humidity, light intensity, gases and ambient temperature are presented in this table. The proposed model for fire detection is trained for fire conditions to measure its capabilities in terms of true detection. The data is observed for fire conditions and same are stored in cloud for its analysis. Based on the analysis of observed data set for normal and fire conditions presented in Table 3.2 and Table 3.3, certain threshold value for each sensor node is defined. Whenever the sensed value exceeds threshold of each sensor node a fire alert is triggered at base station for its analysis. MATLAB interface of cloud platform provides the study of variations in different parameters and their inter relation during fire event. For the verification of fire event a user at base station runs MATLAB code for the analysis of recent entries of temperature, smoke, light and humidity parameters. The control station also presents the comparison of recent temperature values and the wind speed for evaluating the fire spread. The observed data for abnormal conditions are represented as graphical plots in ThingSpeak cloud for its understanding. With the base of sample observed data from Table 3.3, the analysis and verification process of the sensor values in ThingSpeak cloud is presented in Figure 3.17.

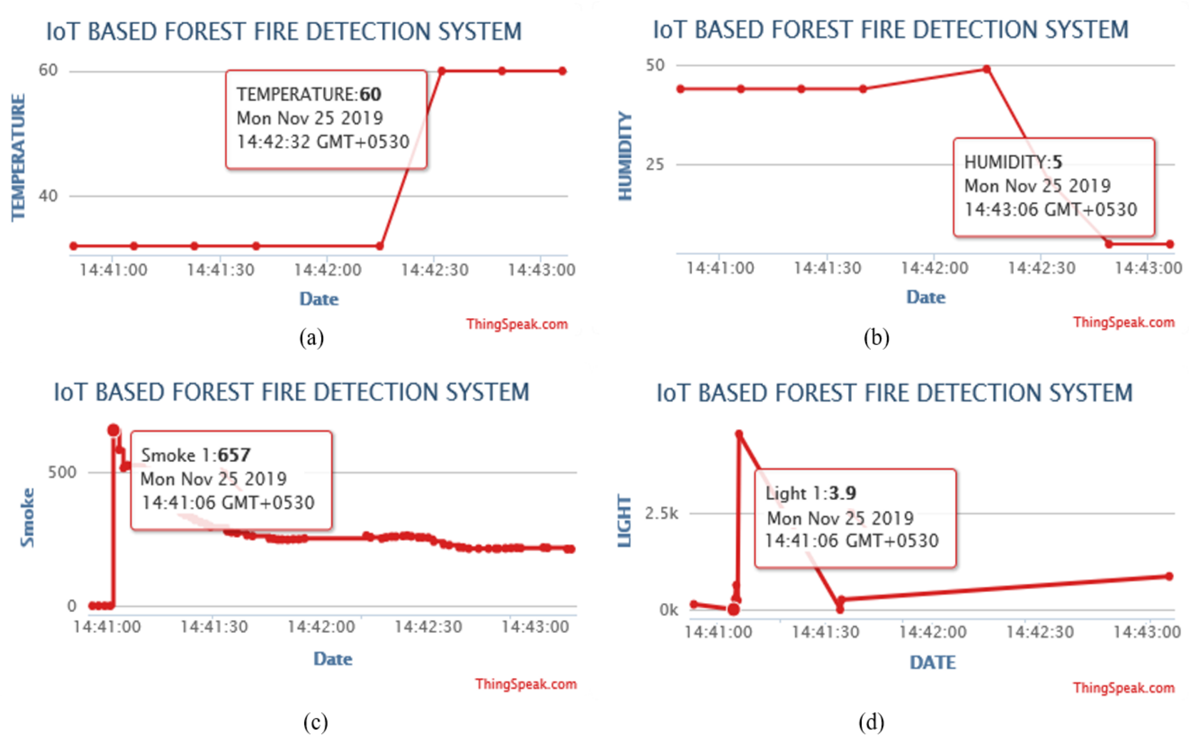


Figure 3.17: Detected event (a): rise in temperature (in °C), (b): decrease in humidity (in %), (c): presence of smoke (in ppm), (d): intensity of light (in Klux)

Figure 3.17 depicts the graphical representation of various recorded environmental parameters during the fire event. It presents the output results of the data collected from ThingSpeak cloud and shows the variations of the parameters like humidity, light intensity, gases and ambient temperature respectively. In Figure 3.17, (a) represents the plot of recorded temperature values at one location, (b) represents the plot of recorded humidity values of other location, and (c & d) represents the plot of smoke and light intensity from different locations. It is seen from the graphical representation that with the increase in ambient temperature the relative humidity value decreases and also the value of smoke and light intensity increases during fire conditions. The cloud platform provides the clear verification and analysis of all sensor values for measuring the state of environment during fire event.

3.4 COMPARATIVE ANALYSIS

The proposed forest fire detection approach based on IoT analytics is compared with existing state of art techniques for standard deviation and average response time. The comparison of proposed approach for the detection of event using deterministic deployment with existing techniques is depicted in Table 3.4.

Table 3.4: Performance analysis in terms of standard deviation and average response time for deterministic deployment

Platform	Approaches	Standard Deviation (ms)		Average Response Time (ms)	
		Without Load	With load (512 Kbps)	Without Load	With load (512 Kbps)
ThingSpeak	IoT Atlas [170]	8.12	13.87	30.57	48.26
	M2M [171]	12.9	21.25	52.35	78.51
	GSMA [172]	10.92	17.88	46.24	66.47
	Proposed	7.56	12.45	24.56	40.28
CloudStack	IoT Atlas [170]	11.24	18.62	68.35	85.42
	M2M [171]	15.27	25.64	122.32	175.63
	GSMA [172]	13.21	22.31	92.54	120.36
	Proposed	9.88	16.54	58.24	68.34

Response time and the standard deviation of the data obtained from ThingSpeak and CloudStack platform are the performance metrics explored in this study. The table 3.4 presents the performance analysis of standard deviation and average response time in ThingSpeak and CloudStack platforms for the deterministic deployment. The performance of the WSNs and IoT based fire detection approach is evaluated using response time and standard deviation metrics. Response time is defined as the time taken to retrieve data from cloud and standard deviation deals with the statistical measures of dispersion rate of the data from the cloud. The obtained outcomes of proposed early fire detection system is compared with other existing techniques considering two cases for network bearing of with and without load conditions. First case is evaluating the performance in same cloud analytics and other case is evaluating the performance of system with different cloud platform. It is observed from the table that the proposed model on two cloud platforms performs better than the existing models, IoT Atlas, M2M and GSMA.

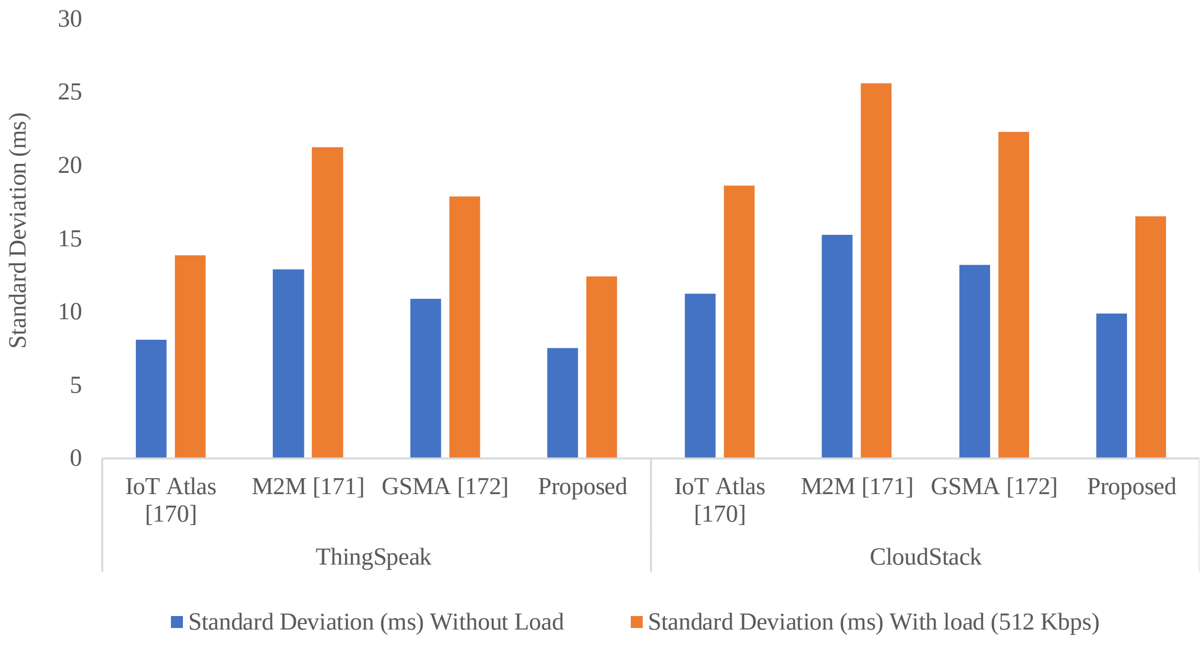


Figure 3.18: Comparative analysis of standard deviation for deterministic deployment

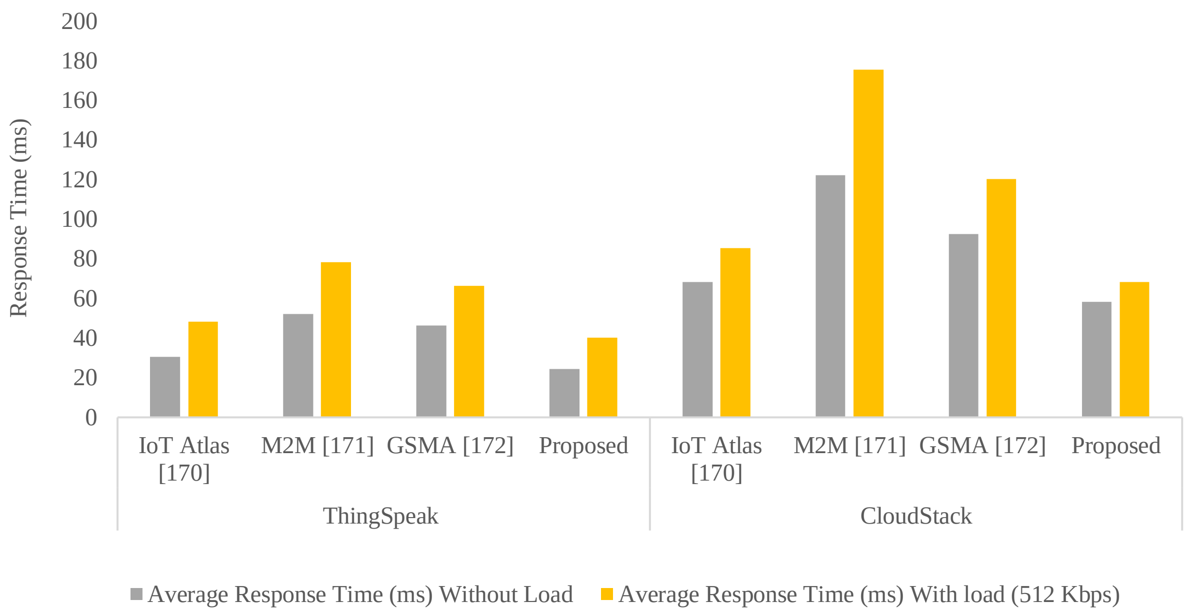


Figure 3.19: Comparative analysis of response time for deterministic deployment

The bar graph shown in Figure 3.18 and Figure 3.19 depicts the analysis of standard deviation and average response time for deterministic deployment on various framework with load and without load conditions. The calculated standard deviation with load and without load condition for same cloud analytics is 7.56 ms and 12.45 ms whereas for other cloud platform it is observed as 9.88 ms and 16.54 ms. The calculated response time with load and without load condition at same cloud platform is 7.56 ms and 40.28 ms whereas for other cloud platform it is observed as 58.24 ms and 68.34 ms. Table 3.5 depicts the comparison of proposed approach for event detection using random deployment with existing techniques.

Table 3.5: Performance analysis in terms of standard deviation and average response time for random deployment

Platform	Approaches	Standard Deviation (ms)		Average Response Time (ms)	
		Without Load	With load (512 Kbps)	Without Load	With load (512 Kbps)
ThingSpeak	IoT Atlas [170]	16.24	24.2	40.21	51.23
	M2M [171]	18.35	28.47	68.32	80.35
	GSMA [172]	21.24	35.21	63.2	96.34
	Proposed	13.17	18.24	31.28	56.38
CloudStack	IoT Atlas [170]	23.14	30.51	73.29	98.36
	M2M [171]	27.2	32.14	130.36	193.28
	GSMA [172]	31.04	36.12	98.35	175.06
	Proposed	16.32	21.07	67.39	98.35

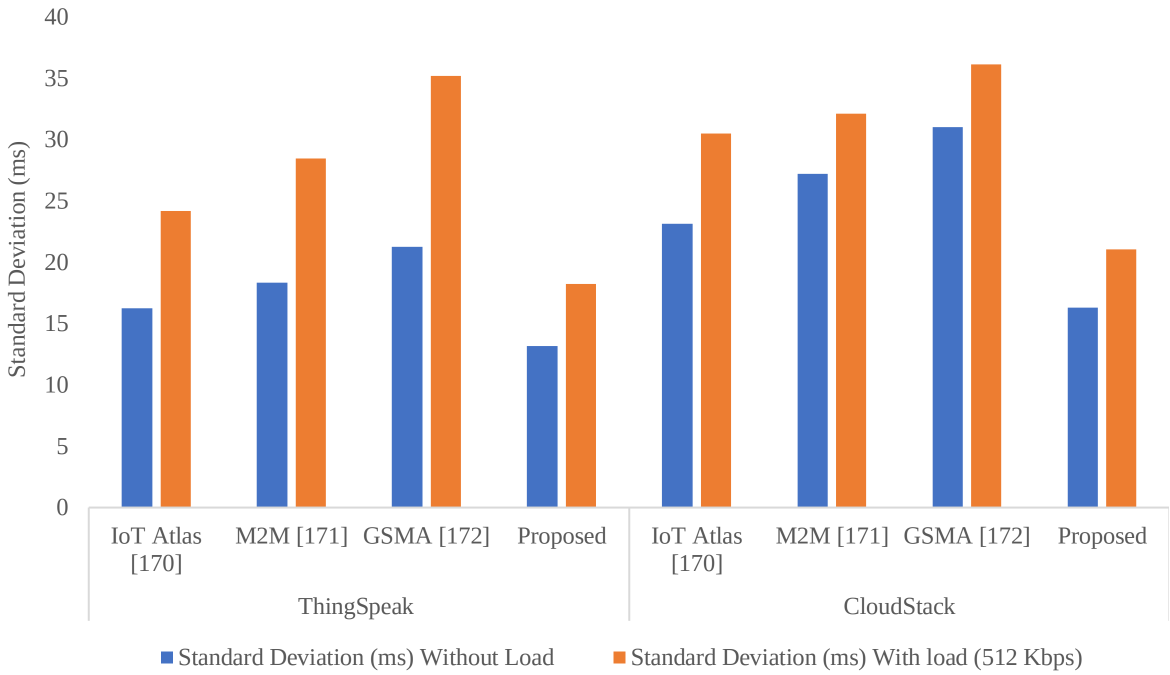


Figure 3.20: Comparative analysis of standard deviation for random deployment

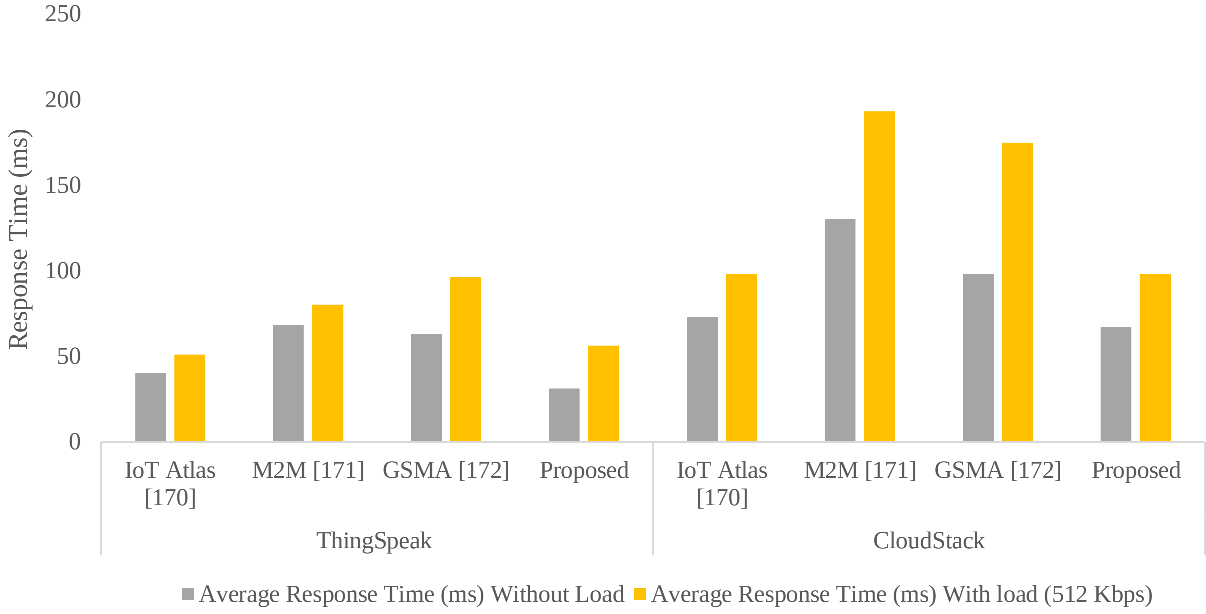


Figure 3.21: Comparative analysis of response time for random deployment

The bar graph shown in Figure 3.20 and Figure 3.21 depicts the standard deviation and response time for random deployment on various framework with load and without load conditions. The calculated standard deviation with load and without load condition at same cloud platform is 13.17 ms and 18.24 ms whereas for other cloud platform it is observed as 16.32 ms and 21.07 ms. The calculated response time with load and without load condition at same cloud platform is 31.28 ms and 56.38 ms whereas for other cloud platform it is observed as 67.39 ms and 98.35 ms. Table 3.4 and 3.5 presents the comparative analysis of the proposed and existing models under two cloud platforms, namely, Thingspeak and Cloudstack. It is observed from the table that the proposed model on two cloud platforms performs better than the existing models, IoT Atlas, M2M and GSMA. It is observed from the performance analysis that the proposed approach outperforms the existing techniques providing less average response time and standard deviation. The detection accuracy of the proposed approach indicates the efficiency of model in terms of early prediction. The results obtained confirms the improvement over previously reported approaches using WSNs and IoT.

3.5 CONCLUSION

Forest fire detecting at an earlier phase has gained much attention among the researchers. In recent times, an increased awareness arises in the preservation of biodiversity, and thus, planning strategies are innovated in forest fire management. Developing an efficient nodes deployment scheme is an important part of the real-time applications. Since an efficient design will enhance the performance of the systems, in this chapter, an efficient data collection and real time analysis of data is explored. The main focus of this study is monitoring the forest environment using WSNs. The sensed data is preserved at Thingspeak, an IoT based cloud analytics platform that manages the sensed information like humidity, light intensity, atmospheric gases and ambient temperature from real-time environment. This chapter discusses the decision-making process when any fire events take place and thus, by collecting, monitoring and real time analysis of measured data. The proposed system is efficient in monitoring the forest fires through sensors and ThingSpeak IoT cloud platform. Sensor information for humidity, light intensity, gases and temperature transmitted to ThingSpeak cloud in real time. System is capable of collecting, monitoring and analyzing the data for decision making. The performance of the system is improved in terms of response time and standard deviation and achieves 7.56 ms of standard deviation and 24.56 ms of response time for deterministic deployment. In case of random deployment, the proposed system achieves better response time 31.28 ms and standard deviation 13.17 ms in comparison with other state if art techniques. The design is efficient and delivers a realistic and less costly method for gathering and monitoring data in real time globally. The system is effective for the analysis of environmental parameters in real time and delivers an effective solution for early detection of fire events.

CHAPTER 4

AN EFFICIENT LOCALIZATION ALGORITHM FOR ESTIMATING SENSOR NODES LOCATION

CHAPTER 4

AN EFFICIENT LOCALIZATION ALGORITHM FOR ESTIMATING SENSOR NODES LOCATION

In this chapter we present that randomly chosen anchor nodes are sufficient in locating the unspecified regular sensor nodes in a WSNs. The process of localization is initiated through the information connectivity among nodes along with the distance matrix. The distance matrix is employed for estimating the sensor network topology through range free approach. The location information of anchor nodes is utilized for localizing the regular sensor nodes in a network. The experimental results of localization algorithm is conducted considering various WSNs scenarios and the simulation are carried out using MATLAB. The performance of localization algorithm presents significant improvement for accurately estimating the positions of unspecified sensor nodes.

4.1 INTRODUCTION

In recent times for the environmental monitoring through sensor wireless communication devices are studied extensively. For forest fire detection, several studies highlight potential sensor devices which are gaining attention. The smart sensor devices can perform the real time detection of any problem and present condition of atmosphere that can be accessed from anywhere at any time from any individual. Wireless Sensor Networks serves variety of applications such as healthcare, defence, industrial, and many others. The objective of this study is to present an algorithm for the localization of unspecified sensor nodes that triggers the event. Critical events such as fires can occur across different environments such as forests, commercial, residential, and/or even open spaces. While newer techniques have evolved to detect and provide alerts on fire emergencies, early detection methods relied mostly on humans. Today, human-based observations have been replaced by Satellite-based systems. However, these Satellite-based observations are not continuous with time [173], and not suited for the early detection of fire instead of their efficiencies in monitoring, covering areas of any size.

With recent advances in technology of Wireless Sensor Networks (WSNs) has gained attention from researchers. Here, the development of various sensors makes it much easier to gather the correct information parameters from the environment. With increasing number of devices that may be added to cover an area of any size, a key advantage of WSNs is their scalability. Recent sensor technological innovations have aided in the gathering of various environmental parameters in real time. Sensors works collaboratively for the detection of a critical event; in the case of wildfire, it predicts well before the risk of such a disaster emergency so that first respondents may be dispatched to event locations on time [174]. As noted, fires can occur in open spaces, forests and residential areas. One of the easiest ways to detect fire is the use of smoke detectors. Other means include the use of sensors, which are responsive towards ionization and obscuration. A problem with these sensors is the generation of false alarm via similar color of fire regions, for example, the smoke from toasting bread and/or cigarette smoking. Even so, the advantages of WSNs towards critical event detection and the periodic collection of data made it suitable for manufacturing applications. The periodical collection of data is essential for operations such as the tracking of critical events and the monitoring of environment, reducing costly human labour and errors [175].

In WSNs, the localization can determine the location coordinates of a number of regular nodes in sensor network. Some sensor nodes in a WSN are generally equipped with GPS, which enable them to know their own locations. Nodes with known positions are classified as reference or anchor nodes. In contrast, nodes initially with unknown location are classified as unknown sensor nodes. Any sensor nodes in a network is capable of estimating its location by implementing range-free or range-based methods when there exists three or more than three anchor nodes in its two-dimensional coverage field. The accuracy of the localization is highly influenced by the number and the position of anchor nodes. Localization may be considered as the process to determine the locations of sensor devices connected within a network, such as a WSNs. WSNs comprises a huge number of multi-functional sensor nodes that are organized in a region of interest for the measurement of any phenomenon [4]. The term localization refers to the computation of unspecified target location. Global positioning system (GPS) is one solution which offers the location coordinates of individual sensor modules. However, the use of GPS enabled sensor modules are not realistic in application of forest fire monitoring as it requires sensor modules in large numbers and GPS enables sensor makes the system very costly. Therefore, sensors are required to self-organize a coordinate system for their position estimation. Localization process finds the location coordinates of regular sensor nodes through inter-communication among localized nodes and un-localized nodes. The localization process is more critical as if sensor module does not have the knowledge about their location, then the transmitted information does not cover the position of geographical region at which the fire event takes place. Moreover, the routing services heavily rely on the location information of the sensor nodes for finding shortest path of information transmission. In sensor network the localization algorithm [177, 178] typically consists of three operational phases:

i. Distance Approximation

ii. Calculation of Position

iii. Localization Process

In the distance approximation phase, the relative distance among the sensor nodes is estimated via measurement techniques. Coordinates of the unspecified nodes are computed in the position calculation phase utilizing the information of anchor nodes and other neighboring sensor modules. The final phase, the localization process, generally determines how the information related to the position and distance is manipulated to allow most or every node in WSN to estimate their own position [179].

Additionally, localization algorithm may embed other algorithms for the reduction of errors and to refine the position of nodes. The distance is estimated by using four most common methods, including the angle of arrival (AoA), the time of arrival (ToA), the time difference of arrival (TDoA), and the received signal strength indicator (RSSI). AoA is a method for the distance estimation in which each sensor evaluates the relative angles among the received radio signals. In ToA method, the measures that are based on time are used for the approximation of distance between two nodes. TDoA is a method utilized to determine the distance among the mobile station and its nearest base station. RSSI methods are applied to translate received signal strength into distance, most commonly for computing lateration and angulation positions. The lateration positioning computation depends on the accurate measurements of three non-collinear anchor nodes. Multi-lateration refers to the lateration that consists of more than three anchors. In contrast, the computation of position via angulation or triangulation depends on the knowledge of angles in place of distance [180].

4.2 Formulation of a Problem

In this section we formulate the problem of localization consisting number of steps. The problem of computing the distance between regular nodes and then identifying location coordinates is discussed in this section.

4.2.1 System Model

Each sensor module in a Wireless Sensor Networks is homogenous and offers similar circular range of transmission. The two sensor modules are referred as connected when they both are in range of transmission to each other. Each sensor module has the knowledge about its own ID and the ID of its neighbour sensor module. The graphical representation of Wireless Sensor Networks is expressed as $G(U, V)$, where

$$U = \{N_1, N_2, \dots N_r\} \tag{4.1}$$

U is a set of regular sensor nodes and V represents node pairs (N_i, N_j) which are connected to each other. The symmetrical binary relation for U is expressed as Eq. (4.2).

$$N_i \sim N_j \overset{\sim}{\Leftrightarrow} (N_i \sim N_j) \in V \tag{4.2}$$

When the node pair is not connected i.e., $(N_i \sim N_j) \notin V$ then the relation is expressed as $N_i \nsim N_j$

4.2.2 Commuication Model

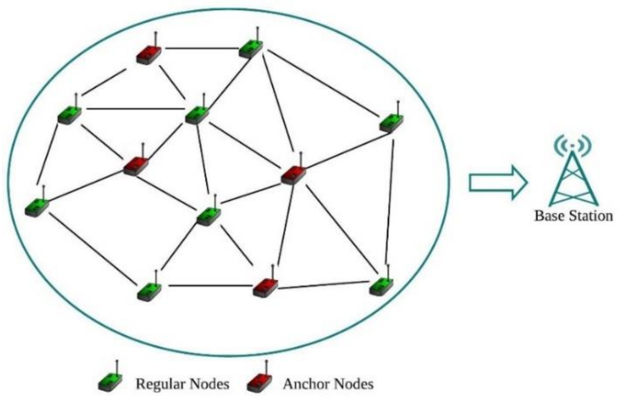


Figure 4.1: Wireless Sensor Networks communication scenario

A Wireless Sensor Networks scenario is depicted in Figure 4.1 where red sensor nodes are the anchor nodes and green sensor nodes are regular sensor nodes. In a sensor network each of sensor node connects with its neighbor directly and connected sensor nodes begins to transmit and receive information from each other. The sensed information through multiple hops or relay nodes transferred to the sink node [181]. The sink node gathers this information from connected sensors and directly connects it with the control station. Therefore, the base station has the knowledge about the connected sensor nodes in a network and signal strengths. The distance among the connected sensor modules is computed by implementing received signal strength indicator. The initial signal strength is known and based on the power dissipated, RSSI measures the signal strength based on mathematical expressions as shown in Eq. (4.3).

$$P_R = lD^{-\propto} \tag{4.3}$$

Where, P_R represents the power of received signal, l is a constant value which considers frequency, D is the distance among connected sensor nodes and $\propto$ represents attenuation coefficient. Hence the distance among the regular nodes is computed as shown in Eq. (4.4).

$$D = \left(\frac{P_R}{l}\right)^{-\frac{1}{\propto}} \tag{4.4}$$

The information about distance among connected sensor nodes and RSSI through base station leads the formation of distance matrix of WSNs [182]. It is impossible to localize the unspecified regular nodes in a network without presence of anchor nodes or any reference points. The distance matrix alone is capable for estimating the distance among network connection but in a network where some sensor nodes are connected to only one neighbor node the obtained topology is not unique. Therefore, for accurate distance approximation a regular node must be connected with at least four neighbor nodes. Then last phase of the problem is position estimation of regular sensor node, which is achieved by introducing anchor nodes to each regular node for position estimation.

In a given location of anchor nodes that are (x_A, y_A), (x_B, y_B) and (x_C, y_C) and the distances from the target to the anchors (D_A, D_B and D_C), target location (x_e, y_e) is estimated. When the distance is larger between the two terminals, the received power is low. With the help of this received signal strength, the distance among transmitter and receiver is computed. If the distance between the two terminals is known, the location is estimated using more than two terminals. Figure 4.2 depicts three receivers where target is transmitting and each receiver gets the different signal strength indication because each receiver is at a different distance from the transmitter.

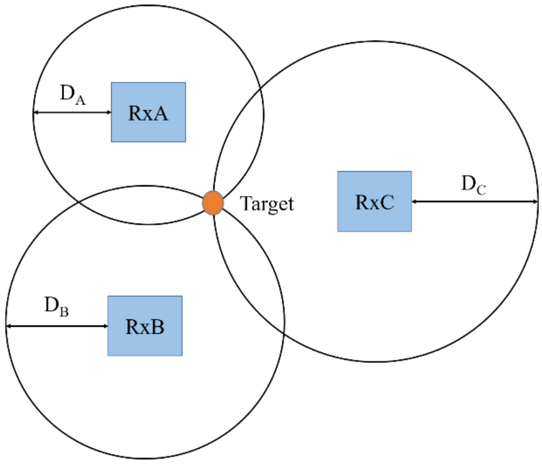


Figure 4.2: Position computation using trilateration

$$(x_A - x)^2 + (y_A + y)^2 = D_A{}^2 \tag{4.5}$$

$$(x_B - x)^2 + (y_B + y)^2 = D_B{}^2 \tag{4.6}$$

$$(x_C - x)^2 + (y_C + y)^2 = D_C{}^2 \tag{4.7}$$

Equation 4.5, 4.6 and 4.7 are the formula for circles that are generated. Each circle being the radius that equals to the distance between the target and that particular receiver. The point where these three circles intersect is the location of target. Here, we can also find the actual geometric coordinates.

The hybrid algorithm based on trilateration can be implemented for the calculation of position. These two methods combined to improve the accuracy. Trilateration is the localization method that calculates the position based on distances from three references to a common point. A circle is drawn surrounded each reference point and the estimated position is computed by the intersection of the circles as shown in the Figure 4.3.

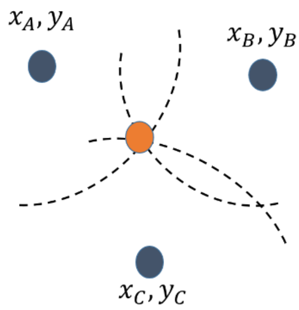


Figure 4.3: Position calculation based on three references to a common point

Trilateration is based on the principle that any given occasion is subjected to specific radio frequency characteristics as this process is based on the strength of received radio signal between transmitter and receiver. In this method there is a set up phase in which a grid is defined and the RSSI information is manually calculated and stored in the database. In normal operations, a node entering the area will sense a signal received by the anchor nodes, which will then be compared with the predefined database. The position is estimated based on the closest match with the database. In our network, the position is calculated via the sink node. The main reason behind this is to keep the mobile node functional only without adding any computational cost in order to save as much energy as possible. The samples of RSSI may suffer from random variations interference, shadowing, and noise [183]. The time-average of samples is carried out for the removal of these variations. Therefore, the distance is approximated using the mode of these filtered samples and most likely referred to as line of sight path. Distance estimation and the position computation are essential for the location calculation. There are various localization algorithms designed for the distance estimation but no single algorithm may be superior for use in the entire WSNs applications. As an example, the algorithm which is designed considering mobile sensor nodes may not work efficiently with the static sensor nodes. A framework can only be designed by combining all of the techniques that can serve for the different applications. Recent research on localization algorithms in WSNs has appeared in [184]. Here, we highlight the more popular localization techniques and range-free algorithms of localization, including the mobile reference nodes and anchor sensor nodes. A range free location estimation algorithm is proposed where the distance and position of the regular sensor nodes are localized using anchors information.

4.3 PROPOSED METHODOLOGY

In this section, a localization algorithm for computing the location of unspecified regular nodes is presented. The position is estimated based on network connection where each regular nodes in a network estimates its location only through reliable nodes or anchor nodes. A network of n wireless sensor modules are uniformly scattered in a square area. Each of the sensor node in a network is assumed to have same transmission range and connects directly with other node. The process flow of proposed location estimation algorithm is presented in Figure 4.4.

The framework of the proposed localization scheme consists of six fundamental phases: first phase is declaration of regular and anchor nodes; second phase is identification of anchor and regular nodes initial location and collection of information. The region is estimated by computing four edges using one-hop anchor information in estimative region phase. The estimative region values are further used for finding the grid array in the fourth phase. The fifth phase of the proposed localization algorithm includes computation of valid grid points by eliminating invalid grids. The sum of all valid grids is the estimated location of regular node. The last phase includes the computation of normalized error and accuracy for the observed location estimation. A detailed stepwise depiction of the proposed location estimation algorithm is presented in the sub-sections below.

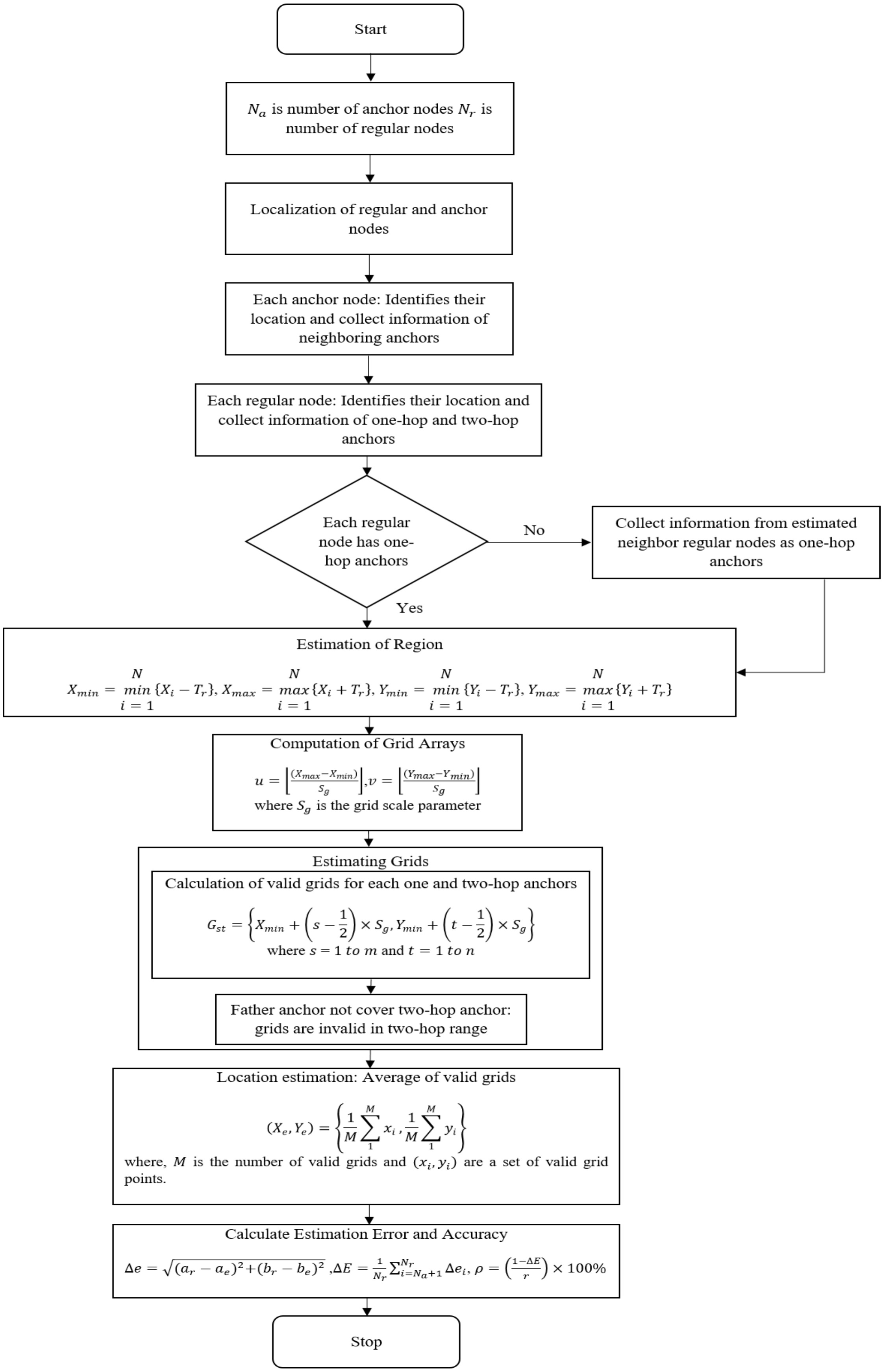


Figure 4.4: Flowchart of proposed location estimation algorithm

4.3.1 Initialization of Regular and Anchor Nodes

In this phase $N_1, N_2, \ldots N_r$ number of regular nodes are deployed in a sensor network where each sensor connects directly with neighbour sensor. N_a represents number of anchor nodes which is in a ratio of $(N_a < N_r)$. Each of the regular node and anchor node offers same transmission range T_r.

4.3.2 Location Identification and Information Collection

In this phase each of the anchor node N_a identifies its location and collects the information about neighbouring anchor nodes within two-hop range. The information which is collected by implementing flooding technique termed as anchor's message.

On the other hand, each of the regular node N_r identifies its location and collects the information about neighboring anchor nodes and head anchor in one-hop and two-hop range. After this phase each of the regular node in a network has the knowledge about neighboring anchor nodes within one-hop and two-hop range.

4.3.3 Estimative Region

Estimative region is the third phase which uses one-hop anchors information for evaluating four edges of estimative region as represented in Eq. (4.8), (4.9), (4.10), (4.11). Each regular node after the process of second phase have N number of one-hop anchor nodes. For the region estimation of regular node, a circumrectangle is drawn based on four computed edges. The centre of circumrectangle is the anchors coordinate of length, breadth $(2 \times R)$. The coordinates of length and breadth of a circumrectangle are parallel to X and Y axis.

$$\begin{aligned} X_{min} &= \min_{i=1}^{N} \{X_i - T_r\} \\ X_{max} &= \max_{i=1}^{N} \{X_i + T_r\} \\ Y_{min} &= \min_{i=1}^{N} \{Y_i - T_r\} \\ Y_{max} &= \max_{i=1}^{N} \{Y_i + T_r\} \end{aligned} \tag{4.8}$$

The estimative location of regular sensor node lies in the overlapping region of four circumrectangles. X_{min}, X_{max}, Y_{min}, and Y_{max} are the coordinates of estimative region R_e and X_i, Y_i represents coordinates of one-hop anchor node.

4.3.4 Computation of Grid Arrays

In this phase the grid arrays are computed using grid scale S_g and estimative region R_e parameters.

$$u = \left\lfloor \frac{(X_{max} - X_{min})}{S_g} \right\rfloor$$
$$v = \left\lfloor \frac{(Y_{max} - Y_{min})}{S_g} \right\rfloor \qquad (4.9)$$

When the value of $(X_{max} - X_{min})$ is less than S_g or $(Y_{max} - Y_{min})$ is less than S_g the size of grid array is 0. In order to deal with this situation grid scale S_g is reduced to $\frac{S_g}{2}$ until $m \neq 0$ and $n \neq 0$ is obtained.

4.3.5 Computation of Grid Arrays

In next phase the valid grid points are computed and invalid grid points are removed. The regional grid is represented by the grid point center. The array of grid points $G_{u\times v}$ is thus computed as expressed in Eq. (4.10).

$$G_{st} = \left\{X_{min} + \left(s - \frac{1}{2}\right) \times S_g, Y_{min} + \left(t - \frac{1}{2}\right) \times S_g\right\} \qquad (4.10)$$

Where $i = 1\ to\ u$ and $j = 1\ to\ v$. After the computation of grid arrays, the next step is the estimation of valid grid points and elimination of invalid grid points. In this phase location of regular sensor node is identified through the valid grid points. The grid points are formed by evaluating the distance among the grid points and one-hop, two-hop anchor nodes. The obtained grid is considered to be valid if it lies in one-hop distance for each one-hop anchor nodes and lies in two-hop distance but not in one-hop distance for each two-hop anchor nodes. The head anchor information is further utilized for reducing valid grids. The grid point in two-hop distance is valid when the estimated anchor is a head anchor instead of two-hop anchor. If this condition is not satisfied then the considered grid point is invalid.

After the elimination of all invalid grids the average of the valid grid points is computed. The average value of grids is the estimated location (X_e, Y_e) of regular node which is evaluated by Eq. (4.11).

$$(X_e, Y_e) = \left\{\frac{1}{M}\sum_{1}^{M} x_i, \frac{1}{M}\sum_{1}^{M} y_i\right\} \tag{4.11}$$

Where M represents number of valid grids and (x_i, y_i) represents set of all valid grids.

4.3.6 Calculation of Estimation Error and Accuracy

Sensor are deployed in (100×100), (200×200) and (500×500) matrix. The transmission range R of sensor nodes is fixed as 15 units and the size of grid is $0.1 \times R$. The calculation of estimation error is expressed as Eq. (4.12) and average error is expressed as Eq. (4.13).

$$\Delta e = \sqrt{(a_r - a_e)^2 + (b_r - b_e)^2} \tag{4.12}$$

$$\Delta E = \frac{1}{N_r}\sum_{i=N_a+1}^{N_r} \Delta e_i \tag{4.13}$$

$$\rho = \left(\frac{1 - \Delta E}{r}\right) \times 100\% \tag{4.14}$$

The percentage accuracy is measured as expressed in Eq. (4.14). Here, Δe is the estimation error, ΔE is average error, ρ is estimation accuracy, N_a is number of anchor nodes, N_r is number of sensor nodes, $(X_r - Y_r)$ are real positions and $(X_e - Y_e)$ are estimated positions.

4.4 RESULTS AND DISCUSSION

The network topology used is mesh by placing the head anchor at the corner. The sensor node broadcasts message to the head anchor, which collects the message including RSSI information. Then, the location estimation algorithm is implemented for evaluating the distance of unknown regular nodes in a network. For the network implementation, 100×100 m^2, 200×200 m^2 and 500×500 m^2 grid matrix are used with four head anchors at the corner. The head anchors are located within the each other's communication range, the head anchors connects directly with the sink node shown in green color. However, in the larger network deployment communication from head anchor to sink node, it will follow a multi-hop path in accordance with the mesh topology.

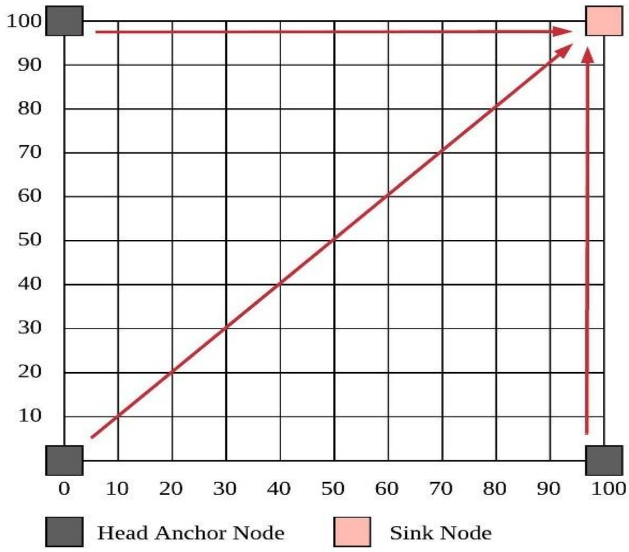


Figure 4.5: Implementation of the network for distance approximation using head anchors

To create the framework for the localization of sensor node, we used MATALB version 9.1. The head anchor receives a message from an unspecified regular in the network and therefore gets the information of RSSI values of regular node. Then, all of the head anchor transmits the message containing RSSI information to the sink node as shown in Figure 4.5. After gathering all the messages, the sink node merges them into a single message. The algorithm then performs location estimation by evaluating estimative region and obtaining valid grids. The initial phase of experimentation is the conversion of signal strength to actual distance. The distance approximation is starting step of the algorithm process, after which the database is created and head anchor performs the data collection. The localization algorithm interfaces with the sink node for estimating the distance of regular nodes. The location estimation algorithm is responsible for the data processing.

4.4.1 Sample Visualization and Test Phase

To check performance of algorithm for location estimation, we deployed 3 unspecified regular nodes at coordinates (6, 42), (40, 66) and (52, 63) marked as yellow square sign. By applying the location estimation algorithm, the nodes are approximately located at coordinates (4, 42), (41, 64) and (53, 61) marked as positive (+) sign in red color as shown in Figure 4.6.

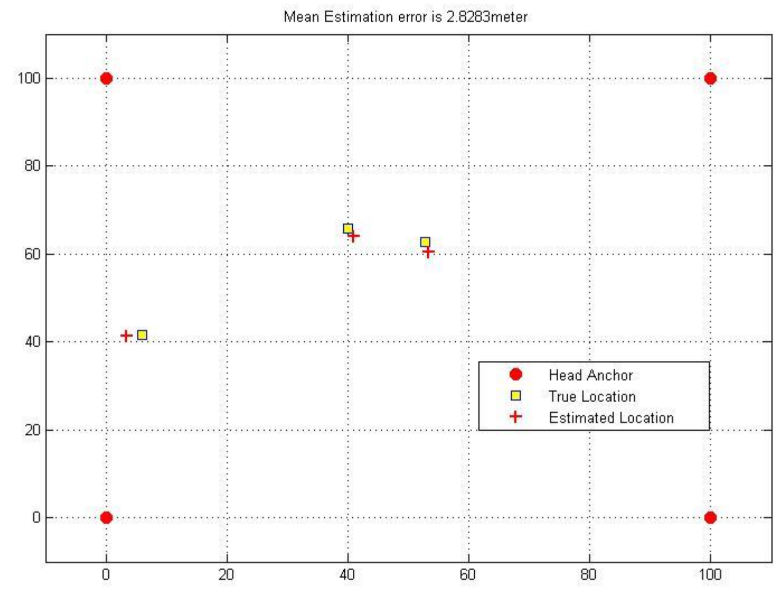


Figure 4.6: Test phase deployment of 3 regular nodes and their location estimation

The final location estimation with the proposed algorithm is approximately nearer to the true location of regular sensors shown as red mark in the above figure. To test the efficiency of proposed algorithm we have deployed large number of regular sensor nodes at different locations within the 100×100 m^2 grid. The accuracy of the actual and estimated position is discussed in the experimental analysis section. The performance analysis in terms of accurate location identification from the location estimation algorithm is tested considering three different cases.

4.4.2 Experimental Analysis

Figure 4.7 depicts the deployment of mobile node over the area. In case 1, the regular nodes are taken as 50, head anchors are taken as 4 for the network size of 100×100 m^2. In the figure below, red circles represent the location of head anchors, the yellow color square represents the true location of regular sensor nodes, whereas red positive (+) sign represents the estimated location of regular nodes.

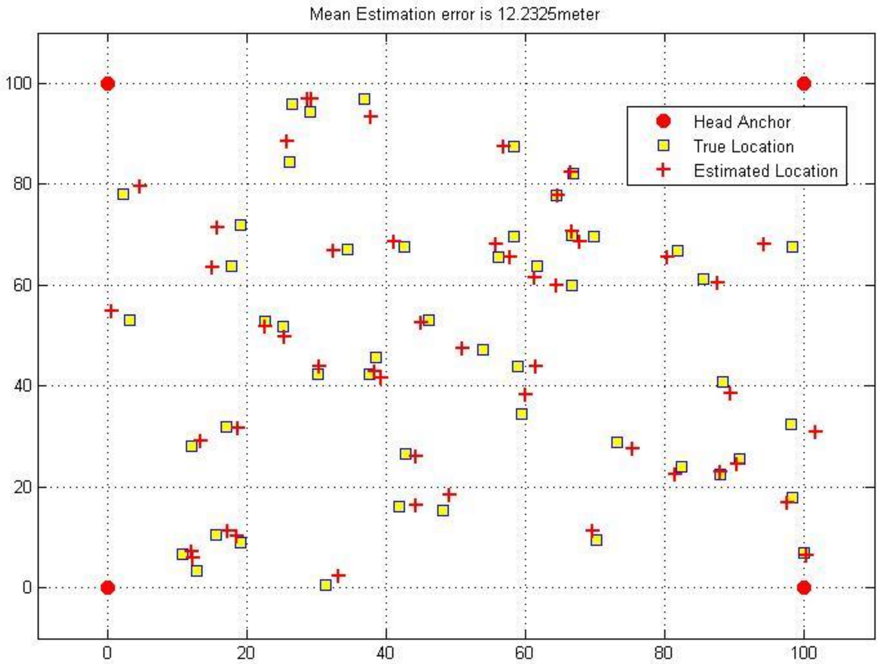


Figure 4.7: Deployment of 50 regular sensor nodes, with 4 head anchors in 100×100 m^2 grid

In case 1, the 50 regular nodes are plotted over the network size 100, keeping the head anchor node 4 as constant. Table 4.1 represents the position estimation of regular nodes with respect to head anchor nodes over the network size 100. The position of each regular node with respect to 4 head anchors is tabulated in Here, the head anchors are 4 and the regular nodes are 50 wherein table represents the distance only for 10 sensor nodes. The head anchor nodes assist other regular nodes in a network for estimating their location. For experimental case 1 the estimation accuracy is better with less estimation error of 12.23 m.

Table 4.1: Position estimation of regular sensor nodes in the 100×100 m^2 grid network

Head Anchors	Regular Sensor Nodes									
	1	2	3	4	5	6	7	8	9	10
1	21.69	126.9	114.64	49.85	91.60	26.00	93.15	66.27	97.26	87.66
2	85.99	82.98	74.948	52.08	101.2	90.24	13.03	119.5	125.4	105.8
3	86.07	97.68	91.45	102.50	44.48	78.31	128.60	33.72	19.18	37.33
4	119.7	17.52	28.86	103.6	61.94	116.6	89.61	105	81.48	70.09

Figure 4.8 depicts the deployment of 100 regular nodes in a network for their position estimation. In case 2, the regular nodes are considered as 100, whereas head anchors remain constant as 4 and the network size is chosen as 200×200 m^2. In this figure, red circles represent the location of head anchors, the yellow color square represents the true location of regular sensor nodes, whereas red positive (+) sign represents the estimated location of regular nodes.

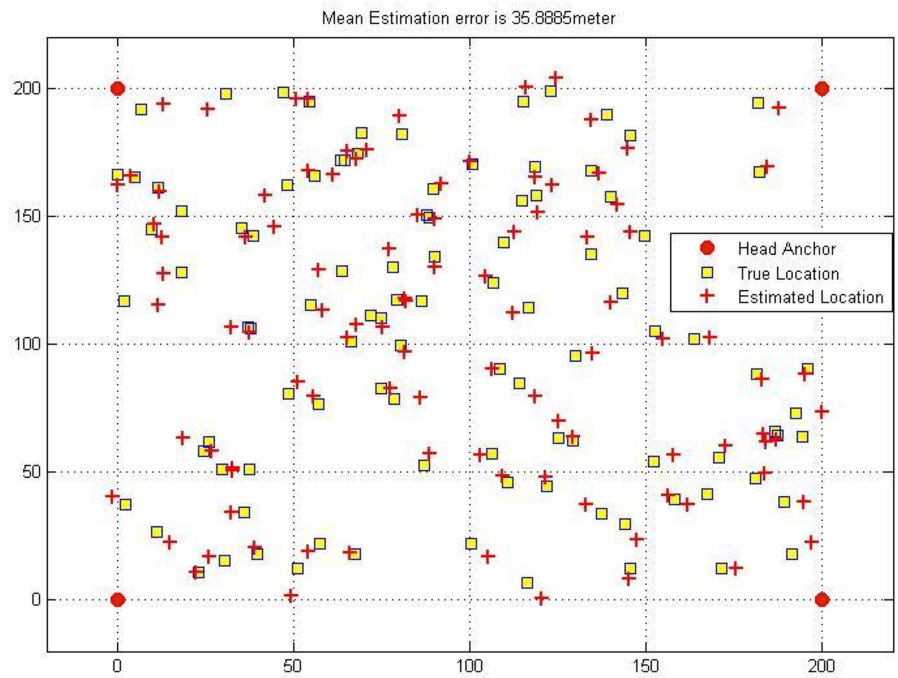


Figure 4.8: Deployment of 100 regular sensor nodes, with 4 head anchors in 200×200 m^2 grid

For case 2, 100 regular nodes are plotted over the network size 200 m, keeping the head anchor node 4 as constant. Table 4.2 represents the position estimation of regular nodes with respect to head anchor nodes. Here, the position of regular node with head anchor is computed and presented in below table. The head anchor nodes assist other regular nodes in a network for estimating their location. For experimental case 2 with the increase in grid size and anchor ratio, the estimation accuracy of regular nodes is better than that case 1 where the deployed sensors are less. The mean estimation error for case 2 is observed as 35.89 m.

Table 4.2: Position estimation of regular sensor nodes in the 200×200 m^2 grid network

Head Anchors	Regular Sensor Nodes									
	1	2	3	4	5	6	7	8	9	10
1	268.3	6.81	184.3	168	212.9	225.9	105.2	233.1	169.6	141.9
2	189.8	198	246	88.47	136.6	206.3	98.23	137.5	97.38	63.82
3	190.2	193.5	38.45	196.8	179.9	121.5	208.6	198.7	189.1	226.3
4	14.50	276.8	167.4	135.4	75.23	79.37	205.2	63.96	128.4	187.4

The position estimation for 100 regular nodes with 4 head anchors is depicted in Figure 4.9. In this case 3, the regular nodes are considered as 100, whereas head anchors remains constant as 4 and the network size is chooses as 500×500 m^2. In this figure, red circles represent the location of head anchors, the yellow color square represents the true location of regular sensor nodes, whereas red positive (+) sign represents the estimated location of regular nodes.

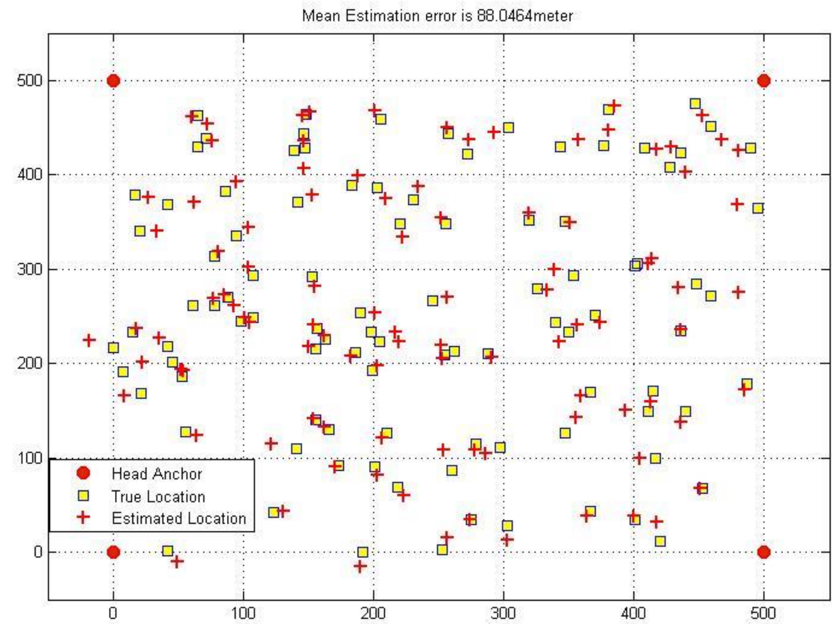


Figure 4.9: Deployment of 100 regular sensor nodes, with 4 head anchors in 500×500 m^2 grid

For case 3, 100 regular nodes are plotted over the network size 500 m, keeping the head anchor node 4 as constant. Table 4.3 represents the position estimation of regular nodes with respect to head anchor nodes. Here, the position of regular node with head anchor is computed and presented in below table. The head anchor nodes assists other regular nodes in a network for estimating their location. For experimental case 2 with the increase in grid size and anchor ratio, the estimation accuracy of regular nodes is better than that case 1 and 2 where the deployed sensors are less. The mean estimation error for case 3 is observed as 80.05 m.

Table 4.3: Position estimation of regular sensor nodes in the 500×500 m^2 grid network

Head Anchors	Regular Sensor Nodes									
	1	2	3	4	5	6	7	8	9	10
1	309.7	458.4	390.9	440	339.2	437.8	312.7	462.8	382	474.7
2	455.0	528.4	112.4	469.8	580	646.3	287	284.2	297.7	95.89
3	262.8	197.3	615.1	253.3	164.5	67.21	427	452.7	411	621
4	424.4	328.6	488	302.2	498.4	480.1	408.5	267.5	334.1	411.6

Table 4.4: Statistical results from experimental analysis

Head Anchor	Anchor Ratio	Regular Nodes	Performance evaluation of Proposed Location Estimation Algorithm		
			Average Estimation Error	Accuracy	Time (s)
4	6	50	0.0381	60.12	4.125
4	6	80	0.0428	61.46	6.018
4	6	100	0.0456	61.85	7.65
4	6	150	0.0553	62.12	9.745
4	6	200	0.0604	62.87	11.256
4	10	50	0.0363	62.27	6.247
4	10	80	0.0396	63.74	7.365
4	10	100	0.0424	64.22	8.019
4	10	150	0.0508	65.47	11.334
4	10	200	0.0546	66.65	12.065
4	15	50	0.0321	67.12	8.364
4	15	80	0.0365	67.84	9.317
4	15	100	0.0406	68.21	11.127
4	15	150	0.0462	69.68	12.063
4	15	200	0.0527	70.36	13.209
4	20	50	0.0279	68.74	10.512
4	20	80	0.0296	69.19	12.335
4	20	100	0.0378	69.94	13.416
4	20	150	0.0415	70.37	14.031
4	20	200	0.0486	71.44	16.027

The statistical results of proposed location estimation algorithm in terms of average estimation error, accuracy and computational time for various simulation environment are tabulated in Table 4.4. The performance is evaluated for the varying anchor ratio with constant head anchors and number of regular nodes in a range of 50 to 200. The table also represents the head anchor nodes which are used for computing the distance of each regular node in a grid. It is observed from the experiment that only 20% to 30% of the anchor ratio is used and unused anchors further saves the energy which further enhances the lifetime of network. It is also observed that with the increase in anchor ratio while keeping head anchors constant, the average estimation error reduces and percentage accuracy increases.

4.5 COMPARATIVE ANALYSIS

The performance analysis of proposed location estimation algorithm has been simulated in MATLAB considering following parameters tabulated in Table 4.5. The performance of the proposed scheme is compared with grid scan localization [185] and distributed range free localization scheme [186] for percentage accuracy and average estimation error.

Table 4.5: Parameters considered for performance analysis

Simulation Factors	
Grid area of Simulation	100×100 m^2, 200×200 m^2, 500×500 m^2
Unspecified regular nodes	50, 80, 100, 150, 200
Head Anchors	4
Anchor Ratio	10 to 30
Mobility	Random

The comparative analysis of proposed system is carried out with existing location estimation approaches. Table 4.6, represents the comparative analysis of algorithm for percentage increase in anchor ratio with other existing approaches. The comparison analysis results are presented in Figure 4.10 and Figure 4.11.

Table 4.6: Comparative analysis of location estimation

Anchor Ratio	Accuracy (%)			Normalized error (%)		
	DRLS	Grid Scan	Proposed	DRLS	Grid Scan	Proposed
0.05	25%	35%	62%	1.03	0.8	0.5
0.1	48%	50%	70%	0.78	0.654	0.4
0.15	57%	60%	74%	0.654	0.59	0.38
0.2	60%	65%	78%	0.624	0.563	0.31
0.25	64%	70%	80%	0.6	0.5	0.3
0.3	70%	73%	84%	0.594	0.4	0.22
0.35	72%	75%	85%	0.526	0.395	0.2
0.4	74%	73%	85%	0.468	0.38	0.2
0.45	72%	74%	86%	0.53	0.388	0.18

The comparative results for percentage accuracy is depicted in Figure 4.10. It is observed from the analysis that with constant head anchor nodes and increasing anchor ratio, proposed system achieves minimal difference in average estimation error. On the other hand, the performance of proposed location estimation scheme depends upon the number of iterations in order to obtain the global optimum. We have compared the performance of proposed scheme for number of iterations performed by varying number of regular nodes and anchor ratio.

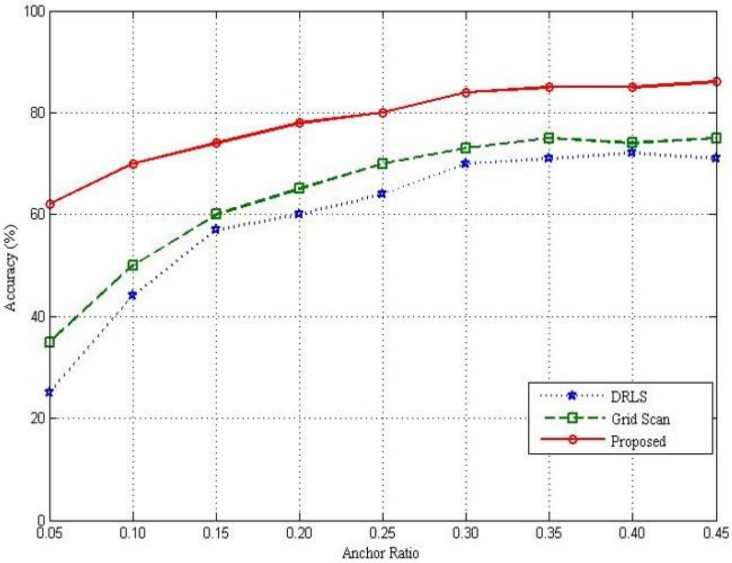


Figure 4.10: Comparison of percentage accuracy

Figure 4.10, presents the percentage improvement accuracy of location estimation with the increase in anchor ratio. It is observed from the analysis that 40% of anchor ratio is a saturation point for the accuracy improvement and beyond this point the accuracy improvement remains constant. The proposed algorithm achieves 85% of percentage accuracy at 40% anchor ratio which is better in comparison with other state of art location estimation schemes.

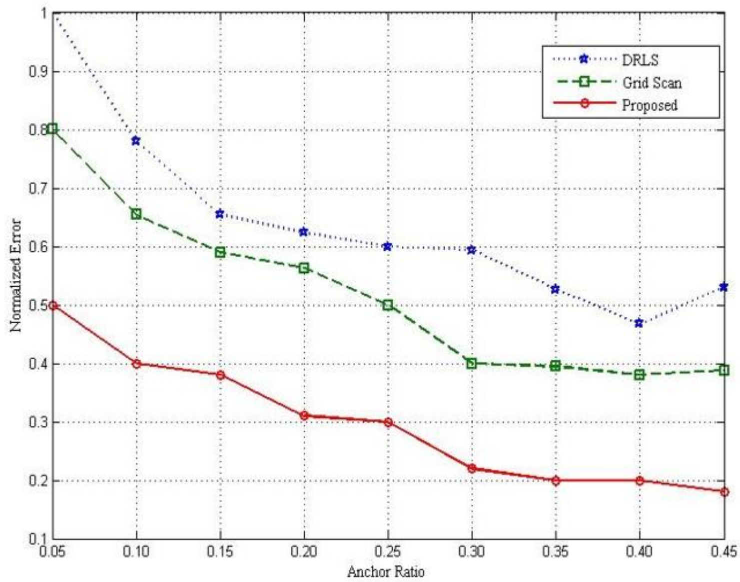


Figure 4.11: Comparison of normalized error

Figure 4.11, presents results in terms of reduction of normalized error with increase in anchor ratio. It is observed from the analysis that with 40% anchor ratio in a network the proposed system achieves 20% of average estimation error which is in terms better with existing approaches. The experimental results emphasize that with the increase in anchor ratio the localization estimation error reduces and percentage accuracy for regular nodes location estimation increases. The proposed scheme of location estimation achieves better estimation accuracy with less average estimation error in comparison with other state of art location estimation schemes.

4.6 CONCLUSION

In conclusion there are large numbers of parameters that must be measured for better quality location estimation. Received signal strength indicator provides the best solution for the localization problem estimating the distance among regular sensor nodes. Radio frequency, transmission power, orientation of nodes and the localization algorithms are the parameter that we have analyzed in our experiments affecting the estimation of distance. On the basis of these analyses, we have proposed an algorithm for the estimation of distance and location. The transmission power is the most important factor for efficient distance estimation. The proposed algorithm computes the location of regular sensor nodes with minimum connectivity and reducing computational costs. Initially the distance between regular nodes is estimated using head anchors. Then the location of regular nodes is identified using the anchor nodes. The increase in anchor ratio provides better accuracy of location estimation. The information of one-hop and two-hop anchor nodes is utilized for finding grids and average of valid grids is the estimated location regular sensor node. The head anchor information is utilized for eliminating invalid grids and improving the location estimation accuracy. The algorithm provides better level of accuracy for position estimation which is computed with the ratio of anchor nodes and head anchors deployed in the sensor network. The proposed algorithm achieves better accuracy of estimation with increase in anchor ratio and for anchor heads. The range-based approaches require extra hardware with the sensor nodes for the measurement of different parameters, which thereby increases the size, weight, energy and cost of the network. The proposed algorithm estimates position through neighboring nodes and does not require any extra hardware, hence saving the energy, weight and size costs. The experimental result of the proposed algorithm presents the localization accuracy without compromising complexity and cost. The algorithm can be implemented for different wireless platform for locating the nodes accurately. The future work can be extended by considering its application for the real time positioning of wireless implantation. Furthermore, the experiments can be extended by providing security to the system by utilizing some security algorithms along with the unknown node localization algorithm. These security algorithms can enhance the level of security and also, we can achieve better energy computation.

CHAPTER 5

DESIGNING A FIRE DETECTION ALGORITHM USING IMAGE PROCESSING TECHNIQUE

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DESIGNING A FIRE DETECTION ALGORITHM USING IMAGE PROCESSING TECHNIQUE

5.1 INTRODUCTION

This chapter portrays the detection of the fire events based on the declaration from the emergency request from the Monitoring Center (MCs). In coordination with previous chapters of detecting fire at earliest and localizing faulty and event triggering nodes, this chapter aims to design a detection algorithm for the confirmation of fire events. It emphasizes the importance of image processing based fire detection systems. Monitoring systems using image processing has gained much more attention among the researchers on the inspiring qualities such as low-expenses, reliability and flexibility towards combining with other technologies. Therefore, the forest fire detection system is designed by developing detection algorithms using images and the image processing methodologies, in order to detect the events of fire based on the confirmation from the Monitoring Centers [187].

Monitoring the forest area has become a vital part of the detection process that helps to reduce the potential risks as well as damages. The verification of forest fires at earlier stage is an important solution to improve the fire detection system. It can be detected at the earlier stages by developing an efficient detection process. The developed detection model should guarantee the reduced rate of the false detection. Smoke is the symptom that can allow monitoring centers to find out the event of fires [188]. Since it spreads quickly, the sensor nodes have to be localized properly, which has been discussed in the earlier chapter. While capturing the images, the smoke creates a disturbance to the scene which is one of the challenging tasks. It prompts to develop fire detection models without any false alarms. At present there are three methods available to monitor the forest fires as discussed below.

5.1.1 Observing Fires through Sensors Associated with Towers

Humans are observing the forest area residing from the towers. In case any abnormal events occur, then they are informed to the concerned authorities. Regardless, the chance of false prediction and the risk to human life is high. Moreover, the sensor used such as IR cameras for fire detection provides only line of sight vision [189]. The cost of deployment and installation of watch tower is very high and fire detection is not reliable.

5.1.2 Satellite Monitoring Process

Satellites are associated with the orbiting nature of the earth, so as to monitor and recognize the fire region. It makes use of two satellites to monitor the forest area, one is Advanced Very High Resolution Radiometer (AVHRR) and other is monitoring through the Moderate resolution Imaging Spectroradiometer (MODIS) [17, 18]. However, it consumes a lot of time to observe the forest area and also the quality of images are not good enough. Due to the varied climatic conditions, the resolution of the images is feeble. Along with that, the detection process in real-time becomes expensive because of the low resolution and the high time consuming, it is mostly not fitted to the forest environment.

5.1.3 Sensor Based Monitoring Process

To overcome the challenges pertaining in satellite based image systems, sensor based detection models are discovered. By placing the sensor nodes at an accurate location, the MCs can easily observe the forest area. In some cases, it becomes impractical due to the natural disasters, otherwise, the services provided by sensor nodes are satisfactory. Mostly sensor systems make use of the smoke characteristics to recognize the forest fire events. However, the carbon in smoke takes little extra time to attain the deployed sensors. It brings delay in the data transmission systems. Sensors in the nearest proximal regions help for forest fire detection processes. The sensing capability of the sensor nodes becomes delicate, when it is placed at the larger distance. Therefore, it is applicable to the indoor applications [190].

In alignment with the sensor applications, the advancement made in digital camera technologies have resolved the challenges pertaining to conventional fire detection systems. Based on the characteristics features of the forest fire, the forest images are captured, analyzed and measured using image processing techniques. It is recognized by flame (or) smoke features. The fire flames are employed for the confirmation process which has both intrinsic and extrinsic properties. It is characterized by both the attributions of static and dynamic. The attribution of static includes color, shape and texture of the produced flames. Whereas, the dynamic features are the differentiation of distributing the colors, textures, area, contour and frequency.

5.2 Processing Fundamentals

The developments made by the technologies have also increased the complexity of controlling the fire events. It poses unique challenges that differ from various environmental scales. Therefore, a prior fire detection with highest sensitivity and accuracy rate are the essential factors to cope with the fire events and the losses. Conventional detection technologies like heat and smoke detectors are not fitted to the noisy environment like dense forests, buildings, open spaces and so on [191]. It degrades the performance of the detection system such as rate of high false positive alarms, missed alarms, delay and lowered accuracy. Image based fire detection has become an active research area in recent times. Inspired by the advantages of image processing techniques such as rapid detection model, flexible environment and high accuracy, even under noisy and non-noisy environments has been explored in our study. The image data is processed by any algorithms to estimate the presence of fire and its severity score. Henceforth, the detection algorithm is the main focus of this study which fascinates the performance of the detecting fire events.

The detection process in the forest fire can be characterized into two forms, flame and smoke characteristics of fire [192]. Based on the different atmospheric constraints, the burning of the fuels will react in varied forms such as oxygen level presented in air, combustion process, light emission and the heat exhaustion. The flame characteristics belongs to the type of gas module that transforms the characteristics of liquid and solid fuels. Normally, the fires are red in colors, and depending on the temperature color of fire varies. The flame with high temperature is named as core region and the flame with low temperature is named as boundary region. In the angle of visual characterization, the flame is displayed as flickering textural features. The flame varies as per the frame region of the images. Figure 5.1 represents the sample image of the forest fire in flame characteristics.

Figure 5.1: Sample image flame characteristics in forest fire

The visibility of the smoke is clear, even from an extended distance and color of smoke varies depending on the temperature. Bluish white and white can be perceived in low temperature and grayish and black in high temperature. Generally, it drifts upwards without changing its stability. The range of the smoke alters according to the frames and the smoke particles disappear at the elapses of time.

Figure 5.2: Sample image of smoke characteristics in forest fire

In the viewpoint of techniques in image processing, it has three important operational stages such as image preprocessing, conversion, and classification. The input is subjected through each of these stages and serves the image data with the claims of detecting the forests. Above it, the conversion stage is an important stage of the detection algorithms for separating luminance from chrominance. Conventional algorithms rely on the manual processing of features and then, some machine learning classifiers are used to classify the events of fires [193]. It throws a major drawback that the manual processing and selection features have lowered the performance of the systems in many aspects. Though different models were suggested to detect the forest fires, complex features introduce complex fire types and scenarios. The intrinsic characterization of the image processing based fire detection system is discussed in subsection below.

5.2.1 Histogram Equalization

This technique of image enhancement is widely employed to incline the contrast of the images by altering the intensity values. It offers a simple, easy and effective model for the image enhancement process. It is the technique used to develop a linear cumulative histogram value of the given input images. Based on the obtained histogram values, the pixel values are redistributed according to the intensity ranges [194]. The conventional histogram equalization technique is described below:

Let us assume an input image, $I(p,q)$ with an aggregate of n pixels, in which the gray level ranges from $[X_0 \; to \; X_{N-1}]$. The probability density function $P(r_k)$ for the image level r_k is given as Eq. (5.1).

$$P(r_k) = \frac{n_k}{n} \tag{5.1}$$

Where, n_k represents the count of the r_k in the image, n is the aggregate number of pixels with $k = 0 \; to \; N-1$. Finally, the histogram of the image is estimated by the arrangement of n_k against the r_k values. Thereafter, the altered intensity is estimated by the cumulative functions which is given as Eq. (5.2).

$$C(r_k) = \sum_{i=0}^{k} P(r_i) \tag{5.2}$$

The cumulative intensity helps to arrange the image under dynamic range, $[X_0, X_{N-1}]$ which is again elaborated as Eq. (5.3).

$$f(X) = X_0 + (X_{N-1} - X_0)C(X) \tag{5.3}$$

The above equation further reduces the unequal histograms that change the brightness of the image.

5.2.2 RGB Color Model

RGB color model is implemented for the background subtraction of the image. Color is the most significant characterization of exploring the characteristics of flame images [195]. It has many features on analyzing the flames of the fire events as mentioned below.

a) Recognizing the flames based on the color rather than intensity range of the image.
b) In the angle of the computational process, the rich source of different color information has reduced the analytic capability.
c) Analysis of different color computation is quite expensive.
d) Therefore, texture and shape features are being characterized in image flame.

RGB color space is mostly adopted in analyzing the real-time images. It is the base color that helps for obtaining other different colors. Each of the colors acts as a base for spectral components. It performs on the basis of Cartesian products of coordinating systems.

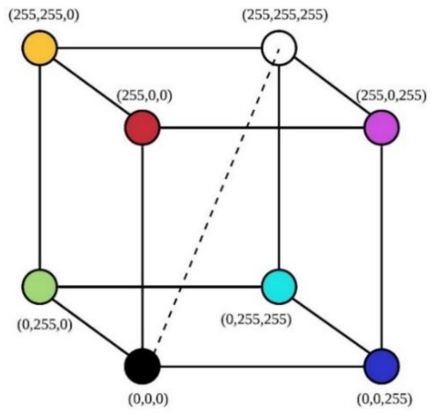


Figure 5.3: Color cube of the RGB color system

Figure 5.3 presents the color cube of the RGB color system. It is inferred through the figure, that primary colors R, G and B are resided at the corners and the other corners are resided by secondary colors such as Cyan (C) at one axis, Magenta (M) and Yellow (Y) on another axis. Similarly, for other corner, black is origin where color white is resided at other corner exactly opposite to black color. As the scale extends from black color to white color, the line draws that adjoins two adjacent points and the color is represented as Grey. It has three components, (R) component represents red color, (G) component represents Green color and (B) component represents blue color. These components are named as monochrome intensity images. The depth of the pixel is estimated from the number of color bits employed to denote the pixels of RGB spaces.

5.2.3 YCbCr Color Model

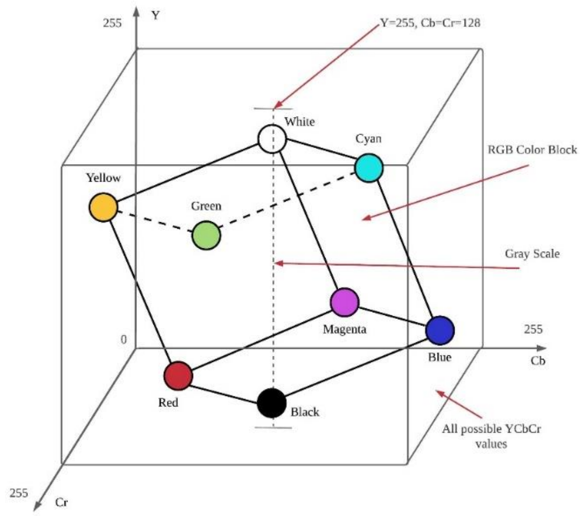


Figure 5.4: YCbCr space model

This color model is developed by the ITU-R BT.601 recommendation for the applications of digital videos. It is mainly found on video and digital photographic systems. It is based on the YUV color space. Figure 5.4 presents the YCbCr color space model. YCbCr color space is obtained from the color cube of RGB color spaces. Each color in the RGB components has varied YCbCr values. Y represents the Luminance value, whereas Cb and Cr represents the Chrominance blue and Chrominance red values. The blue difference is expressed as the blue value minus Luminance value and red difference is expressed as red component value minus Luminance component. The main feature of this color space model is that it shows an excellent performance under varied illumination [196].

5.3 PROPOSED FRAMEWORK

In this part, the workflow of the proposed fire detection algorithm using image processing techniques is discussed. The work is done on the determined locations of the fire in the forests. It takes input as a color image which is being collected from the public repositories. The entities of the proposed methodology is displayed in Figure 5.5. The highlights of this detection algorithm is to verify the firing region of the given input images.

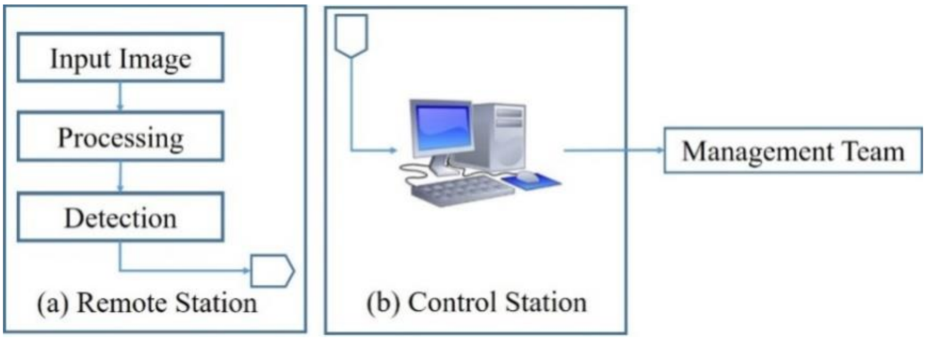


Figure 5.5: Entities of the proposed methodology

The proposed methodology contains three entities, remote station, control station and management Team. The role of the remote station is dealing with the computational process, the role of control station is to deal with the analytic process and the management team takes the responsibility of administering the prevention (or) detection of fire events with minimal losses. Among these entities, control station is the core phase of our research study due to the activities involved in receiving the sensed information, examining the collected information and then issuing the alarms to the concerned authorities. The main objective behind this study is to design an efficient image processing model for testing its potential for the verification of forest fires. The algorithm is designed for determining the true alarm detection and false alarm detection using forest fire images and fire like object images. The verification of forest fire is critically important for the reduction of false alarms and to take precautionary measures from its prevention [197]. The flow process of proposed fire verification algorithm consists of image-preprocessing, background subtraction and classification phases. The verification of fire event is confronted with the following stages as depicted in Figure 5.6.

The framework of the proposed fire verification scheme consists of five phases: first phase is image acquisition where fire and non-fire image are collected for testing, second phase is pre-processing of image in which the intensity of the image is enhanced for the identification fire color pixels. The input image is processed for the extraction of red, green and blue components in third phase of image extraction. In fourth phase the extracted RGB components are further converted to YCbCr model for separating luminance from chrominance. Then some rule based classification is applied in fifth phase of image processing for the classification of fire event and non-fire events in input image. A detailed stepwise depiction of the proposed fire verification algorithm is presented in the sub-sections below.

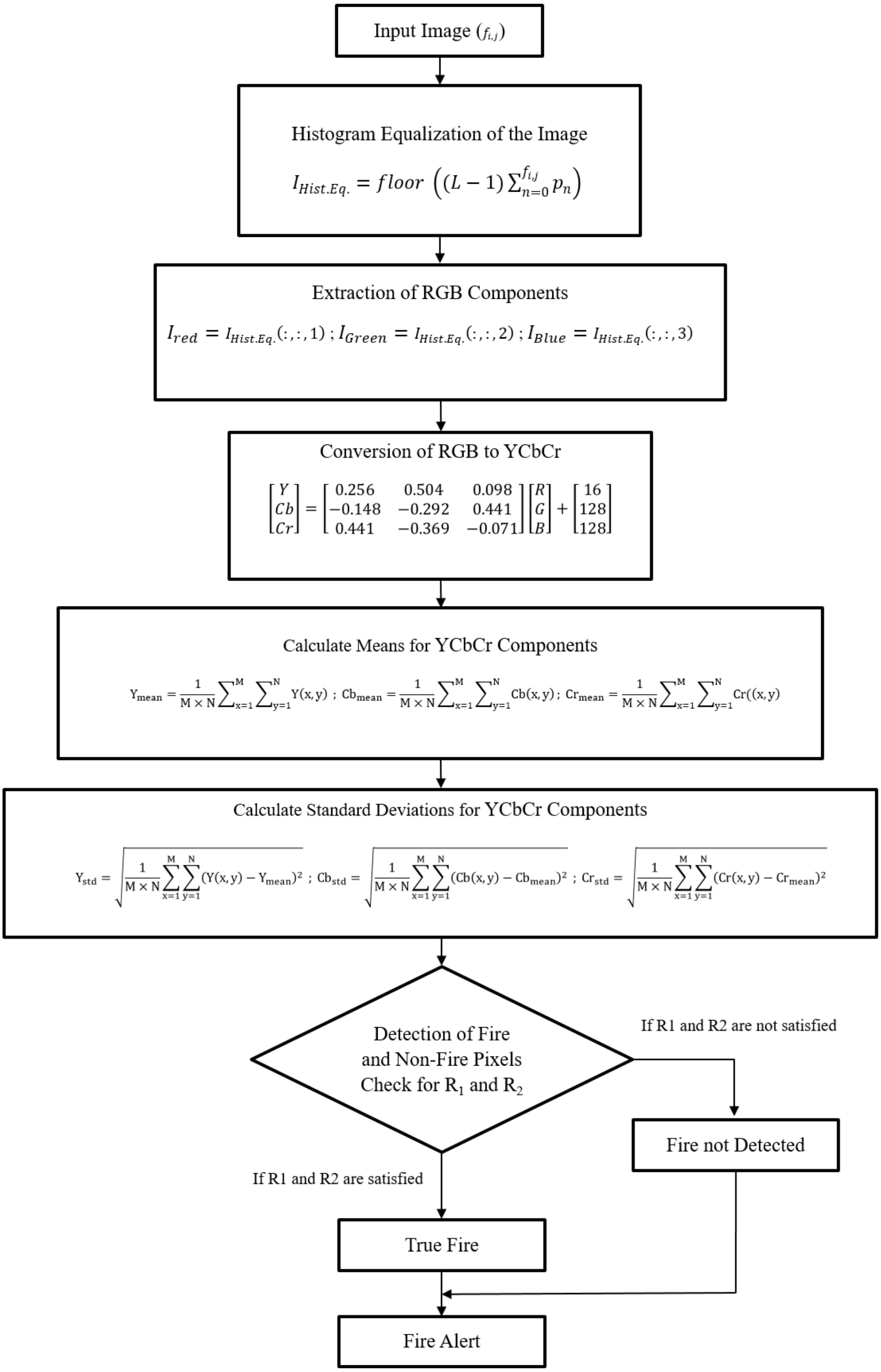


Figure 5.6: Flow diagram of proposed fire verification algorithm

5.3.1 Image Acquisition

It is the foremost step which depicts the information related to the collection forest fire images from datasets. In this, forest fire images are collected from a public repository. Here, $(f_{i,j})$ is the set of input images which are fed into the next stage of pre-processing. The forest fire images from Flickr fire database, Corsican fire dataset and Landsat-8 dataset are collected and analyzed for the verification of fire and non-fire events. The sample image from each dataset which are included in this experimentation is depicted in Figure 5.7.

(a) **(b)** **(c)**

Figure 5.7: Sample image of Forest fire (a) Flickr fire database, (b) Corsican fire database, (c) Landsat-8 fire database

5.3.2 Image Pre-Processing Phase

Image pre-processing involves removal of missing data, redundant data and so on. Thus, an efficient preprocessing technique is suggested to remove the irregularities of the demographic data [198]. Histogram Equalization is employed here to process the acquired images. The use of histogram equalization is to improve the intensity of the colored images. At the first step, the image is transformed to RGB matrix and then further transformed into HSI format. Based on the obtained HSI format, equalization value is applied over the intensity matrix. This process has ensured the quality of the images. The HSI matrix is the combination of Hue value, Saturation value and the Intensity value of the images. This matrix is constantly updated for all the HSI matrices. Considering the HSI matrix, as a base, the RGB matrix is formed.

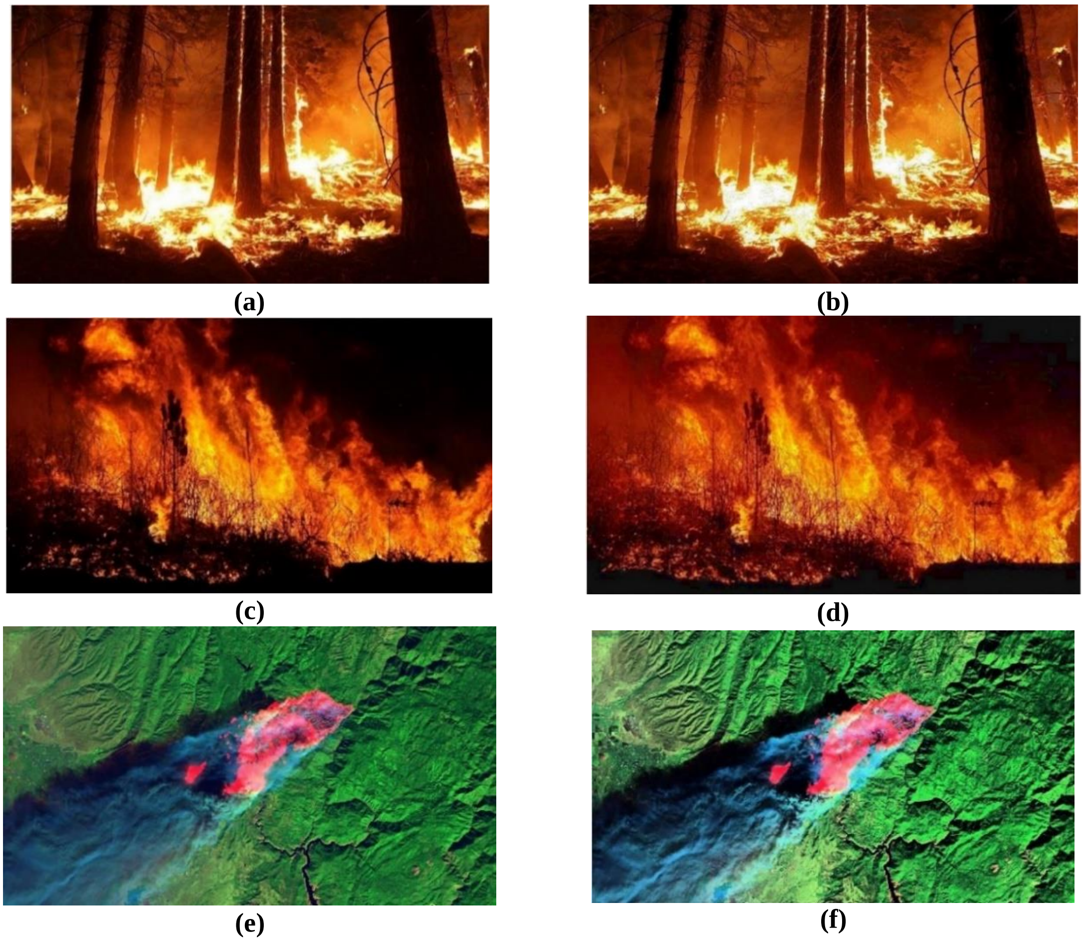


Figure 5.8: (a), (c), (e) Original forest fire images before histogram equalization from Flickr, Corsican and Landsat-8 dataset (b), (d), (f) after histogram equalization

Generally red, yellow and orange are the colors that are relevant for the verification of forest fire. The proposed system adopts histogram equalization for increasing the intensity level of fire life colors in an input image. Figure 5.8, depicts the histogram equalization results where (a), (c) and (e) represents input images of forest fire from various datasets and (b), (d), (f) represents the output results after the histogram equalization process. The histogram equalization is applied on the input image for enhancing its intensity which is expressed in Eq. (5.4).

$$I_{Hist.Equ} = floor(L-1)\sum_{n=0}^{f_{i,j}} p_n \tag{5.4}$$

Where, $f_{i,j}$ is the input image having pixel intensities ranges from *0* to *L-1*, also L represents total amount of possible intensity ranges (256), p_n is the normalized histogram which is calculated as Eq. (5.5) where $n = 0,1, \dots, L-1$.

$$p_n = \frac{Number\ of\ pixels\ with\ intensity\ n}{Total\ number\ of\ pixels} \tag{5.5}$$

5.3.3 Background Subtraction

After the stage of image pre-processing background subtraction is the third phase of the proposed fire verification algorithm. Background subtraction is one of the important stage that defines the flexibility and the reliability of the classification model. The background elements of the forest fire image are separated by implementing RGB model [199]. The histogram equalized image is subjected to the RGB model for the extraction of RGB components which is expressed as Eq. (5.6).

$$\begin{aligned} I_{Red} &= I_{Hist.Equ}(:,:,1) \\ I_{Green} &= I_{Hist.Equ}(:,:,2) \\ I_{Blue} &= I_{Hist.Equ}(:,:,3) \end{aligned} \tag{5.6}$$

Where, I_{Red}, I_{Green}, and I_{Blue} represents the extracted components of red, green and blue color from the input histogram equalized fire image. The three extracted components combining with each other and forms a pixel. The value of Red (R) components is always higher than the component of Green (G) and Blue (B). Figure 5.9 depicts the extracted RGB components from the input images where (b), (f), (j) represents red component, (c), (g), (k) represents green component and (d), (h), (l) corresponds to the extraction of blue component from the input histogram equalized image.

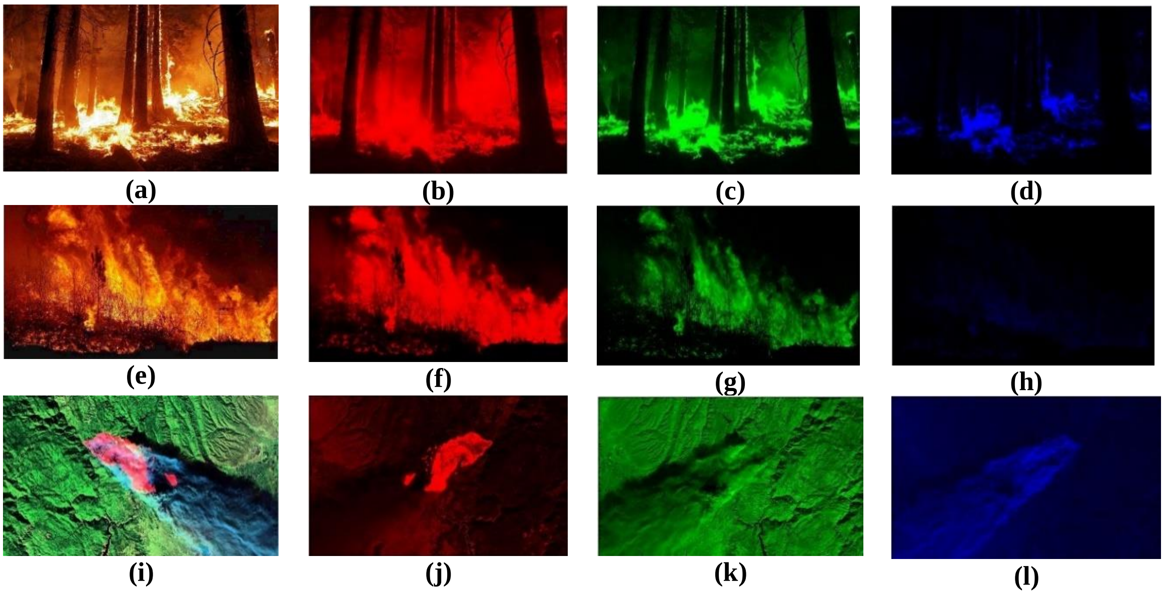


Figure 5.9: Extraction of RGB components, (a), (e), (i) Histogram equalized images, (b), (f), (j) Evaluation of red component, (c), (g), (k) Evaluation of green component and (d), (h), (l) Evaluation of blue component from histogram equalized image

5.3.4 Conversion to YCbCr

After the extraction of RGB components from input image the fourth stage is to convert the RGB components to YCbCr model. This RGB color featured image is subjected to the YCbCr model for discrimination of luminance and chrominance [200]. YCbCr model is implemented in next step to extract the data related to luminance of an image. Since the color of the fire is yellowish-white at the highest temperature, therefore YCbCr model is performed over the regions of the image. The RGB values are converted to YcbCr model and this transformation is done by using Eq. (5.7).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.256 & 0.504 & 0.098 \\ -0.148 & -0.292 & 0.441 \\ 0.441 & -0.369 & -0.071 \end{bmatrix} \begin{bmatrix} I_{red} \\ I_{Green} \\ I_{Blue} \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \tag{5.7}$$

Where (Y) component represents the Luminance value, component (Cb) represents the chrominance blue value and component (Cr) represents chrominance red value. Figure 5.10, depicts transformation of YCbCr model from the RGB values where (a), (d), (g) illustrates the luminance (Y) component, (b), (e), (h) represents the extracted (Cb) component and (c), (f), (i) represents the extracted (Cr) component from the given RGB values.

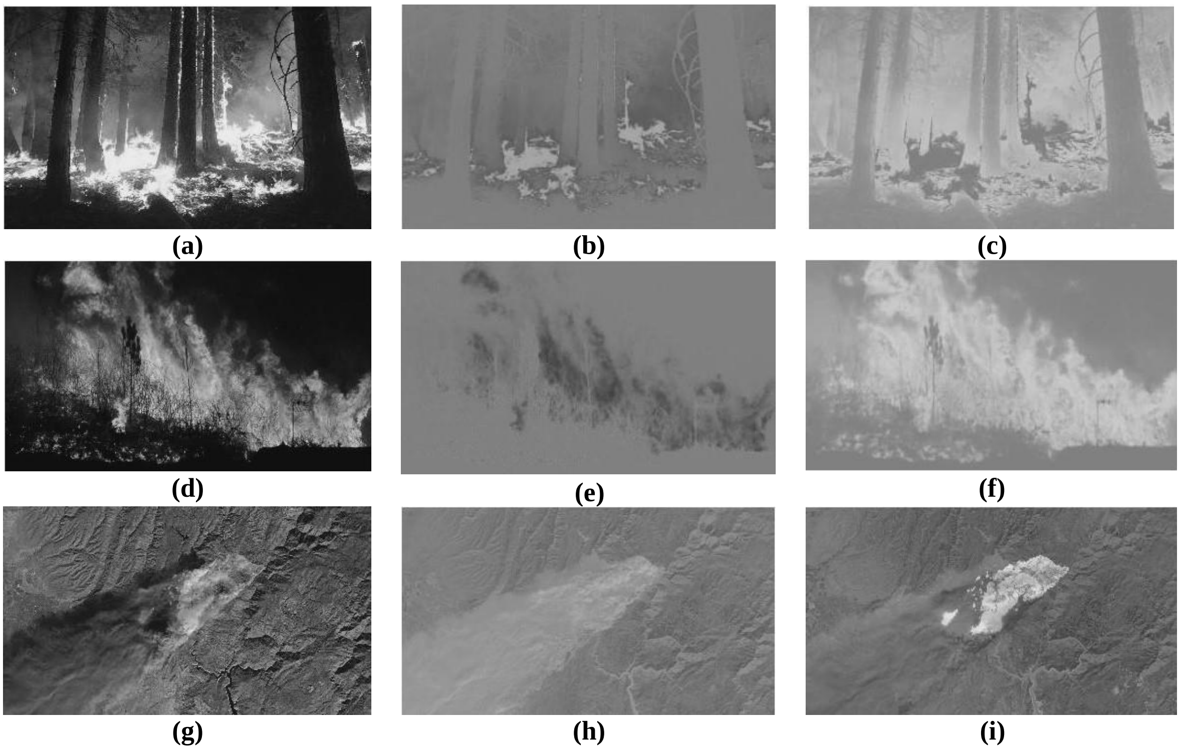


Figure 5.10: (a), (d), (g) Extraction of Y component, (b), (e), (h) Extraction of Cb component and (c), (f), (i) Extraction of Cr component from input RGB image

5.3.5 Classification Phase

Classification is the final step of the fire verification algorithm. The task of classification process is to find out the regions of fire and non-fire events. Along with the coordination of previous steps, the classification process is done by calculating the standard deviation of the obtained mean value of YCbCr modelled image. The verification of fire and non-fire images is carried out through rule based classification where the rules are formulated based on mean value and standard deviation value of YCbCr model. The mean and standard deviation of the YCbCr modelled image is calculated as expressed in Eq. (5.8) and Eq. (5.9).

$$\begin{aligned} Y_{mean} &= \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} Y(x,y) \\ Cb_{mean} &= \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} Cb(x,y) \\ Cr_{mean} &= \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} Cr(x,y) \end{aligned} \tag{5.8}$$

$$Y_{std} = \sqrt{\frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}(Y(x,y) - Y_{mean})^2}$$

$$Cb_{std} = \sqrt{\frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}(Cb(x,y) - Cb_{mean})^2} \qquad (5.9)$$

$$Cr_{std} = \sqrt{\frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N}(Cr(x,y) - Cr_{mean})^2}$$

Where, $M \times N$ represents the total amount of pixels present in fire image, (x, y) defines the spatial location for each pixel value. *Y(x,y)* represents the pixel value for Luminance *Y* component, *Cb(x,y)* represents the pixel value for Chrominance blue *Cb* component and *Cr(x,y)* represents the pixel value for Chrominance red *Cr* component. The rules are formulated for the segmentation of fire region from the input image. These rules are applied over the extraction of the fire pixels. There are two rules which help to find the pixel information of the fire. Rule 1 matches the threshold value with the new segmented image and segments the region of the fire. In some cases, a small deviation is observed between the Cr and Cb components pixels of the fire region. Since, Cb component possesses a low intensity range and the Cr component has the highest intensity range. Thus, the rule 1 is framed to detect fire pixels which is expressed as Eq. (5.10).

$$R_1(x,y) = \begin{Bmatrix} 1, \ if\ Y(x,y) \geq Cb(x,y) \\ 0, \ else \end{Bmatrix} \& \begin{Bmatrix} 1, \ if\ Cr(x,y) \geq Cb(x,y) \\ 0, \ else \end{Bmatrix} \qquad (5.10)$$

Rule 2 segments the center region of fire from the input image. The mean value of YCbCr model has unique information about flame which has the brightest region. The rule framed for the segmentation of center region of fire where Y component value is higher than the mean of Y component. Similar to that, Cb component value is lesser than mean of Cb component. Along with that, Cr component value is greater than Cr component mean value. The rule 2 for the detection of the fire center region is represented as Eq. (5.11).

$$R_2(a,b) = \{1, if(Y(a,b) \geq Ymean(a,b)) \\ \cap (Cb(a,b) \leq Cbmean(a,b)) \\ \cap (Cr(a,b) \geq Crmean(a,b))\}; 0, else \tag{5.11}$$

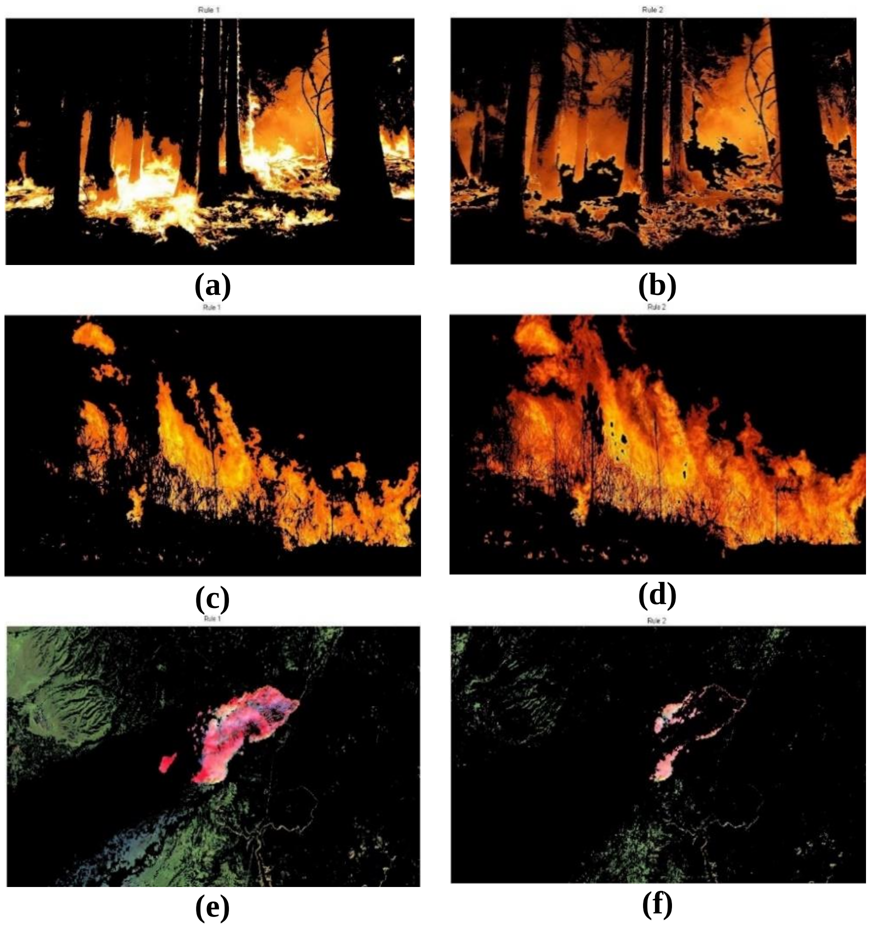
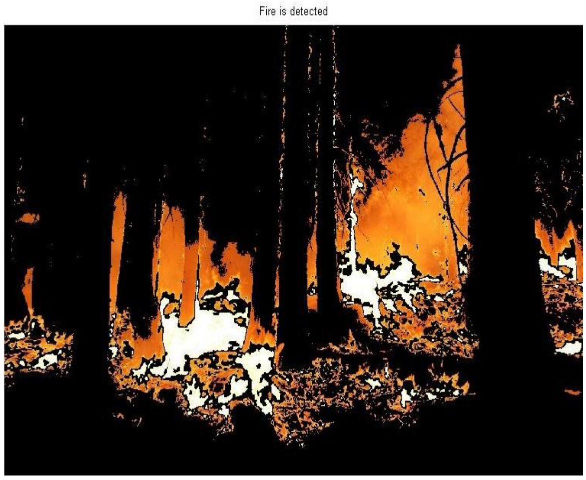
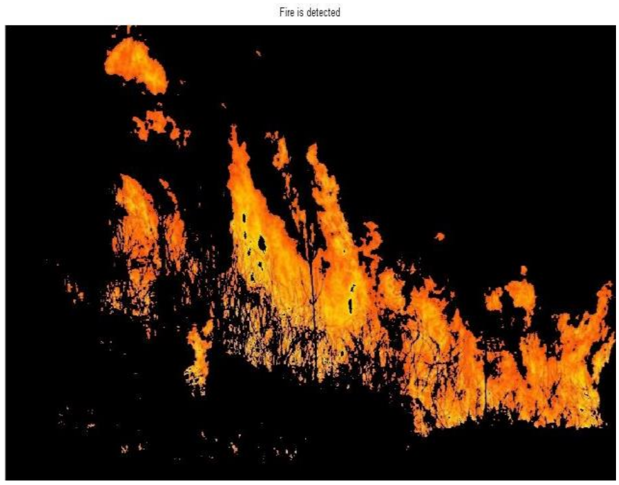


Figure 5.11: Rule based classification of fire region, (a), (c), (e), Rule 1 based segmentation of fire region (b), (d), (f) Rule 2 based segmentation of center region

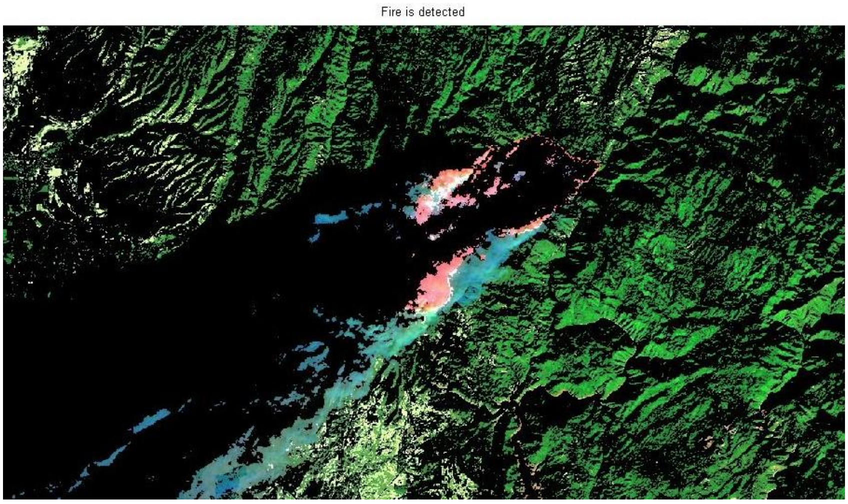
Figure 5.11 depicts the rule based classification of fire pixels where (a), (c), (e) represents the segmentation of fire region based on rule 1 and (b), (d), (f) represents the segmentation of fire center region for the confirmation of fire event.



(a)



(b)



(c)

Figure 5.12: Classification results for fire verification, (a) Flickr fire database, (b) Corsican fire database, (c) Landsat-8 fire database

The verification of fire event is the last stage of the proposed fire verification algorithm. Figure 5.12 depicts the confirmation of fire event as an output of the proposed scheme where (a), (b) and (c) represents the verification of fire from sample images of Flickr, Corsican and Landsat-8 fire database. The classification of fire and non-fire region in an image is carried by obtaining the mean and standard deviation values from the YCbCr model. Then, the rule 1 and rule 2 are formulates based on mean and standard deviation values pertaining to the segmentation of the flame region helps for finding out the fire and non-fire pixels. Once the rules are satisfied, then a fire alarm is processed at the base station confirming the verification of fire and non-fire events.

In the last stage abnormal events are captured in each location using the classification process and the required steps are taken to prevent the losses.

5.4 Results and Discussion

In this section the analysis of the obtained results using proposed methodology is discussed. Initially, fire and non-fire forest fire images are collected from various datasets and obtained results are explained and discussed with the existing methods, [58] [101] & [169]. Figure 5.13 presents the analysis of proposed fire verification scheme where the input images are processed through various stages for the detection of fire and non-fire events.

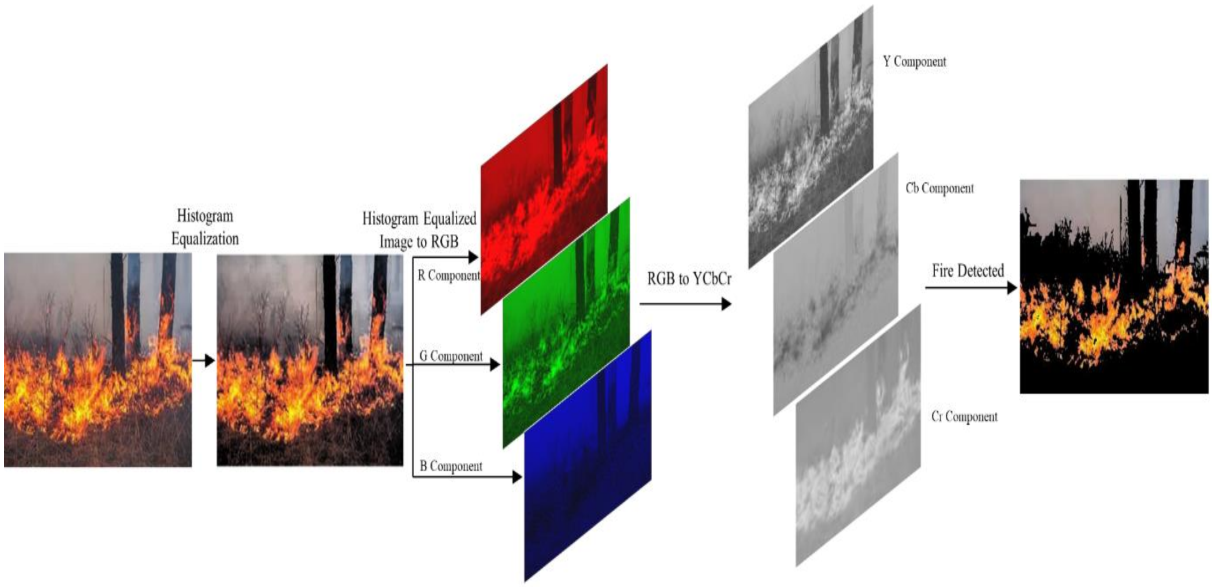


Figure 5.13: Analysis of proposed scheme using sample input image of forest fire

Initially, the image is enhanced by the use of histogram equalization which significantly enhanced the contrast of the image. The enhanced image is further subjected to feature extraction step where RGB components of the images are computed. The extracted RGB components are processed through the next stage where RGB components transformed to YCbCr components. In the next step rule based classification is applied where two rules are formulated for the verification of fire present and non-fire regions. The mean and standard deviation values of the YCbCr components are computed for rule based analysis. If the input image falls under Rule 1 and Rule 2, then it is considered as fire image and whereas, the input image does not fall under Rule 1 and Rule 2, then it is categorized as non-fire image. The evaluation of the verification algorithm is carried out in terms of True and False Detection Rate, which is further compared with other existing fire detection models, so as to prove the efficiency of the proposed fire verification approach. To experiment and evaluate the proposed fire detection algorithm, images from three datasets are collected and employed in our study. Images from Flickr-Fire, Corsican Fire and Landsat-8 Fire datasets are analyzed for evaluating the performance of proposed fire verification algorithm. Flickr-Fire is an eminent database that holds images for different kinds of fire and non-fire images. It consists of 2000 images with size of 1024*768 pixels. It is mainly used for classifying the fire and non- fire regions. Corsican dataset consists of 500 images with the pixel size of 1024*768. It is mainly applicable for segmentation of the different fire colors such as red, orange and yellow-white colored fire and the detection process. Landsat-8 contains various sorts of land images that contain both fire and non-fire regions. It is mainly applicable for segmentation of the fire region and the detection process of active fire regions. The classification model has two outputs, one is labelled as ‘fire detection’ and other is labelled as ‘fire not detected’. The performance of proposed scheme is validated through these three datasets in terms of True positive, True negative, False positive, False negative, recall, precision F-score and accuracy parameters.

Table 5.1: Performance evaluation for percentage true positive and false positive

Parameters	**Dataset Fire Images**		
	Flickr-Fire dataset (250)	Corsican Fire Database (348)	LANDSAT-8 (220)
True Positive	243	339	212
Percentage True Positive	97.2	97.41	96.36
	Dataset Non Fire Images		
	Flickr-Fire dataset (215)	Corsican Fire Database (253)	LANDSAT-8 (250)
False Positive	18	19	21
Percentage False Positive	8.3	7.5	8.4

The success of the designed detection model is evaluated by scoring a reduced number of false positive rate and maximizing the performance of the detection approach with different forms of input images. Table 5.1 presents the performance evaluation of proposed scheme in terms of percentage true positive and false positive. The performance of proposed scheme is evaluated on two set of images fire and non-fire which are taken from Flick-fire, Corsican and Landsat-8 datasets. For the evaluation of percentage true positive a set of 250 fire images from Flickr-fire, 348 fire images from Corsican and 220 fire images from Landsat-8 dataset are collected and analyzed.

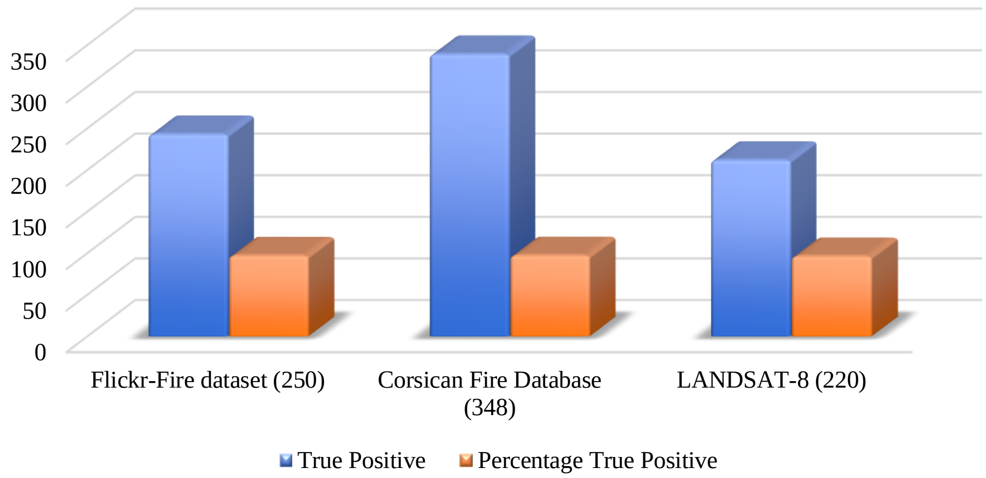


Figure 5.14: Performance evaluation for percentage true positive

The Figure 5.14 depicts the representation of percentage true positive evaluation for Flick-fire, Corsican and Landsat-8 datasets. The obtained results presents the efficiency of proposed scheme in terms of percentage true prediction. It is observed from the experiment that the proposed scheme achieves higher percentage of true positive prediction such as 97.2% for Flick-fire, 97.4% for Corsican fire and 96.3% for Landsat-8 fire datasets. Similarly the test conducted for non-fire images for estimating the performance of the proposed scheme in terms of false positive. The non-fire image dataset consists of 215 images from Flickr-fire, 253 images from Corsican and 250 images of fire like region form Landsat-8 dataset. Figure 5.15 represents the percentage evaluation of false positive prediction for same datasets. It is observed from the evaluation the system achieves lesser percentage of false positive prediction such as 8.3% for Flick-fire, 7.5% for Corsican fire and 8.4% for Landsat-8 non-fire datasets.

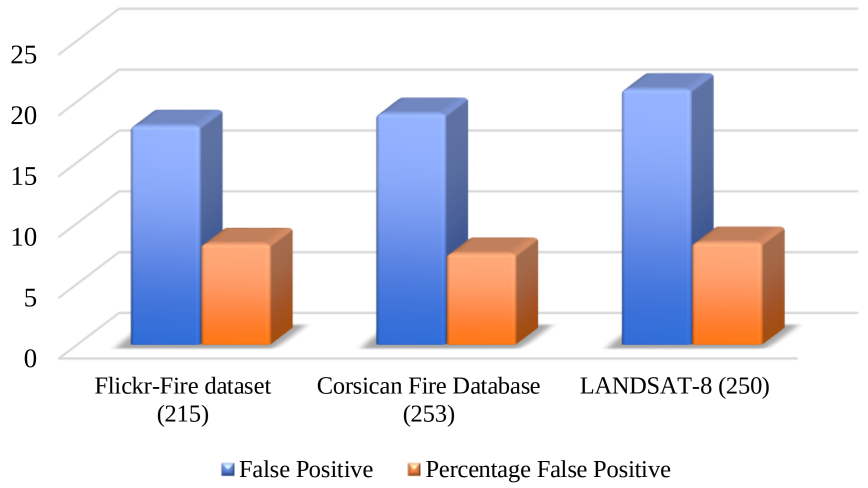


Figure 5.15: Performance evaluation for percentage false positive

Figure 5.14 and 5.15 presents the graphical representation of the performance results of the three datasets based on true and false positive predictions. The evaluation of true and false positive predictions are explored in the detection of fire and non-fire images. The proposed scheme of fire verification achieves better results in terms of true positive and false positive. In coordination with this, the performance of the system is also analyzed for the parameters like accuracy, precision, F-score and recall. Table 5.2 displays the obtained results of each dataset of fire and non-fire images pertaining to the metrics such as Accuracy, Precision, Recall, F-score, True positive, True negative, False positive and False negative.

Table 5.2: Analysis of proposed scheme for various performance indices

Performance Indices	**Flickr-Fire dataset**		**Corsican Fire Database**		**LANDSAT-8**	
	Fire Images	Non Fire Images	Fire Images	Non Fire Images	Fire Images	Non Fire Images
Accuracy	95.38	95.62	96.2	95.8	93.74	93.1
Precision	92.57	92.33	91.36	92.64	92.62	93.35
Recall	94.25	93.72	93.65	92.35	93.14	93.08
F-Score	93.56	92.65	94.24	94.76	93.18	92.6
True Positive	97.2	95.1	97.4	94.62	96.36	92.45
True Negative	93.5	93.5	92.46	92.54	91.66	91.44
False Positive	7.8	8.3	8.64	7.5	8.16	8.4
False Negative	7	8.25	8.15	7.85	8.44	8.56

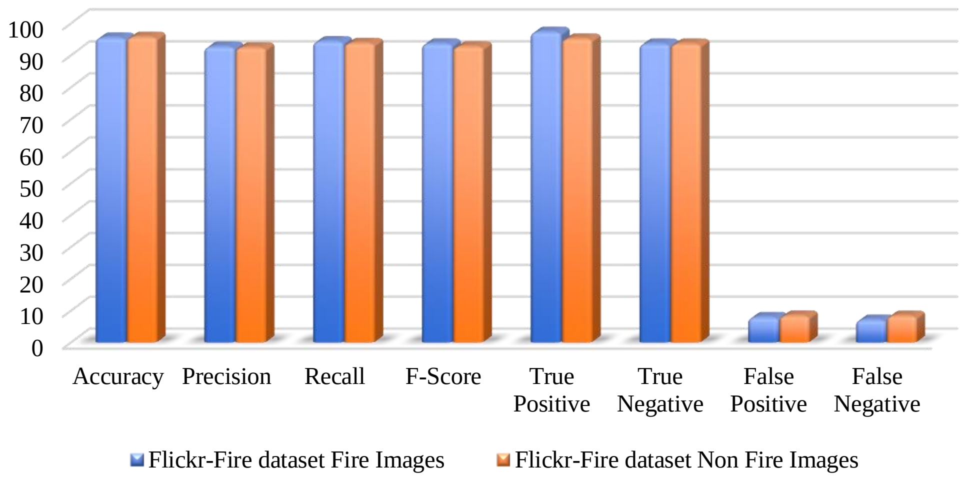


Figure 5.16: Performance evaluation of proposed scheme for Flickr-fire dataset

The Figure 5.16 presents the results achieved for various performance indices using Flickr Fire datasets. The obtained results from the analysis of Flickr-Fire dataset are measured as 95.38% accuracy; 92.57% Precision; 94.25% Recall; 93.56% F-score; 97.2% True positive; 93.5% True negative; 7.8% false positive and 7% False negative. Similarly, the analysis of non-fire images are measured as, 95.62% accuracy; 92.33% Precision; 93.72% Recall; 92.65% F-score; 95.1% True positive; 93.5% True negative; 8.3% False positive and 8.25% False negative.

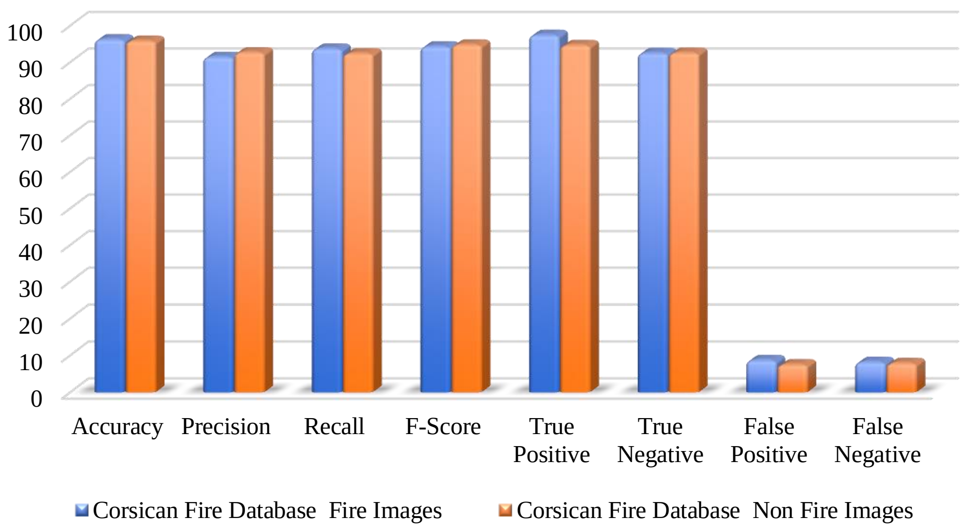


Figure 5.17: Performance evaluation of proposed scheme for Corsican fire dataset

Figure 5.17 depicts the bar graph representation of the obtained results considering various performance indices for Corsican fire dataset. The performance analysis for fire images are measured as 96.2% accuracy; 91.36% Precision; 93.65% Recall; 94.24% F-score; 97.4% True positive; 92.46% True negative; 8.24% False positive and 8.15% False negative. Similarly, the analysis of non-fire images are measured as, 95.8% accuracy; 92.64% Precision; 92.35% Recall; 94.76% F-score; 94.62% True positive; 92.54% True negative; 7.5% False positive and 7.85% False negative.

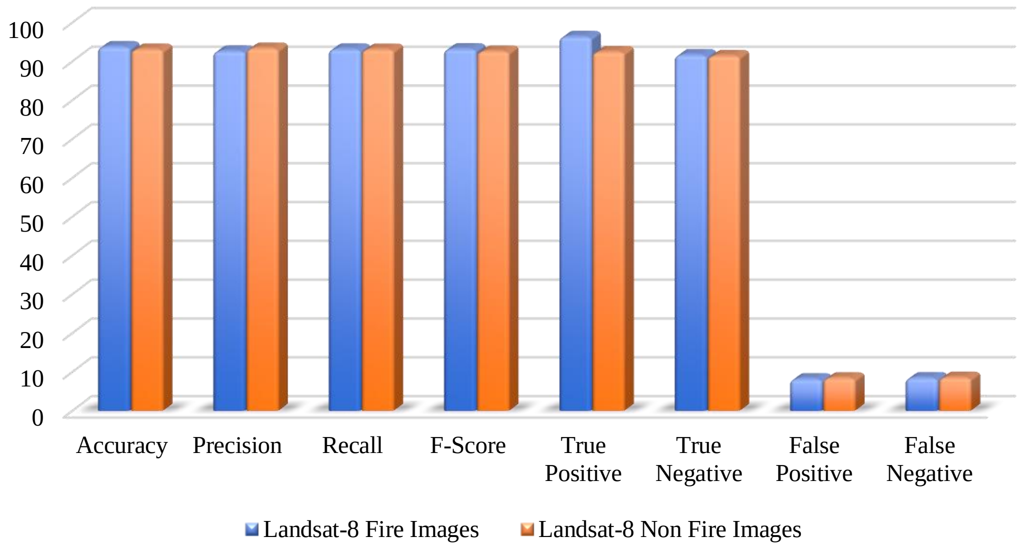


Figure 5.18: Performance evaluation of proposed scheme for Landsat-8 fire dataset

The Figure 5.18 presents the results achieved using the Landsat-8 database. The analysis of fire images are measured as 93.74% accuracy; 92.62% Precision; 93.14% Recall; 93.18% F-score; 96.36% True positive; 91.66% True negative; 9.45% False positive and 8.44% False negative. The accuracy, 93.1%; Precision, 93.35%; Recall, 93.08%; F-score, 92.6%; True positive, 92.45%; True negative, 91.44%; False positive, 8.4% and False negative, 8.56% are observed for non-fire images. The overall performance is measured for two set of images, fire and non-fire images using rule based classification scheme. The proposed fire verification approach provides average higher accuracy for the classification of fire and non-fire regions.

5.5 Comparative Analysis

This section presents the comparative examination of the proposed scheme with existing state of art approaches. The proposed fire verification scheme is tested with different dataset for measuring its performance and compared with other existing techniques. Table 5.3 represents the comparison results through the analysis of proposed scheme with state of art approaches in terms of True positive rate, True negative rate, False negative rate, False positive rate, Recall, Precision and F-score measures.

Table 5.3: Comparative results of the proposed scheme with existing techniques

Method	TP rate (%)	TN rate (%)	FN rate (%)	FP rate (%)	Recall (%)	Precision (%)	F-score (%)
Berni *et al.* [101]	0.876	0.896	0.1547	0.124	0.853	0.8625	0.8625
Song *et al.* [58]	0.8825	0.867	0.1436	0.11	0.865	0.89	0.8724
Chen *et al.* [169]	0.9024	0.9	0.12	0.145	0.884	0.871	0.8775
Proposed	**0.95**	**0.935**	**0.0765**	**0.078**	**0.9425**	**0.9257**	**0.9356**

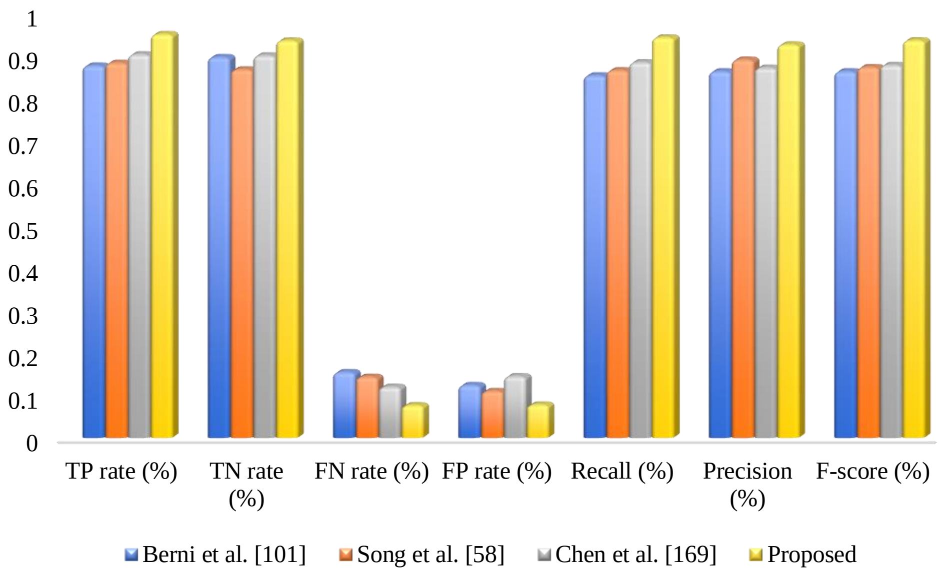


Figure 5.19: Comparison graph between existing and proposed fire verification approach

The overall evaluation of the fire verification scheme achieves 95%, True positive rate; 93.5%, True negative rate; 7.6%, False negative rate; 7.8%, False positive rate;

94.25%, Recall; 92.57%, Precision and 93.56%, F-score. It is observed from the comparison that proposed verification scheme achieves better results with the existing fire detection approaches. Figure 5.19 presents the bar graph representation of the comparative analysis of proposed fire verification approach with other existing techniques. The designed algorithm of fire verification performs better than the conventional detection approaches in terms of F-score, precision and recall.

Table 5.4: Comparison of proposed approach with other techniques for true and false detection

Parameter	Techniques			
	Berni et al. [101]	Song et al. [58]	Chen et al. [169]	Proposed
True Detection	88.47	89.25	91	**93.86**
False detection	11.53	10.75	9	**6.14**

The table 5.4 presents, comparison of proposed fire verification approach in terms of True and False detection rate with existing approaches. It is observed that proposed approach achieves better True detection rate of 93.86% and false detection rate of 6.14% than other approaches.

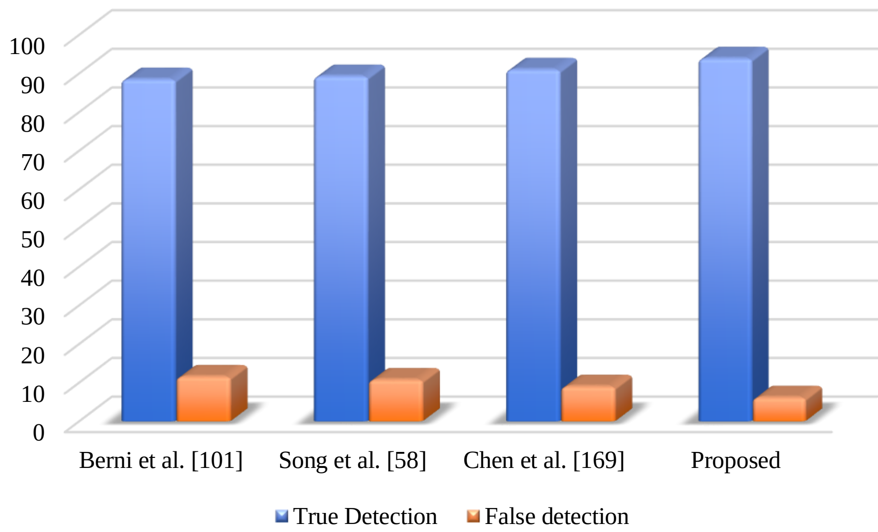


Figure 5.20: Comparison graph on efficiency of the proposed methodology for true and false detection rate

The Figure 5.20 presents the efficiency of the proposed methodology by comparing it with the existing detection approaches. It is noticed from the graph that the proposed method excels the existing detection approaches in terms of true detection rate and false detection rate. Relied on the given input images, the proposed method classifies the fire pixels and non-fire pixels of the image with higher accuracy.

5.6 CONCLUSION

The fires prevailing in the areas of smart cities (or) forest region becomes a major concern among the governing bodies. In this chapter, we have detailed the fire verification process on the basis of approval of fire events using image processing techniques. Though WSNs are employed to collect the data, the processing of the collected data plays a key role in the detection process. The process of confirmation of fire event has been tackled using image processing techniques. To begin the process, the scope of image preprocessing and the feature extraction processes are employed for image enhancement and background subtraction. Then, the enhanced image is processed to the RGB extractor for the evaluation of Red, Green and blue components. The extracted RGB values are further subjected to YCbCr model for its transformation. The verification process is carried out using the rule based classification stage. The proposed methodology is applied, executed and tested on three well-known datasets of both fire as well as non-fire images. The R color component in the RGB color space model has influenced the performance of the detection approach. Thus, an algorithm using RGB color model, in which intensity of R component has been significantly analyzed and then employed for the classification model. The proposed results have stated the performance of the detection approach in terms of F-score, precision, recall true detection and false detection rate. Compared to the conventional approaches, the proposed detection approach has achieved 93.8% of fire true detection rate with 6.14 % of false detection rate.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

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The demand for automatic forest fire detection system have increased due to large number of reported forest fire incidents in the recent years. The detection of forest fire at early stage and intervention is critically important in reducing the fire risk as the uncontrollable behavior of fire disturbs the ecosystem which may leads to global warming and ozone layer depletion. This thesis primarily focuses on the efficient deployment of sensor nodes in region of interest for real time monitoring of environment and to provide a feasible early forest fire detection framework. Wireless Sensor Networks provides an optimal solution to predict the fire event at its early stage by analyzing the sensed data in real time through efficient deployment of sensor nodes. The sensor nodes are deployed randomly and deterministically for measuring the efficiency of monitoring environment in real time. Different techniques have been developed for estimating the location of unspecified sensor nodes in a network and for the verification of fire present. The verification of fire presence is carried out on the basis of image processing to reduce the false alarms rate. This section concludes complete research work along with the contribution and future directions of this research work.

6.1 CONCLUSION AND CONTRIBUTION

This study includes the designing of a reliable and efficient framework for the detection of forest fire at early stage. The techniques developed are capable of monitoring the environment in real time, locating the faulty sensor nodes or event triggering nodes in a network and confirming the fire event in order to reduce the false alarm rate.

From the extensive literature review, the importance of early forest fire detection system is revealed to reduce or stop the adverse effects of this environmental or man-made cause. Regular monitoring of environment is essential to measure the state of region at any time for detecting the adversaries as early as possible. The alternative techniques studied in the literature presents certain limitations in terms of high detection to notification delay, localization errors and high false alarms. These shortcomings are addressed in this work by designing a framework for the detection of forest fires based on Wireless Sensor Networks, Internet of Things and image processing technique. In the first part of this research, the sensor modules are placed in region of interest for measuring the state of environment at any time. The sensor modules are deployed randomly and deterministically for evaluating the deployment efficiency in terms of minimum detection to notification delay and reliable transmission of information locally and towards sink node. Data is collected using the sensor nodes deployed and same was stored at cloud for analysis. The tests were conducted for indoor and outdoor experimentation to check the validation of the system. The sensed field data is stored on the ThingSpeak cloud regularly where the entries of relative humidity, gases or smoke, light intensity and ambient temperature are plotted and analyzed for the detection of adversaries. The experiments are conducted for both random and deterministic deployment schemes. The improvement in response time and standard deviation is observed from the experimentation in comparison with other existing techniques. The system achieves 24.56 milliseconds of average response time for deterministic deployment and 31.28 milliseconds of average response time for random deployment of sensor modules. The framework is efficient and delivers a realistic, less costly technique for gathering and monitoring environment globally in the real time scenario.

The second part of the research estimates the location of unspecified sensor nodes in a sensor network. An improved algorithm for the identification of location coordinates of unspecified sensor node is proposed. Initially, the inter distance among the regular sensor nodes is estimated by introducing four head anchor nodes. The task of position estimation is accomplished by introducing one-hop, two-hop anchor nodes with known positions for the computation of location coordinates of regular nodes. In the proposed location estimation scheme, the head anchor are referred to as reference points for distance estimation. For the identification of location of regular sensor nodes, one-hope and two-hop anchor nodes information is utilized. The region is estimated by computing four edges in one-hop range for each regular node. The estimative region is the overlapping region where the circumrectangle of these four edges overlaps. In the next step, valid grid arrays are computed and the average of valid grids is the estimated location of regular sensor node. The proposed algorithm estimates position through neighboring nodes and does not require any extra hardware, hence saving the energy, weight and size costs. The experimental result of the proposed algorithm provides improved localization accuracy without compromising complexity and cost. The proposed scheme presents accurate estimation of unspecified sensor node location and it presents the accuracy improvement of 21.87% in comparison to grid scan.

Later in this research work, the confirmation of a fire alert is carried through the proposed fire verification algorithm. The fire verification algorithm is proposed for the classification of fire image and non-fire images for the reduction of false alarms using image processing approaches. A histogram equalization, RGB color space and YCbCr model based approach is designed for the extraction of information from input image. Rule based classification is framed for the sorting of fire images and non-fire images. Histogram equalization provides the intensity enhancement of fire color pixels in the input image which is further processed for the extraction of RGB components. The extracted RGB components are subjected to the conversion stage where image is transformed to YCbCr color model for separating luminance from chrominance. The proposed fire verification algorithm provides effective classification proficiency while providing accuracy improvement for true detection comparative to other existing approaches. The rule based classification method yielding the maximum accuracy of 93% for true detection with minimum 6.14% of false detection rate.

The novelty of the proposed framework lies in optimal performance of WSNs and IoT based monitoring system and its robustness is verified through 6-fold cross-validation. The proposed system is capable of notifying an early warning alert of the forest fire along with coordinates in the form of emails to users. The comparative analysis of the proposed framework presents the percentage improvement in terms of detection to notification delay, accurate localization and rare false alarms with existing state of techniques. The proposed framework provides superior performance deploying sensor network in real time environment and employing image processing approach which provides the flexibility for confirmation of fire alert to reduce the rate of false detection. After several experiments and result based analysis it is concluded that the goal of this research is achieved by aiding real time analysis, localization and confirmation of fire event through Wireless Sensor Networks and Internet of Things, thereby assisting early forest fire detection systems.

6.2 FUTURE SCOPE

Despite of all the efforts to contribute towards accurate and early forest fire detection by developing a framework for real time monitoring and several other techniques, there is still a scope for the future development and investigation. The future aspects that can be explored further for the extension of this research work are presented as follows.

- **i.** Time synchronization and management of sleep cycle would be considered for both sensor modules and sink/coordinator node in order to minimize the energy consumption.
- **ii.** The performance of this system can further be enhanced by taking movement characteristics of fire into consideration and also from the detected fire region, it is helpful to know the fire spread by making use of geometric parameters.
- **iii.** The proposed system performance is limited for smoke detection. In future, the work can be extended for detecting forest fire in fog environment.

LIST OF PUBLICATIONS

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JOURNALS PUBLISHED/ACCEPTED

1. A. Sharma, & P. K. Singh, (2020). Taxonomy on Localization Issues and Challenges in Wireless Sensor Networks. Recent Advances in Electrical & Electronic Engineering (Formerly Recent Patents on Electrical & Electronic Engineering), Vol. 13, Issue 2, 193-202.
https://www.eurekaselect.com/169925/article

2. A. Sharma, P. K. Singh, A. Sharma, & R. Kumar (2019). An efficient architecture for the accurate detection and monitoring of an event through the sky. Computer Communications, Vol. 148, 115-128.
https://doi.org/10.1016/j.comcom.2019.09.009

3. A. Sharma, P. K. Singh, & Y. Kumar, (2020). An Integrated Fire Detection System using IoT and Image Processing Technique for Smart Cities. Sustainable Cities and Society, Vol. 61, 102332.
https://doi.org/10.1016/j.scs.2020.102332

4. A. Sharma, P. K. Singh, "Localization in Wireless Sensor Networks for Accurate Event Detection" International Journal of Healthcare Information Systems and Informatics, 2019. Vol. 16, Issue 3. (Accepted)

JOURNALS COMMUNICATED

1. A. Sharma, P. K. Singh, Y. Kumar "UAV Based Framework for Effective Data Analysis of Forest Fire Detection Using 5G Networks: An effective Approach Towards Smart Cities Solutions" in International Journal of Communication Systems. (Minor Revisions)

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1. A. Sharma and P.K. Singh, "An insight to forest fire detection techniques using wireless sensor networks," *Proceedings of the International Conference on Signal Processing, Computing and Control (ISPCC), 2017*.
2. A. Sharma and P.K. Singh, "Comparative Study on Satellite and Wireless Sensor Networks Based Techniques in the Context of Forest Fire Detection," *Proceedings of the International Conference as INDIACom-2018*.

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