VEHICLE ACCIDENT AUTOMATIC DETECTION AND INFORMING SYSTEM

Project report submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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UNDER THE GUIDANCE OF

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DECLARATION

We hereby declare that the work reported in the B.Tech Project Report entitled **" Vehicle Accident Automatic Detection and Informing System"** submitted at **Jaypee University of Information Technology, Waknaghat, India** is an authentic record of our work carried out under the supervision of **Dr. Nishant Jain.** We have not submitted this work elsewhere for any other degree or diploma.

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This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

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Date:

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ABSTRACT

In this Project, we recommended a traffic accident detection and introduced a framework for consequently recognizing, recording, and detailing traffic accidents at crossing points. A framework with these properties would be helpful in deciding the reason for accidents and the highlights of the crossing point that sway wellbeing. Moreover, we proposed and structured the metadata vault for the framework to enhance the interoperability.

This model simply detects the accident or collisions at the traffic lights by identifying collisions at the intersection and then informing to central data, so that a life can be saved.It only detects the collisions between cars only but for future use it can be extended to other 4 wheelers as well 2 wheelers and an informing system can also be installed that redirects to Ambulance for the emergency if it detects an accident on the intersection of Traffic lights.

An implementation of the proposed technique will be performed using python programming language. This describes the methodology used for image processing for traffic accident detection classification using different libraries and algorithms with real time images.

CHAPTER 1

INTRODUCTION

Consistently, vehicular accidents cause deplorable loss of lives, cost numerous nations huge measures of cash, and produce considerable blockage to a country's transportation framework. 50%-60% of the deferrals on urban roads are related with episodes, and on urban surface lanes, an enormous level of traffic accidents and most postponements happen at or close to crossing points. Crossing points are a typical spot for crashes, which might be because of the way that there are a few clashing developments, just as a horde of various convergence structure qualities. Convergences likewise will in general experience serious crashes because of the way that few sorts of harmful accidents, for example, edge and left-turn impacts, normally happen there.

Subsequently, precise and brief detection of accidents at convergences offers enormous advantages of sparing properties and lives and limiting clog and delay. Traffic accident detection utilizing computer vision and Image processing has pulled in much consideration as of late. Ikeda et al. [1] plot a picture processing-innovation based programmed unusual occurrence detection framework. This framework is utilized to distinguish four kinds of episodes, to be specific

1) Stopped vehicles
2) Slow vehicles
3) Fallen articles
4) Vehicles that have endeavored path progressive changes.

1.1 Overview

Although, lot of study has been done to make a structure that can identify an accident through video observation, real-time execution of every one of these frameworks have not been realized at this point. Real-time execution of an accident detection through video with traffic reconnaissance has consistently been trying since one needs to find some kind of harmony between the speed of the framework and the exhibition of the frameworks, for example, accurately recognizing accidents and furthermore diminishing bogus caution rate. Preferably we need a framework that could augment the quantity of edges handled every second simultaneously ready to accomplish a worthy execution rate. This carries us to the objective of this examination. The motive of this exploration is to build up an accident detection module ati roadway crossing points with video processing that is appropriate for real-time usage. In this proposal we built up an accident detection module that utilizes the parameters separated from the distinguished and followed vehicles which can accomplish great real-time execution.

A significant stage in programmed vehicle crash checking frameworks is the detection vehicles in every video outline and precisely following the vehicles over numerous edges. With such following, vehicle data, for example, speed, change in speed and change in direction can be resolved to encourage the procedure of crash detection. As appeared in the Figure 1.1 [1] given the recognized vehicles, following can be seen as a correspondence issue in which the objective is to figure out which distinguished vehicle in the following edge compares to a given vehicle in the present edge. While for a human expert, the errand of following can regularly be performed easily, this assignment is very trying for a computer. In this way in this proposition more accentuation has been given to the real-time execution of vehicle detection and following.

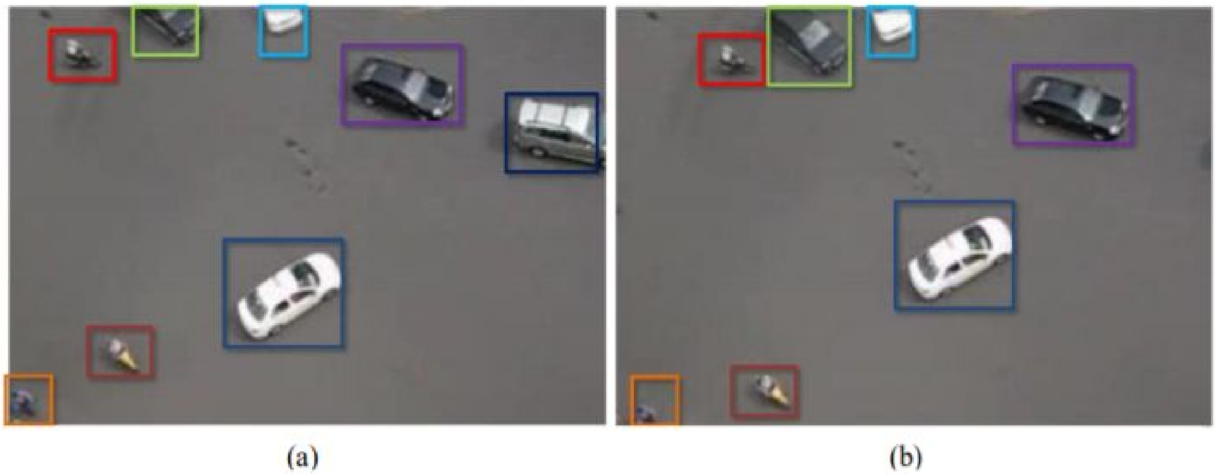


Figure 1.1: An example of vehicle tracking (a) Frame at time t (b) Frame at time t+1 [1]

As shown in Figure 1.1, given the identified vehicles, following can be seen as a correspondence issue in which the objective is to figure out which recognized vehicle in the following casing compares to a given vehicle in the present edge. While for a human expert, the undertaking of following can regularly be performed easily, this errand is very trying for a computer. In this way in this proposal more accentuation has been given to the real-time usage of vehicle detection and tracking.As appeared in the Figure given the identified vehicles, following can be seen as a correspondence issue in which the objective is to figure out which distinguished vehicle in the following edge relates to a given vehicle in the present edge.

1.2 Motivation

With the calculation capacity of the advanced CPU processors, numerous unpredictable real-time applications have been made conceivable and actualized in different fields around the world. One of the broadly utilized real-time applications is video surveillance frameworks. Video surveillance frameworks are utilized for security observing, peculiarity detection, traffic checking and numerous different purposes. Video surveillance frameworks have diminished the need of human nearness to screen exercises caught by video cameras. And furthermore one of the upsides of visual surveillane frameworks is video can been put away and dissected for future reference. One of the significant utilizations of video surveillance frameworks is traffic surveillance. Broad research has been done in the field of video traffic surveillance. Video traffic surveillance frameworks are utilized for vehicle detection, following, traffic stream estimation, vehicle speed detection, vehicle grouping, and so on. One of the broadly utilized uses of traffic surveillance frameworks is vehicle detection and following. By recognizing and following vehicles, we can identify vehicle's speed, direction, traffic thickness, and so on and if there is any irregularity, the recorded data can be sent to the traffic specialists to make vital move. Table 1.1[3] shows the presentation correlation of different episode detection advances. Along these lines video-based traffic surveillance frameworks have been favored everywhere throughout the world.

Type	Advantage	Disadvantage
Inductive Loop Detector	● Relative low cost ● Large knowledge base ● Relative good performance	● Installation and maintenance require stopping of traffic ● Can be damaged by heavy vehicles and road repair.
Microwave(Radar)	● Installation and maintenance doesn't require stopping of traffic ● Compact Size	● Relatively low accuracy of data
Active infrared	● No Data	● Can be damaged in strong precipitation and low visibility ● High price
Passive infrared	● Installation and maintenance doesn't require stopping of traffic ● Better than visible wavelength sensor in fog ● Compact size	● Have an unstable detection zone ● One sensor is focused in collecting information from one lane
Ultrasonic	● Wide range of recevied traffic data	● The signall can be attenuated or distorted because of environmental factors ● Poorly detect cover by snow cars

Magnetometer	● Suitable for installation in bridges and other solid surface where other detectors cannot be installed	● Limited in use ● Average cost
Video Image Processing	● Provides an image of movement in real time ● Monitor simulataneoulsy with many lens ● No traffic interuption for installation or repair	● It is requierd expensive data transmission equipments ● Different algorithm is required for day and night use ● Possible error in data of traffic ● Exposed to atmospheric conditions and harsh climate

Table 1.1: Performance comparison among existing incident detection technologies[3]

As indicated by World Health Organization reports about 1.2 million lives are lost each year because of traffic accidents. What is all the more astounding is the way that traffic accident related passings is one among the main ten reasons for death worldwide, the rundown that incorporates tuberculosis, coronary illness and AIDS as appeared in Table 1.2[4]. And furthermore the expense of these accidents means a stunning 1-3% of the world's Gross National Product. In the United States, it is assessed that vehicle accidents represent more than 40,000 passings and cost over $164 billion every year. Among these, traveler vehicle crashes represent by far most of passings. With no preventive estimates these figures are assessed to increment to 65% throughout the following 20 years. Studies have demonstrated that the quantity of traffic related fatalities is exceptionally reliant on crisis. A portion of the situations delineating traffic accidents and its results 4 reaction time . At the point when an accident happens, reaction time is basic, each additional moment that it takes for help to show up can mean the contrast among life and demise. So there emerges a requirement for a framework that can identify accidents naturally and report it to the concerned specialists rapidly by which the crisis reaction time can be made quicker, in this way possibly sparing a great many lives. With the utilization of video-based traffic surveillance frameworks, accidents can be recorded and be sent to the traffic observing focus so the approaching traffic can be cautioned of an event of accident and be occupied to maintain a strategic distance from traffic clog. This carries us to the inspiration of this exploration. The inspiration of this examination is to build up an accident detection module at roadway convergences through video processing and report the identified accident alongside the accident video to the concerned specialists, with the goal that quick move can be made and possibly spare a great many lives and property.

World	Deaths in millions
Coronary heart disease	7.20
Stroke and other cerebrovascular diseases	5.71
Lower respiratory infections	4.18
Chronic obstructive pulmonary disease	3.02
Diarrhoeal diseases	2.16
HIV/AIDS	2.04
Tuberculosis	1.46
Trachea, bronchus, lung cancers	1.32
Road traffic accidents #9 on the list	1.27
Prematurity and low birth weight	1.18

Table 1.2 Top 10 causes of death worldwide [4]

1.3 Contribution

The fundamental commitment of this project is the real-time execution of vehicle detection and following alongside accident detection at roadway crossing points. As talked about before albeit a lot of research has been done identifying vehicle detection and following the greater part of the frameworks neglect to execute them in the real-time on account of the multifaceted nature of the calculation. In this postulation another technique has been adjusted to follow the identified vehicles in every video outline that is appropriate for real-time execution and furthermore accident detection modules have been added to vehicle detection and following modules that can work in real-time. We utilize the low-level highlights, for example, region, direction, centroid, shading, luminance of the removed vehicle districts to accomplish a sensible following rate. To decide accidents, speed, zone and direction of the followed vehicle were utilized. The understanding of this proposal is to process the greatest video outlines as could reasonably be expected and furthermore accomplish a great execution rate at the same time.

CHAPTER 2

BACKGROUND

2.1 Related Work

Various regular road occurrence detection calculations have been created in the previous quite a few years. Methods dependent on choice trees for design acknowledgment, time arrangement examination, Kalman channels, and neural systems have been endeavored however met with changing degrees of accomplishment in their detection execution [2]. Then again, just a couple of analysts have researched the detection of traffic crashes at crossing points [2].

In 2005, Green et al. [4] assessed a sound-incited video recording framework used to break down the explanations behind traffic crashes at convergences. The framework naturally records potential episodes when initiated by sound (horns, conflicting metal, screeching tires, and so forth.). It was conveyed in 2001 at the crossing point of Brook and Jefferson Streets in Louisville, KY. The transportation engineers utilized this data to make a few upgrades to the crossing point, which brought about 14% decrease in accidents. Another examination portrayed in a 2001 report thought about the improvement of a framework for naturally recognizing and revealing traffic crashes at convergences [4] the investigation would decide crashes legitimately from the acoustic sign of the accident.

An acoustic database of ordinary traffic sounds, development sounds, and crash sounds was created utilizing the hints of crash tests, routine traffic sounds at crossing points, and development sounds from building destinations. Tests indicated that the false alarm rate (FAR) (false positive) was 1%. The end was that the framework should have been additionally assessed in circumstances with routine traffic stream and accident events.

2.2 Traffic Accident Detection and Informing System

Traffic Accident Detection and Informing System is an image-impelled moving picture recording and detailing system used to investigate and assess the event of traffic crashes at convergences. The system comprises of a charge-coupled-gadget camera situated on the edge of the crossing point to get a perspective on occurrences, an image processing unit that identifies images that could be identified with a traffic crash, an advanced video recorder (DVR) that has recorded all the circumstances of the convergence for the past about fourteen days, and a correspondence unit that send the AMPs to the TMC. At the point when the Accident Detection and Informing System recognizes an occasion that could be a crash and catches the AMPs (which incorporate 5 s before the occasion and 5 s after the occasion) from the DVR, the system sends the AMPs to the TMC by the virtual private system.

2.3 Performance Measures

The information from the police reports were utilized to coordinate each crash report to an AMP by the Accident Detection and Informing System. The exhibition of the episode detection model is for the most part assessed utilizing the records:
False Alarm Rate (FAR) [4], which is characterized as

FAR = No. of false alarm case/ total no. of input patterns

where, input pattern is a 10 second moving picture for accident detection. A good accident detection system should have a very low FAR.

2.4 Traffic Image Analysis

There are essentially four significant advances engaged with the video-based accident detection systems, different looks into have been done on every individual area separately and great execution have been acquired. These are the accompanying advances -

1. Movement division and vehicle detection

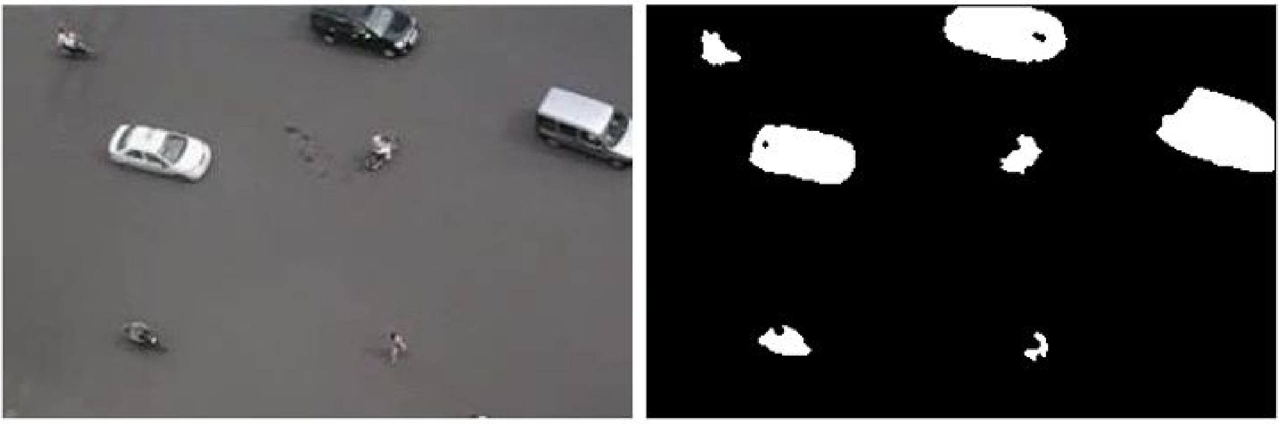
2. Vehicle following

3. Processing the aftereffects of following to figure traffic parameters

4. Accident detection utilizing the traffic parameters

2.4.1. Motion segmentation and Vehicle Detection

Motion segmentation is the way toward isolating the moving articles from the foundation. The motion segmentation step is fundamental for recognizing the vehicles in the image arrangement. Figure 2.1[2] shows a case of vehicle detection. Figure 2.1(a)[2] is the first image and Figure 2.1(b)[2] shows the recognized vehicle locales. To decide accidents, speed, region and direction of the followed vehicle were utilized. The knowledge of this postulation is to process greatest video outlines as could be expected under the circumstances and furthermore accomplish great execution rate at the same time. To decide accidents, speed, zone and direction of the followed vehicle were utilized. The understanding of this theory is to process greatest video outlines as could reasonably be expected and furthermore accomplish great execution rate at the same time.



(a) (b)

Figure 2.1: Example of vehicle detection (a) Original image (b) Detected vehicle regions

There are four main approaches to detect vehicle regions, they are

1. Frame differencing method

2. Background subtraction method

3. Feature based method

4. Motion based method

2.4.1.1. Frame Differencing Method

In the casing distinction strategy moving vehicle districts are recognized by taking away two back to back image outlines in the image arrangement. This functions admirably if there should arise an occurrence of uniform brightening conditions, else it makes a non-vehicular area and furthermore outline differencing strategy doesn't function admirably if the time interim between the edges being deducted is excessively enormous. A portion of the vehicle detection strategies utilizing this strategy.

2.4.1.2. Background Subtraction Method

Foundation deduction technique is one of the broadly utilized strategies to recognize moving vehicle districts. In this progression either the as of now put away foundation outline or the foundation generated from the aggregated image grouping is deducted from the info image edge to identify the moving vehicle areas. This distinction image is then thresholded to separate the vehicle locales. The issue with the put away foundation outline is that they are not versatile to changing light and climate conditions which may make non-existent vehicle areas and furthermore works for fixed foundations.

In this manner there is a need to generate a foundation that is dynamic to the enlightenment and climate conditions. Different strategies dependent on insights and parametric models have been utilized. A portion of the methodologies [14] expected Gaussian likelihood circulation for every pixel in the image. At that point the Gaussian appropriation model is refreshed with the pixel esteems from the new image outline in the image succession.

Single Gaussian appropriation based foundation demonstrating functions admirably if the foundation is moderately fixed and it comes up short if the foundation contains shadows and non-significant moving districts (e.g., tree limbs). This drove the examination to utilize more than one Gaussian (Mixture of Gaussians) to fabricate increasingly powerful foundation demonstrating strategies. In Mixture of Gaussian techniques [13] – [14] hues from a pixel in a foundation object are depicted by numerous Gaussian conveyances. These techniques had the option to create great foundation displaying. In all the above depicted strategies a few parameters should be evaluated from the information to accomplish accurate thickness estimation for foundation [15]. Anyway more often than not this data isn't known in advance.

2.4.1.3. Feature Based Method

Since the foundation deduction techniques need accurate demonstrating of foundation to recognize moving vehicle locales, specialists moved their concentration to identify moving vehicle districts utilizing highlight based strategies. These strategies utilized sub-highlights, for example, edges or corners of vehicles. These highlights are then assembled by examining their motion between sequential casings. In this manner a gathering of highlights presently sections a moving vehicle from the foundation. The upsides of these techniques [13] is that the issue of impediment between the vehicle locales can be taken care of well, the component based strategies have less computational multifaceted nature contrasted with foundation deduction strategy, the sub-highlights can be additionally broke down for characterizing the vehicle type and there is no need of fixed camera. Koller et al. [13] utilized removal vectors from the optical stream field and edges as sub-highlights for vehicle detection. Beymer et al. [3] utilized corner vehicles as highlights for estimating traffic parameters. Edges are utilized as highlights to distinguish vehicles by Dellart et al. [10]. Smith [11] utilized a mix of corners and edges to recognize moving vehicles. Yet, the impediment of these systems is that on the off chance that the highlights are not gathered accurately, at that point there might be a disappointment in distinguishing vehicles effectively and furthermore a portion of the systems are computationally perplexing and needs quick processing computers for real-time execution.

2.4.1.4. Motion Based Method

Motion based methodologies were likewise used to identify the vehicle locales in image groupings [12]. Optical stream based methodologies were utilized to identify moving items in the techniques [512]-[12]. These strategies are exceptionally compelling on little moving items. Wixon [12] proposed a calculation to identify striking motion by coordinating edge to-outline optical stream after some time; along these lines it is conceivable to foresee the motion example of every pixel. This methodology expect that the article will in general move a reliable way after some time and that frontal area motion has diverse saliency. The downsides of optical stream based strategies are count of optical stream expends time and the inward purposes of an enormous homogeneous article (for example vehicle with single shading) can't be highlighted with optical stream. A portion of the methodologies utilized spatio-transient force varieties to distinguish motion and in this manner section the moving vehicle locales.

2.4.2. Camera Calibration

When the vehicle locales are distinguished and reasonable highlights, for example, territory, direction, shading, and so forth are determined, it is fundamental for the 2D data got from the image to be mapped to the 3D data as for the real-world. Geometric camera alignment is the way toward deciding the 2D-3D mapping between the camera and the world facilitate systems [12]. In this manner there is a need to change over the camera directions to world directions utilizing the inside (chief point, central length, angle proportion) and outside parameters of the camera (position and direction of the camera in world arrange system). We can arrange the camera alignment strategies in two sorts: photogrammetric adjustment and self-adjustment. In photogrammetric alignment [12], an article whose 3D world directions is known in earlier is seen by a camera to discover the adjustment parameters. In self adjustment methods [12], the situation of the camera is changed to record static scenes and images with known inner parameters, from which alignment parameters can be recouped. Figure 2.2[12] shows imaging for point of view change

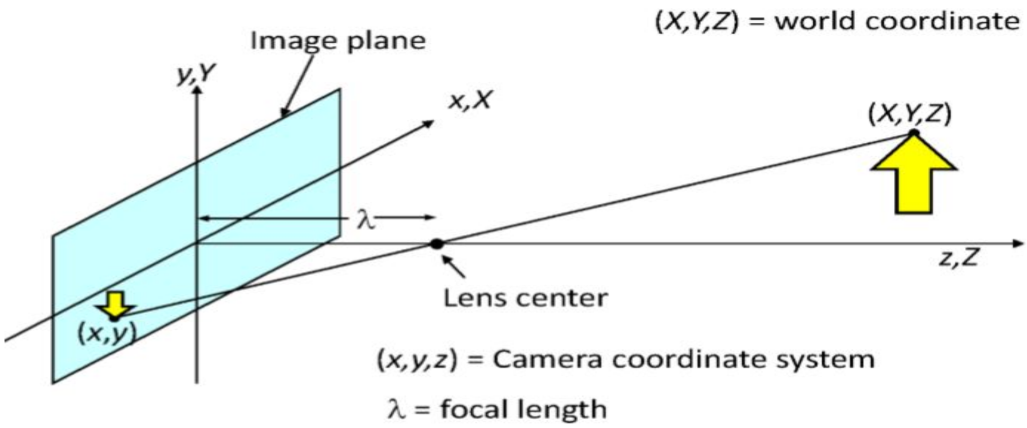


Figure 2.2: Imaging Geometry: Perspective Transformation[12]

2.4.3. Vehicle Tracking

When the vehicle locales are recognized it is important for these vehicle districts to be followed in the image groupings with the goal that fundamental data about the vehicle, for example, speed, vehicle direction, vehicle measurements can be processed and utilized for additional utilization.

Vehicle following is a significant stage in crash detection systems. Given the recognized vehicles, following can be seen as a correspondence issue in which the objective is to figure out which distinguished vehicle in the following casing compares to a given vehicle in the present casing. Throughout the years different inquires about have been led identified with vehicle following. These methodologies can be delegated follows.

1. Region-Based Tracking

2. Active Contour Tracking

3. Color and Pattern-Based Tracking

4. Markov Random Field Tracking

5. Feature- Based Tracking

6. Other approaches

2.4.3.1. Region-Based Tracking

In this strategy the image outline containing vehicles is deducted from the foundation outline which is then additionally prepared to acquire vehicle districts (masses). At that point these vehicle locales are followed. Different techniques have been proposed dependent on this methodology. Gupte et al. [14] proposed a strategy that performed vehicle following at two levels: locale level and vehicle level. The strategy depends on the foundation of correspondences between locales. Representation of vehicle following (a) Frame at time t (b) Frame at time t+1 (c) Frame at time t+2 (a) (c) 20 vehicle travels through the image grouping utilizing maximally weighted chart. In any case, the hindrance of these techniques is that they experience issues in taking care of shadows, impediment.

2.4.3.2. Active Contour Tracking

The following methodology used to follow vehicles was following the forms speaking to the limit of the vehicle. These are known as dynamic form models or snakes. When the vehicle areas are distinguished in the info outline the forms of the vehicle are removed and powerfully refreshed in each progressive casing. In the strategy utilized by Koller et al. [18] the vehicle locales are recognized by foundation deduction and followed utilizing force and motion limits of the vehicle objects. This technique utilizes Kalman channels for assessing the relative motion and the state of the shape. The benefit of dynamic shape following over district based following is the diminished computational unpredictability. However, the hindrance of the technique is their powerlessness to accurately follow the impeded vehicles and following should be introduced on every vehicle separately to deal with impediment better.

2.4.3.3. Color and Pattern-Based Tracking

Chachich et al. [14] utilized shading marks in quantized RGB space for following vehicles. In this work, vehicle detections are related with one another by utilizing a various leveled choice procedure that incorporates shading data, appearance probability and driver conduct. In [5], an example acknowledgment put together way to deal with respect to street vehicle detection has been concentrated notwithstanding following vehicles from a fixed camera. In any case, the following dependent on shading and example coordinating isn't excessively solid. There are significantly more focal points of video based traffic accident detection systems since the accidents can be recorded and investigated and these chronicles can be utilized to improve the security highlights at roadways and convergences. Furthermore, significantly once the accident has been distinguished, the mechanized announcing of the accident can be utilized to decrease the crisis reaction time which on its own makes the video based traffic surveillance systems better than other non-vision based systems.

2.4.3.4. Markov Random Field Tracking

Kamijo et al. [18] proposed a technique to portion and track vehicles utilizing spatiotemporal Markov arbitrary fields. In this technique the image is partitioned into pixel squares and a spatiotemporal Markov irregular field is utilized to refresh an article map utilizing present and past image. This technique dealt with impediments well. In any case, the downside of this technique is that it doesn't yield data about vehicle directions in the world arrange system. Also, so as to accomplish accurate outcomes the images in the succession are prepared with a backward request to guarantee that vehicles subside from the camera. The exactness diminished by a factor of two when the arrangement isn't prepared backward, in this manner making the calculation unsatisfactory for on-line processing.

2.4.3.5. Feature-Based Tracking

In include based following [10], reasonable highlights are removed from the vehicle districts and these highlights are handled to follow the vehicles accurately. These calculations have low intricacy and can operate in real-time and furthermore can deal with impediments well. Beymer et al. [3] utilized a component following strategy in which the vehicle point highlights are followed all through the detection zone (section and leave locale). The element gathering is finished by developing a diagram after some time, with vertices speaking to sub-include tracks and edges speaking to the gathering connections between tracks. Kanhere et al. [10] utilized 3D world directions of the element purpose of the vehicle and gathered those focuses so as to section and track the individual vehicles. Surface based highlights were utilized for following in [12]. Scale-Invariant highlights were utilized for following by Choi et al. [13]. The downside of highlight based following is the acknowledgment rate of vehicles utilizing two-dimensional image highlights is low, on account of the non-straight twisting because of viewpoint projection and the image varieties because of development comparative with the camera.

2.4.4 Accident Detection Systems

After vehicles in image arrangement are recognized and followed accurately appropriate traffic parameters (for example speed, direction, traffic stream) are removed from the vehicle, the computer traffic parameters are utilized to distinguish episodes at interstates and roadway crossing points. Many research works have been done in the past to address this issue as there are various favorable circumstances in distinguishing accidents. Prior research identified with traffic accident detection systems included distinguishing anomalous occurrences, for example, traffic jams, recognizing tumbled down obstructions, and so forth. Proposed an image processing based automatic unusual episode detection system. The system is utilized to identify four kinds of episodes specifically halted vehicles, slow vehicles, fallen items and vehicles that have endeavored path progressive changes. Kimachi et al. [4] considered vehicle practices causing episodes (for example traffic accident) utilizing image processing strategies and fluffy rationale to foresee an episode before it happens. Trivedi et al. [6] depicted a technique for creating circulated video systems for episode detection and the executives utilizing 23 omnidirectional cameras. Blosseville et al. [11] utilized image processing methods to recognize shoulder episodes.

A portion of the methodologies talked about above were restricted to identify unusual episodes at roadways; in this manner more accentuation was given to decide accidents by later scientists. Atev et al. [14] utilized a vision-based way to deal with anticipate crash at traffic convergences. In this strategy the vehicles are followed utilizing their centroid position and data about the vehicle, for example, speed, position, width and stature are figured and a bouncing box is drawn around each followed vehicle. Utilizing the jumping box data around every vehicle crash is resolved dependent on the sum to which the bouncing box crosses. Hu et al. [14] utilized vehicle speed and direction data to anticipate traffic accidents utilizing neural systems administration preparing of traffic parameters. Ki and Lee [14] utilized variety in speed, territory, position and heading of the followed vehicle to get an accident record which would decide the event of accidents at convergences.

2.5 Limitations of existing Vehicle Tracking and Accident Detection Systems

A portion of the confinements of the current vehicle detection, following and accident detection systems are given underneath -

1. The vast majority of the current vehicle detection and following systems have high computational unpredictability.

2. A portion of the vehicle detection systems utilize refined foundation demonstrating techniques which adds to the intricacy of the calculation.

3. A portion of the current vehicle following systems need rapid processors for usage.

4. A portion of the systems utilize significant level learning calculations, for example, HMM, neural system to identify accidents which make the real-time usage troublesome.

5. Real-time usage of these systems isn't achievable on low speed processors In this section we have quickly examined the current vehicle following and accident detection systems and their favorable circumstances and weaknesses.

Extensive research work has been done identified with this field and not many systems have been utilized in viable circumstances. Anyway there is opportunity to get better in all the systems that have been looked into

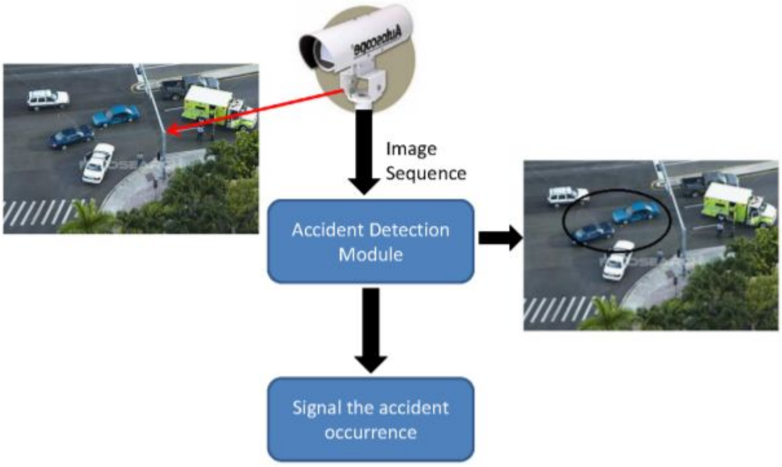


Figure 2.3: Brief overview of the accident detection system[13]

CHAPTER 3

METHODOLOGY

3.1. Illustration of Block Diagram

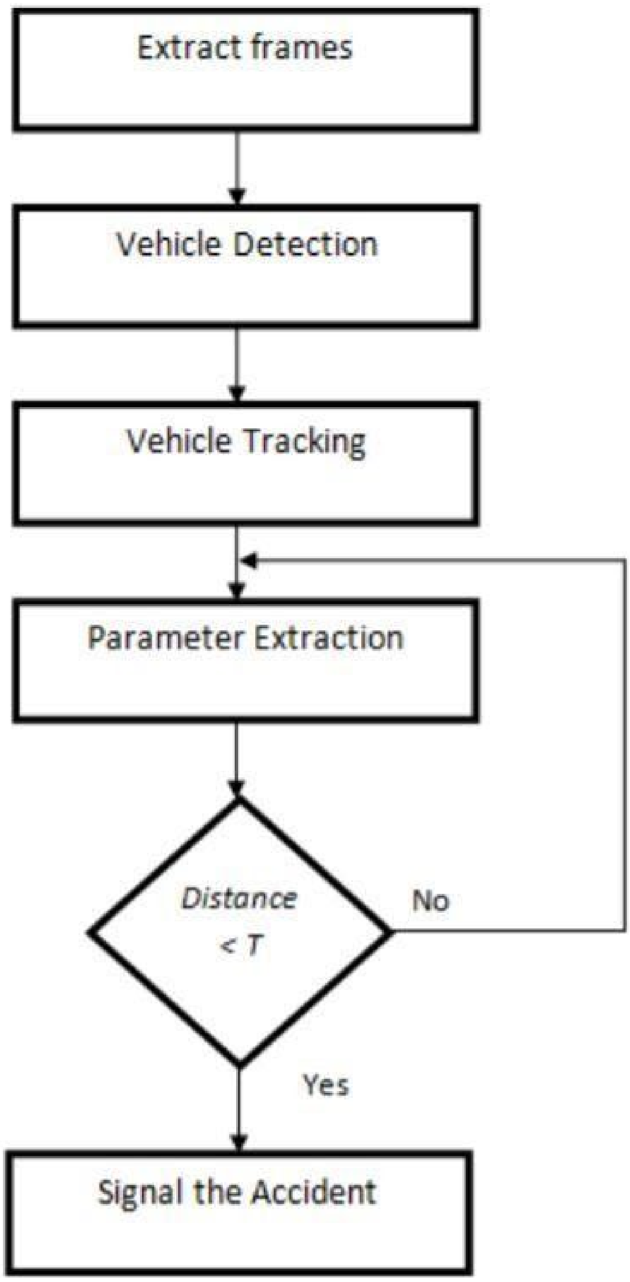


FIGURE 3.1: BLOCK DIAGRAM OF THE ACCIDENT DETECTION SYSTEM[15]

In this project vehicle following is done dependent on low-level highlights and low-level human visual-system (HVS) demonstrating. Low-level highlights (e.g., shading, direction, size) are commonly utilized in view of their low computational unpredictability. Our technique utilizes a weighted mix of low-level highlights alongside a human vision based calculation of visual divergence for vehicle following. In spite of the fact that HVS models have discovered far reaching use in an assortment of purchaser image processing applications, they presently can't seem to be utilized widely for vehicle following. The detail depiction of the whole system is as per the following:

The initial step of the procedure is the casing extraction step. In this edges are extricated from the video camera input.

The second step of the procedure is the vehicle detection step. Here the as of now put away foundation outline is deducted from the info edge to identify the moving locales in the casing. The distinction image is further thresholded to recognize the vehicle districts in the edge. Thus the vehicles in each edge are identified.

In the third step low-level highlights, for example, territory, centroid, direction, luminance and shade of the removed vehicle districts are figured. And furthermore for every one of the locales distinguished in outline at time t, similitude list is figured with the entirety of the districts identified in outline at time t+1 utilizing human vision based model investigation.

In the following stage, Euclidean separation is figured between the low-level highlights of every vehicle in outline n and the various vehicles recognized in outline n+1. This Euclidean separation vector is joined with the as of now registered similitude list for a specific vehicle locale in outline n. In light of the base separation between vehicle locales following was finished.

In the subsequent stage, the centroid position of a followed vehicle in each edge is figured and dependent on this data and the edge rate; the speed of the followed vehicle is processed as far as pixels/second.

Since the situation of the video camera is fixed, the camera parameters, for example, central length, dish and tilt edge of the vehicle remains the steady and it very well may be processed utilizing camera adjustment calculation. From this data the pixel directions of the vehicle in each edge is changed over to real-world directions.

By this 9 transformation, the speed of the vehicle regarding miles/hr is registered. In view of the speed data, position and low-level highlights of the followed vehicle reasonable limits are characterized to decide the event of accidents. This is the general portrayal of the proposed system for accident detection at roadway crossing points.

3.2. Variation in Position of the Vehicles

Change in centroid position of the vehicles in outlines It and It+1 can be utilized as a factor to decide the event of accident. Much the same as the adjustment in territory of the vehicles, when an accident happens the bouncing of two vehicles meet causing an adjustment in generally speaking situation of the vehicles. In this way change in centroid of the vehicles in sequential casings can be utilized as a descriptor to decide the event of an accident. Change in centroid is given by: $\Delta x = x\ at\ It+1 - x\ at\ It$ (5.6) $\Delta y = y\ at\ It+1 - y\ at\ It$ The accompanying articulation is utilized as a factor for traffic accident detection: $PI = 1,\ if\ \Delta x \geq c,\ if\ \Delta y \geq$ where PI is the position list and c,d are limits. shows a representation of deciding accidents utilizing centroid data.

3.3. Variation in Orientation of the Vehicles

Variety in direction of the vehicles can be utilized as a factor to decide the event of an accident. As on account of speed, zone and centroid of the vehicles, the direction of the vehicle in outlines It and It+1 are looked at. In the event that there is a huge change in the direction of the vehicles identified and followed between two successive casings, at that point a chance of accident is resolved. *in orientation* $= \Delta\Theta = \Theta\ at\ It+1 - \Theta\ at\ It$. The direction record OI is given by:
$OI = 1,\ if\ \Delta\Theta \geq e\ 0$, where e is the edge for change in direction of the vehicles.shows a delineation of deciding accidents utilizing change in direction.

3.4. Overall Accident Index

Subsequent to figuring the speed, zone, position and direction record of the vehicles, the general accident list is decide by the entirety of individual files. The general accident list is then contrasted with the accident limit with decide the event of accident. In the event that the accident file surpasses a specific limit, at that point an event of accident is flagged, in any case the system discovers that there is no accident and the procedure is rehashed until an accident is recognized. The general Accident Index (AI) is given by: $AI = VI + DI + PI + OI$ The event of accident is controlled by: $Signal\ Accident = 1,\ if\ AI \geq accident$(5.11) A diagram of the accident detection process is appeared in the and the accident detection calculation is summed up as follows:

1. Vehicle districts are distinguished in image outlines.

2. Low-level highlights, for example, region, direction, centroid, luminance and shade of the distinguished vehicles are separated.

3. Vehicles are followed utilizing the following calculation.

4. Rates of the followed vehicles are determined.

5. Speed, Area, Position and Orientation Indexes are determined.

6. By and large Accident Index is determined utilizing the total of individual records and event of accident is distinguished.

3.5. Locating the point of accident

When an accident is controlled by the system, the subsequent stage is to find where the accident has happened. This data can be gotten utilizing the situation of the vehicles that were engaged with the accident at a specific edge. By utilizing this data the client is educated about the event of accident alongside where the accident has happened. This data is valuable since when accidents has been recognized and assume this data must be transmitted to a data place or broke down for future purposes, having the accident cut recorded alongside the purpose of event of accident diminishes the repetitive image outlines should be transmitted and furthermore the end client can identify the event of accident without dissecting the video being transmitted. This outcomes in extensive sparing of breaking down time.

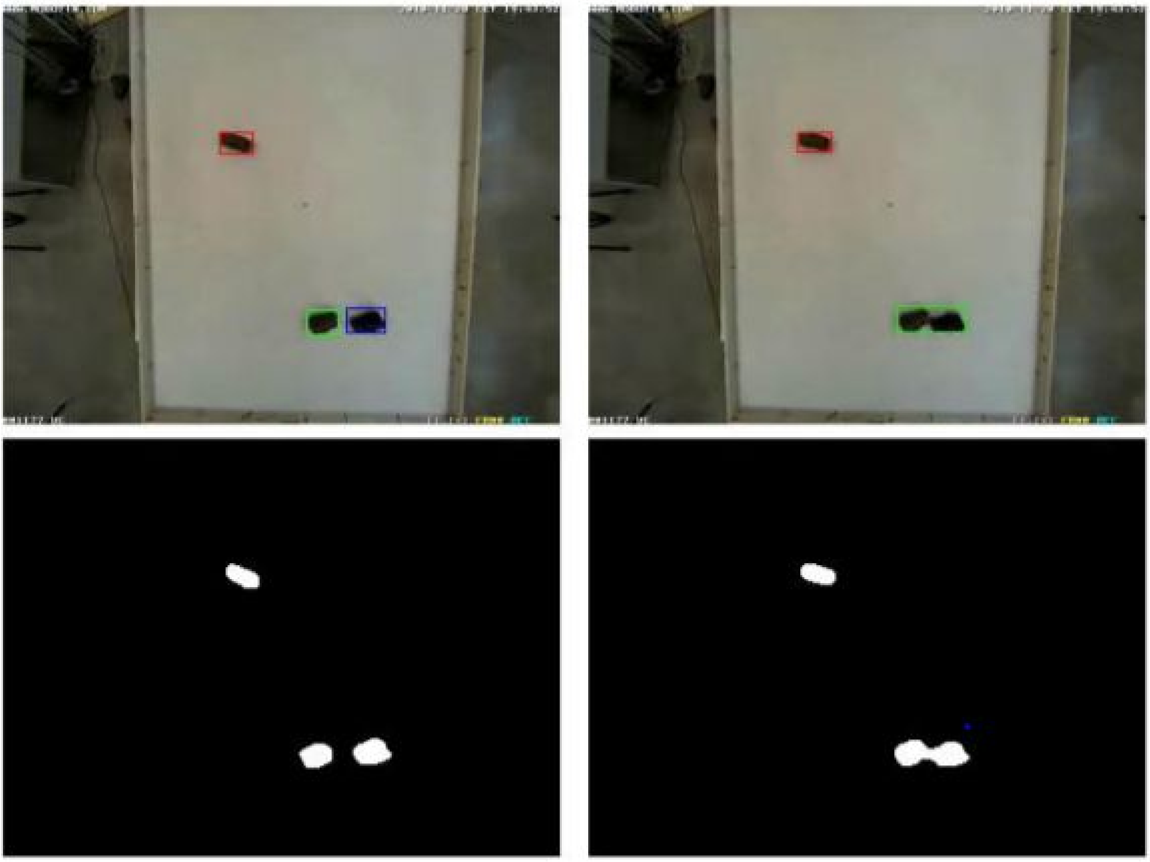


FIGURE 3.2: ILLUSTRATION OF ACCIDENT DETECTION USING CHANGE IN AREA (A) FRAME AND ITS CORRESPONDING BINARY IMAGE BEFORE OCCURRENCE OF AN ACCIDENT (B) FRAME AND ITS CORRESPONDING BINARY IMAGE AFTER OCCURRENCE OF AN ACCIDENT [15]

CHAPTER 4

SYSTEM OVERVIEW

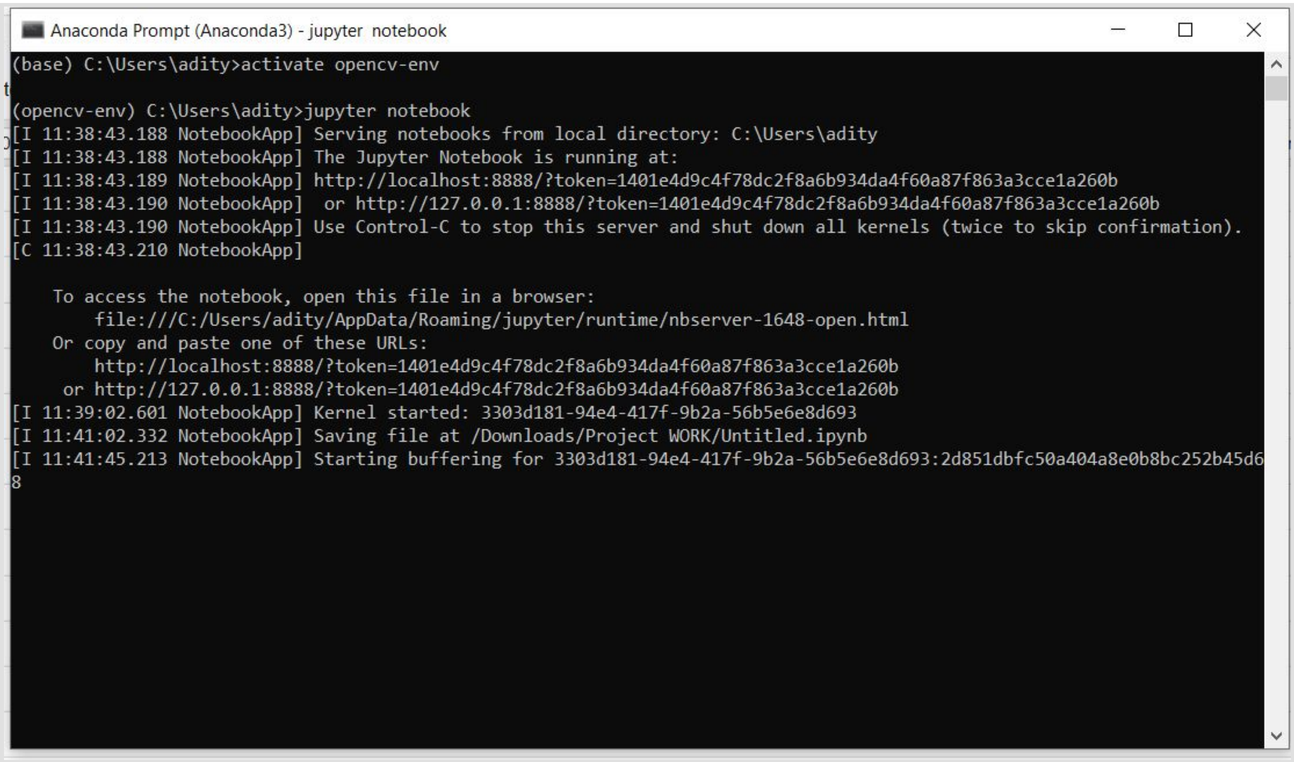
4.1. Experimental Setup and Initialisation

Steps to download the requirements below:

Download Python 2.7.x version, numpy and OpenCV 2.4.x version.Check if your Windows either 32 bit or 64 bit is compatible and install accordingly.

```
sudo apt-get install python
pip install numpy
```

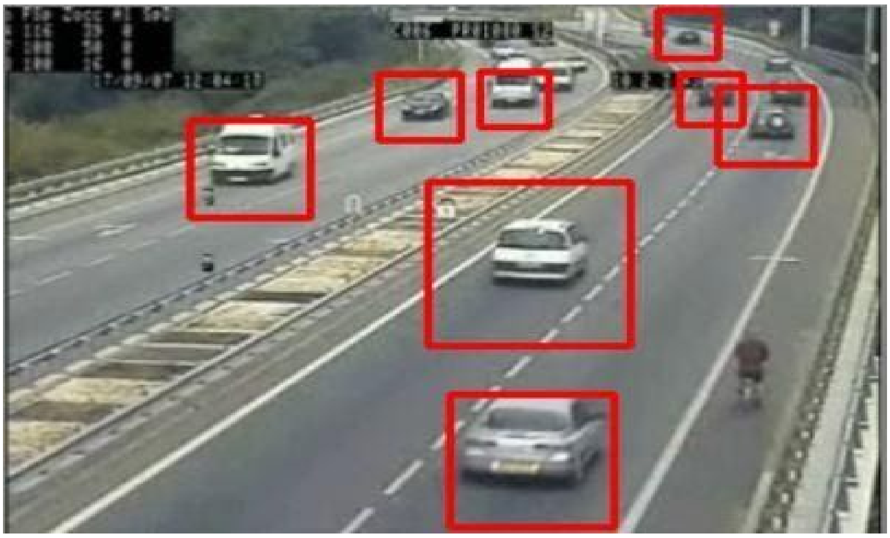
1. install OpenCV
2. Make sure that jupyter notebook is running in your python then try to install opencv.
3. Put the cars.xml file in the same folder.

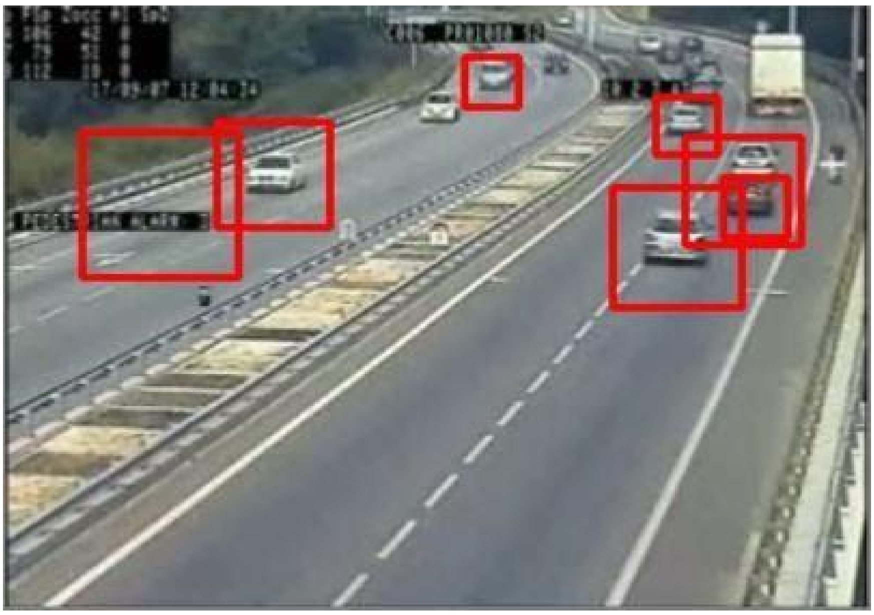


```
import cv2
cap = cv2.VideoCapture('video.avi')
car_cascade = cv2.CascadeClassifier('cars.xml')

while True:
    ret, frames = cap.read()
    gray = cv2.cvtColor(frames, cv2.COLOR_BGR2GRAY)
    cars = car_cascade.detectMultiScale(gray, 1.1, 1)
    for (x,y,w,h) in cars:
        cv2.rectangle(frames,(x,y),(x+w,y+h),(0,0,255),2)
    cv2.imshow('video2', frames)
    if cv2.waitKey(33) == 27:
        break
cv2.destroyAllWindows()
```

Detection of Vehicle:-





4.2. Advantages of the System

Coming up next are the benefits of the system

1. System can operate in real-time with regular CPU processor and with the utilization of fast processor; the processing rate can be speeded up further.

2. The vehicle detection and following calculation utilized in the system have low computational expense.

3. Vehicle following strategy utilized in the system utilizes low-level highlights which have low multifaceted nature when contrasted with the current systems.

4. The system centers around real-time execution of accident detection at traffic crossing point where the event of accidents is assessed to be more.

5. As a result of the quick working time, future upgrades can be added to the system to make it increasingly strong.

4.3. Limitations and Assumptions

The accompanying rundown the restrictions and suppositions utilized in the proposal -

1. The system can't distinguish the items other than vehicles like bikes, people, and so forth.

2. The system functions admirably just in light conditions. The exhibition of the system has not been assessed in night conditions.

3. The system doesn't deal with impediment well particularly if some portion of a vehicle is blocked with another vehicle.

4. Despite the fact that the system can accomplish real-time execution, the strategy had been tried and assessed disconnected.

CHAPTER 5

VEHICLE DETECTION AND FEATURE EXTRACTION

5.1. Vehicle Detection

Vehicle Detection is an important stage of the accident detection system in which the moving vehicles are segmented from the background. Figure 5.1 shows a brief description of vehicle detection system.

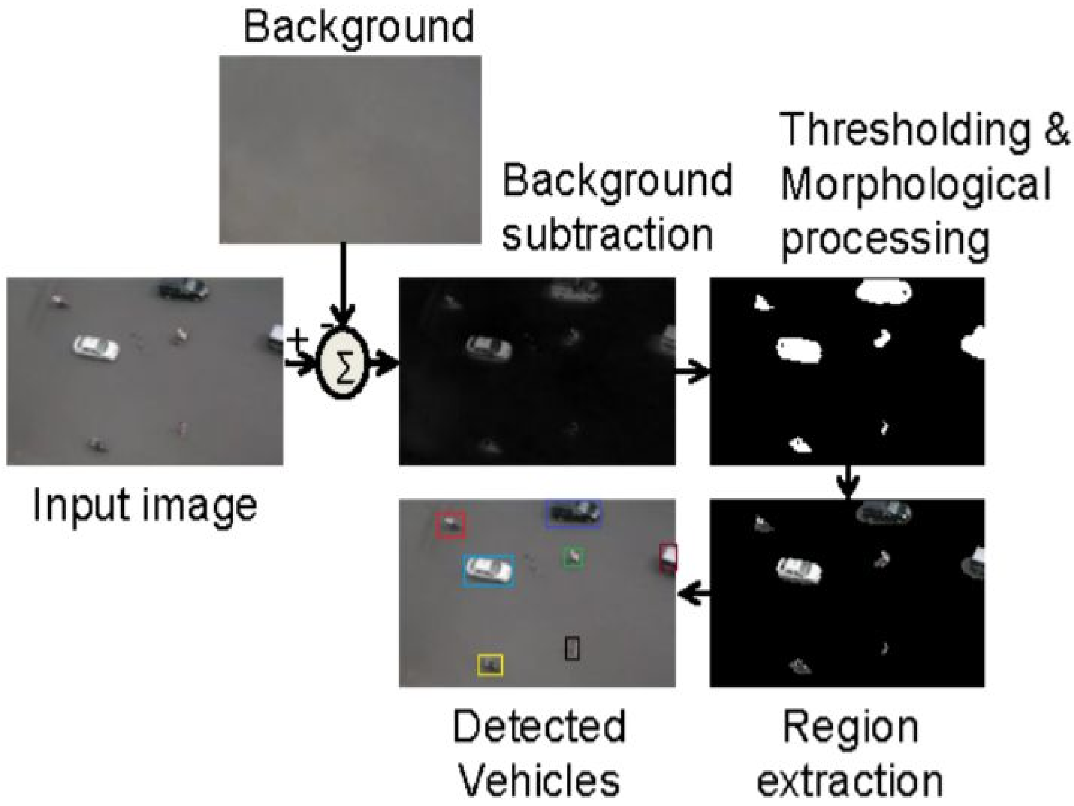


FIGURE 5.1: DESCRIPTION OF VEHICLE DETECTION SYSTEM [15]

The technique that is utilized for identifying moving vehicles is foundation deduction. Since the examination concentrated on real-time execution of the system, foundation demonstrating procedures that have high computational expense were not attempted. And furthermore since the testing of the calculation is done disconnected and the situation of the camera recording the video grouping is static we utilized a put away foundation outline for foundation deduction. When the vehicle locales are distinguished, reasonable low-level highlights are extricated from the vehicle districts. The procedure of vehicle detection is clarified in detail in the accompanying areas.

5.1.1. Background Subtraction

The first step in the algorithm is to subtract the background from the current input frame to detect the vehicles. Figure 5.2 shows examples of background subtraction method. Figure 5.2(a) shows the input frame, Figure 5.2(b) shows the background frame used and Figure 5.3(c) shows the difference image.

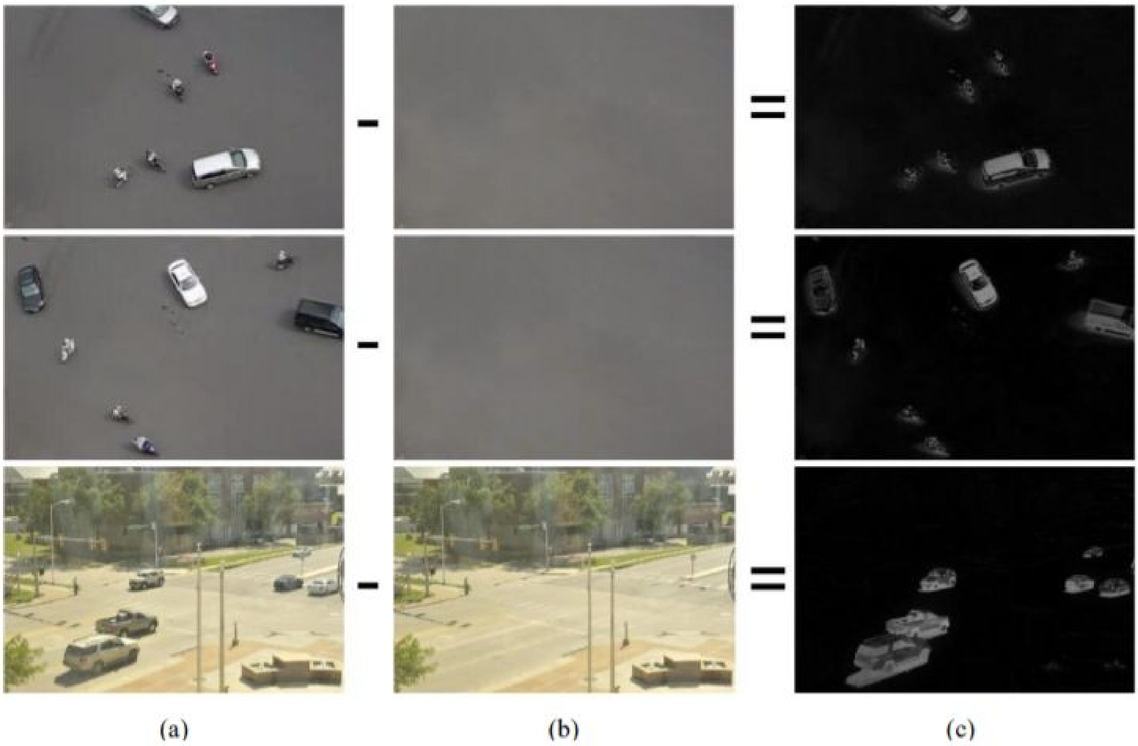


FIGURE 5.2: EXAMPLES OF BACKGROUND SUBTRACTION (A) INPUT FRAME (B) BACKGROUND FRAME (C) DIFFERENCE IMAGE [15]

5.1.2. Thresholding and Morphological Processing

An image processing technique that makes a bitonal (otherwise known as paired) image dependent on setting a limit an incentive on the pixel force of the first image. While most ordinarily applied to grayscale images, it can likewise be applied to shading images.

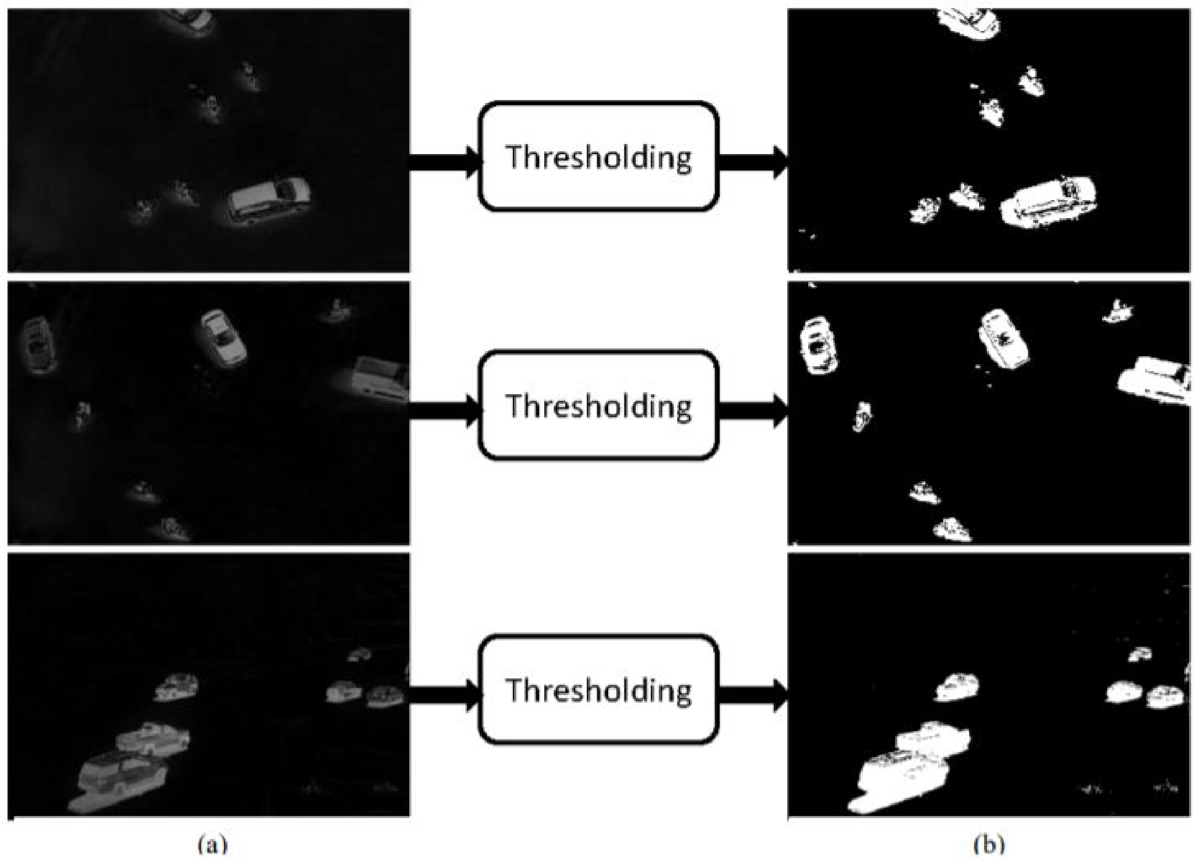


Figure 5.3: Illustration of thresholding (a) Difference image (b) Thresholded image[15]

The binary image bw(x,y) obtained from thresholding suffers from noise and unwanted pixel values. Therefore morphological operations, opening followed by closing is done on the binary image bw(x,y) to obtained a final cleaned image bw final(x,y).

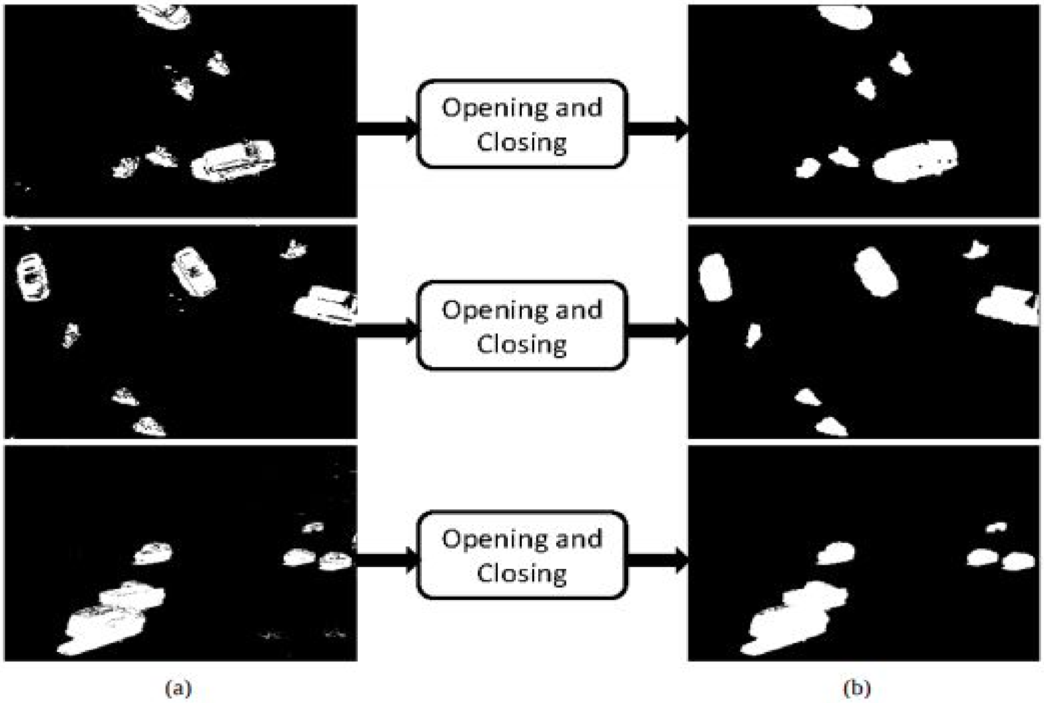


FIGURE 5.4: ILLUSTRATION OF MORPHOLOGICAL PROCESSING (A) THRESHOLDED IMAGE (B) CLEANED IMAGE[15]

morphological processing. Figure shows the thresholded image shows final cleaned image after morphological operations. The final binary image bw final(x,y) consists regions of individual detected vehicles

5.1.3. Connected Component Labeling and Region Extraction

The districts in the parallel image bw final(x,y) are named utilizing associated segment marking. This procedure marks the areas in the double image and yields a gauge of the quantity of associated segments. From this procedure, the quantity of vehicles recognized in the image is assessed. Figure shows associated part naming yield. Figure is the twofold image and Figure is the named image.

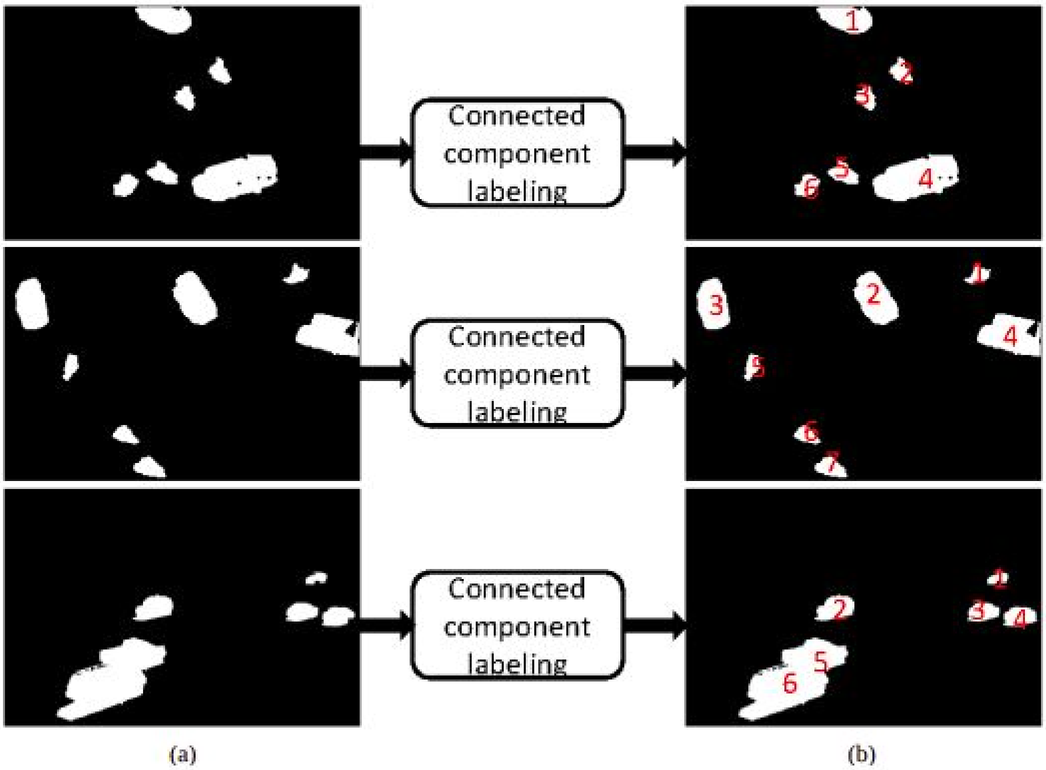


Figure 5.5: Connected component labeling (a) Binary image (b) Labeled image [15]

After associated segment marking, the double guide is applied on the first information outline It(x,y) and consequently we center just around those areas in which the vehicle are distinguished. Figure illustrates the procedure of vehicle district extraction. Figure shows the info image; Figure shows the twofold cover of the vehicle districts and Figure shows the identified vehicle areas from the information image.

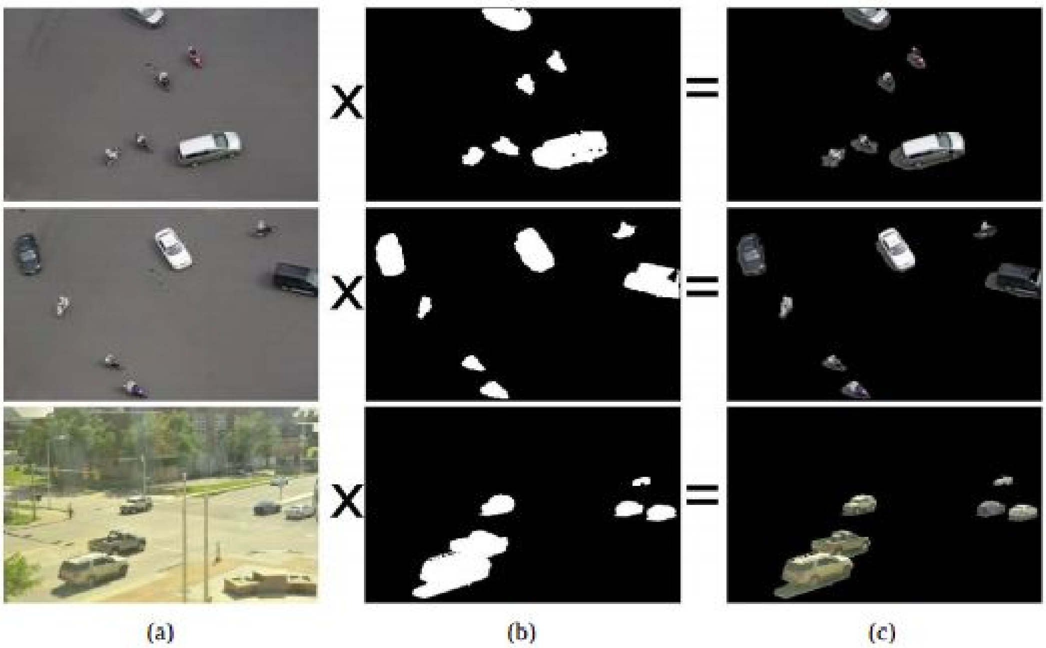


Figure 5.6: Illustration of vehicle region extraction (a) Input image (b) Binary image (c) Detected vehicle regions[15]

5.2. Feature Extraction

After the districts containing vehicles are separated, appropriate low-level highlights are removed from the vehicle locales. The highlights utilized are zone, centroid, direction, luminance and shading. These highlights are utilized in light of their low computational multifaceted nature. Figure Let Xi {i= 1, 2, 3...} mean the individual vehicle districts distinguished in the information image It(x,y) and let fk(Xi) indicate the k th highlight.

5.2.1. Bounding Box

From the associated part named image, the jumping box directions of every vehicle locale is determined. From the bouncing box arranges, the tallness and width data of the vehicle district is evaluated. These bouncing box organizes are utilized to ascertain the highlights of a specific vehicle area. Figure 5.7 [15] shows a case of separated vehicle areas. Figure is the first image with jumping box drawn along every vehicle, Figure shows the separated vehicle districts utilizing the bouncing box data and Figure shows the paired guide related with the vehicle locales.

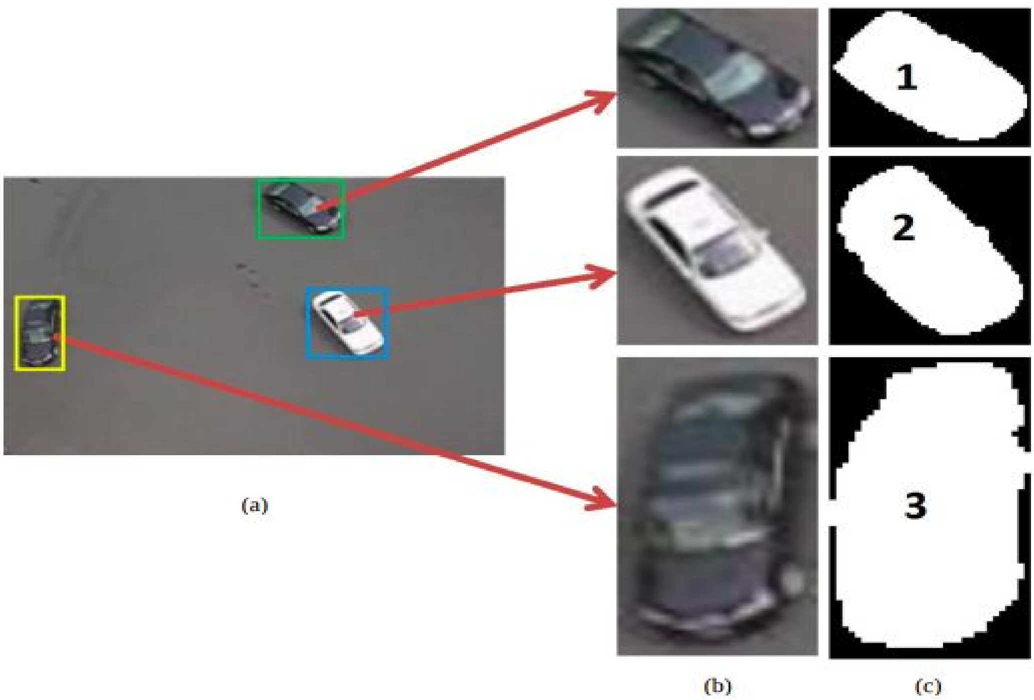


Figure 5.7: Example of extracted vehicle regions (a) Input image with bounding box around each vehicle region (b) Extracted vehicle using the bounding box (c) Labeled vehicle regions [15]

	Test1	Test2
No. of Frames	352	360
Number of vehicles	2	18
Detected Vehicles	2	13
False Detection	8	5
Detection Rate	100%	72.2%

Table 5.1 Vehicle Detection Results from two test videos

CHAPTER 6

VEHICLE TRACKING AND ACCIDENT DETECTION SYSTEM

6.1. Human Visual System (HVS) Model Analysis

The highlights portrayed in Chapter, can help with following vehicles over various casings. Anyway these casings don't unequivocally consider the general visual appearance of every vehicle as checked by the natural eye. To display this perspective, we utilize a visual quality estimator, called MAD (Most Apparent Distortion), as of late created. Given two images (or image districts), MAD will restore a file which is corresponding to how different the two images appear to a human eyewitness. MAD operates by utilizing a mix of visual detection model and a visual appearance model. The detection-based utilizes models of the human differentiation affectability work, luminance covering and complexity concealing to measure inconspicuous (close edge contrasts). The appearance-based model utilizes a log-Gabor change and nearby correlations of log-Gabor coefficient insights trying to demonstrate the visual appearance of plainly obvious contrasts. The MAD list is figured through a weighted geometric mean of these two model yields.

6.2. Vehicle Tracking

The following is done by means of relating by means of: (1) Searching for the locale in outline It+1 whose highlights most intently coordinate the highlights of the given area in outline It and (2) looking for the district in outline It+1, with the least MAD list when contrasted with the given district in outline It .

6.2.1. Feature Distance

In this progression the element vector of the districts extricated from outlines It and It+1 are utilized. To follow the vehicles accurately over each casing, the Euclidean separation between the component vector of every locale Xi {i= 1, 2, 3..} in It and the element vector of every area Xj {j= 1, 2, 3..} in It+1. Let ft(Xi) signify the element vector of the I th locale removed from outline It and ft+1(Xi) mean the element vector of the j th area separated from outline It+1. Let dfeatures(Xi , Xj) indicate the separation among ft(Xi) and ft+1(Xi).

Following is done normally between two continuous casings It and It+1. From the outset case of the system, vehicle areas in two successive casings are recognized and their relating highlights are removed all the while. In following stage utilizing the vehicle highlight vector, include separation vector dfeatures is figured between vehicle locales in outlines It and It+1. Additionally similitude list dMAD is figured between vehicle areas in outlines It and It+1 and the following is finished utilizing a weighted mix of dfeatures and dMAD.

In the event that a counterpart for specific vehicle locale in outline It can't be found in the casing It+1, the vehicle district is thought to be kept separate from the scene and the vehicle is not any more followed and its data are not persisted to the subsequent stage. Additionally if another vehicle locale is identified in the casing It+1, the highlights of the vehicle are separated and utilized for following in the up and coming edges

6.2.2. Speed of the Vehicle

Speed of a specific vehicle locale Xi in outline It is figured utilizing the separation went by the vehicle in outline It+1 and the casing rate of the video from which the image grouping are extricated. The separation went by the vehicle is processed utilizing the centroid position (x , y) of the vehicle in It and It+1. Let Xi indicate a specific vehicle identified in It and Xj signify a similar vehicle distinguished in It+1, expecting the correspondence between the vehicles is resolved utilizing the vehicle following advance. Speed of a specific vehicle locale Xi is given by:

$$Speed(X_i) = \frac{\sqrt{\left(x(X_i)-x(X_j)\right)^2+\left(y(X_i)-y(X_j)\right)^2}}{\frac{1}{frame\ \ rate}}$$

The above condition gives the speed of the vehicle regarding pixels/sec. Inorder to decide the speed of the vehicle regarding real-world joins together (miles/hr), camera adjustment process is utilized as clarified in Chapter, The connection between the image directions and real-world directions is given by the condition. Utilizing the condition the centroid position of a specific vehicle in It and It+1 is changed over from pixel directions to real-world directions. From this progression the speed of the vehicle regarding (miles/hr) is resolved. Comparative procedure is rehashed for all the vehicle areas identified and followed.

6.3. Accident Detection System

When the vehicles are recognized and followed effectively in outlines It and It+1, the subsequent stage in the process is to decide the event of accident utilizing vehicle parameters, for example, the speed, direction and the highlights separated from singular vehicles distinguished in It and It+1. In this project the work done was adjusted for the usage of accident detection system. To decide the event of accident at traffic crossing point the variety in speed, area, direction and position of the vehicles followed are utilized.

6.3.1. Variation in the speed of the Vehicle

Speed of the vehicles is a significant factor while deciding the event of accidents at traffic crossing point. Quick change in the speed of the vehicles is a helpful descriptor for a traffic accident. For instance if a specific vehicle goes with a speed v, after an event of an accident there is fast change in the speed of the vehicle. Along these lines variety in speed of the vehicles across outlines is utilized as a factor for passing judgment on the event of accidents by the system. In the accident detection system vehicles are distinguished and followed accurately and their speed.

Data is separated at each casing the vehicle happens. After effective following of a vehicle in two back to back edges It and It+1, the speed data of the followed vehicle got from It and It+1 is contrasted and that acquired from It-1 and It . Since it is accepted that the vehicles moves at roughly consistent speed, if a vehicle crashes with another vehicle in outline It+1, the speed of the vehicles is relied upon to go down definitely. So when the speed of the vehicle decided in It+1 is contrasted and that acquired in It , there ought to be a bigger distinction in the speed of the vehicle showing that an accident has happened. To decide the event of accident the distinction in speed of vehicles acquired between two successive edges contrasted and that of a predefined limit.

6.3.2. Variation in the Area of Vehicle

Fast change in the zone of the vehicles distinguished and followed can be utilized as a descriptor to recognize accidents. At the point when an accident happens, two vehicles come into contact and there is probability that the bouncing box of the vehicles may converge and for this situation there is a fast change in the territory of the vehicles recognized. To recognize accidents the territory of the vehicles identified and followed in It and It+1 are analyzed and in the event that the adjustment in region of the vehicles surpasses a zone limit, at that point there might be probability of accident.

6.3.3. Variation in Position of the Vehicles

Change in centroid position of the vehicles in outlines It and It+1 can be utilized as a factor to decide the event of accident. Much the same as the adjustment in region of the vehicles, when an accident happens the bouncing of two vehicles converge causing an adjustment in general situation of the vehicles. Consequently change in centroid of the vehicles in back to back edges can be utilized as a descriptor to decide the event of an accident.

6.3.4. Variation in Orientation of Vehicle

Variety in direction of the vehicles can be utilized as a factor to decide the event of an accident. As on account of speed, territory and centroid of the vehicles, the direction of the vehicle in outlines It and It+1 are looked at. On the off chance that there is a critical change in the direction of the vehicles distinguished and followed between two continuous casings, at that point a chance of accident is resolved.

Python Code for Accident-Detection:

```
#Import necessary packages
import numpy as np
import cv2
from gsm import phoneSms
import math, operator
from functools import reduce


#Function to find difference in frames
def diffImg(t0, t1, t2):
  d1 = cv2.absdiff(t2, t1)
  d2 = cv2.absdiff(t1, t0)
  return cv2.bitwise_and(d1, d2)

j=1
#Import video from webcam
cam = cv2.VideoCapture(0)

#Creating window to display
winName = "Accident Detector"
cv2.namedWindow(winName, cv2.WINDOW_AUTOSIZE)

#Reading frames at multiple instances from webcam to different variables
t_minus = cv2.cvtColor(cam.read()[1], cv2.COLOR_RGB2GRAY)
t = cv2.cvtColor(cam.read()[1], cv2.COLOR_RGB2GRAY)
t_plus = cv2.cvtColor(cam.read()[1], cv2.COLOR_RGB2GRAY)


while True:
  #Display video out through the window we created

  cv2.imshow( winName, diffImg(t_minus, t, t_plus))
  ret, frame = cam.read()
  cv2.imshow('video original', frame)
  #Calling function diffImg() and assign the return value to 'p'
  p=diffImg(t_minus, t, t_plus)

  #Writing 'p' to a directory
  cv2.imwrite("/Users/adity/OneDrive/Pictures/Shot/111.jpg",p)

  #From Python Image Library(PIL) import Image class
  from PIL import Image

  #Open image from the directories and returns it's histogram's
  h1 = Image.open("/Users/adity/Documents/Accident-detection-Project--master/New
Dataset/ezgif-frame-"+str(j)+".jpg").histogram()
  h2 = Image.open("/Users/adity/OneDrive/Pictures/Shot/111.jpg").histogram()
```

```
j=j+1

#Finding rms value of the two images opened before
rms = math.sqrt(reduce(operator.add,map(lambda a,b: (a-b)**2, h1, h2))/len(h1))
print (rms)

#If the RMS value of the images are under our limit
if (rms<2500):
#Then there is a similarity between images. i.e., Scene similar to an accident is found
  print ("Accident Detected")
  print ("Informing to data centre......")

#Calls script to send SMS to the specified number
  phoneSms()

#Updates the frames
t_minus = t
t = t_plus
t_plus = cv2.cvtColor(cam.read()[1], cv2.COLOR_RGB2GRAY)

#Destroys the window after key press
key = cv2.waitKey(10)
if key == 27:
  cv2.destroyWindow(winName)
  break
```

CHAPTER 7
INFORMING SYSTEM

7.1. Importance

Technology plays an important role in our lives. Best use of a technology is when it can be used for saving lives of millions of peoples around the globe. Every year millions of lives are lost in road accidents. we can use technology to save this loss of lives.

In today's era of fast moving technology advancement surveillance played an important role. Use of technology to save lives of people is necessary. Nowadays million of lives are lost because of delay in reporting of accidents. On the spot live detection of accident will save millions of lives which are caused due to delay in getting medical aid in time after the accident.

Need of automatic informing system is because in todays fast moving world no wants to stop at the accident site and wants to inform the medical emergency services. People do not want to get into these matters because of fear of police and other formalities so seeing this problem an automatic on the spot live informing system is very much needed. This use of technology will help in saving lives as well as saving resources. It is the best example of using technology for the betterment of society.

Accident detection system with automatic informing system will make this project more helpful as well as powerful. Use of automatic informing system in accident detection will fulfil the role of people as now there is no need of informing medical emergency by the peoples. This system will automatically detect the accident and as soon as accident is detected it will send and alert to the Command center and the operator in the command center will call the respective medical emergencies. operator is becoming a mediator just to confirm any false detection because if medical emergencies is informed without the accident then there is loss of resources which can be used at some other time.

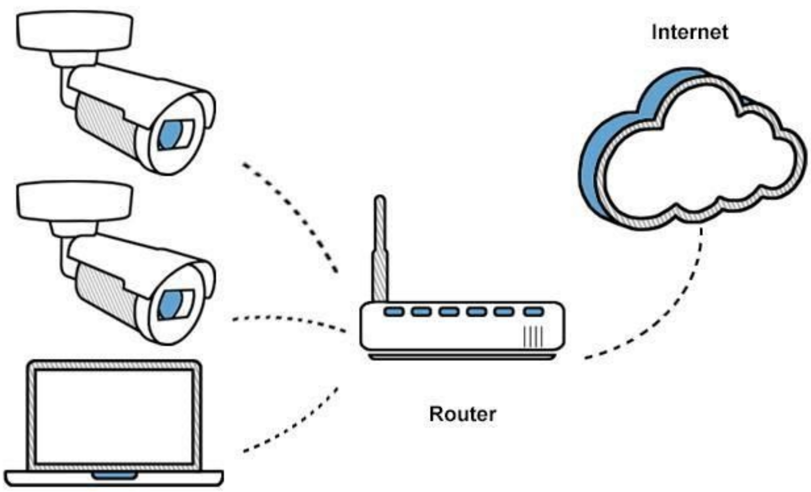


Figure 7.1: Basic Camera connection with the server[19]

7.2. Informing System in Accident Detection

Accident detection system can be used through the CCTV cameras in the national and state highways as well and important city roads. Cameras are taking the live feed of the highways and roads and this live feed of highways and roads can be used for automatic detection of accident if it occur. Informing system which is live and online every time will help in enhancing this accident detection.

As an accident occurs in the national and state highways or city roads the 24x7 informing system will alert the command center that an accident have been occurred in the particular area and then the operator handling the command center system will inform the necessary medical emergencies.

Informing system can be used in providing fast reach of emergency services to the area of accident and will help in saving the lives of people. The combination of accident detection system with live informing system will be really helpful to the society.

7.3. Working of Informing System

Informing system will work on the alerting mechanism. It can be consider similar like Theft surveillance in smart homes. Anti-Theft surveillance system will inform the owner regarding the theft where as in accident detection and informing system the system will inform the concerned authorities regarding the accident with its venue the so that medical emergencies reach the spot of accident fast.

The difference in Accident Detection informing system and anti-theft surveillance is that in anti-theft surveillance the alert is reached to the owner with the photos and location is know to the owner and he can inform the police regarding the theft whereas in accident detection informing system then alert is reached to the command center with the venue where the operator will inform the concerned emergency services.

Accident Detection Informing system works in a chain process. First the accident is detected by the live feed of the camera using the accident detection algorithm, when an accident is occurred then the alert is sent to the command center regarding the accident where the operator of command center verify if accident occurred in the given spot, if there is an accident then the operator will inform the concerned authorities regarding the accident.

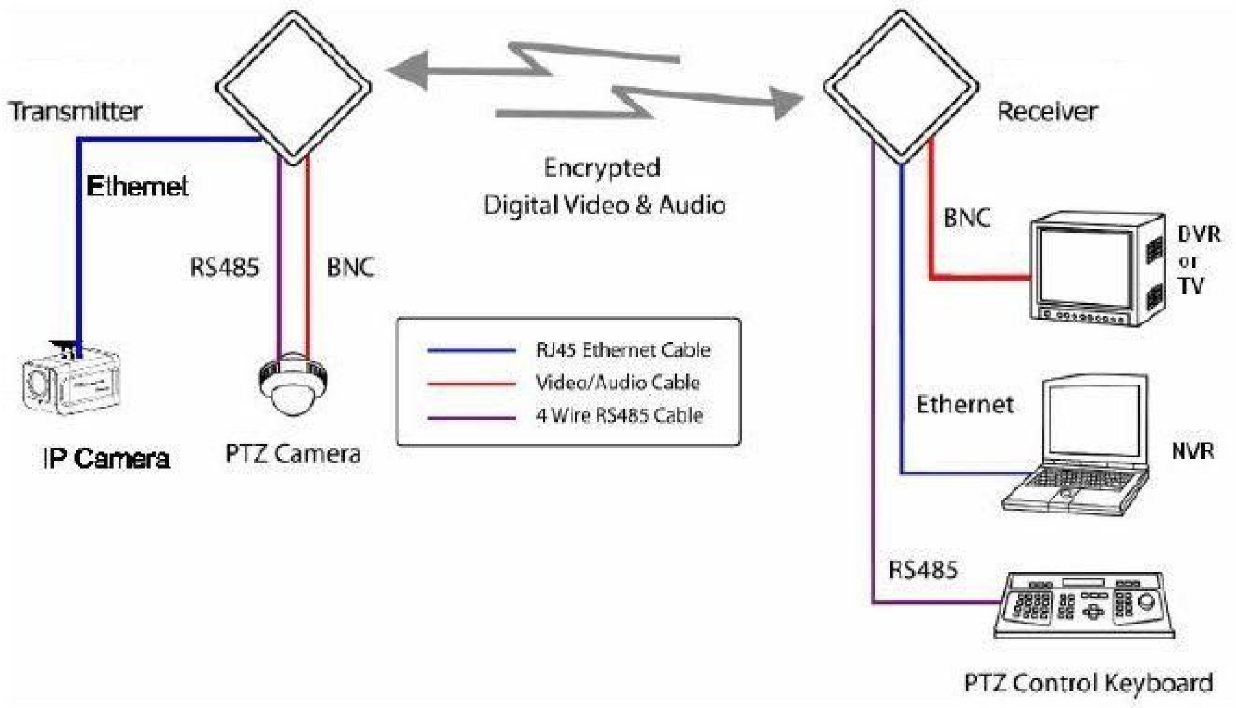


Figure 7.2: Camera feed to the command center

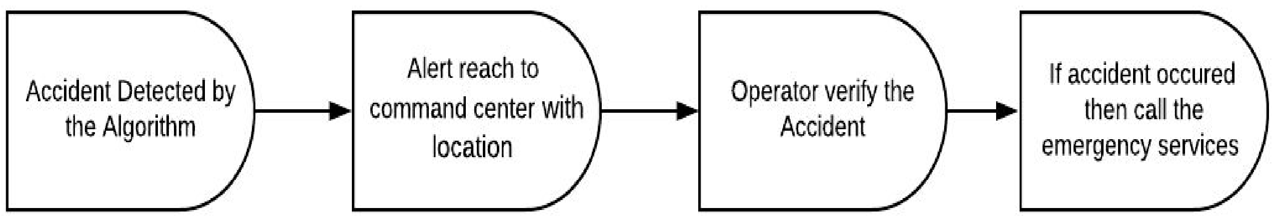


Figure 7.3: Block Diagram of informing system.

7.4. P2P Architecture

Peer-to-peer architecture is used in communicating the camera with the command centers located in the city where the feed of every camera is collected and analyzed. Peer-to-peer architecture (P2P architecture) is an ordinarily utilized PC organizing architecture in which every workstation, or hub, has similar capacities and duties. It is frequently looked into to the great client/server architecture, in which a few PCs are devoted to serving others.

P2P may likewise be utilized to allude to a solitary programming program structured so each example of the program may go about as both client and server, with similar duties and status.

P2P systems have numerous applications, however the most well-known is for content circulation. This incorporates programming distribution and dissemination, content conveyance systems, spilling media and peercasting for multicasting streams, which encourages on-request content conveyance. Different applications include science, systems administration, search and correspondence systems.

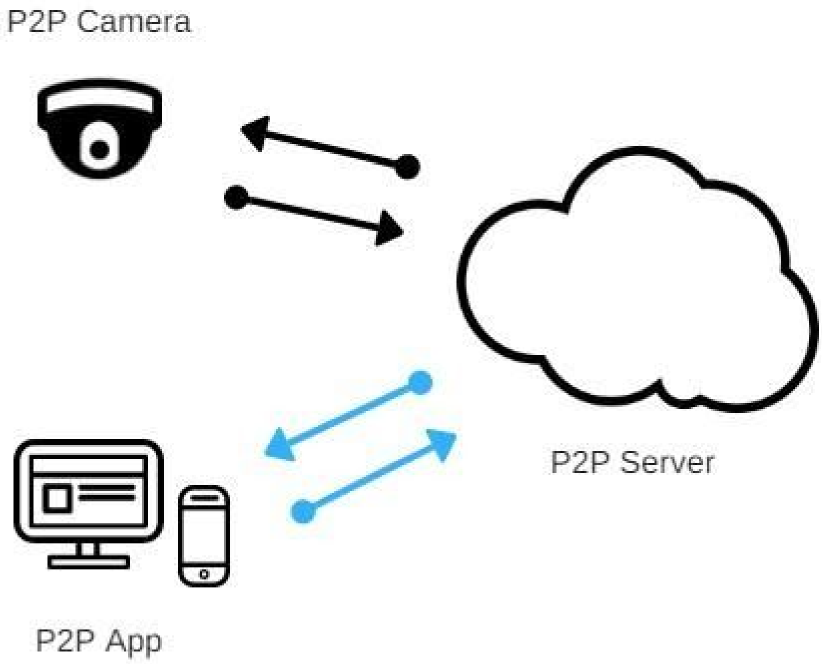


Figure 7.4: peer-to-peer connection

CHAPTER 8

RESULTS

Positive Trials:-

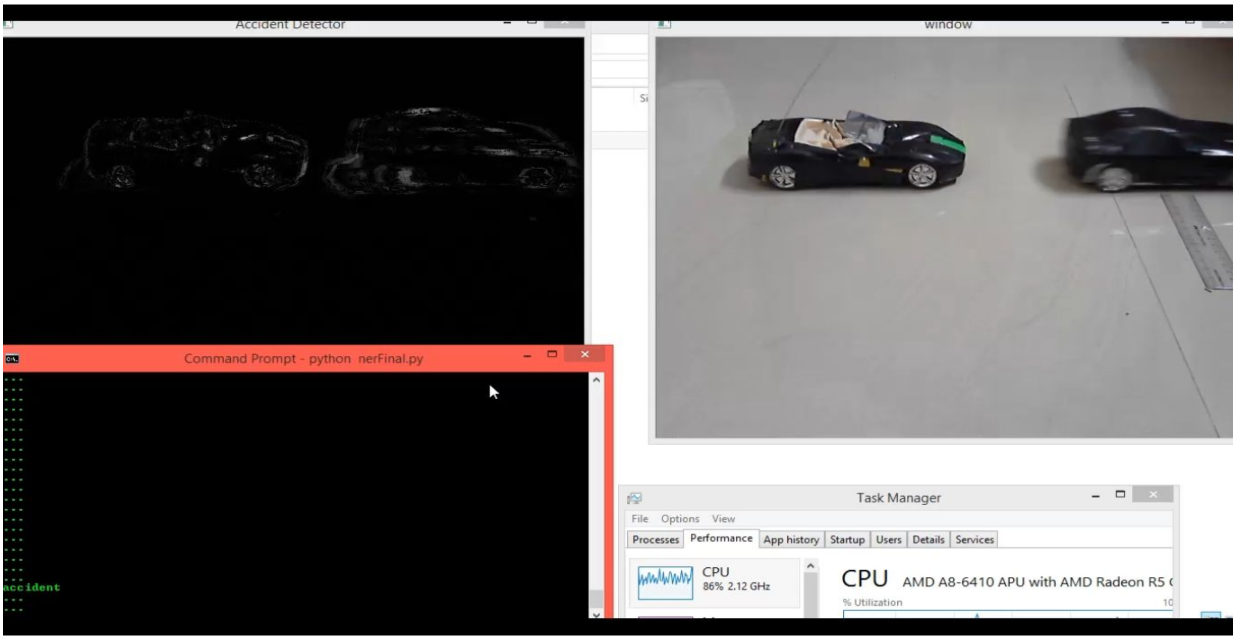


Fig 8.1(i) Results of accident detection from back side

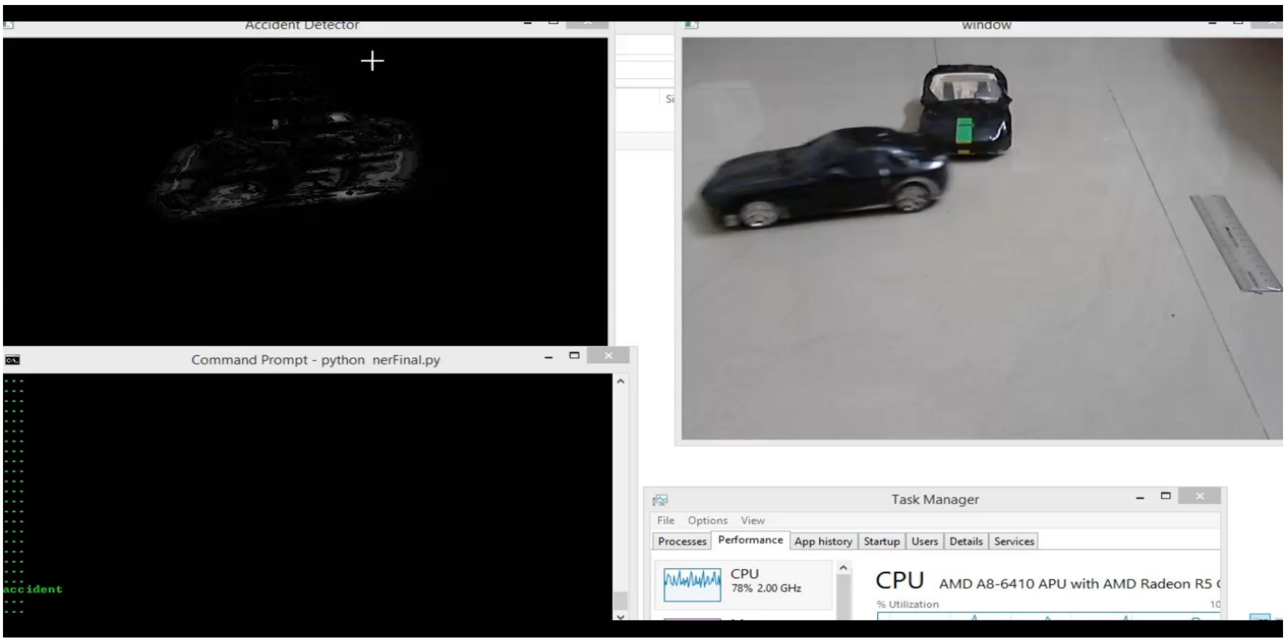


Fig 8.1(ii) Results of accident detection from side wise

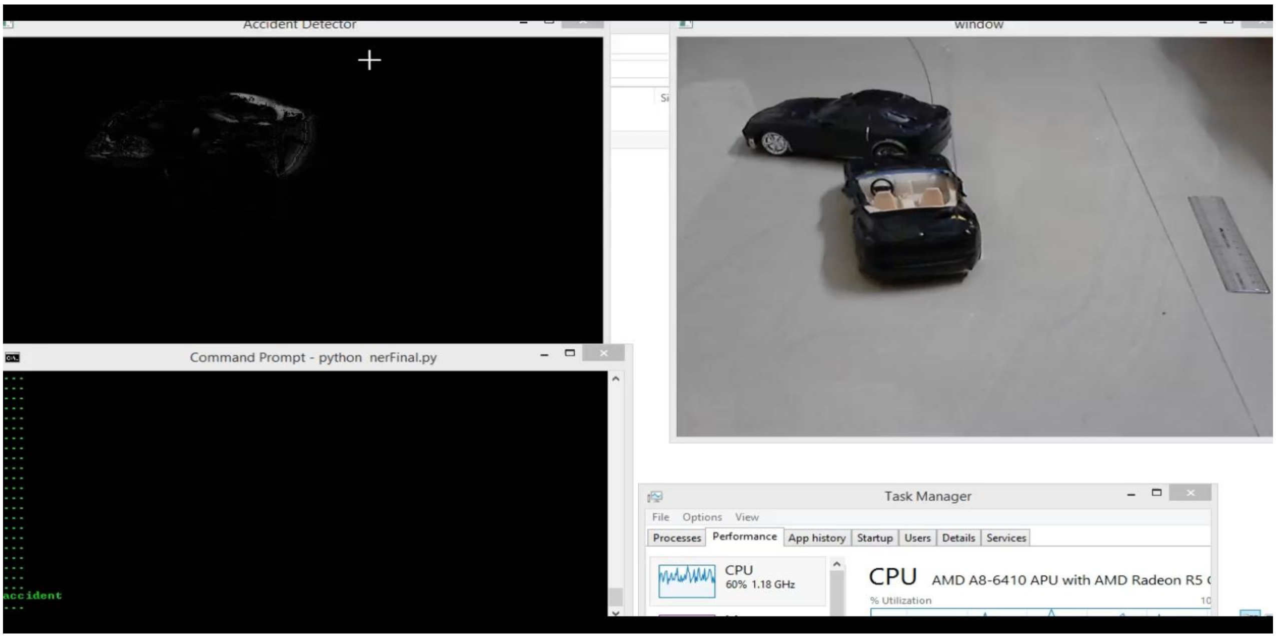
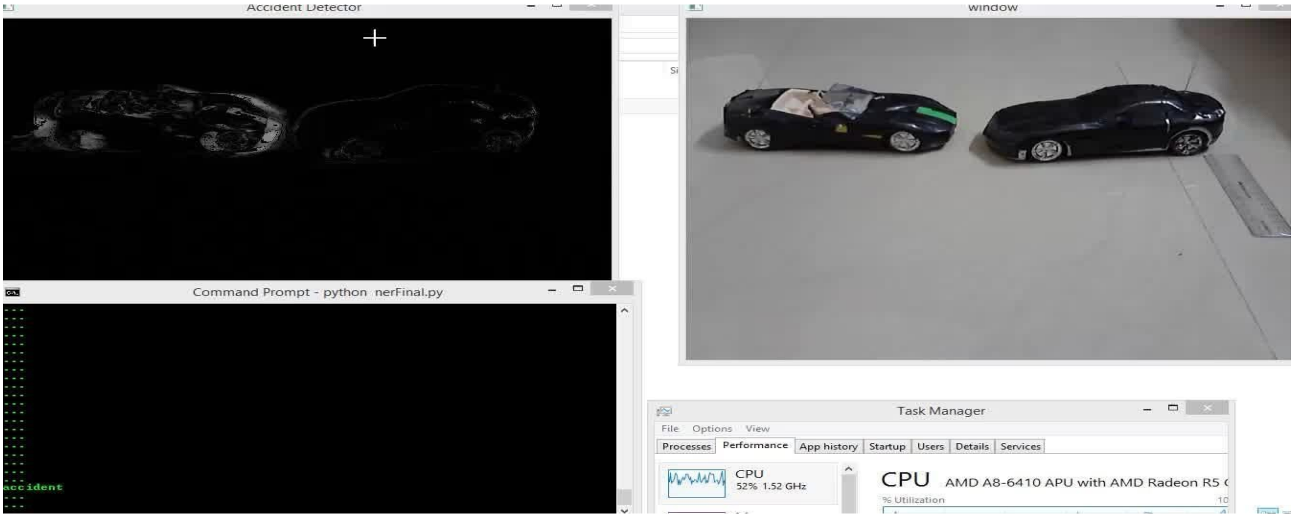
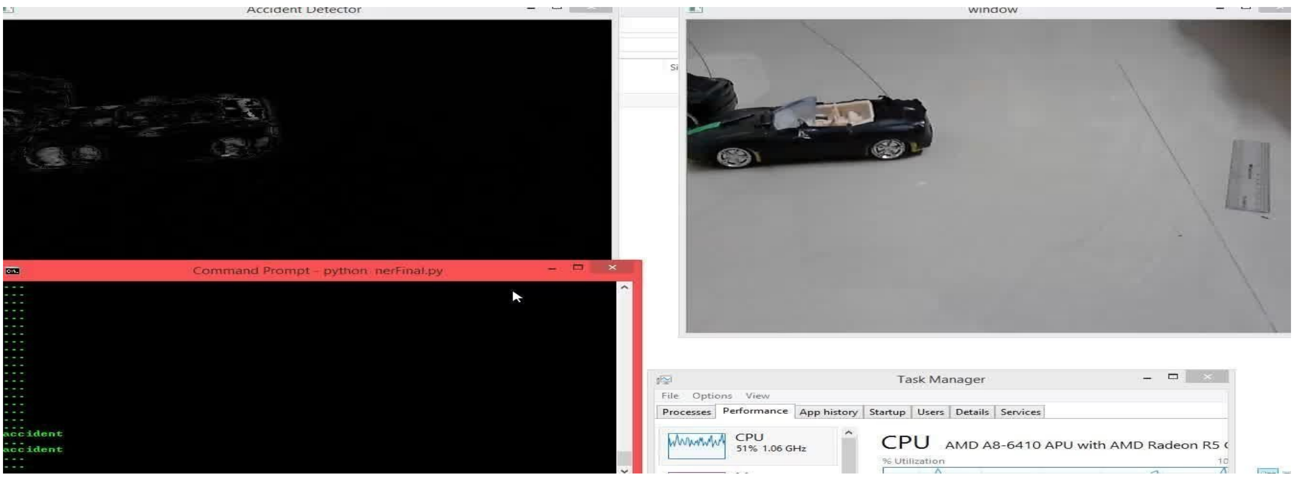
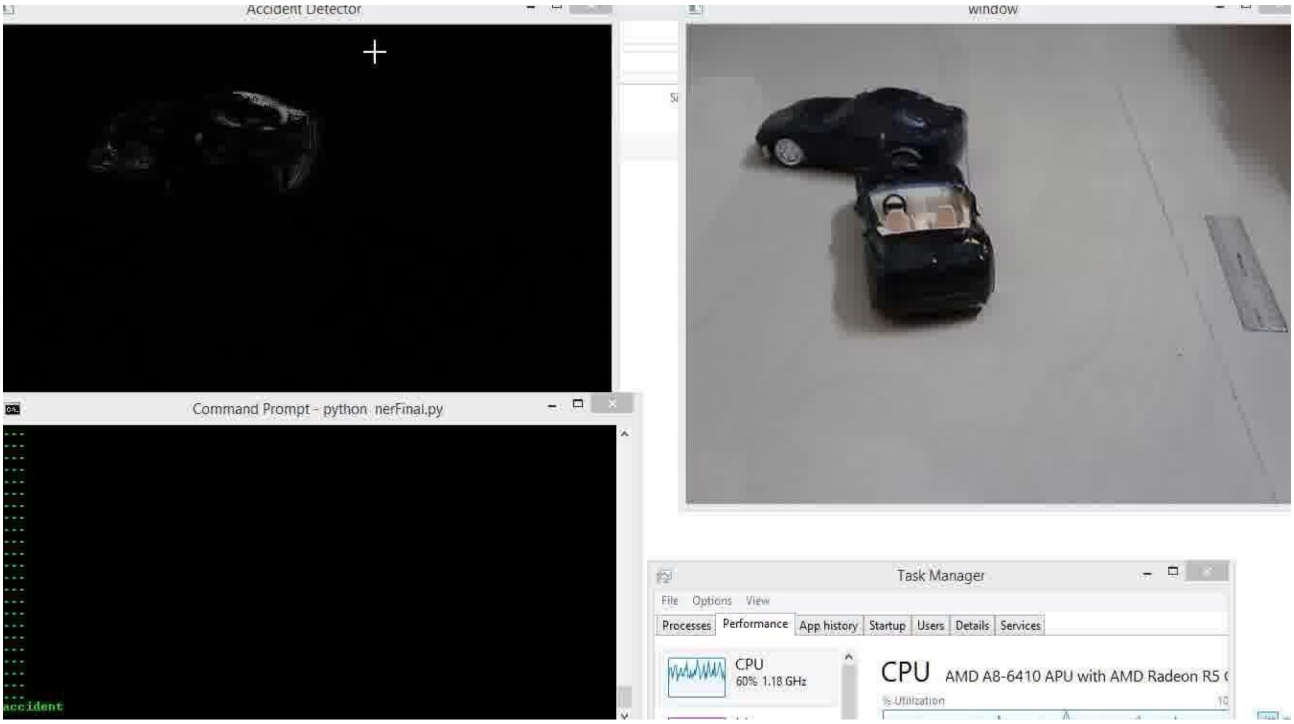


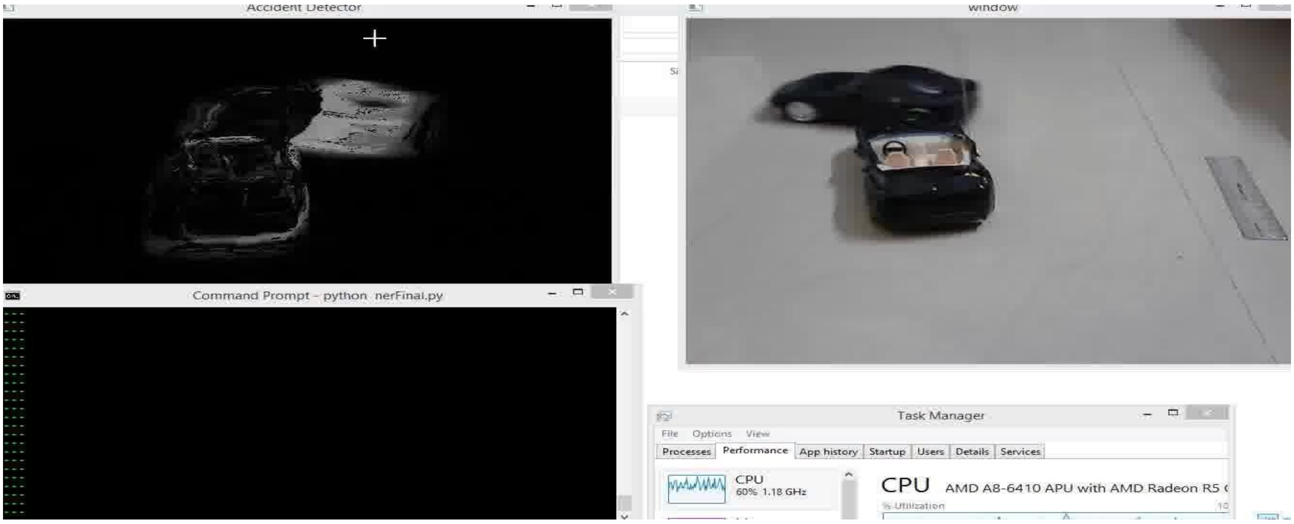
Fig 8.1(iii) Results of accident detection from front

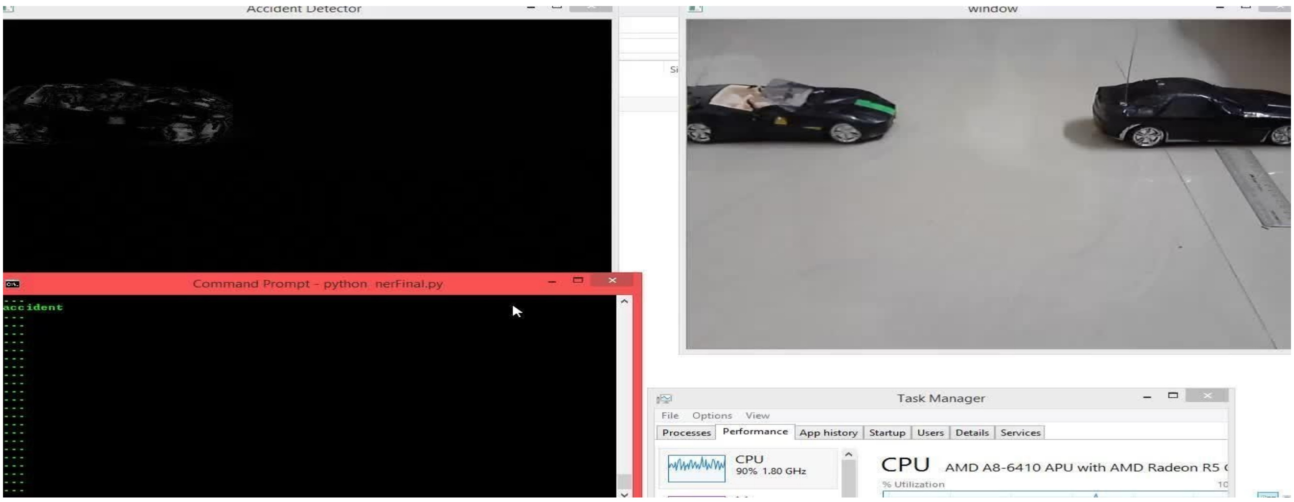


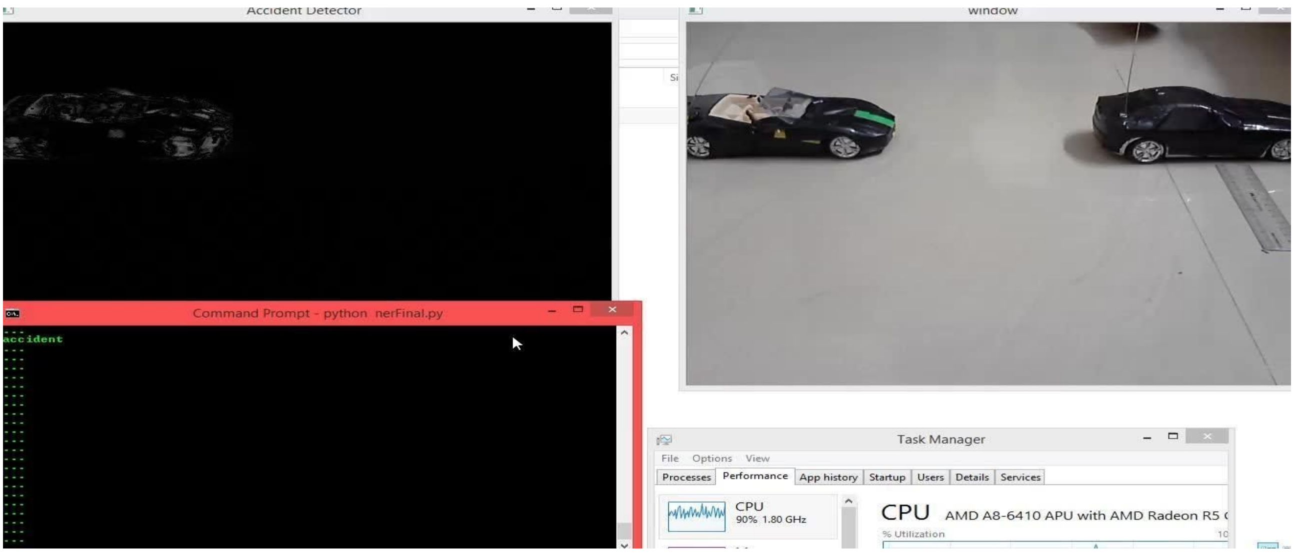


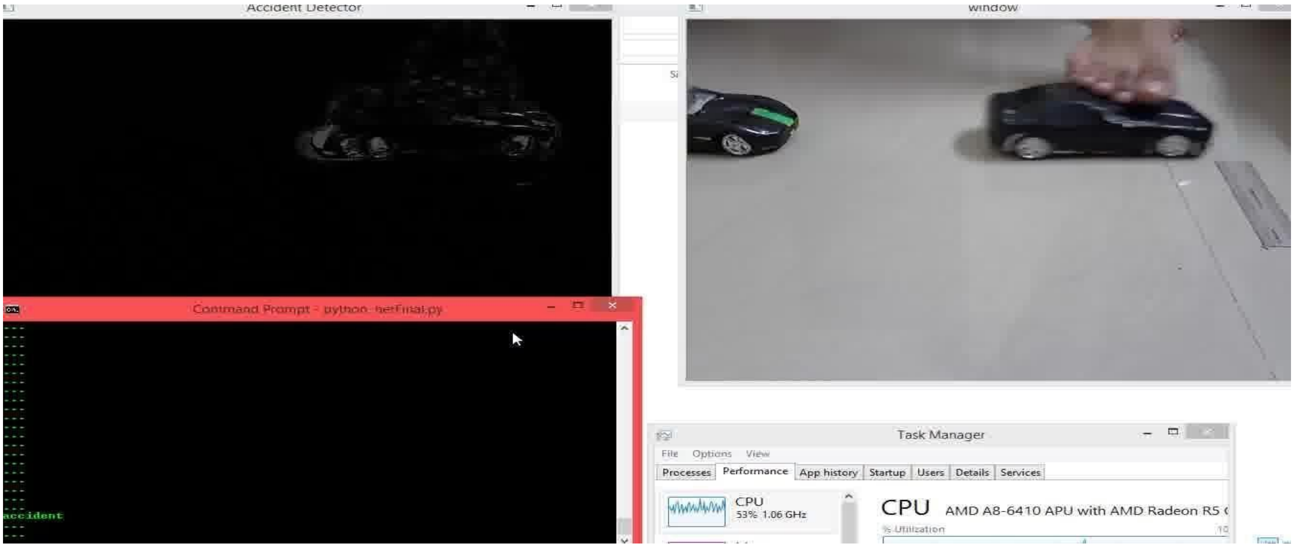

Accident Detector
window
Command Prompt - python nerFinal.py
accident
Task Manager
File Options View
Processes Performance App history Startup Users Details Services
CPU
60% 1.18 GHz
CPU AMD A8-6410 APU with AMD Radeon R5
% Utilization

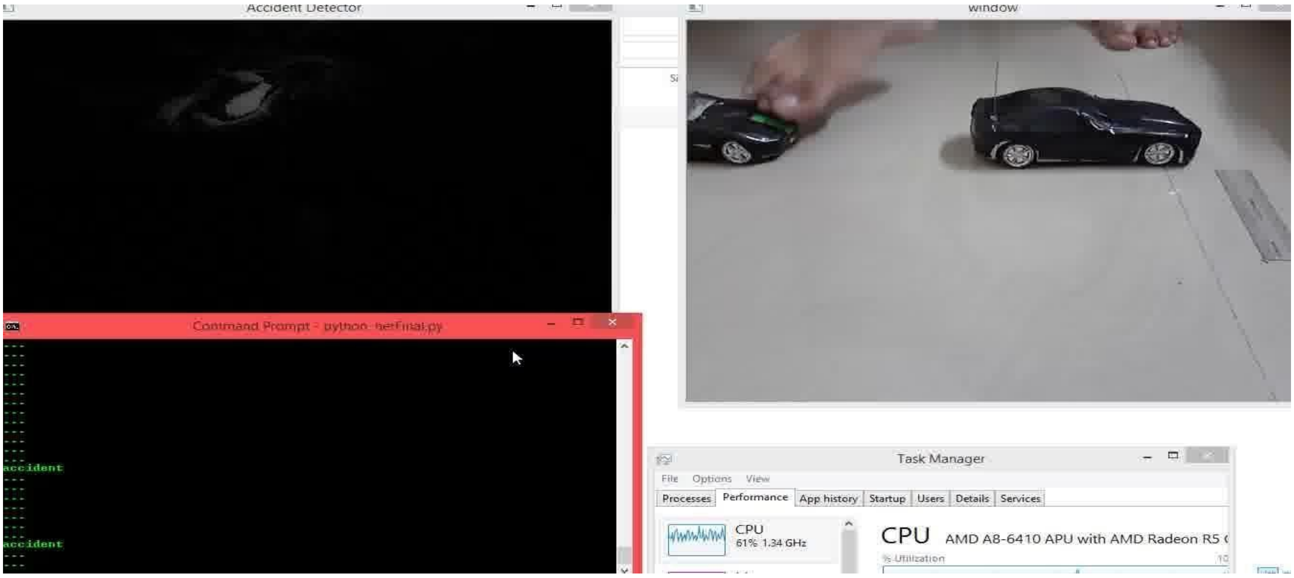
Negative/Defective Trials:-

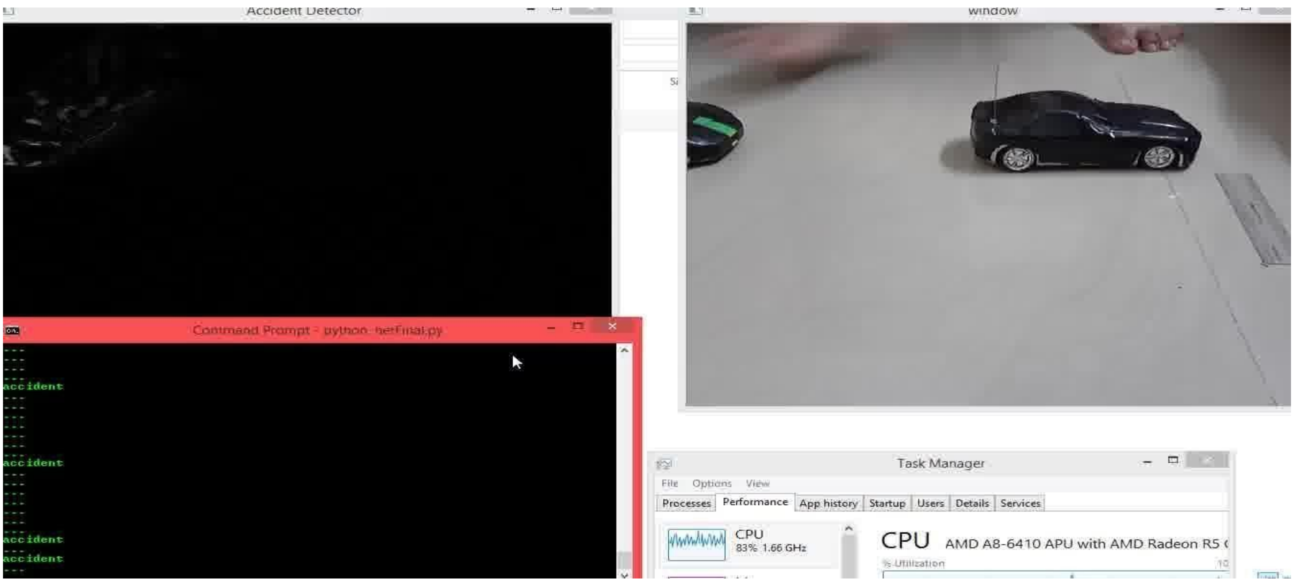







Accident Detector
window
accident
Task Manager
File Options View
Processes Performance App history Startup Users Details Services
CPU
53% 1.06 GHz
CPU AMD A8-6410 APU with AMD Radeon R5
% Utilization


Accident Detector
window
accident
accident
Task Manager
File Options View
Processes Performance App history Startup Users Details Services
CPU
61% 1.34 GHz
CPU AMD A8-6410 APU with AMD Radeon R5
% Utilization


Accident Detector
window
accident
accident
accident
accident
Task Manager
File Options View
Processes Performance App history Startup Users Details Services
CPU
83% 1.66 GHz
CPU AMD A8-6410 APU with AMD Radeon R5
% Utilization

No of Trials	**No. of Vehicles**	**Vehicle Detected**	**Accident Detected**	**Accident not Detected**
15	**2**	**2**	**11**	**4**

Table 8.1 Accident Detection Trials

Efficiency = 73.33%

Table 8.2 Efficiency of Accident Detection

CHAPTER 9

CONCLUSION AND FUTURE SCOPE

9.1. Conclusion

We can have demonstration of a promising approach for an image processing system for automatically detecting, recording, and reporting traffic accidents at an intersection. An important measure in the accident detection algorithm is a low false alarm rate.

So, here we can conclude that till now we have seen the methods for detecting the vehicle accident and approaches to reach the final result. We have tried to implement all those approaches and algorithms for the final outcome of our project and try to have maximum efficiency using all those algorithms.

So overall till now we have detected the cars only as source, In real time image/video. So the system only can detect cars and any other moving objects and also detect when there is collision between two objects.

9.2 Future Scope

Lists of things for future scope-

1. To improve the performance of the detection and tracking algorithm, problems created by shadows.
2. To make the vehicle detection and tracking algorithm operate under night conditions.
3. To collect more traffic data from different camera angles to make the algorithm robust to various conditions and situations.
4. To optimize and increase the processing speed of the detection and tracking algorithm.
5. To improve the classifier so that the system can detect all types of moving objects with greater efficiency.
6. To implement the Informing system in real time when an accident occurs.

REFERENCES

[1] Y. Zhang, R. Q. Hu, L. M. Bruce, N. Balraj, and S. Arora, “Development of real-time automated accident detection system at intersections,” in 83rd Annu. Meeting Transportation Research Board, Washington, DC, 2004.

[2] W. Hu, X. Xiao, D. Xie, T. Tan, and S. Maybank, “Traffic accident prediction using 3-D model-based vehicle tracking,” IEEE Trans. Veh. Technol., vol. 53, no. 3, pp. 677–694, May 2004.

[3] H. Ikeda, T. Matsuo, Y. Kaneko, and K. Tsuji, “Abnormal incident detection system employing image processing technology,” in Proc. IEEE Int. Conf. Intell. Transp. Syst., Tokyo, Japan, Oct. , pp. 748–752, 1999.

[4] M. Kimachi, K. Kanayama, and K. Teramoto, “Incident prediction by fuzzy image sequence analysis,” in Proc. IEEE Int. Conf. VNIS, , pp. 51–57, 1994.

[5] M. M. Trivedi, I. Mikic, and G. Kogut, “Distributed video networks for incident detection and management,” in Proc. IEEE Intell. Transp. Syst. Conf. , pp. 155–160, 2000.

[6] J. Blosseville, J. Morin, and P. Lochegnies, “Video image processing application: Automatic incident detection freeways,” in Proc. Pacific Rim Transp. Technol. Conf., Jul. 25–28, 1993.

[7] J. Versavel and B. Boucke, “Sparing lives and saving time: A unified approach to automatic incident detection,” in Proc. Int. Symp. Automotive Technol. and Autom., Dublin, Ireland, Sep. 25–27, 2000.

[8] P. Michalopoulos and R. Jacobson, “Field implementation and testing of machine vision based incident detection systems,” Transp. Res. Rec.: J. Transp. Res. Board, no. 1394.

[9] X. Jin, D. Srinivasan, and R. L. Cheu, “Comparative appraisal of adaptive ANN-based freeway incident detection models,” in Proc. IEEE 5th Intell. Transp. Syst. Conf., Singapore, 2002.

[10] D. Srinivasan, W. H. Loo, and R. L. Cheu, “Traffic incident detection using particle swarm optimization,” in Proc. IEEE Int. SIS, 2003.

[11] D. Srinivasan, R. L. Cheu, and Y. P. Poh, “Hybrid fuzzy logic-genetic algorithm technique for automated detection of traffic incidents on freeways,” in Proc. IEEE Intell. Transp. Syst. Conf., Oakland, CA, Aug. 2002.

[12] H. Xu, C. M. Kwan, L. Haynes, and J. D. Pryor, “Real-time adaptive online traffic incident detection,” in Proc. IEEE Int. Symp. Intell. Control, Sep. 1996.

[13] T. Shuming, G. Xiaoyan, and W. Feiyue, “Traffic incident detection algorithm based on non-parameter regression,” in Proc. IEEE 5th Intell. Transp. Syst. Conf., Singapore, 2002.

[14] S. Bhonsle, M. Trivedi, and A. Gupta, “Database-centered architecture for traffic incident detection, management, and analysis,” in Proc. IEEE Intell. Transp. Syst. Conf., Dearborn, MI, Oct. 2000.

[15] I. Ohe, H. Kawashima, M. Kojima, and Y. Kaneko, “A method for automatic detection of traffic incidents using neural networks,” in Proc. IEEE Conf. Vehicle Navigat. and Inf. Syst. ,1995.

[16] H. Dia and G. Rose, “Development and evaluation of neural network freeway incident detection models using field data,” Transp. Res., Part C Emerg. Technol., vol. 5, no. 5, pp. 313–331, Oct. 1997.

[17] M. Dougherty, “A review of neural networks applied to transport,” Transp. Res., Part C Emerg. Technol., vol. 3, no. 4, pp. 247–260, 1995.

[18] S. Lee, R. A. Krammes, and J. Yen, “Fuzzy-logic-based incident detection for signalised diamond interchanges,” Transp. Res., Part C Emerg. Technol., vol. 6, no. 5, pp. 359–377, Dec. 1998.

[19] E. R. Green, K. R. Agent, and J. G. Pigman, “Evaluation of Auto incident recording system (AIRS),” Kentucky Transp. Center., Univ. Kentucky, Lexington, KY, Res. Rep. KTC-05-09/SPR277-03-1F, May 2005.