

BREAST CANCER CLASSIFICATION USING DEEP LEARNING ENSEMBLE MODEL

Project report submitted in partial fulfilment of the requirement for
the degree of Bachelor of Technology

in

Computer Science and Engineering/Information Technology

By

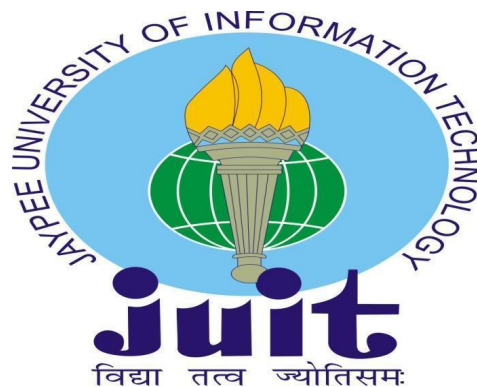
Dikshant Gupta (191448)

Abhimanyu Singh Anand (191417)

Under the supervision of

Dr. Aman Sharma

to



Department of Computer Science & Engineering and Information
Technology

**Jaypee University of Information Technology Waknaghat,
Solani-173234, Himachal Pradesh**

Candidate's Declaration

We hereby declare that the work presented in this report entitled “**Breast Cancer Classification Using Deep Learning Ensemble Model**” in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Engineering/Information Technology** submitted in the department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of our own work carried out over a period from January 2023 to May 2023 under the supervision of **Dr. Aman Sharma** Assistant Professor (SG) Department of Computer Science & Engineering. We also authenticate that we have carried out the above mentioned project work under the proficiency stream **Machine Learning**. The matter embodied in the report has not been submitted for the award of any other degree or diploma.

Dikshant Gupta, 191448

Abhimanyu Singh Anand, 191417

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

Dr. Aman Sharma
Assistant Professor (SG)
Computer Science & Engineering
Dated:

Plagiarism Certificate

JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY, WAKNAGHAT

PLAGIARISM VERIFICATION REPORT

Date:

Type of Document (Tick): PhD Thesis M.Tech Dissertation/ Report B.Tech Project Report Paper

Name: _____ Department: _____ Enrolment No _____

Contact No. _____ E-mail. _____

Name of the Supervisor: _____

Title of the Thesis/Dissertation/Project Report/Paper (In Capital letters): _____

UNDERTAKING

I undertake that I am aware of the plagiarism related norms/ regulations, if I found guilty of any plagiarism and copyright violations in the above thesis/report even after award of degree, the University reserves the rights to withdraw/revoke my degree/report. Kindly allow me to avail Plagiarism verification report for the document mentioned above.

Complete Thesis/Report Pages Detail:

- Total No. of Pages =
- Total No. of Preliminary pages =
- Total No. of pages accommodate bibliography/references =

(Signature of Student)

FOR DEPARTMENT USE

We have checked the thesis/report as per norms and found **Similarity Index** at(%). Therefore, we are forwarding the complete thesis/report for final plagiarism check. The plagiarism verification report may be handed over to the candidate.

(Signature of Guide/Supervisor)

Signature of HOD

FOR LRC USE

The above document was scanned for plagiarism check. The outcome of the same is reported below:

Copy Received on	Excluded	Similarity Index (%)	Generated Plagiarism Report Details (Title, Abstract & Chapters)	
	<ul style="list-style-type: none">• All Preliminary Pages• Bibliography/Images/Quotes• 14 Words String		Word Counts	
Report Generated on			Character Counts	
		Submission ID	Total Pages Scanned	
			File Size	

Checked by
Name & Signature

Librarian

Please send your complete thesis/report in (PDF) with Title Page, Abstract and Chapters in (Word File) through the supervisor at plagcheck.juit@gmail.com

Acknowledgement

First and foremost, we want to express my sincere gratitude to Almighty God for giving us the ability to effectively complete the project work through his divine grace.

We want to express how appreciative and deeply indebted we are to Dr. Aman Sharma, Assistant Professor, Department of Computer Science and Engineering Jaypee University Of Information Technology, Waknaghat. The supervisor's extensive knowledge and deep interest in the "Research Area" are essential to the success of this project. This endeavour was made possible by his never-ending patience, expert direction, constant encouragement, constant and energetic monitoring, constructive criticism, invaluable advice, reviewing numerous subpar draughts and correcting them at all stages.

We want to sincerely thank Dr. Aman Sharma, Department of CSE, for his kind assistance in seeing this research through to completion.

Additionally, we would like to warmly thank everyone who has generously assisted us in making this project a success, whether directly or indirectly. In this particular scenario, we also want to thank the different staff members, both teaching and non-teaching, who have provided their practical assistance and aided our endeavour.

Finally, we must thank our parents for their unfailing support and patience for the success of this project.

Dikshant Gupta
Undergraduate Student
CSE Branch
JUIT, Waknaghat

Abhimanyu Singh Anand
Undergraduate Student
CSE Branch
JUIT, Waknaghat

Table of Content

Chapter	Title	Page No.
	Candidate's Declaration	i
	Plagiarism Certificate	ii
	Acknowledgement	iii
	Table of Content	iv
	List of Abbreviations	v
	List of Figures	vi
	List of Graph	vii
	List of Table	viii
	Abstract	ix
1.	Introduction	1 – 9
2.	Literature Survey	10 – 21
3.	System Design & Development	22 – 42
4.	Experiment & Result Analysis	43 – 58
5.	Conclusion	59 – 60
	References	61 – 65

List of Abbreviations

Abbreviations	Meaning
CNN	Convolutional Neural Network
VGG	Visual Geometry Group
MRI	Magnetic Resource Imaging
ML	Machine Learning
DL	Deep Learning
BACH	Breast Cancer Histology
MSI	Multi Scale Input
UCI	University of California Irvine
NB	Naive Bayes
KNN	K Nearest Neighbor
GLCM	Gray-Level Co-occurrence Matrix
SVM	Support Vector Machine
CAD	Computer Aided Design
DNN	Deep Neural Network
H&E	Hematoxylin and Eosin
FC	Fully Connected
ReLU	Rectified Linear Unit
IDE	Integrated Development Environment

List of Figures

Figure No.	Title	Page No.
1.1	Methodology for Breast Cancer Classification	7
3.1	H&S Images	25
3.2	CNN Architecture	29
3.3	InceptionV3 Flowchart	30
3.4	DenseNet-201 Flowchart	31
3.5	VGG 16 Flowchart	32
3.6	VGG 19 Flowchart	33
3.7	ResNet 50 FlowChart	34
3.8	ResNet-152 Flowchart	35
3.9	Different CNN Layers	37
3.10	Convolutional Layer	37
3.11	Pooling Layer	38
3.12	Fully Connected Layer	39
3.13	Dropout Layer	40
3.14	Ensemble Model	42
4.3	Inception V3 Confusion Matrix	47
4.6	DenseNet-201 Confusion Matrix	48
4.9	VGG16 Confusion Matrix	50
4.12	VGG19 Confusion Matrix	51
4.15	ResNet-50 Confusion Matrix	53
4.18	ResNet-152 Confusion Matrix	54
4.21	Ensemble Model Confusion Matrix	56
4.22	Model comparisons based on accuracy	56

List of Graphs

Figure No.	Graph	Page No.
4.1	Inception V3 Performance over training	46
4.2	Inception V3 Accuracy and Loss Pattern	46
4.4	DenseNet-201 Performance over training	47
4.5	DenseNet-201 Accuracy and Loss Pattern	48
4.7	VGG16 Performance over training	49
4.8	VGG16 Accuracy and Loss Pattern	49
4.10	VGG19 Performance over training	50
4.11	VGG19 Accuracy and Loss Pattern	51
4.13	ResNet-50 Performance over training	52
4.14	ResNet-50 Accuracy and Loss Pattern	52
4.16	ResNet-152 Performance over training	53
4.17	ResNet-152 Accuracy and Loss Pattern	54
4.19	Ensemble Model Performance over training	55
4.20	Ensemble Model Accuracy and Loss Pattern	55

List of Tables

Table No.	Table	Page No.
1.1	Literature Review	11-21
4.1	Classification Report	58
4.2	Comparison with existing literature	58

Abstract

Breast cancer is one of the most prevalent cancers especially among women. Now, the diagnosis of this cancer is something that cannot be taken for granted since someone's life depends on it. So, although pathologists can see if the diagnosis result is cancerous or not, they can't be 100% correct, not even 90% if we look at the surveys. Our aim, therefore, is to create a model that will be more accurate than the pathologist and also the existing methodologies in this field. We went a step further and we were not only detecting cancer but classifying the cancer based on the level of severity into 4 classes. Therefore, our approach was to train and see the performance of 5 of the most well known pre-existing deep learning CNN models which are Inception V3, DenseNet-201, VGG16, VGG19, ResNet-50, ResNet-152 and compare them on various parameters. We found out that VGG16 and VGG19 were the best performing models giving an accuracy of 98% and 96% respectively. We therefore decided to ensemble these two models and we obtained an accuracy of 99% from the resultant model.

CHAPTER-1 INTRODUCTION

1.1 Introduction

Today, there is a huge progress in various technological fields. We are presently experiencing a new industrial revolution. One of the fields which are progressing at an impeccable rate is our health sector. Today we have technologies that can keep people alive that might be dead if treated a decade before. We have various new diagnosis devices which could better facilitate diagnosis of various diseases. We have better operating equipment in hospitals. New studies come up every week for the diseases that earlier were thought to be incurable. Our scientists are diligently working to improve our lives and contributing in prolonging our lives and reducing our suffering. Even things like mental health, spiritual health which were not given that importance earlier are of huge importance in today's time. Your mental stress, depression and almost everything is curable. This is the science which is extending the extent of mortality among humans in such a way that in the coming future, we might even see immortal beings living among us. One of the diseases who's cure and diagnosis have seen massive improvement in recent years is cancer. Cancer is an incurable illness where there is uncontrolled growth of cells in a particular part of the body to form lumps, which we call tumours. Though today more cancer patients can be saved than the extent they could have been saved in previous years, we still are a long way from the extent of curing everyone suffering from cancer. One of the ways of approaching this is by identifying cancer as early as possible, so that there can be significantly less deaths due to cancer. Breast Cancer is one of them.

According to the WHO, the most common type of cancer is breast cancer among women. It is predicted that every one out of three women die because of breast cancer. However, if diagnosed early, they can be saved from their seemingly inevitable death. For the purpose of diagnosis, there are various imaging modalities, which itself is an evolving field. Some of the imaging

modalities include Mammography, Magnetic Resource Imaging (MRI), pathological tests, etc. Among these methodologies, Images from histopathology are regarded as the best and have shown improved accuracy of diagnosis. Via these histology images, pathologists can look at micro elements and the tissue's structure, hence identifying cancer. These images help them to distinguish between normal cells, benign cells and malignant cells. However, examination of these images does require an intense workload of highly specialised pathologists. And the level of knowledge and precision required while diagnosing these images truly test human capabilities. To solve these problems, nowadays we have automated solutions, from traditional machine learning practices to current deep learning practices.

Till date, there have been various rule – based models and ML models made for the purpose of classification of cancerous to non – cancerous ones. Since the past 2 decades, deep learning, a part of machine learning itself, has proven to be quite good at this task. Deep learning models work like the human brain, like a human nervous system is made up of neurons, in a similar fashion, deep learning neural networks seem to mimic this capability to make machines perform tasks like humans do. In the past few years, because of such a huge amount of data and so much better computation power, these models have even been able to outperform humans in these tasks. If we talk about data of images, in particular CNN (Convolutional Neural Network) stands out the most. CNNs are Deep Learning modalities which are used to perform various tasks on images such as object recognition, image segmentation, face recognition, etc. In the biomedical field, due to their ability to learn advanced and complicated features from the image based on the data they are provided, these models have shown remarkable progress in computer vision. That is why researchers use these modalities to perform various tasks including classification of histology images.

Now there have been various CNN models like VGG16, VGG19, Resnet v2, AlexNet, GoogleNet, etc. Some of these models already have prior training on

ImageNet dataset which is one of the largest collections of images and hence they yield high accuracy on various computer vision operations and can also be directly used instead of training these models from scratch. This is called transfer learning. Transfer learning makes it possible to get high accuracies even on systems with low computation power since these systems are pretrained on huge datasets so they do not need to be trained that much.

1.2 Problem Statement

1.2.1 Problem Definition

We need to develop a deep learning model that most accurately classifies breast cancer histopathology images. The most popular approach would be to Ensemble multiple models with high performance. For this one step would be to identify high performance models and choose models such that one can compensate for the limitations of other modals in the overall ensemble to obtain high accuracy hybrid models.

1.2.2 Problem Analysis

Over the time, there have been various improvements in CNN modalities and scanning modalities. In 2019, Adam Yala and other scholars developed a DL model based for mammography images [44] which they claimed to be more accurate than models existing at that time. Michal Chorev in his paper tried to assess the precision and effectiveness of the combination ML and DL approach to detect breast cancer earlier. This combined model is applied to a linked set of electronic health records and digital mammography images. For this method, it was concluded that the combined model could be applied to assess breast cancer comparable to the level of a radiology and could also reduce few missed diagnoses. Comparison study on histopathology images of DL models has done[11]. Another work was done for identification of breast cancer this time on Digital Breast Tomosynthesis (DBT) images. The testing of this model had another

aim of serving as a baseline for future research. Now few good object detection algorithms were required for which a survey paper on object detection was written by a number of scholars and scientists [45] including Z Zou. Another survey paper testing CNN models [11] on BreakHis breast cancer histopathology image dataset for binary and eight classification and on BACH database for four classification. Inception-ResNet-V2 achieved the best result in binary and eight classifications. Another work was done by a few scholars [12] where they tried an ensemble approach. Here, they first implemented fully trained VGG16 [40] and VGG19 [41] models on histopathology image dataset individually, then used fine – tuned VGG16 and VGG19 models, ensembled them and used a 5 fold cross validation method. Also, for the classification of histopathology images, a multi-scale input and multi-feature network (MSI-MFNet) modal was proposed [46] and evaluated on two public benchmark datasets. Another study was done which was aimed to classify malignant and benign breast tumours. The study first involved normalisation and then classification. This study showed that the DL model outperformed previous studies where the same dataset was used. Another paper was published which shared a deep learning model based on Transfer Learning [12]. In that model, the features were extracted from various pre-trained architectures as Inception V3 [38], DenseNet-201 [39], VGG16 [40], VGG19 [41], ResNet-50 [42], ResNet-152 [43], and evaluated based on six evaluation metrics namely sensitivity, specificity, F1 score, accuracy, precision and AUC. Hence, we see even after all this and much more work in the field, there is still a scope of improvement and a lot of progress can still be made in this field.

1.3 Objectives

- Studying tools and techniques for breast cancer classification.
- Implementing different CNN models on breast cancer histology image dataset.
- Comparing implemented CNN models on breast cancer histology image dataset.
- Creating an ensemble model from the models that are having high performance.

1.4 Methodology

1.4.1 Basic steps in constructing a model:

1.4.1.1 Data Collection

- Your data's quantity and quality will determine how precise our model is.
- This stage often provides a representation of the information that will be used for training.
- Use pre-collected data, by the way datasets from UCI, Kaggle etc.

1.4.1.2 Data Preparation

- Accrue data and prepare it for training.
- Try to clean up everything that could need it (remove duplicates, fix errors, handle missing numbers, normalisation, convert data types, etc.)
- Create data visualisations to assist in identifying significant correlations between class imbalances, variables or other exploratory analysis.
- Make separate sets for training and evaluating.

1.4.1.3 Choose a Model

- There are various algorithms for various tasks. Pick the best option.

1.4.1.4 Train the Model

- Training's goal is to deliver an accurate answer or prediction as frequently as is practical.
- Every period in the process is a training one.

1.4.1.5 Analyse the model

- Use a measure or group of measures to "measure" the model's objective performance.
- Although the model is currently being tuned, this unseen data is intended to be reasonably reflective of model performance in the real world.

1.4.1.6 Parameter Tuning

- Hyperparameter tuning, that is covered in this stage, is an "artform" rather than a science.
- By modifying the parameters, you can make the model run better.
- Initialization settings, learning rate, training step count, and distribution, among these simple model hyperparameters, may be used.

1.4.2 Proposed Methodology for Breast Cancer Classification

We propose using a stacking ensemble on selected models that are having high performance to achieve even better all-round performance. The basic architecture of a stacking ensemble is shown in Figure 1.1.

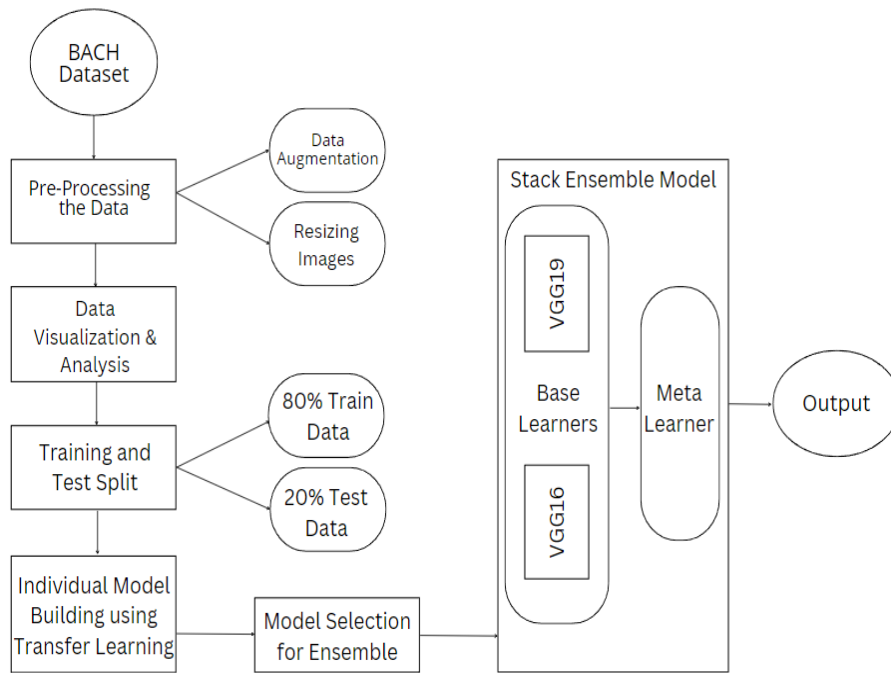


Figure 1.1 Methodology for Breast Cancer Classification

Here, we first trained our six shortlisted models: Inception V3 [38], DenseNet-201 [39], VGG16 [40], VGG19 [41], ResNet-50 [42], ResNet-152 [43]. Then we combined the best performing models among these by creating an ensemble model. The resultant model provided better performance over previous 6 models.

1.5 Organisation

This project report is divided into five chapters which are as follows:

Chapter 1 : - The project is briefly introduced in this chapter. The chapter offers the proffered a quick introduction to the study and an outline of the Breast Cancer Classification. The issue statement for the entire project and the project's goals are also discussed in this chapter. A brief overview of the project's approach is also provided in this chapter, along with details on how the project's ensemble model in order to categorise breast cancer using Keras and transfer learning is created.

Chapter 2 : - This chapter provides the knowledge about the previous work related to the breast cancer classification. Additionally, this chapter contains information on neural networks, machine learning, and deep learning. Numerous journals and related papers that provide details about past work have been listed. The chapter explained how several researchers have attempted to utilise various models to develop an effective classification system for breast cancer utilising methods like ensemble. This chapter includes strategies and their corresponding findings, which aid in determining the method we should employ to train/create our model or project.

Chapter 3 : - This chapter provided details on the procedures we would employ to construct the entire project. Both system development and model development are discussed. The chapter contains details regarding the data set that we'll be working with. Additionally, the chapter has all of the details regarding the libraries we'll be using. Additionally, it provides details on the convolutional neural network (CNN) that will be employed. By explaining each neural network component, it explains the entire theory underlying the convolutional neural network. It contains details regarding the various neural network layers. There is also discussion of the various accuracy measurements

and validating tools. Additionally, it gives details on the system needed to launch and maintain the project.

Chapter 4 : - This chapter provides information on how the entire project's work is done and how we have monitored the work at each level. It provides details on the work done at various levels and also gives the outcomes at various levels. It gives details on the model that we built with the aid of several modules and libraries. It also includes the findings from the numerous performance metrics that we employed during the project. It offers details about the model's precision and the predictions made using the developed model. The information concerning the performance of our entire model or project is provided throughout the entire chapter.

Chapter 5 : - The entire conclusion of the work included in this project report is contained in this chapter. The project's future scope is also mentioned, along with information on all of the project's phases. It also includes details on the project's uses and potential locations for use there to advance computerization in that industry. It provides information on how to enhance the project and what we can do going forward in relation to this project and its enhancement.

CHAPTER-2 LITERATURE SURVEY

This section explains 8 research papers published previously regarding the work done earlier and how they approached this problem. In 2020, there was a study performed by Ghulam, et al. [1] where different imaging modalities as Mammography, MRI, Ultrasound, Tomography and Histopathology were compared as to which would be better for image diagnosis through various parameters, and it was found that Mammography and Histopathology images were the way to go here. In 2018 in a paper published by Meriem, et al. [2] two machine learning models were compared namely, Naive Bayes (NB) classifier and K Nearest neighbour (KNN) classifier. It was found that KNN showed better accuracy of 97.51% over the NB classifier which showed a degree of accuracy of 96.19%. Another work which was published in the same year was done by Sarosa, et al.[3]. Here, binary classification of mammography images were performed by using GLCM (Gray-level co-occurrence matrix) and SVM (support vector machine) combined (SVM). However, accuracy obtained was 63.03% and specificity was 89.01%. In 2021, a survey was conducted by Zebari, et al.[4]. Here, 118 publications published in 2018-2021 were reviewed. The studies showed different stages of CAD and highlighted research gaps. In another paper published in 2018 by Nawaz, et al.[5], a deep learning convolutional neural network DenseNet was introduced. This model obtained an accuracy of 95.4% in the task of multi-classifying breast cancer images from BreakHis dataset. Another paper published by Obaid, et al. published in 2018[6] compared 3 ML models namely SVM, KNN and Decision Tree were used to perform classification on a Wisconsin Breast Cancer (Diagnostic) dataset. In the comparison, it was found that SVM outperformed both other models having accuracy of 98.1%. In 2018, another paper was written by Khourdifi, et al.[7]. In this paper 4 ML models namely, Random Forest, Naïve Bayes, SVM and KNN were compared for classification and it was found that SVM outperformed them all with accuracy 97.9%. The above studies solidify SVM as the best model for image classification among traditional ML models. In 2021, a study conducted by Vijayakumar, et al.[8] to explain deep neural networks for breast cancer

prediction. This paper used multiple activation functions to understand DNN layer wise. Table 1 shows some more studies conducted in this field.

Table 1.1 Literature Review of Selected Research Papers

S. no	Author	Aim	Methodology used	Dataset	Limitation	Performance
1	Ayalew et al. [9]	Applying DL to linked health records and mammograms	On 9611 mammograms, the algorithm was trained to predict two things: malignancy and differentiate normal from abnormal screenings.	Data from Assuta Medical Centre imaging facility [9]	There are better imaging technologies than mammograms now.	77.3% specificity and 87% sensitivity
2	Buda, et al. [10]	Apply DL for mass and architectural detection in DBT	16802 DBT examinations were performed. Further, they were divided in 4 groups, split in train and	DBT examinations from Duke health systems. [10]	Images were collected from a single institution.	65% sensitivity

		images	test and evaluated on DL models.			
3	Shahidi, et al. [11]	Comparison study on histopathology images of DL models	Models like ResNeXt, Dual Path Net, SENet, and NASNet were implemented for binary, 4, 8 classifications on BACH and BreakHis dataset.	BreakHis, BACH [11]	More new models have been created since the time the survey was conducted.	Inception Res-Net outperformed all
4	Hamed, et al. [12]	Ensembling	4 models based on VGG16 and VGG19 were trained.	WSI images from Colsanitas Colombia University, Bogotá,	The data was collected from a single institute.	Accuracy 95.29%

				Colombia [12]		
5	Teresa, et al. [13]	Image classification done in four classes then in two classes using CNN	4 classification is done on CNN models then ensembling is done.	H&E stain images from the Bioimaging 2015 breast histology classification challenge [13]	We have better models than the ones used back then.	The proposed system can be extended for WSI images
6	Bardou, et al. [14]	Classification of Breast Cancer Based on Histology Images	Comparison between SVM based model and CNN based model	Small datasets consisting of 500 and 92 images and WSI images [14]	Small dataset is used	Binary classification yields 96.15% and 98.33%, while multiclass classification yields 83.31% and 88.23%.

		es Using Conv olutio nal Neur al Netw orks				
7	Zhan bo, et al. [15]	Ense mble of multi scale CNN s	Patch extraction, training, selection, combinatio n.	BACH Challeng e dataset [15]	We have better performing models developed for the job	Accuracy of 91.75±2.32% in five fold cross validation
8	R. Krithi ga & P. Geeth a [16]	Using ML and DL techn iques to predi ct breast cance r recurr	Images are enhanced, features are extracted hence classificati on is done	H&E stained images [16]	Prediction is not enough	Issues like accuracy, sensitivity and specificity are addressed

		ence rates				
9	Hirra, et al. [17]	A novel patch based deep learning model proposed to detect and classify images using Deep Belief Network (DBN)	Preprocessing, patch generation, DBN, classification are done in the same order.	H&E-stained images [17]	Better hardware can be used for the whole procedure.	Patch based models outperformed Whole Image based models
10	Shallu Shar	Comparison	In approach 1, handcrafted	Balanced BreakHis	Embedding CNN in a handcrafted	VGG 16 with linear SVM provided

	ma and Rajes h Mehr a [18]	betwe en handc rafted featur es based and Trans fer Learn ing Base d Class ificati on Appr oach	d features are extracted, in approach 2, pre-existin g CNN networks are utilized for baseline modelling and feature extraction.	Dataset [18]	feature based approach could be done.	highest accuracy (patch based and patient based)
11	Vaka, et al. [19]	To detect breast cance r by lever aging Mach ine Learn ing	A new method of Deep Neural Network with Support Value was introduced for better quality images and	8009 annotated Histology images from MG Cancer Hospital & Research Center [19]	Dataset was taken from a single institute.	Proposed DNNS was better in both performance and efficiency.

			<p>fixing other performance parameters. Further, a new algorithm with a mathematical formula was proposed for evaluating efficiency and performance.</p>			
12	Subrato, et al. [20]	Review on different ANN based models for diagnosis of breast	<p>Different pros and cons of ANN models are described. Also, precision, recall, accuracy, etc. are used to</p>	Various publicly available datasets [20]	We have better imaging techniques than mammography	Best performance was achieved by ResNet-50 and ResNet-101

		cancer via mammography	compare models.			
13	Ghulam, et al. [21]	Develop BMI C_Net to classify Breast Cancer into eight distinct types through DL and hierarchical classification	Data collection, image augmentation, feature extraction, model development, feature reduction, model evaluation.	BreakHis [21]	Model is not generic.	Accuracy of 95.48% for first-level classifier and 94.62% and 92.45% for second level classifiers.

14	Rui, et al. [22]	Classifying breast cancer histopathological images using hybrid deep neural networks.	CNN and RNN are integrated based on the richer multilevel feature representation.	3771 breast cancer histopathological images dataset [22]	Accuracy can be better if better models are used.	91.3% average accuracy for 4-class classification task
15	Anabia, et al. [23]	CNN based Heterogeneous Ensemble Technique "DHE-Mit-Clas"	FCNN and DCNN are used and trained upon two publicly available datasets.	ICPR 2012 and ICPR 2014 (MITOS-ATYPIA-14) [23]	Accuracy is less and computational cost is more.	Had high F-score of 0.77

		sifier ”				
16	Chuhan, et al. [24]	Breast cancer binary classification using residual learning-based CNN myResNet-34	Residual learning-based CNN designed. Further, algorithms for stain normalization and elastic distortion with affine transformation were introduced.	BreakHis [24]	We have models that will give higher accuracy.	Around 91% accuracy for image classification.
17	Qasem, et al. [25]	Breast cancer classification using	Pretrained ResNet-50 CNN model for binary classification of breast cancer	BreakHis [25]	Classification is only binary.	Accuracy was 99%

		ResNet-50.	images was used.			
18	Nouman, et al. [26]	WSI images are trained on EfficientNet	Patches are extracted from WSI images and are fed to CNN for feature extraction. Discriminative patches based on features are fed to EfficientNet and features further extracted are fed to SVM.	BreakHis [26]	We have better models providing better performance.	Both SVM and EfficientNet achieved good results.

CHAPTER-3 SYSTEM DESIGN & DEVELOPMENT

3.1 Model Development

3.1.1 Importing the libraries:

Libraries Required are Numpy, OS, glob, random, Keras, tensorflow, matplotlib.

1. Numpy [29]

NumPy is a Python package used for manipulating arrays, matrices, Fourier transforms, and linear algebra functions. It provides multidimensional array objects and a variety of methods for working with these arrays. NumPy allows for logical and mathematical operations to be performed on arrays and includes numerous array functions and indexing styles. It is an open-source project and can be used for free. The primary aim of NumPy is to provide array objects that are much faster than conventional Python lists, with speeds up to 50 times faster. The NumPy array object is commonly referred to as ndarray.

2. OS [30]

The os module is an essential part of many Python programs, especially those that involve interacting with the file system or running system-level commands. It provides a unified way of working with different operating systems and abstracts away many of the low-level details, making it easier to write cross-platform code. By using the functions and classes provided by the os module, you can write Python scripts that can run on different platforms, such as Windows, Linux, and macOS. This makes it easier to develop and maintain code, especially if you need to support multiple platforms. The OS module has several more helpful functions for working with processes, environment variables, user accounts, and more in addition to the capabilities already listed. Every Python developer should be familiar with this robust and adaptable package.

3. Glob [31]

The Python standard library includes the glob module, which makes it possible to use the glob function to locate all file paths that match a given pattern. When working with several files that have identical naming standards, this may be extremely useful. We may look for files with names that fit the specified pattern by utilising wildcard characters in the file pattern. The glob function can be used to discover a specific file by name, but it is most frequently employed to search and connect together several files with the same name. The files may be read in using the glob function, and then combined into a single dataframe for additional analysis.

4. Random [32]

The built-in "random" module in Python can generate pseudo-random numbers and perform other random operations. It's commonly used in applications like simulations, games, and cryptography where unpredictable values are needed. While the numbers are not truly random, they are sufficient for most use cases. For higher randomness, external sources should be used.

5. Keras [33]

For creating and analysing deep learning models, Keras is an open source Python toolkit that is both robust and user-friendly. It interfaces with two well-known frameworks for quick numerical computation, Theano and TensorFlow. Keras gives programmers the ability to build and train neural network models with just a few lines of code. Although powerful libraries for creating neural networks, Theano and TensorFlow can be challenging to learn. By offering a user-friendly interface for creating TensorFlow- or Theano-based deep learning models, Keras streamlines the procedure. With a variety of independent machine learning toolkits, as well as C#, Python, and C++ libraries, Keras is a flexible library.

6. TensorFlow [34]

TensorFlow is a Python library developed and released by Google for fast numerical computations. It serves as a foundational library that can be used to build Deep Learning models directly or indirectly through wrapper libraries built on top of TensorFlow, which simplify the process. Whether you are a beginner or an expert, the TensorFlow tutorial covers all the basic and advanced topics in deep learning and machine learning, including sentiment analysis, deep neural networks, and image processing. TensorFlow, one of the most well-known deep learning frameworks, was created by the Google Team and is free and open source software that was built using the Python programming language. This tutorial aims to help developers easily create deep learning projects using TensorFlow.

7. Matplotlib [35]

Matplotlib is a powerful and flexible toolbox for Python that can be used to create static, animated, and interactive visualisations. With Matplotlib, you can create dynamic charts that can zoom, pan, and update, making it an ideal tool for creating informative and visually appealing data visualisations.

3.2 Loading the Data Set

3.2.1 BACH Data Set [36]

The dataset we used initially consisted of 400 images, 100 belonging to each of the four classes in tagged image file format (.tif) with an average size of 18 Mb each. These four classes are: Normal, Benign, In Situ Carcinoma, Invasive Carcinoma as shown in Figure 3.1.

Normal is the case of no cancer, benign is the case where there is cell growth but it is not fatal. In situ is a kind of malignant growth where cells are uncontrollably grown in a particular region. Invasive however is the case where there is tumour growth in multiple regions. We first converted these images into portable network graphic format (.png) to compress the size of the image, since this compression technique was a lossless compression technique. Further, we used image augmentation techniques to increase the

count of our images to have more accuracy. The total image count increased to 4080 after we applied techniques like rotation, horizontal flip, height shift, zoom range, shear, etc. For training the models, we further added extra layers and trained those layers with 20% test data (816 images) and remaining 80% training data (3264 images). These models were further fine-tuned using hyperparameter tuning to obtain best possible parameters for better performance.

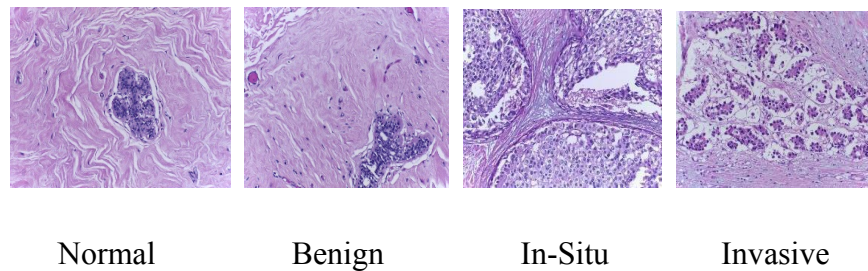


Figure 3.1 H&S Images^[37]

3.2.2 Pre-Processing

In every recognition process, data preprocessing is crucial. A data mining approach known as data Preprocessing serves as to turn the raw data into a format that is both practical and effective. Pre-processing is used to mould the input images into a shape appropriate for segmentation. An essential step before creating a model using these properties is data preparation. Usually, it happens in phases.

- Data Quality Evaluation
- Cleaning of Data
- Transformation of Data
- Data Reduction

3.2.2.1 Data Quality Evaluation

The Data Quality Assessment is a distinct stage in the data quality life-cycle that verifies the source, volume, and impact of any data items that do not adhere to established data quality guidelines. This assessment can be performed once or repeatedly as part of an ongoing project to ensure data quality. However, even with strict data capture procedures that clean the data

upon entry into the database, the quality of the data can deteriorate significantly over time. This is because information such as people's addresses, phone numbers, and life status can quickly become outdated. A data quality assessment can help locate inaccurate records, determine their source, and identify any potential impacts resulting from the inaccuracy. By performing this assessment, possible problems can be identified and rectified.

3.2.2.2 Cleaning of Data

Data cleaning is an integral part of the machine learning process. It is a critical step in building models, and there are no hidden secrets or tricks to it. Though not the most glamorous part of the process, data cleaning can make or break your project. Professional data scientists often spend a significant portion of their time on this stage, as the saying "Better data beats fancy algorithms" holds true. With a clean dataset, even a simple method can produce the desired results, which can be incredibly valuable. Different types of data may require different cleaning methods, but a systematic approach is usually the best starting point.

3.2.2.3 Transformation of Data

Data cleaning and smoothing are essential first steps in preparing data for machine learning. Once the data is clean, the next step is data transformation, which involves converting it into a format that can be used by computers for learning. This process includes joining data, dimensional modelling, de-normalizing, and preparing it for analysis. Without the right technological infrastructure in place, data transformation can be time-consuming, expensive, and labour-intensive. However, the effort is worth it to ensure the highest quality data for accurate analysis and valuable insights that lead to data-driven decision-making.

As more businesses adopt or plan to use machine learning for various real-world applications, it is critical to arrange data so that its analysis produces meaningful insights. Creating and training models is a good idea, but the success of these models depends on the quality of the data used to train

them. Proper data transformation ensures that data is in the correct format for analysis, leading to accurate models and valuable insights.

3.3 Model Selection and Creation

Diagnosis of breast cancer is a tiring task even for highly skilled pathologists. There is still a decent probability that even the most experienced of the pathologists might make mistakes in correctly analysing the severity of the cancer, that is where ML models come into play in further improving the accuracy of these results. Convolutional Neural Networks have become more widely used in recent years for feature extraction from these images. The models we have used are Inception V3[38], DenseNet-201[39], VGG-16[40], VGG-19[41], ResNet-50[42], ResNet-152[43]. These models were pre trained on ImageNet weights.

3.3.1 Learning Algorithms

One of three major categories could be used to classify machine learning algorithms:

1. Supervised learning - Supervised learning involves pairs of input items and their corresponding output values. Using this information, an algorithm creates a model that can predict output values for new samples. It is a powerful tool for solving a wide range of problems and has many practical applications in fields such as medicine, finance, and engineering. With its ability to generalize and make accurate predictions, supervised learning is a powerful tool for making sense of complex data.

A machine learning difficulty is identifying the mathematical relationship between the input X and output Y variables. These X, Y pairs of labelled data are used to construct a model in an effort to determine how to predict the output from the input. Problems with regression and classification fall under the heading of supervised learning difficulties.

2. Unsupervised Learning - is a machine learning task that solely uses the X input variables as inputs. Unlabeled data from such X variables is what the learning algorithm utilises to model the underlying structure of the data.

Clustering and association difficulties are subcategories of unsupervised learning issues.

3. Reinforcement learning - Reinforcement learning is a machine learning branch that focuses on taking appropriate actions to maximise rewards in a given situation. It is utilised by many programs and machines to determine the optimal course of action to take in a particular situation. Unlike supervised learning, where the training data includes a correct answer key, reinforcement learning relies on the reinforcement agent to determine what actions to take to achieve the task at hand. In supervised learning, the model is trained with the correct answer included, while in reinforcement learning, there is no solution. Instead, it is necessary to learn from experience, without the aid of a training dataset.

3.3.2 Models Used In this Project

Convolutional Neural Network Model (CNN)

In simpler terms, CNN is an artificial neural network that excels in identifying and deciphering patterns. CNN has so proven to be most helpful for image classification. A CNN model uses a variety of filters with variable numbers and sizes. The main thing that aids us in finding the pattern is these filters. Although they may be utilised with one-dimensional and three-dimensional data, convolutional neural networks, or CNNs for short, are a specialised kind of neural network model created for working with two-dimensional picture data.

The convolutional layer, which gives the network its name, is at the core of a convolutional neural network. The "convolution" procedure is carried out by this layer. Convolutional and pooling layers are the most common components of CNN models. Because it performs better for data that are represented as grid structures, CNN is a good choice for challenges involving picture categorization. When training, the dropout layer minimises overfitting of the model by deactivating part of the neurons.

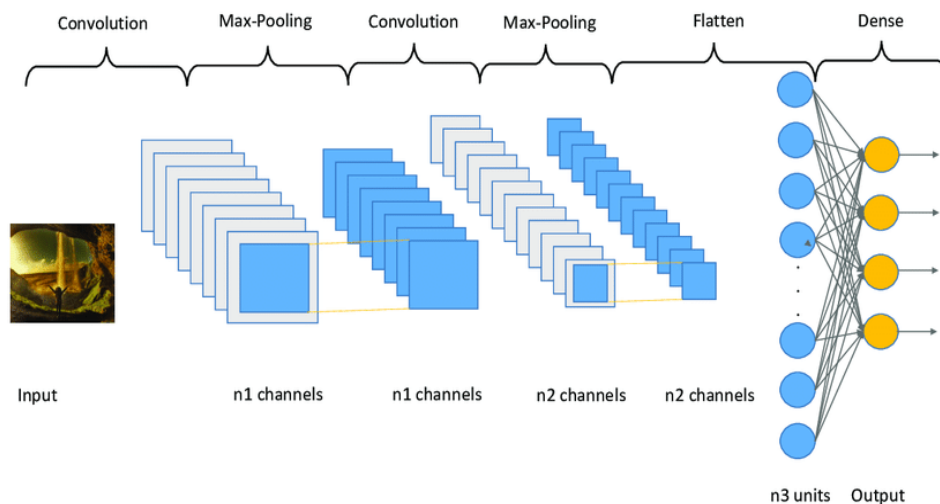


Figure 3.2 CNN Architecture^[48]

Working of CNN

Convolutional neural networks are made up of artificial neurons that are stacked in many layers. Similar to their biological counterparts, artificial neurons are mathematical processes that compute the weighted sum of a number of inputs and output an activation value.

The weights of each neuron determine its behaviour. When fed with pixel values, CNN's artificial neurons can recognise a variety of visual elements.

When you feed an image into a ConvNet, each layer generates a number of activation maps. Activation maps highlight the crucial elements of the image. Each neuron multiplies the colour values of a pixel patch by its weights as input, adds them all together, and then sends the total through the activation function.

The pre-trained Models that we used in the project are:

3.2.2.1 InceptionV3 [38]

On the ImageNet dataset, this model has been observed to demonstrate a 78.1% accuracy rate. The model was created as a result of many concepts that many researchers have developed over time. This model has under 25 million

parameters as shown in Figure 3.3. The symmetric and asymmetric building blocks that make up the model itself include convolutions, average pooling, max pooling, concatenations, dropouts, and completely connected layers. Batch normalisation, which is used extensively in the model and is also applied to the inputs for activation, is used. The loss is computed using Softmax. With the use of Keras and transfer learning, we imported this pre-trained model for the project. Additionally, you gave the model a custom 299 x 299 input shape, selected the imagenet weights, and set the include_top value to false. Next, we added additional layers using sequential, including a dropout layer, a flatten layer, and a dense layer.

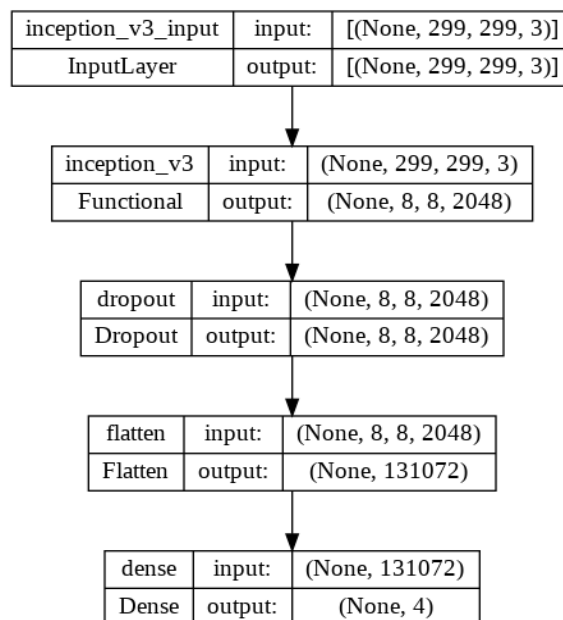


Figure 3.3 InceptionV3 Flowchart

Then, we built our model using categorical crossentropy as the loss function and Adam as the optimizer.

3.2.2.2 DenseNet-201 [39]

This CNN model is 201 layers deep as shown in Figure 4. Its pretrained model can classify images into 1000 object categories. DenseNet was developed to address the issue of reduced accuracy caused by the vanishing gradient problem in deep neural networks. Similarly we used Keras and transfer learning to import this pre-build model. And provided the model an input

shape of 299 x 299 and use the imagenet weights and make the include top value false. Then we used sequential and added a dropout layer, flatten layer, repeat vector layer, and then again a flatten layer and finally a dense layer. Then, we built our model using category crossentropy is the loss function in our model. and Adam as the optimizer.

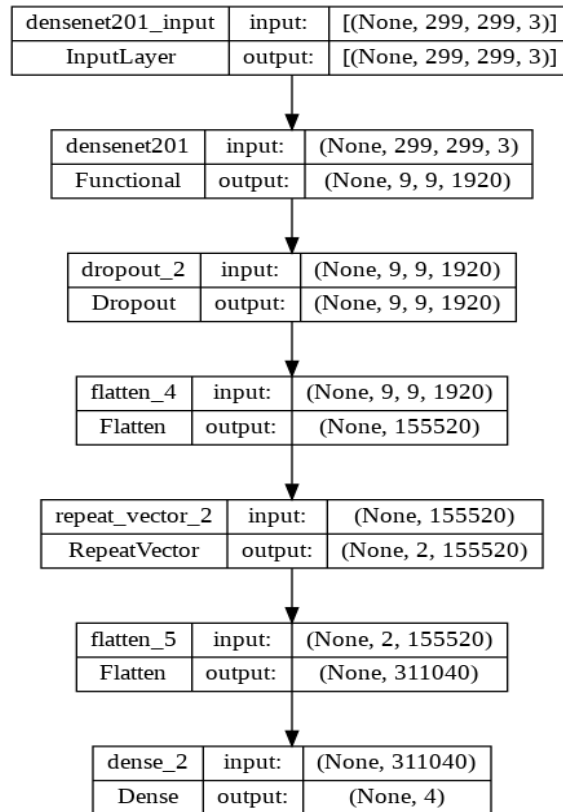


Figure 3.4 DenseNet-201 Flowchart

3.2.2.3 VGG 16 [40]

This model is 16 layers deep as shown in Figure 3.5 and was used to win the ILSVRC ImageNet competition in 2014. This model has approx. 138 million parameters. The VGG16 technique is used for many deep learning image classification problems, smaller network designs, however, typically favoured. But because it's so straightforward to use, it's a great building block for instructional purposes.

For the project we imported the pre-trained VGG 16 model using Keras and transfer learning. And provided the model an input shape of 299 x 299 and use

the imagenet weights and make the include top value false. And freeze some of its layer, then we added additional layers i.e. GlobalAveragePooling2D, dropout layer, 2 x dense layers, a dropout layer and finally a dense layer.

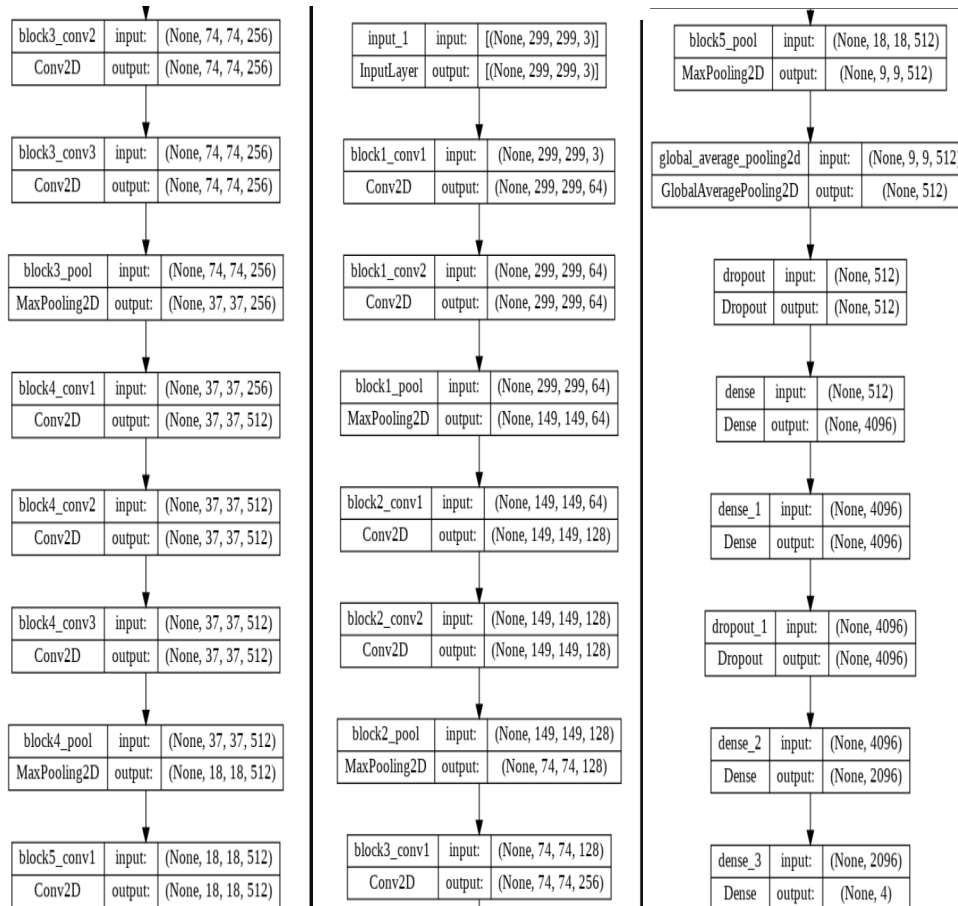


Figure 3.5 VGG 16 Flowchart

3.2.2.4 VGG 19 [41]

There are 19 layers in the VGG-19 convolutional neural network shown in Figure 3.6. A pre-trained version of the network that has been trained on more than a million photos is available in the ImageNet database. There are many animals, a keyboard, a mouse, and a pencil among the 1000, as well as other object categories that the pretrained network can identify.

For the project we imported the pre-trained VGG 19 model using Keras and transfer learning. And provided the model an input shape of 299 x 299 and use the imagenet weights and make the include top value false. And freeze some of its layer, then we added additional layers i.e. GlobalAveragePooling2D,

dropout layer, 2 x dense layers, a dropout layer and finally a dense layer. Then, we built our model using categorical cross entropy as the loss function and Adam as the optimizer.

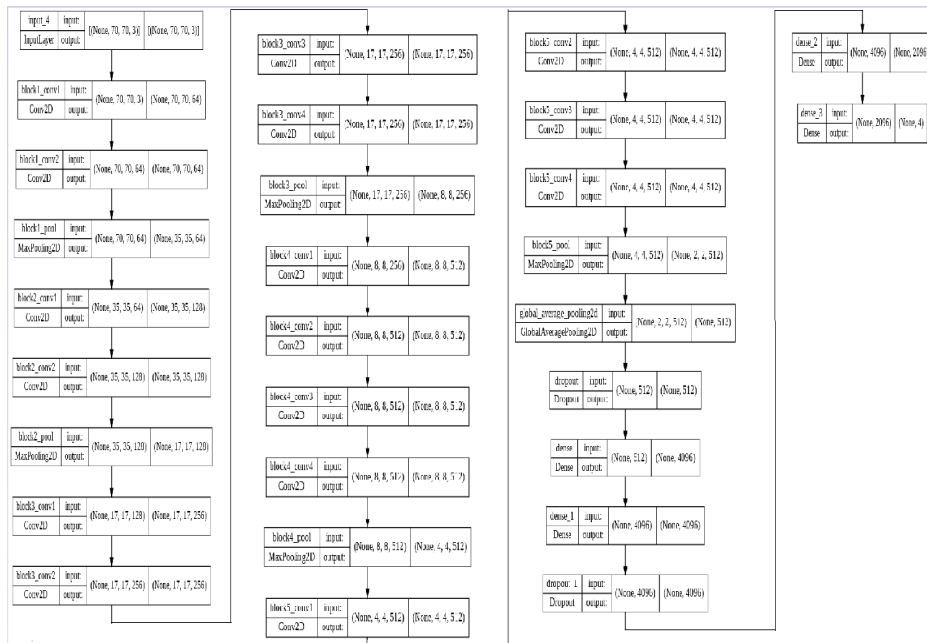


Figure 3.6 VGG 19 Flowchart

3.2.2.5 ResNet-50 [42]

Instead of directly studying the signal representation, understand the residual representation functions, as shown in Figure 3.7, ResNet can have a very deep network with up to 50 layers. This model has approx. 60M parameters. For the project we imported the pre-trained ResNet 50 model using Keras and transfer learning. And provided the model an input shape of 229 x 229 and use the imagenet weights and make the include top value false. And freeze some of its layer, then we added additional layers i.e. one flatten layer and two dense layers as it already has inbuilt layers. Then, we built our model using categorical crossentropy as the loss function and Adam as the optimizer.

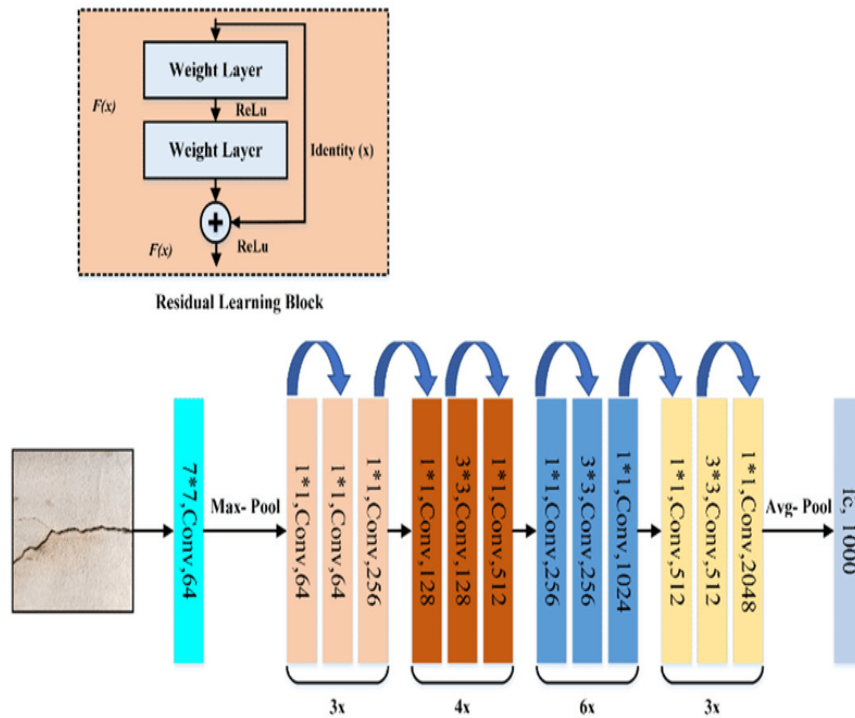


Figure 3.7 ResNet-50 Flowchart ^[49]

3.2.2.6 ResNet-152 [43]

Instead of directly studying the signal representation, understand the residual representation functions, as shown in Figure 3.8, ResNet can have a very deep network with up to 152 layers. This model has approx. 60M parameters. For the project we imported the pre-trained ResNet 152 model using Keras and transfer learning. And provided the model an input shape of 229 x 229 and use the imagenet weights and make the include top value false. And freeze some of its layer, then we added additional layers i.e. one flatten layer and two dense layers as it already has inbuilt layers. Then, we built our model using categorical crossentropy as the loss function and Adam as the optimizer.

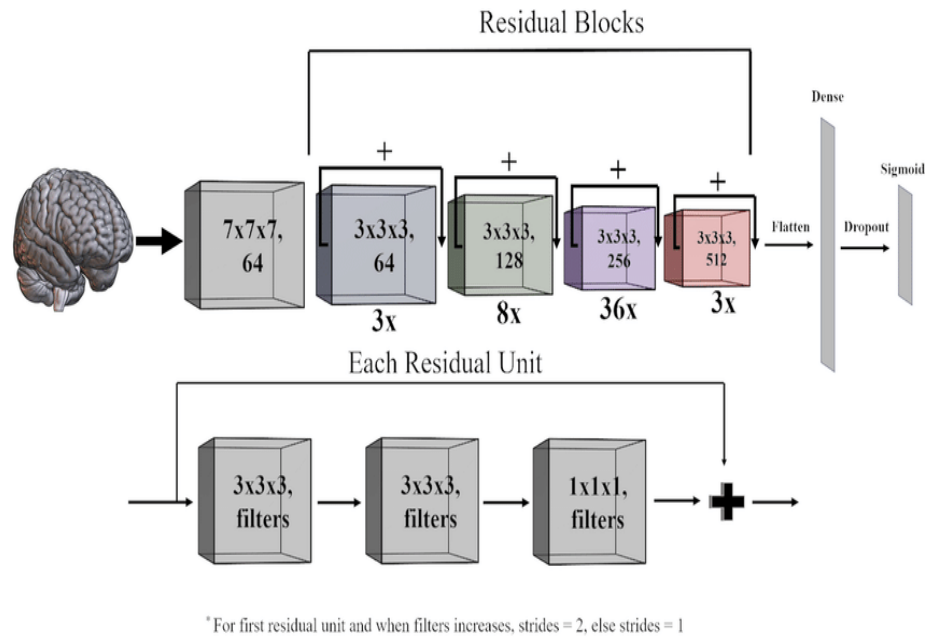


Figure 3.8 ResNet-152 Flowchart^[50]

3.4 CNN Architecture

Convolutional Neural Networks (CNNs) are a type of Deep Neural Network used in visual image processing, with applications in image classification, computer vision, medical image analysis, and more. CNNs are known for their ability to recognise and classify specific features within images, making them a popular choice for a range of image recognition tasks.

In mathematics, convolution is the act of multiplying two functions in order to obtain a third function that explains how one function alters the shape of the other. Convolution is the name CNN uses to describe this mathematical operation. In order to extract features from a picture, two images that can be represented as matrices are multiplied to produce an output.

In order to categorise an object with probabilistic values between 0 and 1, each input image will technically be passed through a sequence of convolution layers with filters (Kernels), Pooling, fully connected layers (FC), and apply Softmax function. To train and test CNN deep learning models, this is done.

The flowchart below illustrates how CNN analyses an input image and classifies the items according to values.

3.4.1 Basic Architecture

There are 2 main parts to a Convolutional Neural Network architecture.

- A convolution tool utilisation of feature extraction process to isolate and pinpoint the unique aspects of a picture for analysis.
- A layer that is completely connected and uses the results of the convolutional process and establishes the image class utilising the features that were previously extracted.

3.4.2 CNN Layers

The fact that these layers appear time and time again shows how deep our network is, and this type of structure is known as a deep neural network.

- Input : The input is provided as raw pixel values.
- Convolutional layer: Transforming the neuron layer's findings are input layers. There is a need to specify the filter to be used. Each filter can only be a 5x5 window that slides over input data and gets pixels with maximum intensities.
- Rectified linear unit [ReLU] layer: supplied a capability for activating the collected image data. In the back propagation situation, the ReLU function is used to stop pixel value changes.
- Pooling layer: carries out a volume downsampling process the length and width of the dimensions.
- FC layer: After focusing on the scoring class, it is possible to determine the input digits' maximum score.

There is a significant rise in complexity as we dig further and deeper into the layers. However, it would be worthwhile to go since while accuracy might improve, time consumption does, unfortunately, too.

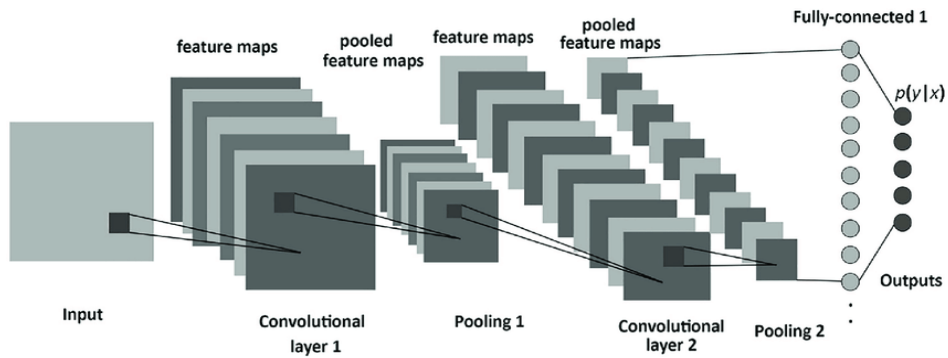


Figure 3.9 Different CNN Layers^[38]

1. Convolutional Layer

This is the initial layer that was used to extract the various features from the input photographs. At this layer, a mathematical operation called convolution is performed between the input picture and a filter with the dimensions $M \times M$. By sliding the filter over the input image, the dot product is obtained between the filter and the elements of the input image in relation to the filter's size ($M \times M$).

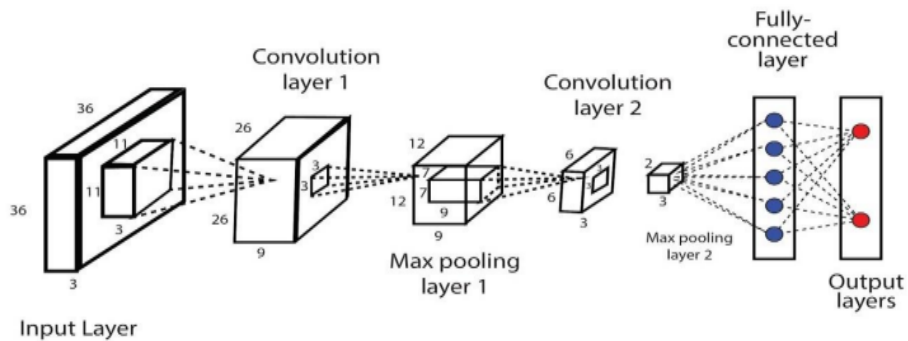


Figure 3.10 Convolutional Layer^[37]

The feature map is what provides details about the image, such as its corners and edges. This feature map is later made accessible to other layers so they can pick up new features from the source image.

2. Pooling Layer

To decrease the size of the feature map and simplify computation, the pooling layer is applied after the convolutional layer. Each feature map is downscaled, and the number of links between layers is decreased. This streamlines the data and makes it simpler for next layers to analyse. It is essential for enhancing convolutional neural networks' effectiveness.

There are many pooling processes, depending on the technology used. The most significant contribution to Max Pooling is made by the feature map. The components of an Image segment of a particular size are averaged out by employing average pooling. Sum Pooling determines the cumulative sums of the components inside the specified segment. The Pooling Layer often serves as a link between the FC Layer and the Convolutional Layer.

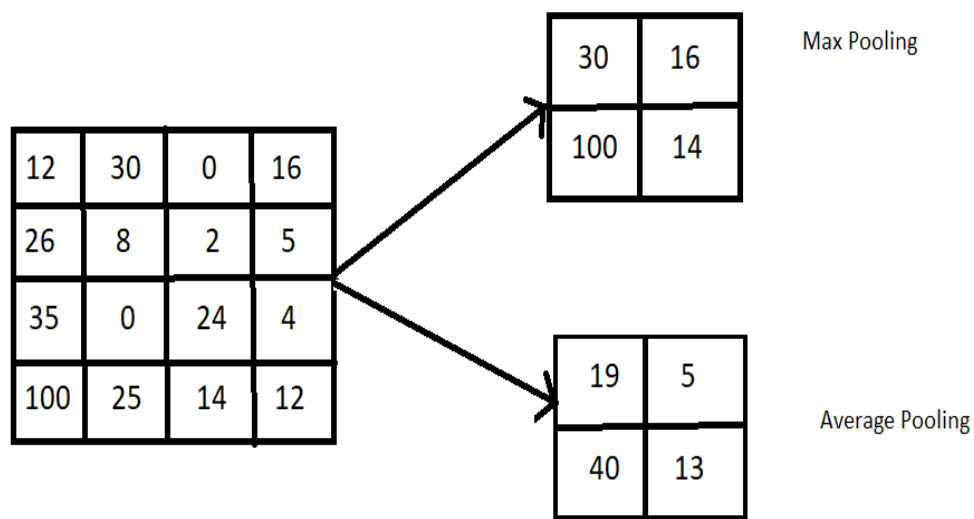
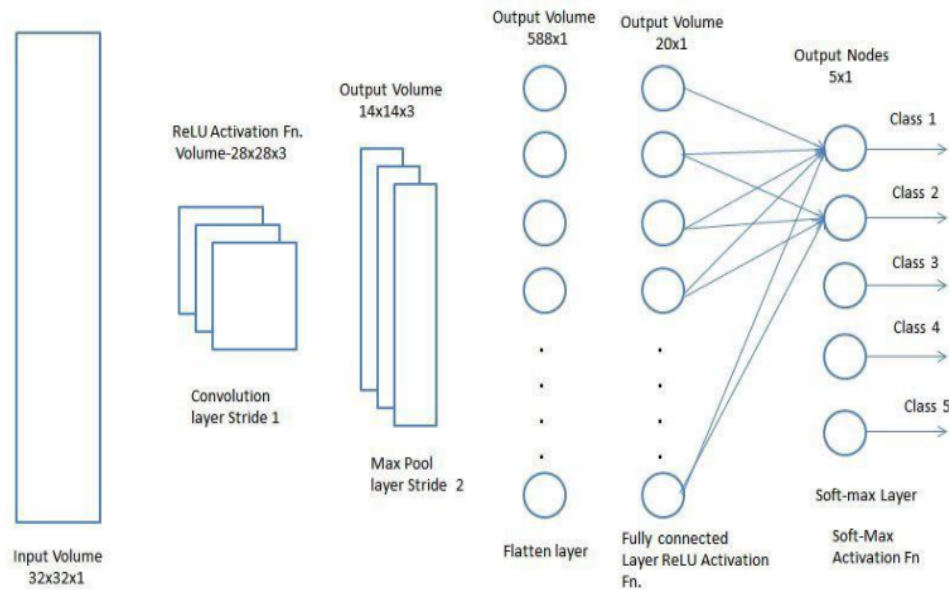


Figure 3.11 Pooling Layer

3. Fully Connected Layer

The Fully Connected (FC) layer, which also has weights and biases, connects the neurons between two layers. These last few layers of a CNN design are usually inserted in front of the output layer.



Source: Internet

Figure 3.12 Fully Connected Layer^[47]

This gives the FC layer with a flattened version of the input image from the layers below. The vector is flattened and then processed through a number of FC levels where quality operations on mathematical functions are performed. The categorization procedure becomes essential at this stage.

4. Dropout

The activation function of a neural network is responsible for introducing nonlinearity into the model. Commonly used activation functions include ReLU, Softmax, tanH, and Sigmoid functions. Each of these functions serves a specific purpose. For instance, the sigmoid and softmax functions are preferred for binary and multi-class classification in CNN models, respectively. By using these functions, the neural network becomes nonlinear and can better model complex relationships in the data.

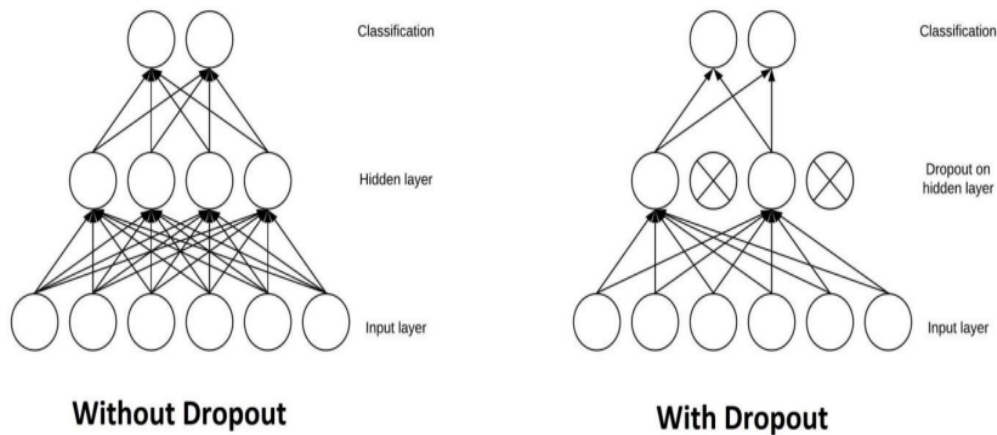


Figure 3.13 Dropout Layer^[47]

In order to solve this issue, a drop-out layer is used, which reduces the size of the model by eliminating a small number of neurons from the neural network during training. At a dropout value of 0.3, 30% of the neural network's nodes are arbitrarily removed.

5. Activation Functions

Activation functions in a neural network are responsible for transforming the weighted sum of inputs into an output. Nonlinear behaviour is often associated with activation functions in the design of network layers. When the output range of an activation function is limited, it may be referred to as a "squashing function." The selection of an activation function can significantly affect a neural network's capacity and performance, and different activation functions may be used in various parts of the model.

Technically, the activation function is applied before or after each network node's internal processing, even though networks are designed to use the same activation function for all nodes in a layer.

There are three basic types of layers that can be present in a network: input layers that accept raw data directly from the domain, hidden layers that receive data from one layer and move it to another, and output layers that generate predictions.

All buried levels typically employ the same activation function. The activation function employed in the output layer, which is frequently different from the hidden layers, will depend on the type of prediction required by the model.

For activation functions that are typically differentiable, one can deduce the first-order derivative from a given input value. This is required because backpropagation of error algorithms, which are often used to train neural networks, require the derivative of the prediction error in order to update the model's weights.

The activation function is one of the most crucial elements of the CNN model. Any type of complicated continuous relationship between network variables is utilised to identify and approximate. To put it simply, it specifies which model information should progress and which should not at the network's end.

The activation function of a neural network is responsible for introducing nonlinearity into the model. Commonly used activation functions include ReLU, Softmax, tanH, and Sigmoid functions. Each of these functions serves a specific purpose. For instance, the sigmoid and softmax functions are preferred for binary and multi-class classification in CNN models, respectively. By using these functions, the neural network becomes nonlinear and can better model complex relationships in the data.

- The process of feature extraction uses a convolution tool to separate and pinpoint the distinctive qualities of an image for analysis.
- A fully connected layer that uses the output of the convolutional process and classifies the image using the previously retrieved features.

Applications:

1. Semantic Segmentation: Rich data should be incorporated into an image segmentation model, a team of Hong Kong academics created the Deep Parsing Network in 2015. Additionally, UC

Berkeley researchers created fully convolutional networks that enhanced semantic segmentation to the state-of-the-art.

3.5 Building Ensemble Model

In model selection and creation or model used (3.3.2) we have seen that we used 5 CNN models that are pre trained with the help of Keras Library and Transfer Learning. The models we have used are Inception V3[29], DenseNet-201[30], VGG-16[31], VGG-19[32], ResNet-152[33]. These models had prior ImageNet weight training. And then observing the performance of each model we find that the VGG-16[31] and VGG-19[32] models are having the highest performance or accuracy above 95%. So we decided to use these two models for our ensemble model.

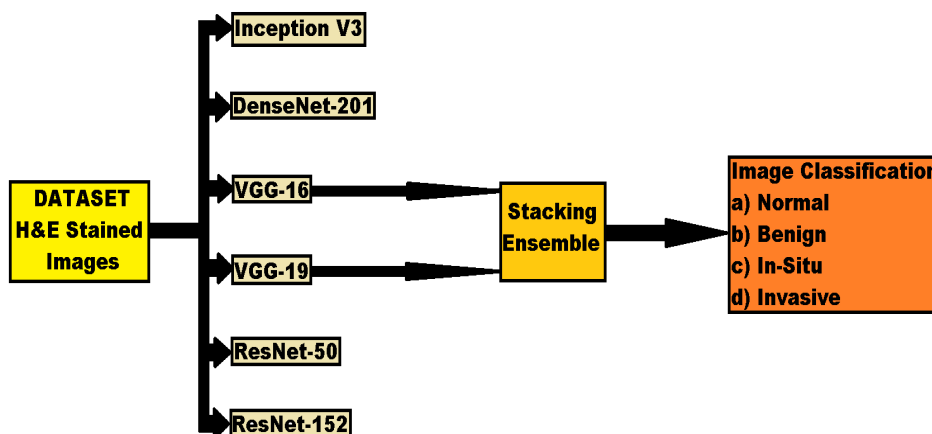


Figure 3.14 Ensemble model

We used a simple ensemble technique in which we are combining the selected models and stacking ensemble on them. And the resultant model provided us better performance.

CHAPTER-4 EXPERIMENT AND RESULT ANALYSIS

4.1 System Configuration

4.1.1 Software Requirements

These are the software configurations used:

Operating System: Windows 11.

IDE: Google Colaboratory, Jupyter Notebook (Used for data augmentation).

Python: Python is a programming language developed by Guido Van Rossum in 1991. One of the distinguishing features of Python is its use of significant whitespace, which enhances code readability. Its object-oriented approach and language constructs are designed to aid developers in producing clear, understandable code for projects of any size. Python supports dynamic typing and garbage collection, as well as various programming paradigms, including procedural, object-oriented, and functional programming.

Google Colaboratory: Colab is a cloud-based Jupyter notebook environment that is completely free to use. It allows your team members to simultaneously modify the notebooks you create, much like editing documents in Google Docs, and the best part is that it requires no setup. Colab supports many popular machine learning libraries that can be easily loaded into your notebook.

Jupyter Notebook: Jupyter is an interactive web tool that is free and open-source. It allows researchers to combine software code, computational results, explanatory text, and multimedia materials into a single document using a computational notebook. While computational notebooks have been available for some time, Jupyter has gained significant popularity in recent years due to its engaged user-developer community and new architecture that enables it to run on a laptop.

4.1.2 Hardware Requirements

These are the Hardware interfaces used Processor: Intel i5 9th Gen 4 cores 8 threads

RAM: 8GB DDR4 RAM

Monitor: 15” full HD colour monitor

Mouse: Scroll or optical mouse

Graphics Device: Nvidia GTX 1650 4GB DDR5 VRAM

Keyboard: Standard 110 keys keyboard

4.2 Learning Curves

A learning curve is a graphical representation of the relationship between performance and time, highlighting the repetitive tasks of an employee or worker. This concept is commonly used to measure the effectiveness of output and project costs. The learning curve was first introduced by psychologist Hermann Ebbinghaus in 1885. The graphical representation of the learning curve indicates initial learning, leading to significant cost savings, and subsequent learning that results in slower, more challenging cost reductions. The slope of the learning curve's graphical representation becomes steeper as the learning progresses.

When a machine learning model is being trained, a learning curve is essentially a plot that shows the evolution over time of a certain statistic relevant to learning. They only use mathematics to express the learning process.

The y-axis will therefore indicate error or performance, while the x-axis will represent time or progress.

These two categories of learning curves are frequently seen in charts:

- *Optimization Learning Curves:* Learning curves based on the measure used to optimise the model's parameters, such as loss or mean square error.

- *Performance Learning Curves*: Calculated learning curves for the metrics used to evaluate and select the model, such as accuracy, recall, precision or F1 score.

Accuracy & Loss are the two most well-known and discussed metrics in machine learning.

4.2.1 Accuracy Curve

Accuracy is one way to evaluate a classification model's performance. In many cases, it is expressed as a percentage. The accuracy is the proportion of forecasts where the predicted value and the actual value agree. For a certain sample, it is a binary value (true or false). Although the value is typically linked to the total or final model accuracy, it is frequently graphed and tracked during the training phase. Accuracy is easier to comprehend than loss.

4.2.2 Loss Curve

A loss function is a critical component of machine learning algorithms that determines the deviation of the predicted value from the true value based on probability or uncertainty. It provides a deeper understanding of the model's performance. Unlike accuracy, which is presented as a percentage, loss represents the total number of errors for each sample in the training or validation sets.

The objective during training is to minimise the loss by obtaining the optimal parameter values for the model, such as weights in neural networks. The most commonly used loss functions include cross-entropy loss, probability loss, log loss, and mean squared error, which produce the same results when calculating error rates between 0 and 1. Loss, unlike accuracy, can be applied to both classification and regression problems.

4.3 Results Obtained from various applied CNN Models

4.3.1 InceptionV3

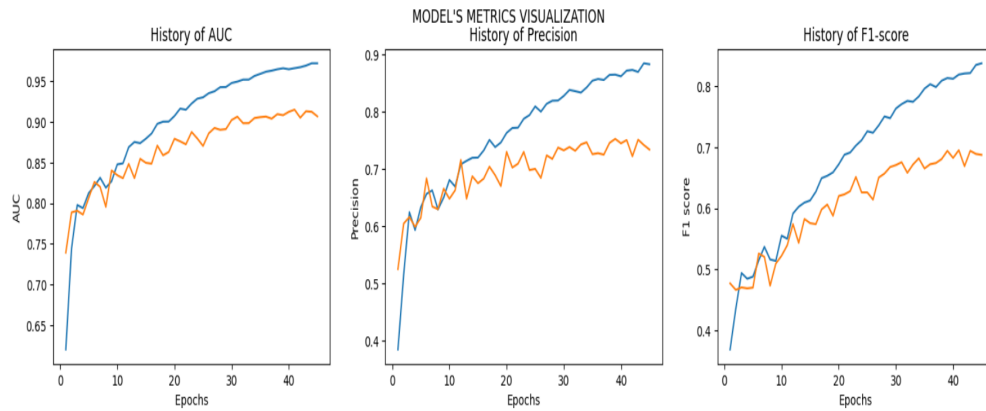


Figure 4.1 Inception V3 performance improvement over training time

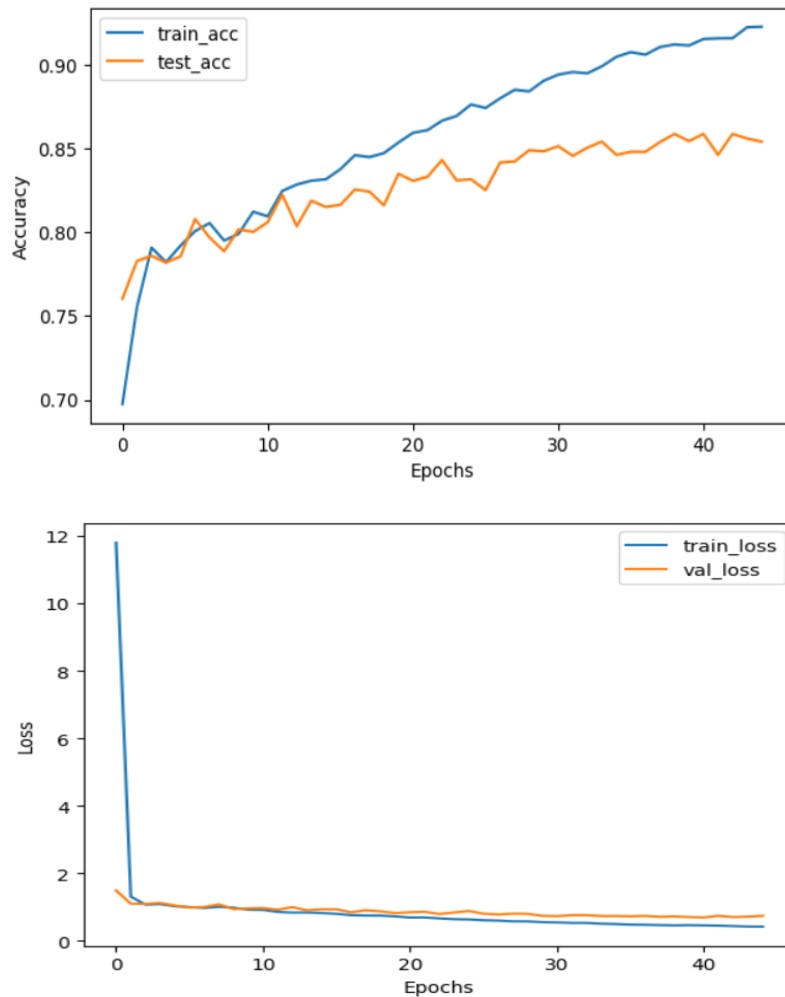


Figure 4.2 InceptionV3 accuracy and loss graph

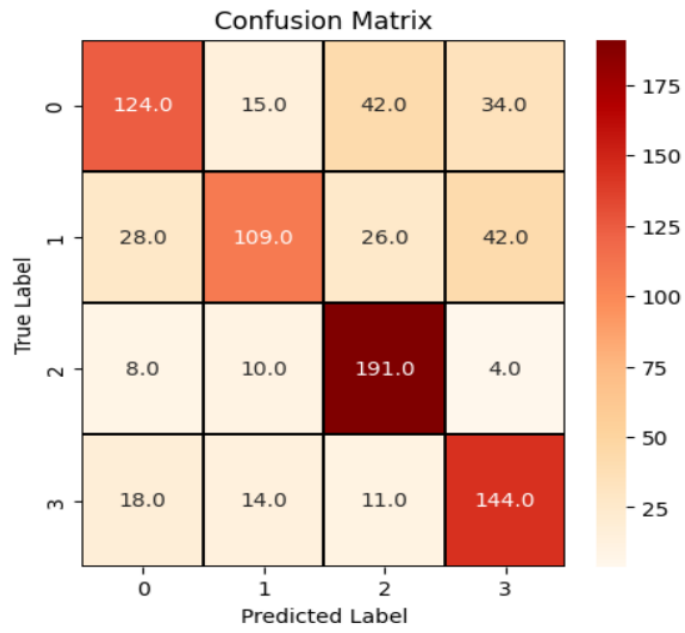


Figure 4.3 InceptionV3 Confusion Matrix

4.3.2 DenseNet-201

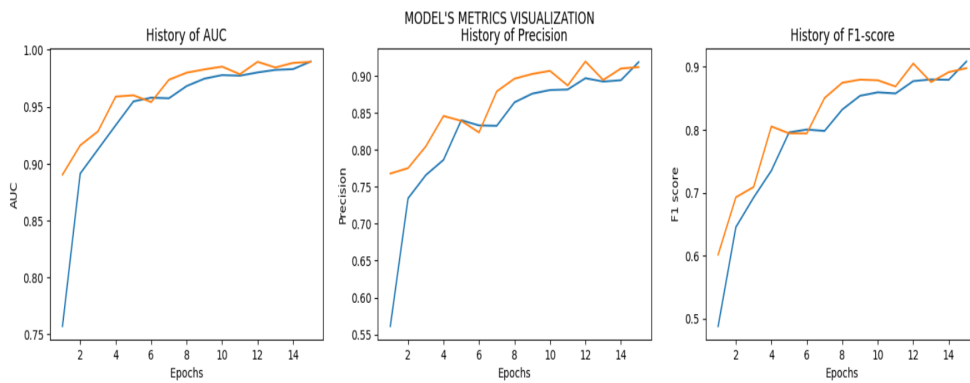


Figure 4.4 DenseNet-201 performance improvement over training time

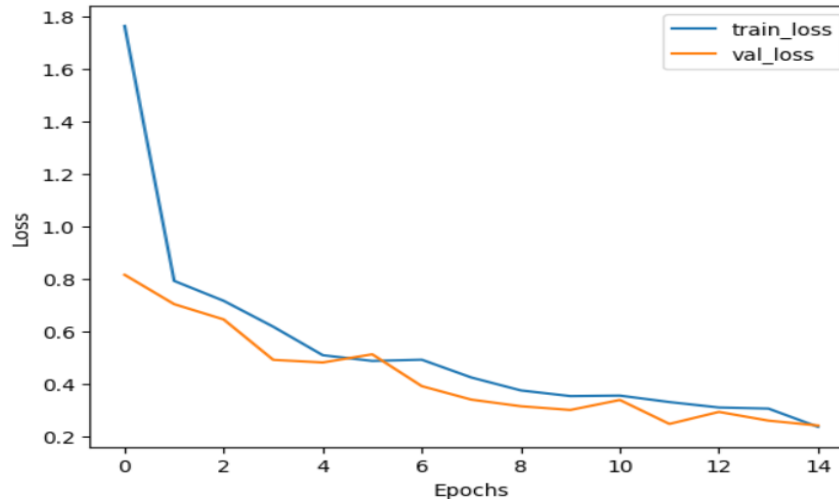
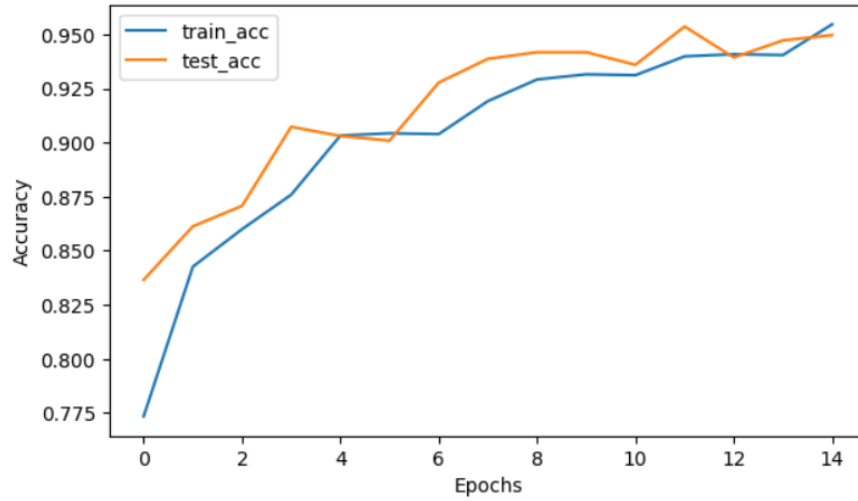


Figure 4.5 DenseNet-201 accuracy and loss graph

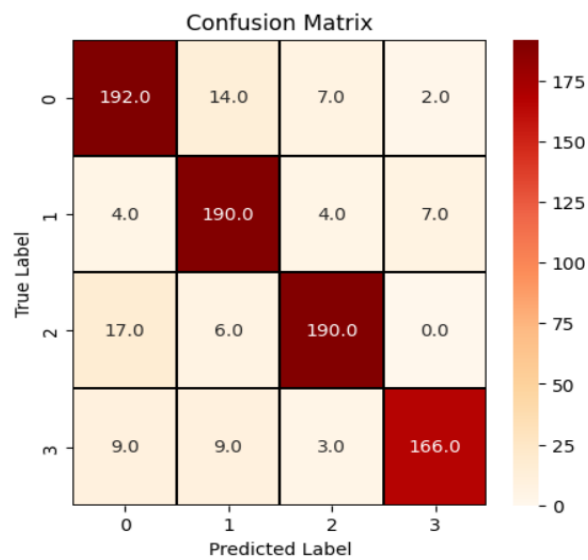


Figure 4.6 DenseNet-201 Confusion Matrix

4.3.3 VGG 16

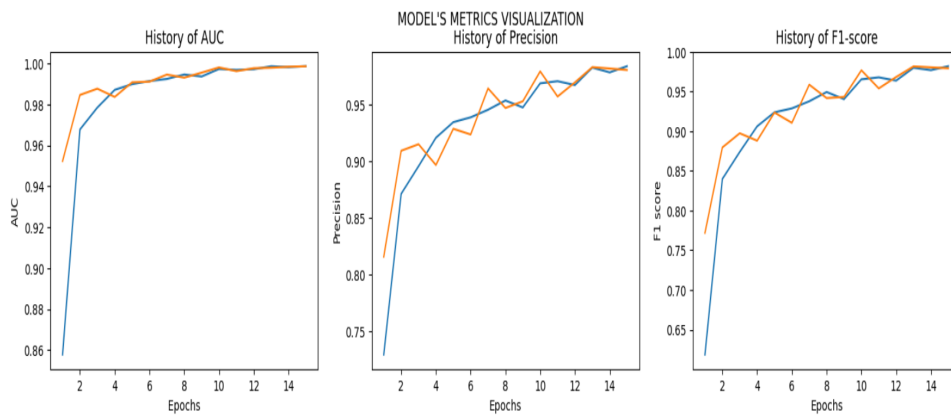


Figure 4.7 VGG16 performance improvement over training time

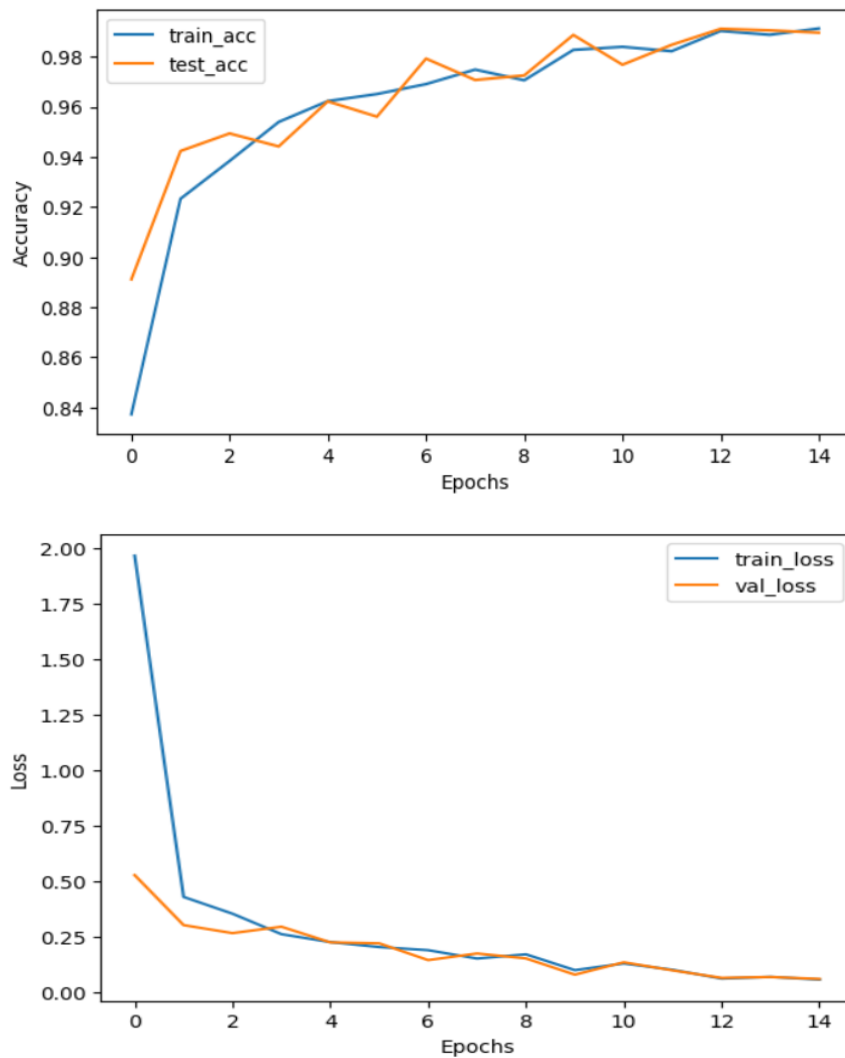


Figure 4.8 VGG16 accuracy and loss graph

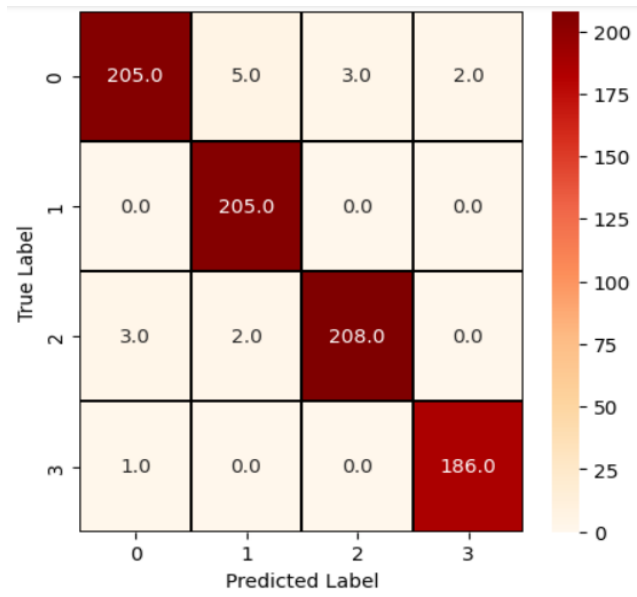


Figure 4.9 VGG16 Confusion Matrix

4.4.4 VGG 19

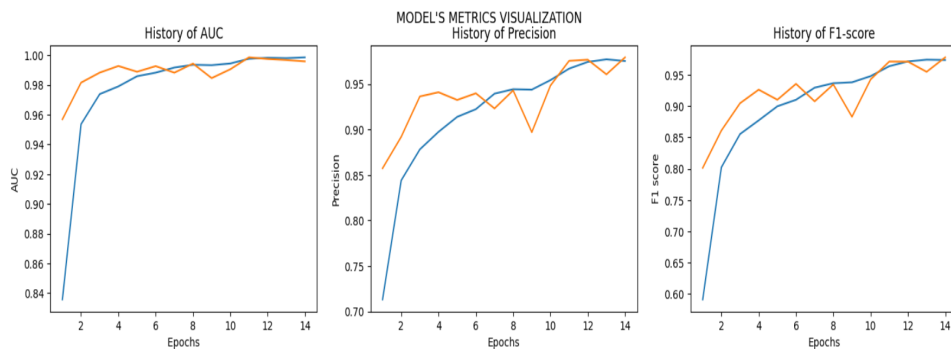
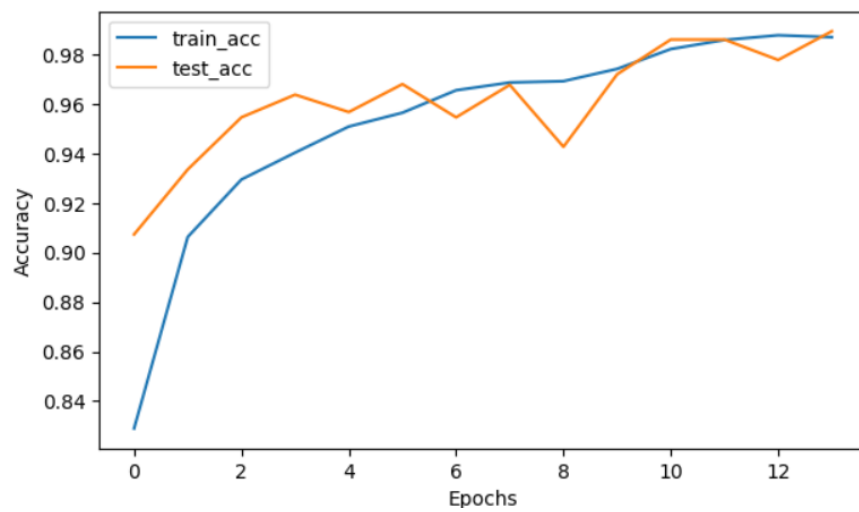


Figure 4.10 VGG19 performance improvement over training time



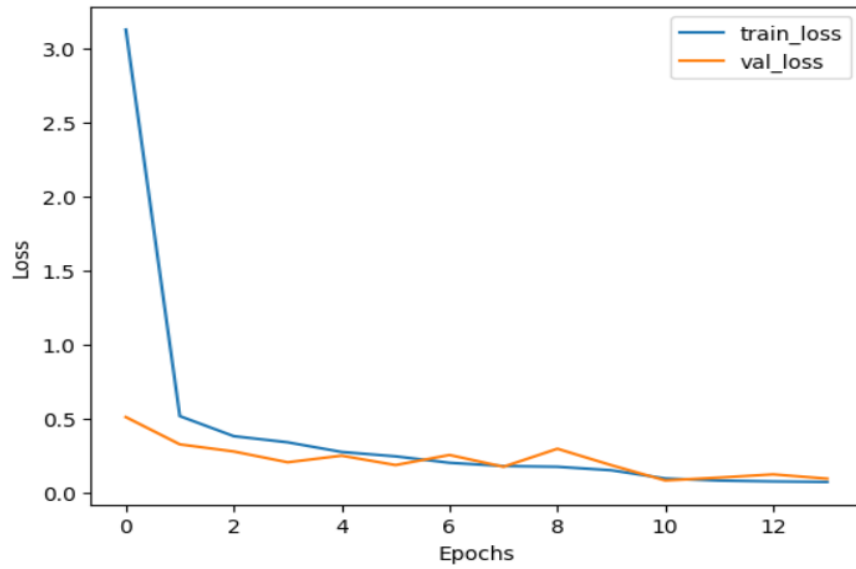


Figure 4.11 VGG19 accuracy and loss graph

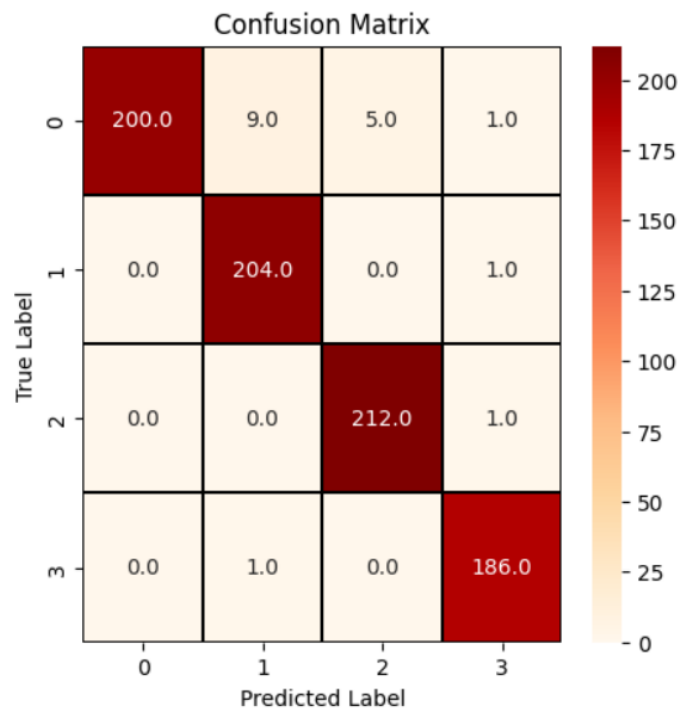


Figure 4.12 VGG19 Confusion Matrix

4.4.5 ResNet-50

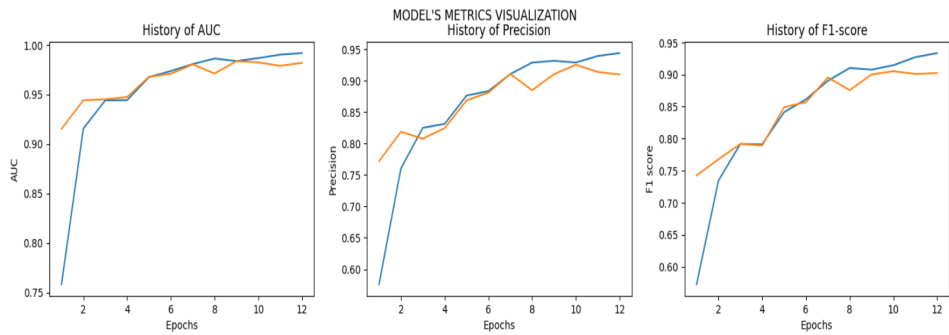


Figure 4.13 ResNet-50 performance improvement over training time

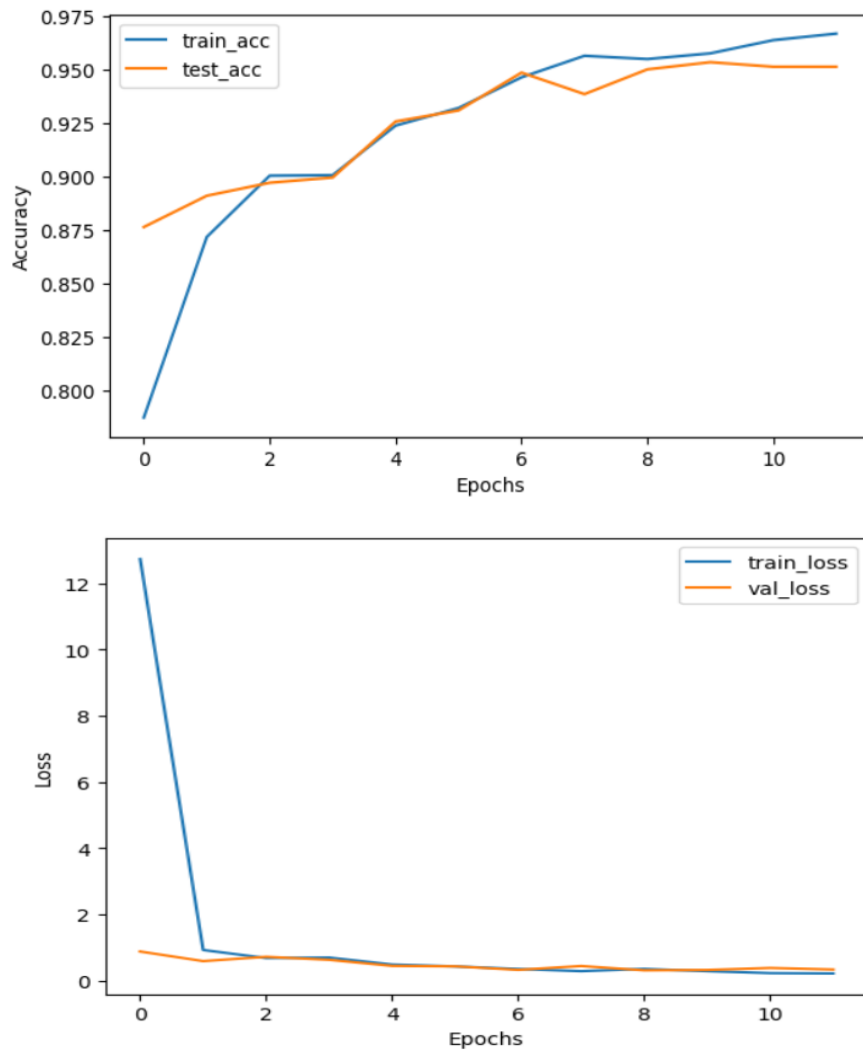


Figure 4.14 ResNet-50 accuracy and loss graph

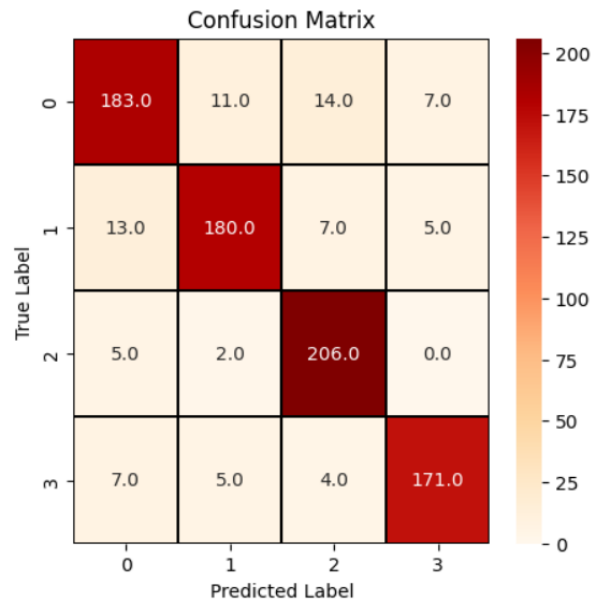


Figure 4.15 ResNet-50 Confusion Matrix

4.4.6 ResNet-152

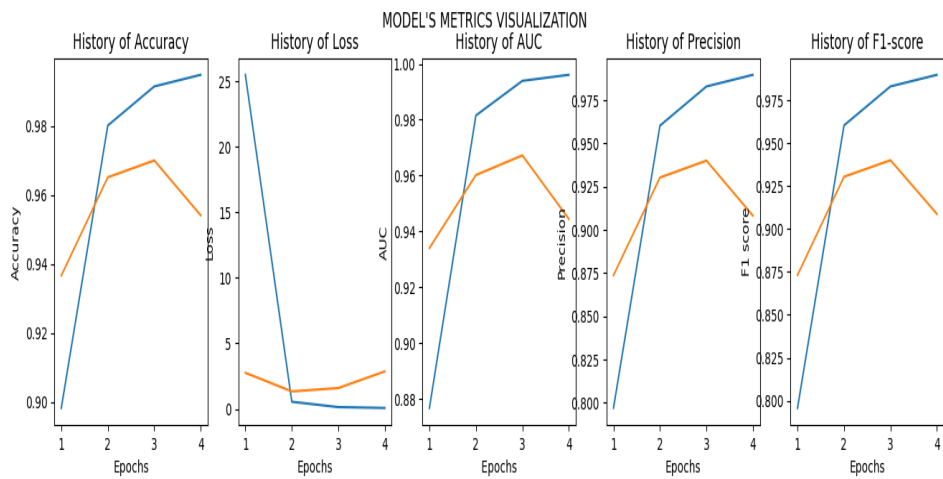


Figure 4.16 ResNet-152 performance improvement over training time

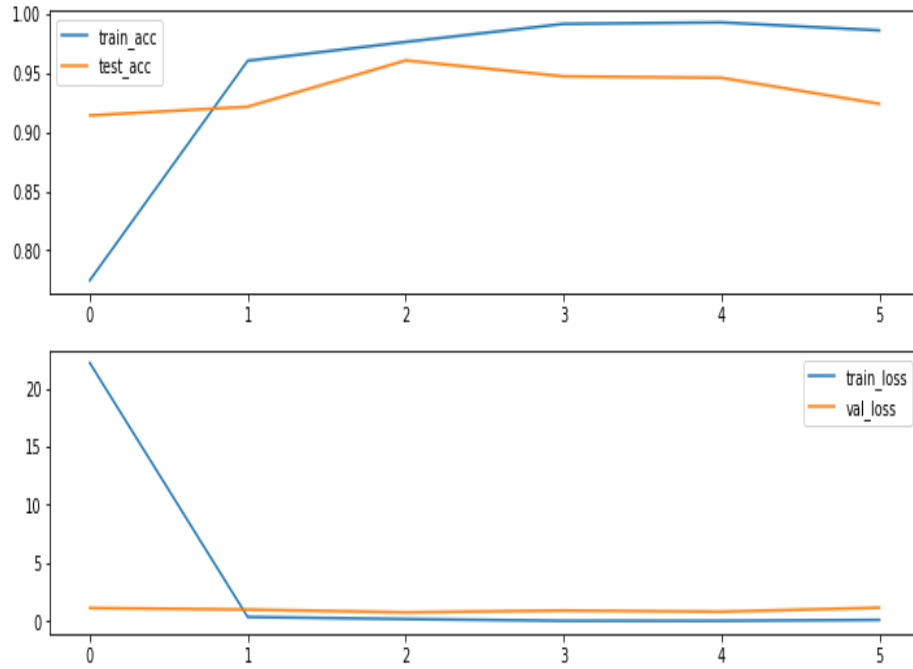


Figure 4.17 ResNet-152 accuracy and loss graph

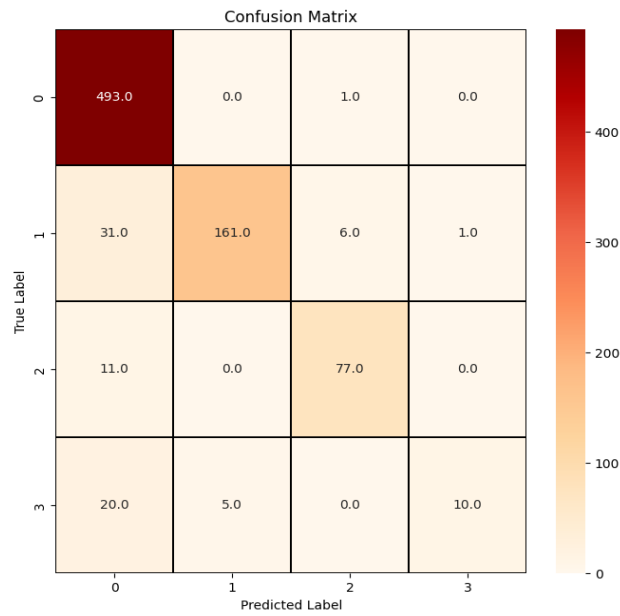


Figure 4.18 ResNet-152 Confusion Matrix

4.4 Results Obtained From Ensemble Model (VGG 16 + VGG 19)

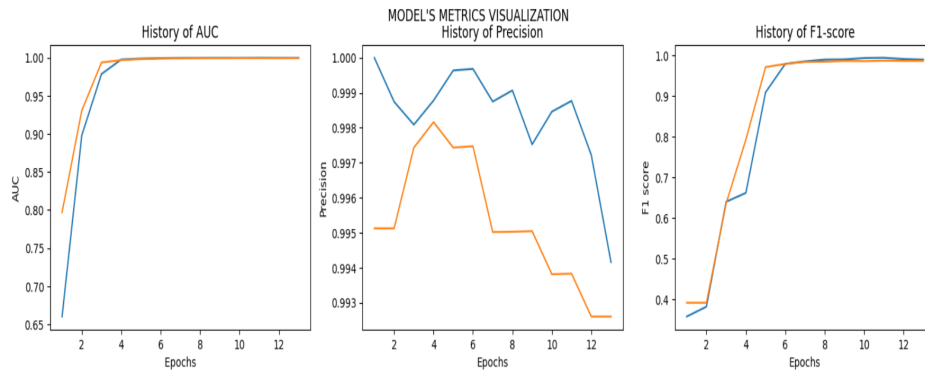


Figure 4.19 Ensemble Model performance improvement over training time

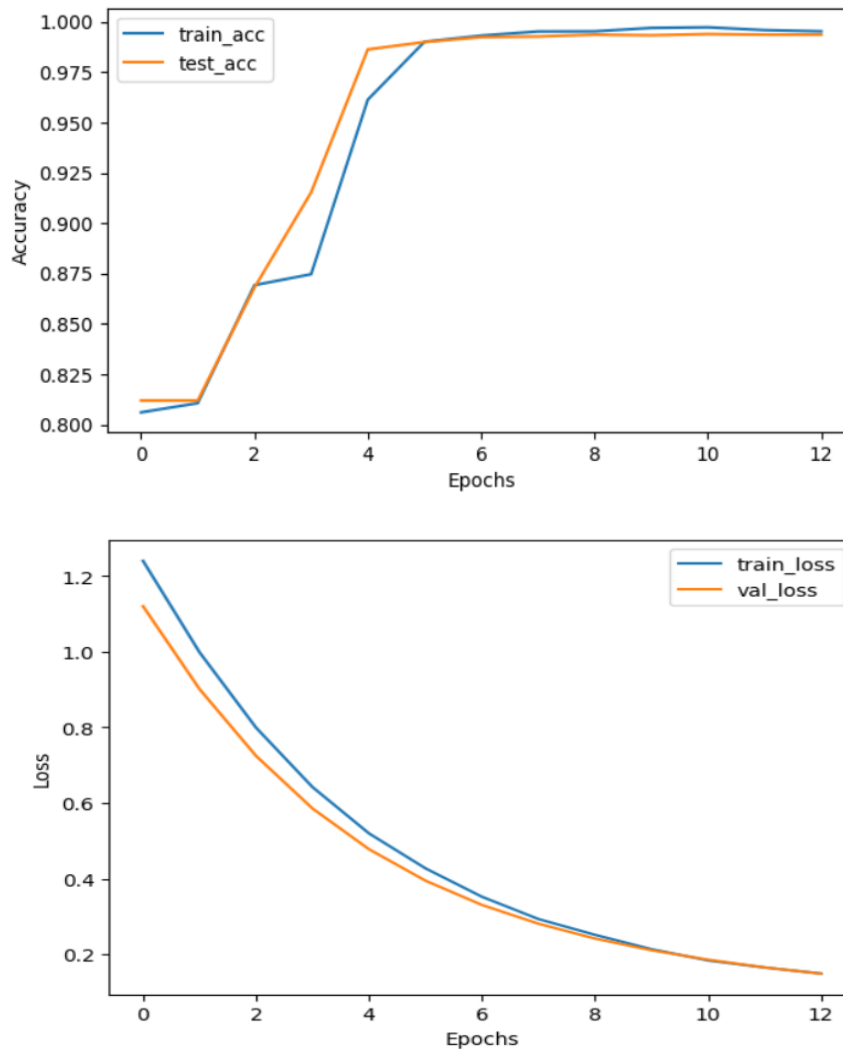


Figure 4.20 Ensemble model accuracy and loss graph

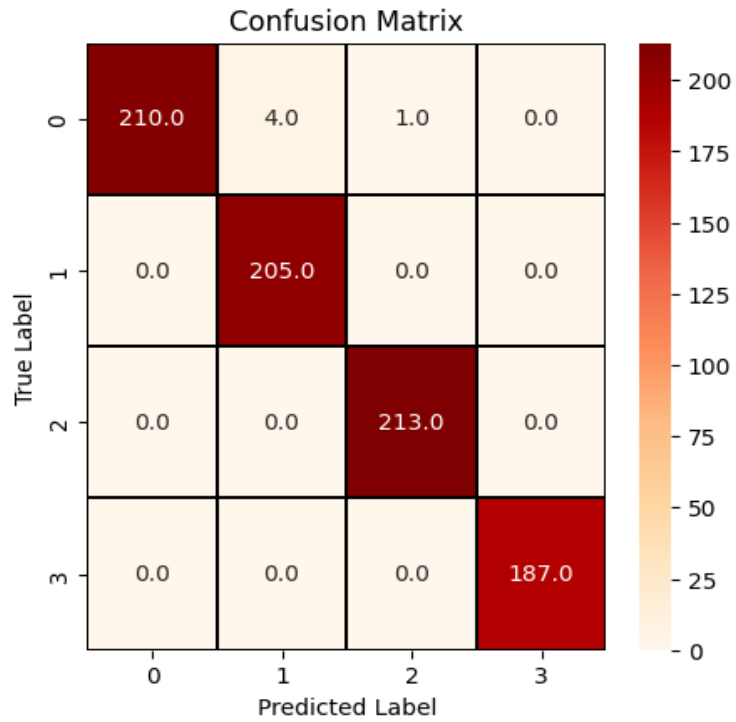


Figure 4.21 Ensemble model Confusion Matrix

4.5 Comparison between Implemented Models On basis of Accuracy

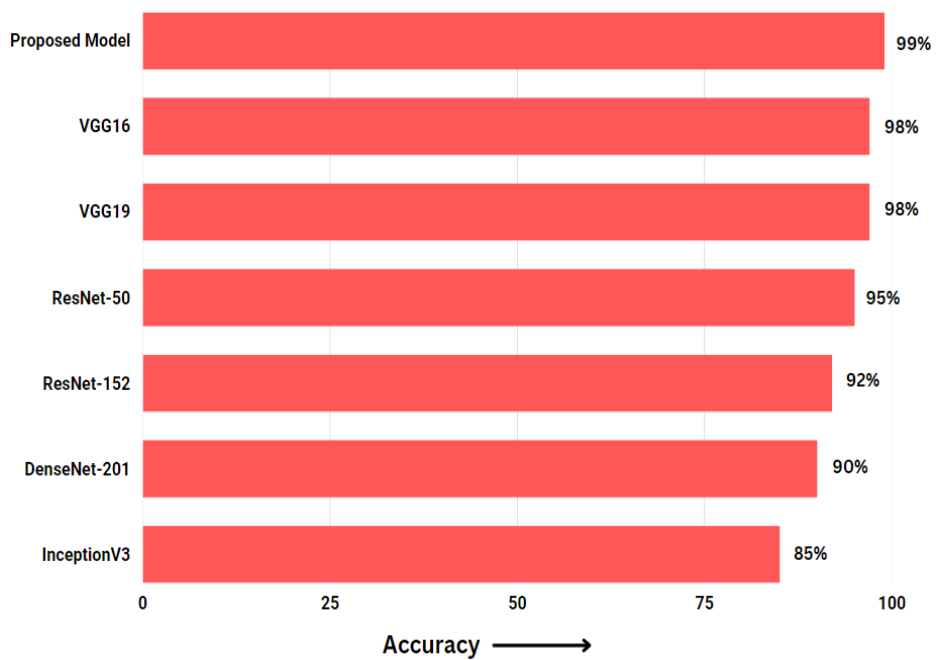


Figure 4.22 Comparison between implemented models on the basis of accuracy

4.5.1 Results Obtained from Ensemble Model when a breast cancer histology image is passed

Test-1 : Breast Cancer Histology Image passed from InSitu class.

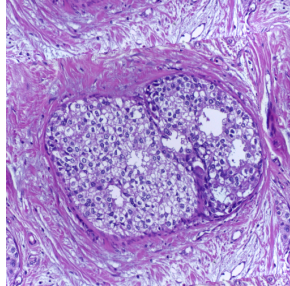


Figure 4.23 Breast Cancer Histology Image from InSitu Class

Model Prediction :

```
1/1 [=====] - ETA: 0s  
1/1 [=====] - 7s 7s/step  
The Model predicts that it is a InSitu tumor
```

Figure 4.24 Model Prediction

Test-2 : Breast Cancer Histology Image passed from Invasive class.

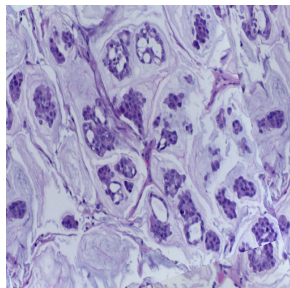


Figure 4.25 Breast Cancer Histology Image from Invasive Class

Model Prediction :

```
1/1 [=====] - ETA: 0s  
1/1 [=====] - 9s 9s/step  
The Model predicts that it is a Invasive tumor
```

Figure 4.26 Model Prediction

4.6 Classification Report

Table 4.1 Classification Report Table

S.No	Model	Precision (Avg)	Recall (Avg)	f1 score (Avg)	AUC (Avg)	Accuracy
1.	Ensemble Model	0.99	0.98	0.98	0.99	0.99
2.	VGG 16	0.98	0.97	0.97	0.99	0.98
3.	VGG 19	0.97	0.97	0.97	0.99	0.98
4.	ResNet-50	0.90	0.89	0.90	0.98	0.95
5.	ResNet-152	0.90	0.91	0.92	0.96	0.92
6.	DenseNet-201	0.79	0.90	0.90	0.94	0.90
7.	InceptionV3	0.73	0.65	0.68	0.90	0.85

4.7 Comparison with existing literature

Table 4.2 Comparison Table

Literature	Accuracy
Merium, et al.[2]	97.51%
Sarosa, et al.[3]	63.03%
Nawaz, et al.[4]	95.4%
Hameed, et al.[12]	95.29%
Proposed Model	99%

CHAPTER-5 CONCLUSIONS

5.1 Conclusions

By taking into account the patient's state and response to therapy, breast cancer presents a unique environment for medical diagnosis. The ability of machine learning to diagnose breast cancer has significantly improved. Despite advances in technology, there are still difficulties in accurately diagnosing and monitoring breast cancers. To enhance the predictive models, it is necessary to integrate the streams of biological, social, and demographic data. There are various models present in Machine Learning which we can use for breast cancer classification. We analysed the models and studied their characteristics. We also studied different research papers in order to choose our model or technique. We have applied five fine tuned CNN models on our dataset and choose two best performing models for our ensemble model. The method we used for our ensemble model is that we are combining the models that are trained on different classifiers together by stacking them. Using the ensemble approach further improved our performance and we were better able to predict the accuracy of our model.

5.2 Future Scope

In this project, a detailed analysis is required to choose the best options for the various parameters before creating a convolutional neural network (CNN). Numerous choices for the number of hidden layers and nodes in each layer can be made while examining neural networks. The neural network used in this project's output layer makes use of the Softmax activation function. But for those layers, additional activation mechanisms can also be researched. That absolutely affects how well our deep neural network performs. And the model's accuracy can be improved if we can identify the more exact and accurate activation function and parameters.

As for future work, we want a proper dataset that has sufficient data. Because the dataset that we have used has only 400 images that is not enough. So we used data augmentation techniques like Image Data Generator to create our

own dataset so that the models can be trained with sufficient data. And we also wanted to work with other CNN models and create even better ensemble model.

5.3 Applications

One of the most cutting-edge areas of medical study is the classification system for breast cancer. Because it is a highly tedious or complicated process for the pathologist to manually check the histopathological scans, the classification method can be utilised in hospitals, medical facilities, and by pathologists to identify the kind of breast cancer. Additionally, it is crucial to conserve time because each second counts and has the potential to save a patient's life. Researchers can utilise the classification system as well. So, these are some examples of the project's applications or the fields where the project can be used.

References

- [1] Murtaza, Ghulam, et al. "Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges." *Artificial Intelligence Review* 53.3 (2020): 1655-1720.
- [2] Amrane, Meriem, et al. "Breast cancer classification using machine learning." *2018 Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT)*. IEEE, 2018.
- [3] Sarosa, Syam Julio A., Fitri Utamingrum, and Fitra A. Bachtiar. "Mammogram breast cancer classification using gray-level co-occurrence matrix and support vector machine." *2018 international conference on sustainable information engineering and technology (SIET)*. IEEE, 2018.
- [4] Zebari, Dilovan Asaad, et al. "Systematic review of computing approaches for breast cancer detection based computer aided diagnosis using mammogram images." *Applied Artificial Intelligence* 35.15 (2021): 2157-2203.
- [5] Nawaz, Majid, Adel A. Sewissy, and Taysir Hassan A. Soliman. "Multi-class breast cancer classification using deep learning convolutional neural network." *Int. J. Adv. Comput. Sci. Appl* 9.6 (2018): 316-332.
- [6] Obaid, O. Ibrahim, et al. "Evaluating the performance of machine learning techniques in the classification of Wisconsin Breast Cancer." *International Journal of Engineering & Technology* 7.4.36 (2018): 160-166.
- [7] Khourdifi, Youness, and Mohamed Bahaj. "Applying best machine learning algorithms for breast cancer prediction and classification." *2018 International conference on electronics, control, optimization and computer science (ICECOCS)*. IEEE, 2018.
- [8] Vijayakumar, K., Vinod J. Kadam, and Sudhir Kumar Sharma. "Breast cancer diagnosis using multiple activation deep neural network." *Concurrent Engineering* 29.3 (2021): 275-284.

- [9] Akselrod-Ballin, Ayelet, et al. "Predicting breast cancer by applying deep learning to linked health records and mammograms." *Radiology* 292.2 (2019): 331-342.
- [10] Buda, Mateusz, et al. "A data set and deep learning algorithm for the detection of masses and architectural distortions in digital breast tomosynthesis images." *JAMA network open* 4.8 (2021): e2119100-e2119100.
- [11] Shahidi, Faezehsadat, et al. "Breast cancer classification using deep learning approaches and histopathology image: a comparison study." *IEEE Access* 8 (2020): 187531-187552.
- [12] Hameed, Zabit, et al. "Breast cancer histopathology image classification using an ensemble of deep learning models." *Sensors* 20.16 (2020): 4373.
- [13] Araújo, Teresa, et al. "Classification of breast cancer histology images using convolutional neural networks." *PloS one* 12.6 (2017): e0177544.
- [14] Bardou, Dalal, Kun Zhang, and Sayed Mohammad Ahmad. "Classification of breast cancer based on histology images using convolutional neural networks." *Ieee Access* 6 (2018): 24680-24693.
- [15] Yang, Zhanbo, et al. "EMS-Net: Ensemble of multiscale convolutional neural networks for classification of breast cancer histology images." *Neurocomputing* 366 (2019): 46-53.
- [16] Krithiga, R., and P. Geetha. "Breast cancer detection, segmentation and classification on histopathology images analysis: a systematic review." *Archives of Computational Methods in Engineering* 28.4 (2021): 2607-2619.
- [17] Hirra, Irum, et al. "Breast cancer classification from histopathological images using patch-based deep learning modeling." *IEEE Access* 9 (2021): 24273-24287.
- [18] Sharma, Shallu, and Rajesh Mehra. "Conventional machine learning and deep learning approach for multi-classification of breast cancer histopathology

images—a comparative insight." *Journal of digital imaging* 33.3 (2020): 632-654.

[19] Vaka, Anji Reddy, Badal Soni, and Sudheer Reddy. "Breast cancer detection by leveraging Machine Learning." *ICT Express* 6.4 (2020): 320-324.

[20] Bharati, Subrato, Prajoy Podder, and M. Mondal. "Artificial neural network-based breast cancer screening: a comprehensive review." *arXiv preprint arXiv:2006.01767* (2020).

[21] Murtaza, Ghulam, et al. "Breast cancer multi-classification through deep neural network and hierarchical classification approach." *Multimedia Tools and Applications* 79.21 (2020): 15481-15511.

[22] Yan, Rui, et al. "Breast cancer histopathological image classification using a hybrid deep neural network." *Methods* 173 (2020): 52-60.

[23] Mahmood, Tahir, et al. "Artificial intelligence-based mitosis detection in breast cancer histopathology images using faster R-CNN and deep CNNs." *Journal of clinical medicine* 9.3 (2020): 749.

[24] Hu, Chuhan, et al. "Classification of breast cancer histopathological image with deep residual learning." *International Journal of Imaging Systems and Technology* 31.3 (2021): 1583-1594.

[25] Al-Haija, Qasem Abu, and Adeola Adebajo. "Breast cancer diagnosis in histopathological images using ResNet-50 convolutional neural network." *2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*. IEEE, 2020.

[26] Ahmad, Nouman, Sohail Asghar, and Saira Andleeb Gillani. "Transfer learning-assisted multi-resolution breast cancer histopathological images classification." *The Visual Computer* 38.8 (2022): 2751-2770.

[27] Burçak, Kadir Can, Ömer Kaan Baykan, and Harun Uğuz. "A new deep convolutional neural network model for classifying breast cancer histopathological images and the hyperparameter optimisation of the proposed model." *The Journal of Supercomputing* 77.1 (2021): 973-989.

- [28] Wang, Pin, et al. "Automatic classification of breast cancer histopathological images based on deep feature fusion and enhanced routing." *Biomedical Signal Processing and Control* 65 (2021): 102341.
- [29] <https://numpy.org/doc/>
- [30] https://python101.pythonlibrary.org/chapter16_os.html
- [31] <https://docs.python.org/3/library/>
- [32] <https://docs.python.org/3/library/>
- [33] <https://keras.io/api/>
- [34] <https://www.tensorflow.org/>
- [35] <https://docs.python.org/3/library/>
- [36] <https://iciar2018-challenge.grand-challenge.org/Dataset/>
- [37] <https://iciar2018-challenge.grand-challenge.org/Dataset/>
- [38] Saini, Manisha, and Seba Susan. "Data augmentation of minority class with transfer learning for classification of imbalanced breast cancer dataset using inception-v3." *Iberian Conference on Pattern Recognition and Image Analysis*. Springer, Cham, 2019.
- [39] Jaiswal, Aayush, et al. "Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning." *Journal of Biomolecular Structure and Dynamics* 39.15 (2021): 5682-5689.
- [40] Albashish, Dheeb, et al. "Deep CNN model based on VGG16 for breast cancer classification." *2021 International Conference on Information Technology (ICIT)*. IEEE, 2021.
- [41] Singh, Rishav, et al. "Imbalanced breast cancer classification using transfer learning." *IEEE/ACM transactions on computational biology and bioinformatics* 18.1 (2020): 83-93.

- [42] Koonce, Brett, and Brett Koonce. "ResNet 50." *Convolutional Neural Networks with Swift for Tensorflow: Image Recognition and Dataset Categorization* (2021): 63-72.
- [43] Reenadevi, R., T. Sathiya, and B. Sathiyabhama. "Breast cancer histopathological image classification using augmentation based on optimized deep ResNet-152 structure." *Annals of the Romanian Society for Cell Biology* 25.6 (2021): 5866-5874.
- [44] Yala, Adam, et al. "A deep learning mammography-based model for improved breast cancer risk prediction." *Radiology* 292.1 (2019): 60-66.
- [45] Zou, Zhengxia, et al. "Object detection in 20 years: A survey." *arXiv preprint arXiv:1905.05055* (2019).
- [46] Sheikh, Taimoor Shakeel, Yonghee Lee, and Migyung Cho. "Histopathological classification of breast cancer images using a multi-scale input and multi-feature network." *Cancers* 12.8 (2020): 2031.
- [47] <https://cse.anits.edu.in/projects/projects2021A10.pdf>
- [48] <https://www.mdpi.com/1099-4300/19/6/242>
- [49] https://www.researchgate.net/figure/The-architecture-of-ResNet-50-model_fig4_349717475
- [50] https://www.researchgate.net/figure/Schematic-of-the-3D-ResNet-152-that-was-used-for-this-analysis-Each-image-was-first_fig4_357899396