A Comparative Study of Brain Tumor Classification Using Deep Learning Models

A DISSERTATION

SUBMITTED MAJOR PROJECT – II FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
INFORMATION SYSTEMS

Submitted by

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2K22/ISY/20

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CANDIDATE'S DECLARATION

I, Tanmoy Das, Roll No – 2K22/ISY/20 students of M.Tech (Department of Information Technology), hereby declare that the project Dissertation titled "A Comparative Study of Brain Tumor Classification Using Deep Learning Models" which is submitted by me to the Department of Information Technology, Delhi Technological University, Delhi in partial fulfilment of the requirementfor the award of degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "A Comparative Study of Brain Tumor Classification Using Deep Learning Models" which is submitted by Tanmoy Das, Roll No – 2K22/ISY/20, Department of Information Technology, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ACKNOWLEDGEMENT

I wish to express my sincerest gratitude to Prof. DINESH K VISHWAKARMA and DR. VIRENDER RANGA for their continuous guidance and mentorship that they provided me during the project. That showed me the path to achieve my targets by explaining all the tasks to be done and explained to me the importance of this project as well as its industrial relevance. They were always ready to help me and clear my doubts regarding any hurdles in this project. Without their constant support and motivation, this project would not have been successful.

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Abstract

Brain tumor is a significant and often fatal disease, necessitating early detection for effective treatment. In this paper, we compare four deep learning techniques—DenseNet-121, ResNet-50, VGG-16, and Inception-V3—for classifying brain tumors using MRI images. The evaluation is based on accuracy, precision, F1-score, AUC ROC score, and Cohen Kappa score on the brain-tumor-detection-mri dataset from Kaggle, consisting of 2400+ images across two classes. Our results show an accuracy of 94.5% for DenseNet-121, 97.5% for ResNet-50, and 94% for both VGG-16 and Inception-V3, with a Cohen Kappa score of 73%. These findings provide insights into the strengths and weaknesses of each technique, aiding in the selection of the most suitable approach for medical image classification.

Skin cancer is a prevalent disease worldwide, with increasing incidence rates. Early detection is crucial for successful treatment, as evidenced by statistics from the World Health Organization. In this proposed paper, we aim to develop a robust deep learning model for detecting benign or malignant skin cancer. We employ state-of-the-art pretrained deep neural network models, including Xceptron, EfficientNet, ResNet, and VGG-16, fine-tuned for our task. Our models achieve accuracies of 89.0%, 87.05%, 71.0%, and 83.33%, respectively. Additionally, we evaluate precision, recall, and F1-score for detailed analysis. The findings from our experiments are presented in this research work, offering valuable insights for skin cancer detection using deep learning techniques.

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List of Abbreviations

CNN	Convolutional Neural Network
VGG	Visual Geometry Group
RESNET	Residual Network
DENSENET	Densely Connected Network
EFFICIENTNET	Efficient Network
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
ROC	Receiver Operator Characteristics
AUC	Area Under Curve

Chapter 1

INTRODUCTION

Two of the most deadliest diseases threatening the human health of the world are skin cancer and brain cancer. Though different, both types of cancer can have disastrous effects if undiagnosed and hence untreated. Gaining an appreciation of The severity of these malignancies and the urgent need for efficient interventions entail awareness of how common they are, risk factors for and consequences of the illness, which, for cancer, INCLUDE Cancer and skin cancer are monstrous problems, with each having complicational – involved risks. The actuality of these malignancies and the huge morbidity and mortality they may get highlighted the importance toward preventive, early detection and targeted therapy strategies. We can work to lessen the burden of these diseases and enhance the prognosis for inflicts the affected individuals, awareness raising and advocating research, and putting an practice. Recent research has been done on the use of deep Cancer detection and diagnosis in medical imaging are used to learn about X-rays, mammograms, MRI[1] is a radiological scan that may consist of abnormalities, lesion tumors. Convolutional neural networks[2] are a subset of deep learning architectures that have been designed Image analysis needs—they demonstrate great performance in such applications. High sensitivity and specificity, these algorithms can identify small patterns suggestive of cancer by understanding complex features and spatial correlations within images, along with Researchers are now looking into possibilities to refine deep learning model quality through GANs[3]. generalization; create synthetic images for training; enhance medical Imaging datasets.

1.1 Classifications of Brain Tumor for Cancer Detection

The uncontrolled growth of cells in the brain or the tissue surrounding the brain is called a brain Cancer presents a massive hurdle to the field of oncology even though the brain tumor Although they are not as widespread as the cancers of the lung or breast, they can still make an enormous difference in Neurological Function and Health The American Brain Tumor Association (ABTA) It further stated that such reports put the estimation of new cases of primary brain tumours at 87,000 people yearly in the United States alone. Deep Learning applies state-of-the-art algorithms in the data of analysis of medical images and segments them accordingly. Regions, subtypes of classification of tumors, outcome forecasting of patients, and optimum treatment plans. This gives new solutions to problems that come with brain cancer detection. Deep learning algorithms guarantee the early detection of brain tumors, making it possible to find out tumor boundary delineation[4], individualized treatment planning based on patient molecular application and prediction models by integrating multi-modality dataset profiles and disease prognosis Imaging features, genomic profiles, as well as clinical variables. Furthermore, deep learning was hugely potential of revolutionize neuro-oncology, advance our knowledge of brain cancer biology, and enhance patient outcomes using both artificial intelligence and big-data analytics. We be considered to use medical imaging with the MRI images[1] for the detection of the tumours accurately.

1.2 Classification of Skin Cancer Benign Vs. Malignant

Skin cancer is one of the most common types of cancer today, leading to the deaths of millions of yearly. The World Health Organization, also known as WHO estimates 132,000 melanomas and 2 to 3 million non-melanoma skin cancer cases. One major risk factor for skin cancer is overexposure to ultraviolet (UV) radiation. the sun or artificial sources, like tanning beds. history of sunburns, pale skin, a family history of skin cancer, and specific genetic variables al play into its development. Skin Cancer is more common in the elderly, and the overall frequency of cancer increases with age. characterized by it has many types of skin cancer, among which melanoma, because it tends to spread to other deadly cancers tissues if it is not detected and treated shortly afterwards. Melanoma remains a major cause of morbidity and mortality globally despite strides made in its detection and treatment to Important need for health promotion and preventive care. Recent Studies on Deep Learning-Based Skin Cancer Detection Showed Noticeable Advances in early diagnosis and intervention accuracy. Deep learning with convolutional neural network (CNN)[2] models are demonstrated in works of Esteva et al. (2017) and Haenssle et al. (2018)[5]. Models are built from large training data sets with images of dermatoscopy: and these however, obtained sensitivity comparable to dermatologists at differentiating between benign and malignant melanoma. Tschandl et al. (2019) have realized pioneering breakthroughs that extended the Multi-class classification method performs very well in the automation in diagnosing melanoma and other skin diseases. Furthermore, careers "the topic of recent innovations for segmentation" Brinker et al. (2019) described classification within skin lesions types utilizing deep learning system, and Hekler.

Chapter 2

LITERATURE REVIEW

In this thesis we have classified two different type of dataset. One is Brain Tumor detection using MRI images. Other one is Skin Cancer detection with normal image dataset. Both of these dataset is very different from each other. So, we have researched about some of the recent studies in this topic to gather some information upon the ongoing research work in this field.

2.1 Recent Studies on Brain Tumor Classification Using Deep Learning

Medical evaluation and treatment planning heavily depend on identifying and categorising brain tumors. Deep learning approaches have demonstrated favorable results in this arena, delivering automated and precise methods for analyzing medical images, including MRI scans. We investigate several deep learning frameworks and techniques, such as very deep convolution neural networks [6](VGG), Densely connected convolutional networks [7](DenseNet), Deep residual learning[8] (ResNet), EfficientNet[9], Xception[10], and other related methods, that have been put forward for brain tumor detection within this summary of the written works.

Brain tumor detection challenges use the VGG design, which is distinguished through its deep stack of convolution layers with narrow reception fields. These neural networks perform effectively in retrieving features from imaging data, making it feasible to identify and classify cancers efficiently. DenseNet resolves the gradient vanishing issue and enables the reuse of characteristics by establishing solid links between layers. DenseNet architecture has enhanced accuracy in brain cancer identification by recognizing intricate spatial connections in MRI data, resulting in more accurate tumor delineation and categorization. The residual connections of ResNet facilitate deep neural network training ,which also lessens deterioration. In brain cancer identification, it has been demonstrated that ResNet architectures perform better at retrieving meaningful information from MRI data, allowing for accurate tumor diagnosis and characterization.

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Several researchers have studied novel methods for identifying brain tumors like integrating optimization methods such as Grey Wolf Optimizer[11] and Sine-Cosine Efficient[12] with deep learning. These hybrid approaches aim to enhance efficiency and improve cancer detection accuracy by improving the parameters or methods of training deep learning-trained models. In summary, deep learning methods have transformed the detection of brain tumors by offering precise and automated MRI evaluation of images and automated MRI evaluation of images. Significant progress has been made in tumor localisation and classification tasks using architectures including VGG, DenseNet, ResNet, EfficientNet, Xception, and hybrid techniques. Enhancing early detection rates and enabling individualized treatment plans for brain tumor patients are possible outcomes of additional research and development in this area.

2.2 Recent Studies on Skin Cancer Detection Using Deep Learning

Skin cancer, specially melanoma is a huge concern worldwide. Early detection can help in the prognosis of this cancer and can cure patients. Deep learning models, Particularly CNN has shown promising results in detecting the cancer. This paper will compare between several models which is based on CNN architecture – Xceptron, EfficientNet, ResNet, VGG-16.

Xceptron is relatively new in the field of deep learning. While it is not as popular as the other deep learning models like EfficientNet, RestNet, it has its own characteristics which make it unique from others. It combines traditional CNN models with advance techniques. It is specially designed to handle high resolution images which makes it perfectly suitable for medical image processing. It's feature extraction mechanism make it different from other traditional deep learning models. Its multi-scale feature extraction mechanism, combined with enhanced skip connections and robust preprocessing, enables it to capture detailed and complex features from medical images effectively. However it is a fairly new model so more research is needed in this model so we decide to use it in our paper.

EfficientNet, introduced by Tan and Le (2019), utilizes a compound scaling method to balance network depth, width, and resolution, resulting in a highly efficient model with state-of-the-art performance across various tasks. It needs very small amount of data to train itself which makes it suitable for medical image processing because of the scarcity of the data. It's ability to achieve high accuracy with lower parameters and lower computation cost makes it efficient compares to the other existing models. Tschandl et al. (2020**)** Demonstrated that EfficientNet outperformed other models on the ISIC 2019 dataset, achieving higher accuracy and AUC scores. Also another studies shows Kawahara et al. (2021) Showed that EfficientNet, when fine-tuned on dermoscopic images, provided significant improvements in melanoma detection accuracy.

ResNet (Residual Networks), introduced by He et al. (2015), addresses the vanishing gradient problem by using skip connections, allowing for the training of very deep networks. Vanilla CNN has the problem of vanishing gradient. In the neural network, the learning involves by updating the previous weight which depend on the loss function. It is generally happened by stochastic gradient decent algorithm (SGD) or other variant of this. For updating the biases the algorithm uses partial derivative of the loss function through each of the layer on the neural network. It is very difficult to update the weights for smaller gradient as it becomes

negligible when back propagating through the network. To solve this issue ResNet or Residual Network is used where it used Residual Block and skip connection to solve the issue of vanishing gradient problem. Esteva et al. (2017) Utilized a ResNet-50 model trained on a dataset of over 120,000 images, achieving dermatologist-level classification performance. Brinker et al. (2019**)** Compared several CNN architectures and found ResNet-50 to be one of the top performers in melanoma classification tasks, demonstrating high sensitivity and specificity.

VGG-16 is a simple deep neural network architecture which is very simple to understand. It is introduced in 2014 by Simonyan and Zisserman et al. with only 16 layers stacked one after another. It makes the architecture more uniform and it can be used as the baseline to understand the performance of the highly sophisticated deep neural networks. VGG-16 is conductive to transfer learning which is useful in medical imaging where annotated data are limited. Codella et al. (2017) utilized VGG-16 in their ensemble approach for skin lesion analysis, showing its effectiveness when combined with other models. Han et al. (2018) applied VGG-16 for skin cancer classification and reported significant improvements in detection rates when using fine-tuned VGG-16 models compared to traditional methods.

Table 1: Comparison Table of Various Approaches

Paper Name & Authors	Techniques	Performance Matric	Performance Score
Abdusalomov, Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance[1]	Xception, Inception V3, ResNet 50, VGG 16, EfficientNet	Accuracy, Precision, Recall, F1-score	1.[95.6,95.7.95.9,95.8] 2.[96.4,96.7,97.1,96.9] 3.[96.5,96.6,96.8,96.7] 4.[97.6,97.4,97.7.97.5] 5.[97.8,97.7,97.9,97.8]
D. Kaur, S. Kaur, "Comparative Study of Different Deep Learning Techniques for Diagnosis of Brain Tumor,"[13]	DNN,SVM,CNN,ELM-LRF CNN, RNN	Accuracy, Mean Suare Error	1.[98,1.48] 2.[88,4.95] 3.[96,2.34] 4.[97,2.01] 5.[98.6,1.40]
Comparative Analysis Of Brain Tumor Detection Using Deep Learning Methods K. Rajesh Babu, Et EL.[14]	ANN, CNN (UnAugmented), CNN(Augmented)	Accuracy, Precision, Sensitivity, Specificity	1.[89.6,90.4,88.2,91.6] 2.[92.3,95.2,93.4,93.5] 3.[94.1,96,95.5,97.4]
Sara Hosseinzadeh Kassani, A comparative study of deep learning architectures on melanoma detection, Tissue and Cell,[15]	AlexNet, ResNet 50, VGG 19, Xception	Precision, Recall, F1-Score, Accuracy	1.[0.84,0.81,0.82,0.80] 2.[0.93,0.92,0.92,0.92] 3.[0.88,0.88,0.88,0.88] 4.[0.90,0.90,0.90,0.90]
Mohammad Ali Kadampur, Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images, Informatics in Medicine Unlocked,[16]	ResNet, SqueezeNet, DenseNet, Inception V3	Precision, F1-Score, ROC-AUC	1.[94.24,94.22,98.61] 2.[97.40,94.57,99.77] 3.[97.51,96.27,99.09] 4.[98.19,95.74,99.23]

Chapter 3

METHODOLOGY

In the Methodology part we will be discussing about the dataset used, process flow and other theoretical aspects like information about the dataset, preprocessing, training testing split. Two different types of cancer are being detected in this research. We will discuss about the different approaches that have been incorporated in these approaches.

3.1 Detecting Brain Tumor using Deep Learning

Brain tumor diagnosis with deep learning methods employs a number of strategies, such as feature extraction using convolutional neural networks (CNNs), model adaptation using transfer learning, and dataset diversity enhancement through data augmentation. While attention mechanisms and uncertainty estimating approaches help to improve model focus and confidence evaluation, ensemble learning combines predictions from numerous models. Interpretability techniques help physicians trust and comprehend the decisions made by the model. By combining these approaches, scientists hope to improve clinical utility and diagnostic accuracy in the identification of brain tumors, which will ultimately lead to better patient outcomes.

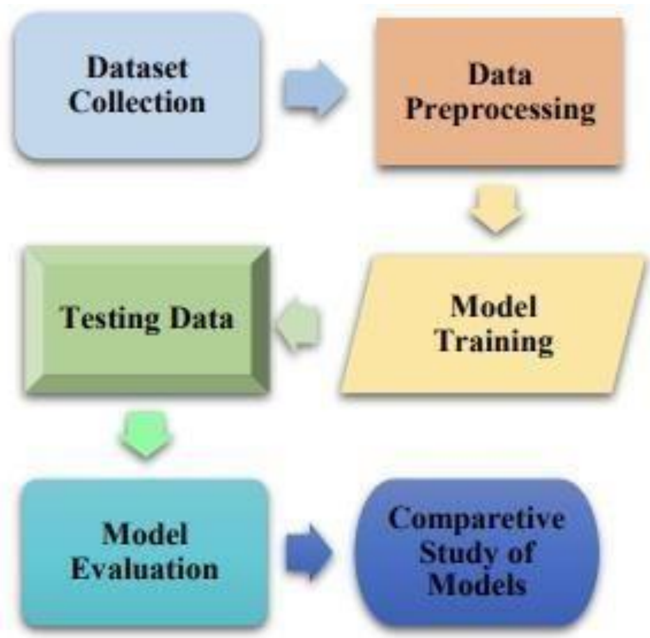

Figure 1 : Workflow Diagram

3.1.1 Data Collection

The workflow diagram illustrates our research process, beginning with collecting 2D MRI image data from Kaggle (Brain-Tumor-Detection-MRI). This data is a 2D representation of MRI images, as actual MRI images are 3D. For the simplicity of the experiment, we will use 2D versions. Import and Load data: Data are directly taken from the Kaggle dataset. It has over 2400 MRI images divided into two subclasses. One is a tumor; another is a non-tumor.

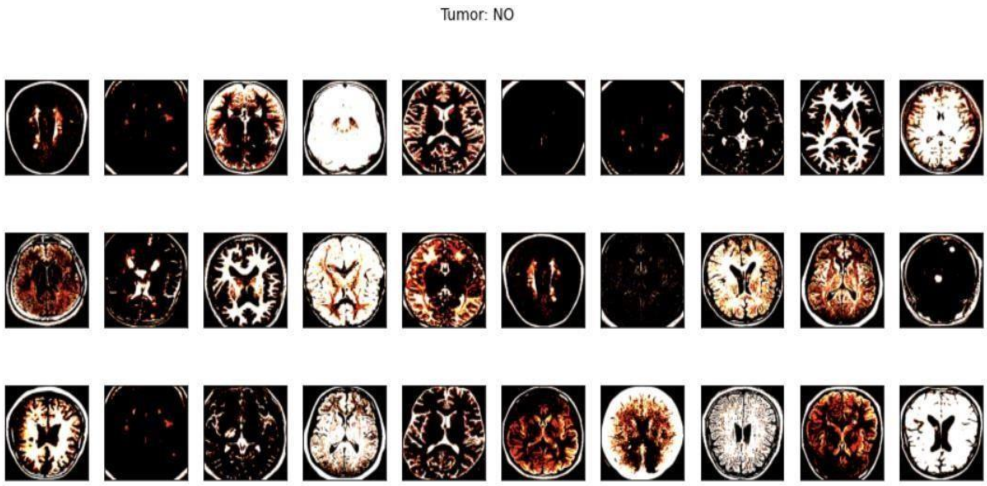

Figure 2 : Sample Data (No Tumor)

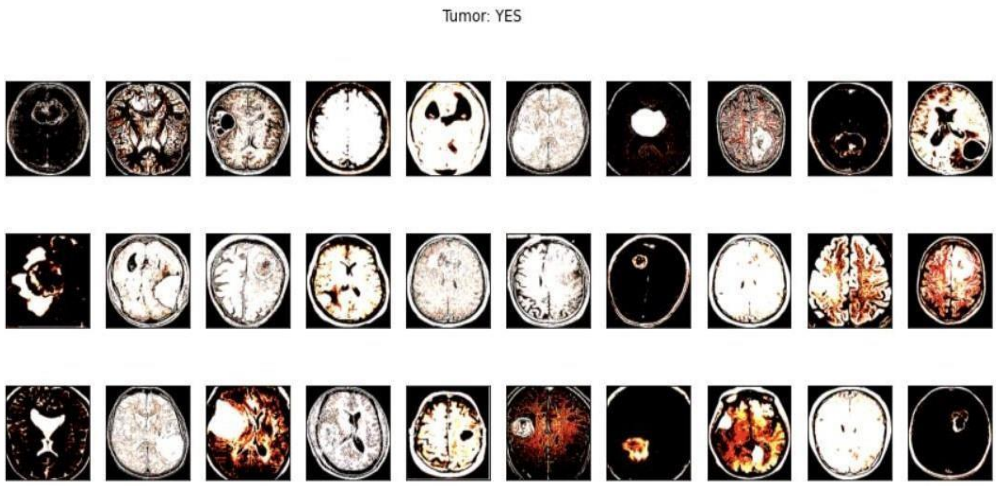

Figure 3 : Sample Data (Tumor)

3.1.2 Data Pre Processing

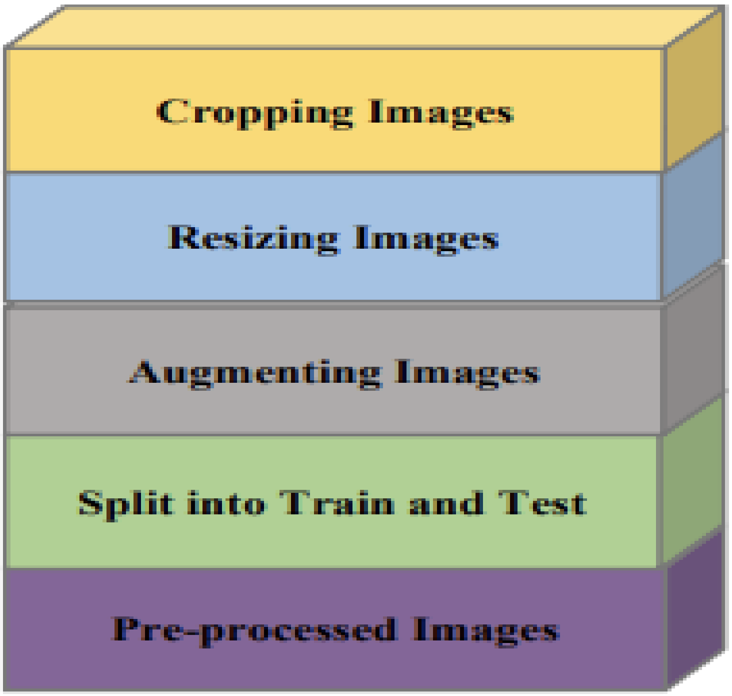

Figure 4 : Steps for Data Pre Processing

The steps mentioned above are used for data preprocessing. Firstly, our model does not take input of any size of data. The deep learning model generally takes 224 × 224 × 3 as the input size of the image. However, the image dataset we got from Kaggle has images of different sizes. To fix that, we need to resize the data. Unthinkingly resizing will distort the images. We can miss some of the information present in the images. To handle that, we must crop our dataset to preserve our image. For cropping, we need to use contouring from the OpenCV library. After that, we can resize to 224 × 224 × 3 size images. After this step, image augmentation has to be done. As our dataset has only 2400 images, any deep learning model needs a high number of inputs to understand the data's features and train itself according to the features. So, we need to augment[17] our images to get a more significant number of images. For this task, we have used several augmentation techniques, such as tilting the image from 15 degrees left to 15 degrees right by changing the degree by one step. We can use width shift, horizontal flip, vertical flip, image scaling, brightness changes, etc. After image augmentation, we will slip the dataset into the train and test module with a 3:1 ratio. Training data will be directly fed to the deep learning models to understand the features of each image. After that, the testing data will be used to test the model's performance. These are all the necessary steps that have been taken into consideration to preprocess the data.Now, the data can be fed to deep learning model

3.1.3 Model Training

After the data preprocessing stage, the data is ready to be fed to the deep learning models. Now, the training dataset will be fed to each model separately and run for 30 epochs, and each epoch will have 50 steps.

3.1.4 Model Testing

After training the model, it is time to perform the test of the model and evaluate the model performance. Previously, we have stored the test dataset. The test dataset will be considered for the evaluation of the model.

3.1.5 Model Performance Evaluation

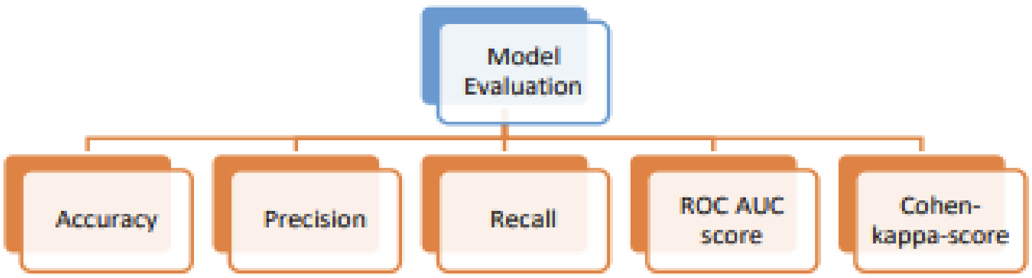

Figure 5 : Performance Evaluation Matrices

These are the matrices we will use to evaluate the model's performance.

Accuracy $= \frac{T^P + T^N}{T^P + T^N + F^P + F^N} \times 100 - (1)$

$$Precision = \frac{T^P}{T^P + F^P} \times 100 \text{ -- } (2)$$

$$Recall = \frac{T^P}{T^P + F^N} \times 100 \text{ -- } (3)$$

$$cohen\ kappa\ score = \frac{2*(T^P*T^N - F^P*F^N)}{(T^P+F^P)*(F^P+T^N)+(T^P+F^N)*(F^N+T^N)} \text{ --}(4)$$

Here, T^P *stands* for true positive value, T^N is for actual negative values, F^P for false positive values and F^N is for false negative values.

3.2 Detecting Skin Cancer using Deep Learning

Deep learning provides a variety of ways for detecting skin cancer, taking advantage of its capacity to understand complicated patterns from medical pictures. The core is comprised of Convolutional Neural Networks (CNNs) with architectures designed specifically for dermatological image processing. The use of transfer learning makes it possible to refine pre-trained models such as VGG, Inception, or ResNet using collections of skin lesions, allowing for efficient learning even with the inclusion of sparse labelled data. To improve robustness and generalisation, ensemble techniques combine predictions from several models or data augmentations. Accurate classification is aided by attention processes, which concentrate on prominent areas within lesions. Additionally, Generative Adversarial Networks (GANs) produce artificial images, enhancing datasets and enhancing model efficacy. While interpretable models clarify important traits leading to diagnoses and build clinician trust, Bayesian techniques offer uncertainty estimates that are essential for clinical decision-making.

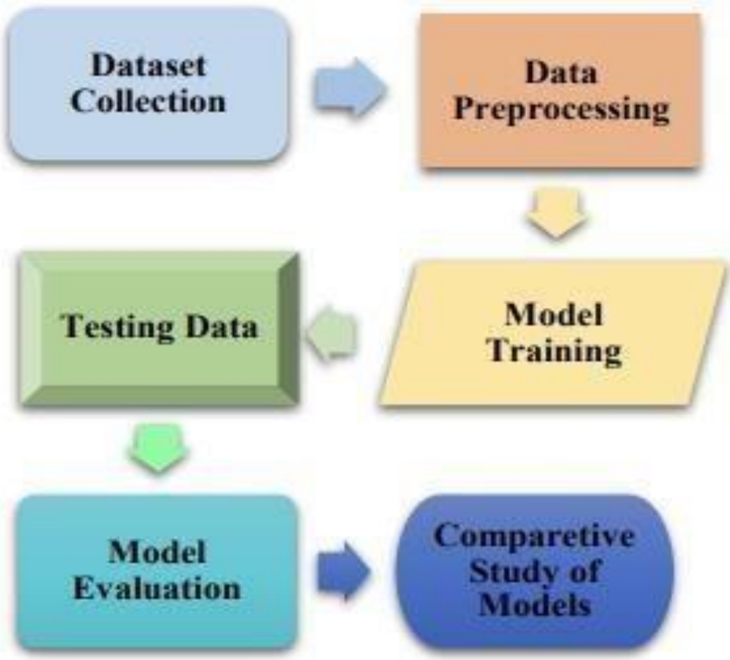

Figure 6 : Methodologies

3.2.1 Dataset Collection

The workflow indicates our progress will begin from the collection of the images. The Dataset which have been used in this research paper is collected from the Kaggle. The name of the dataset is "Skin Cancer: Malignant vs. Benign". The data is from ISIC

(International Skin Imaging Collaboration) – Archive. Dataset consist of 2 types of photos. One is benign and the other one is malignant. Each image have a size of 224× 223 × 3 pixels. Total 3297 images are present in the whole dataset. Imported data is already divided into two classes. One is called Benign class and other is called as Malignant class. In the Fig 2 and Fig 3, few sample pictures are given to understand the context of the images.

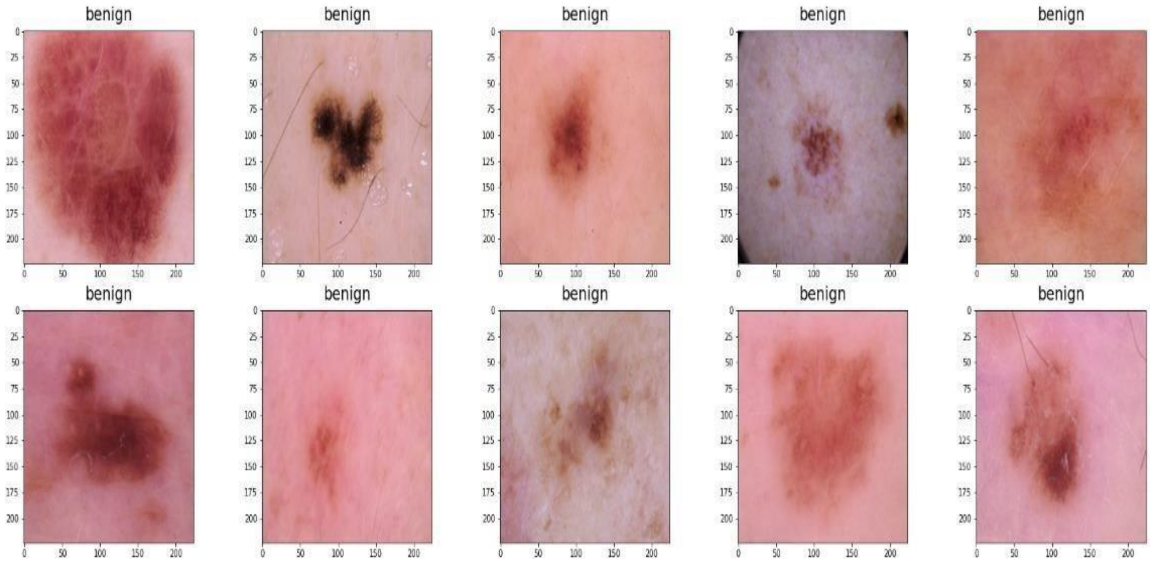

Figure 7 : Sample Data (Benign)

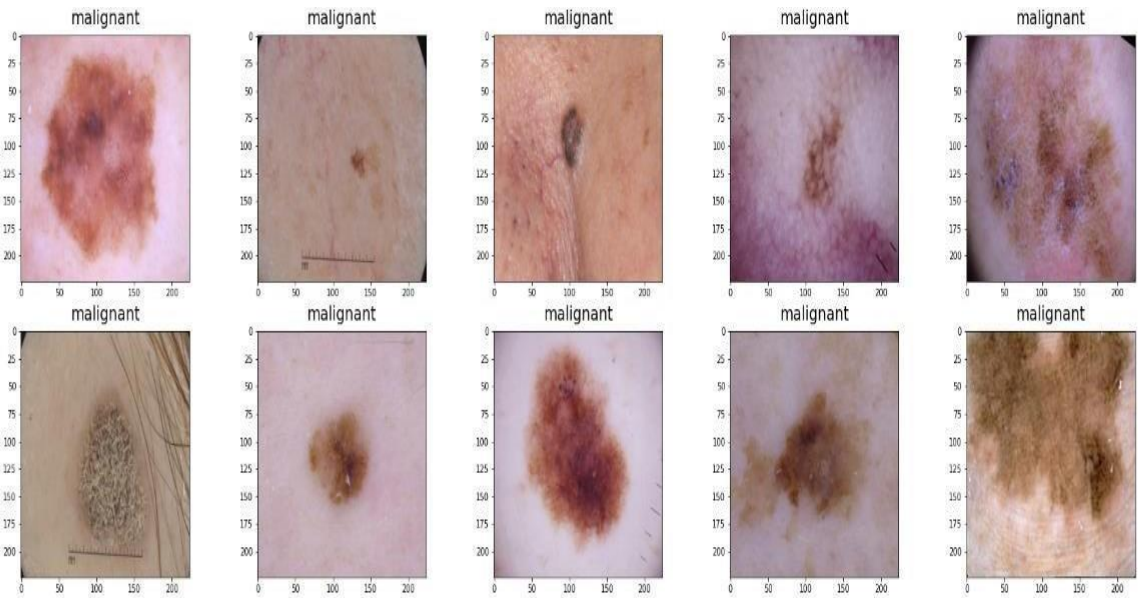

Figure 8 : Sample Data (Malignant)

3.2.2 Dataset Collection

Image preprocessing needs few standard steps to be considered in order to get clean image. This clean image will drastically improve the deep learning models performance. These steps are cropping the image, resizing it to the standard 224× 224 × 3 pixel format, augmenting the image to get more input samples to be trained, normalize the image, reduce noise from the image etc. Deep learning models generally takes 224× 224 pixels as inputs but the dataset which is given have different size of images. So at first, we need to resize them into appropriate size. There is a problem in resizing the image. Features of a image can be present be present anywhere in the image. The first task is to get those exact feature images then resize them. For this task, cropping is required which will extract only the portion where actual features are present. After this step the input images needs to resize to appropriate size according to the model. Next step is to augment the input images, as the number of images in the input dataset is lot less and deep learning models needs a high number of input to train them. For augmentation Imagedatagenerator is required from Keras library. We have perform rotation of images, width shift, height shift, zoom in, horizontal flip, vertical flip of the images to get more images. Then normalization is required. It will bring the range of pixel values to a certain range [0-255]. The last step is to reduce noise. Some images have unwanted spots all over the images which will bring down the accuracy of the model performance. So It needs to be removed. Gaussian Blur and Median Blur are some popular methods to remove noises. After the data preprocessing stage, the data is ready to be fed to the deep learning models. Now, the training dataset will be fed to each model separately and run for 30 epochs, and each epoch will have 50 steps. After training the model, it is time to perform the test of the model and evaluate the model performance. The dataset itself divided into training and testing set, so we used testing dataset to evaluate the performance.

3.2.3 Model Training

After the data preprocessing stage, the data is ready to be fed to the deep learning models. Now, the training dataset will be fed to each model separately and run for 30 epochs, and each epoch will have 50 steps.

3.2.4 Model Testing

After training the model, it is time to perform the test of the model and evaluate the model performance. Previously, we have stored the test dataset. The test dataset will be considered for the evaluation of the model.

3.2.4 Model Performance Evaluation

These are the matrices we will use to evaluate the model's performance. Accuracy = Tp+

TN Tp+TN+FP+FN × 100 – (1) $Precision$ = Tp Tp+FP × 100 -- (2) Reducing Noise Normalization Augmenting Images Resizing Images Cropping Images Fig 4:Steps for Data Preprocessing Model Evaluation Accuracy Precision Recall F1 score AUC-ROC score $Recall$ = TP TP+FN × 100 -- (3) $F1$ $score$ = 2×TP 2×Tp+FP+FN --(4) Here , TP $stands$ for true positive value, TN is for actual negative values, FP for false positive values and FN is for false negative values.

Chapter 4

RESULTS and DISCUSSION

4.1 Results of Brain Tumor Detection

After analysing the Brain-Tumor-MRI dataset using various Deep Learning models, we calculated various evaluation matrices to measure the performance of each model. We Pre-processed Images Split into Train and Test Augmenting Images Resizing Images Cropping Images Figure 4:Step for Data Preprocessing Model Evaluation Accuracy Precision Recall ROC AUC score Cohenkappa-score classified the image dataset as tumor or Non-tumor. These matrices are listed below:

Table 2 : Performance of Different Models for Brain Tumor Detection

	Accuracy (%)	Precision (%)	Recall (%)	ROC-AUC Score	Cohen-Kappa-Score
DenseNet-121	94.5	94.6	94.5	0.984	0.89
Inception	73.0	73.8	72.7	0.82	0,45
VGG-16	94.0	94.0	94.0	0.990	0.88
ResNet-50	97.5	97.5	97.5	0.996	0.95

The model training graph can observe a neural network's performance throughout training, and it usually displays measures like accuracy or loss over epochs. It shows how the system is learning and converges towards its optimal performance. On the other hand, the model's capacity to minimize losses is demonstrated by the model loss graph, showing the decrease in loss values for functions throughout training epochs. These diagrams shed light on the deep learning models' learning dynamics and convergence when taken together.
Here, we show a graph of model accuracy and model loss for each model.

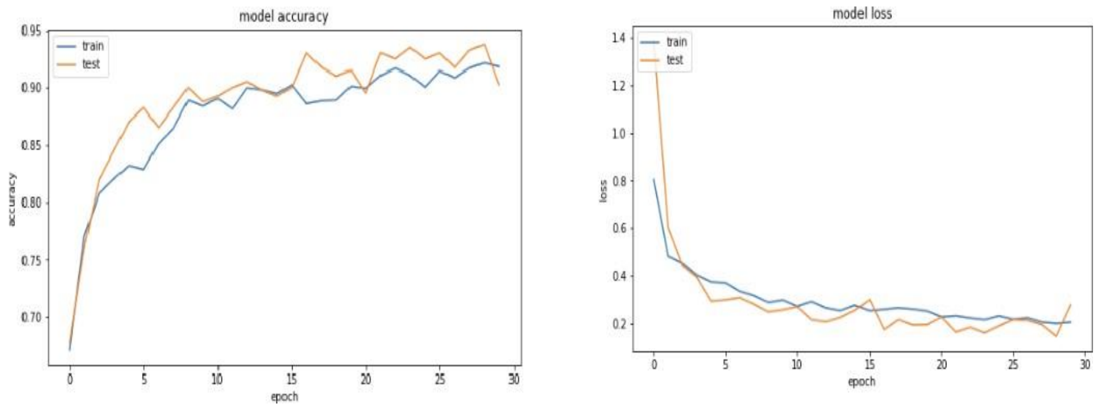

Figure 9 : Accuracy and Loss of DenseNet 121

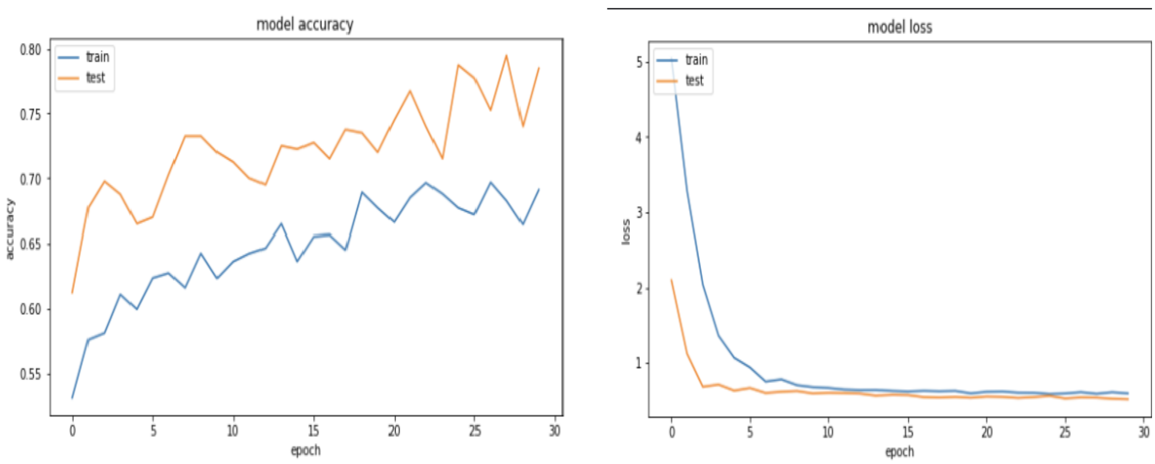

Figure 10 : Accuracy and Loss of Inception V3

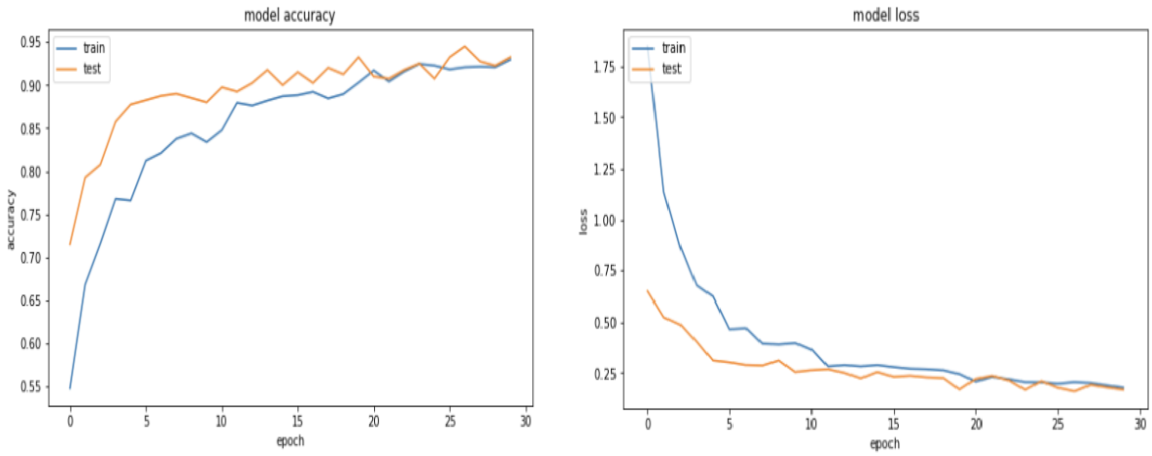

Figure 11 : Accuracy and Loss of VGG -16

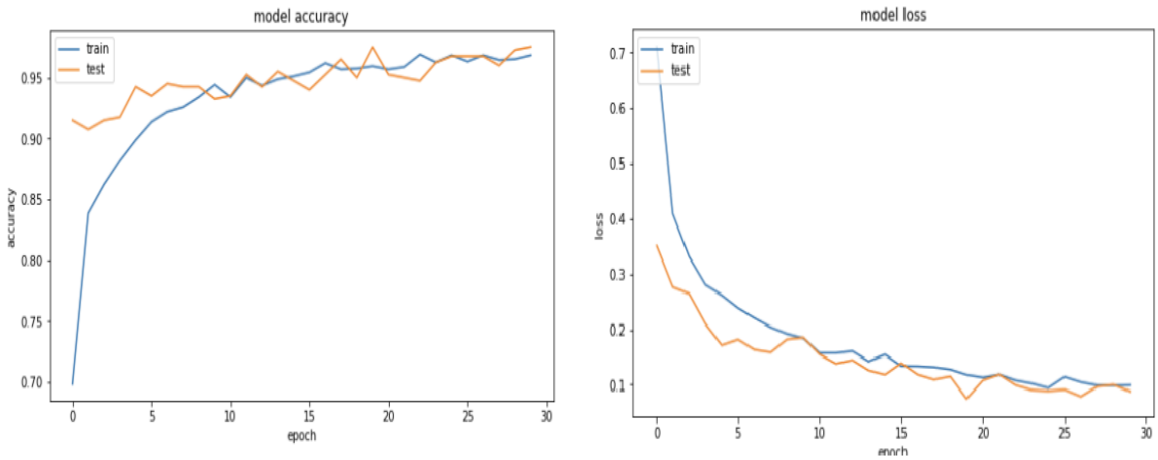

Figure 12 : Accuracy and Loss of ResNet

To Detect the performance of different models, At first we need to first calculate the confusion matrix of each model. We have calculated the confusion matrices. The results are given below :

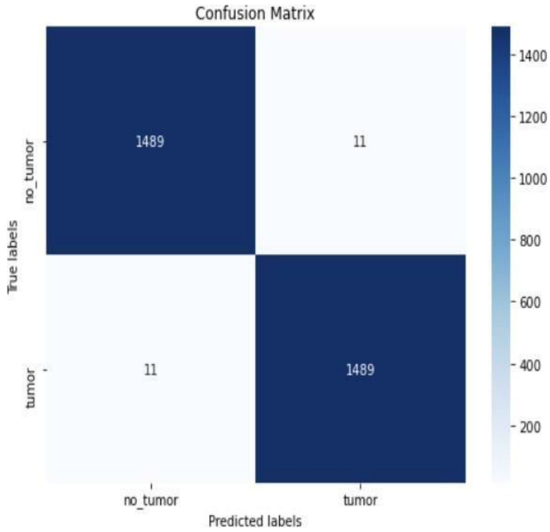

Figure 13 : Confusion Matrix of DenseNet

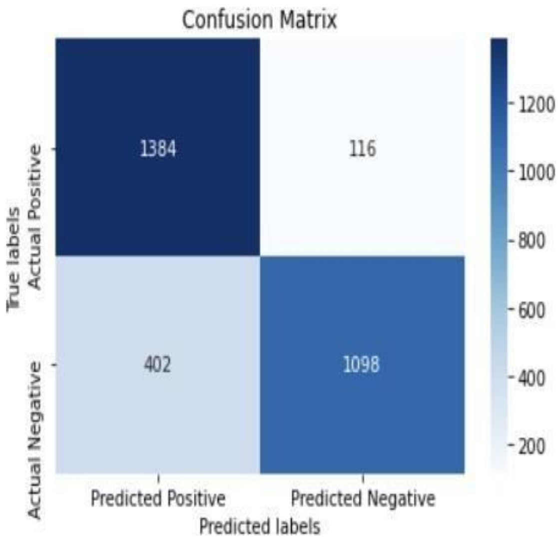

Figure 14 : Confusion Matrix of ResNet

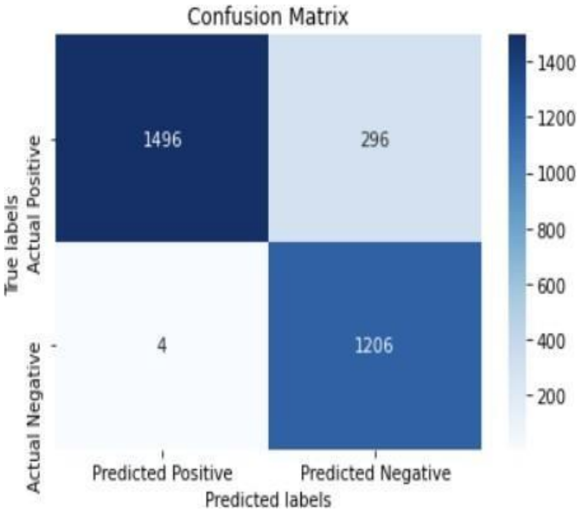

Figure 15 : Confusion Matrix for VGG 16

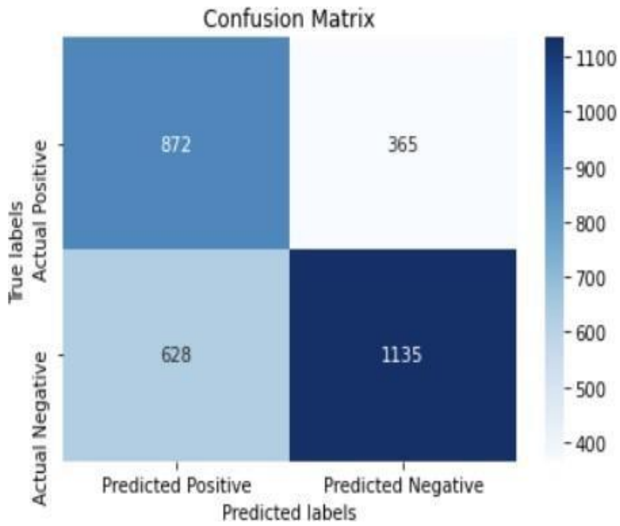

Figure 16 : Confusion Matrix of Inception V3

All the models have shown great result in terms of the dataset. As the dataset is very limited so achieving this type of result is really good for future researchers.

This study uses a collection of MRI scans to examine how well four deep learning models classify brain tumors. The models that were looked studied were Inception-v3, DenseNet-121, ResNet-50, and VGG-16. The analysis provides insight into the effectiveness of each model. The evaluation criteria are accuracies, precision, recall values and AUC-ROC score. The results indicate that all models achieved high accuracy, with the following values:

DenseNet-121 with 94.5% accuracy, ResNet50 with 97.5% accuracy, VGG-16 with 94.0% per cent accuracy and Inception-V3 with 73.0% per cent accuracy. Precision, which measures the actual positive rate among predicted positives, reveals that ResNet-50 has the highest precision at 97.5%. Recall value describes how many positive values our positive values can be attained overall. The result shows that ResNet is a top performer at 97.5% and 94.5%, respectively. The AUC-ROC score, which evaluates the classifier's ability to distinguish between tumor and non-tumor, highlights ResNet and VGG-16 as the most robust models, scoring 0.996 and 0.99. Cohen-Kappa score signifies the degree to which two or more raters can diagnose, evaluate, and rate behaviour; the ResNet and the DenseNet models have achieved the highest scores with 0.95 and 0.89.

4.2 Results of Skin Cancer Detection

After analysing the Skin Cancer : Benign Vs. Malignant dataset using various Deep Learning models, we calculated various evaluation matrices to evaluate the performance of each deep learning model. We classified the image dataset as Benign or Malignant. These matrices are listed below:

Table 3 : Model Performance of Skin Cancer Detection

	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	AUC-ROC Score
Xceptron	88.6	89.5	89.0	0.89	0.888
Efficient Net	87.4	87.5	86.5	0.86	0.868
ResNet-50	69.2	70.5	70.0	0.70	0.700
VGG-16	83.0	83.0	83.5	0.83	0.835

These Models have run of Kaggle with each model different parameter. Each has their unique way of feature extraction policies. To compare all of the four models we have train them with equal size of 30 epochs and 50 batch size. The learning of each models are shown below :

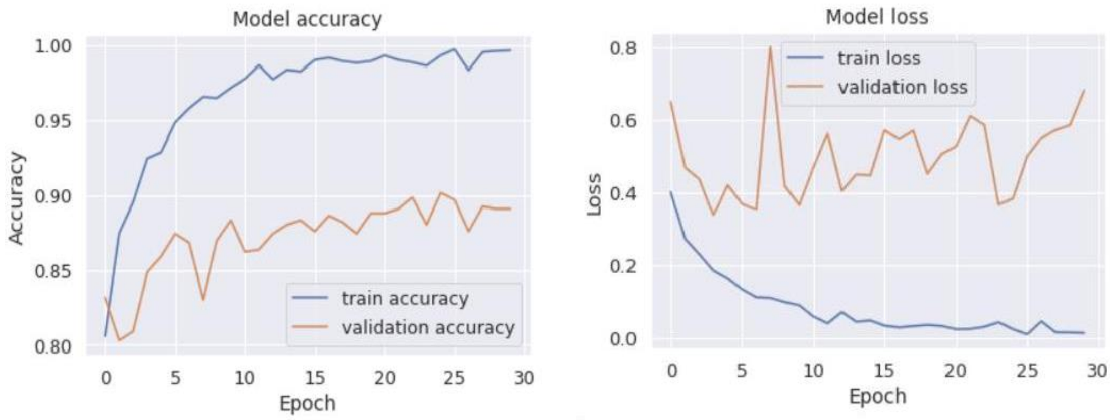

Figure 17: Accuracy and Loss of Xceptron

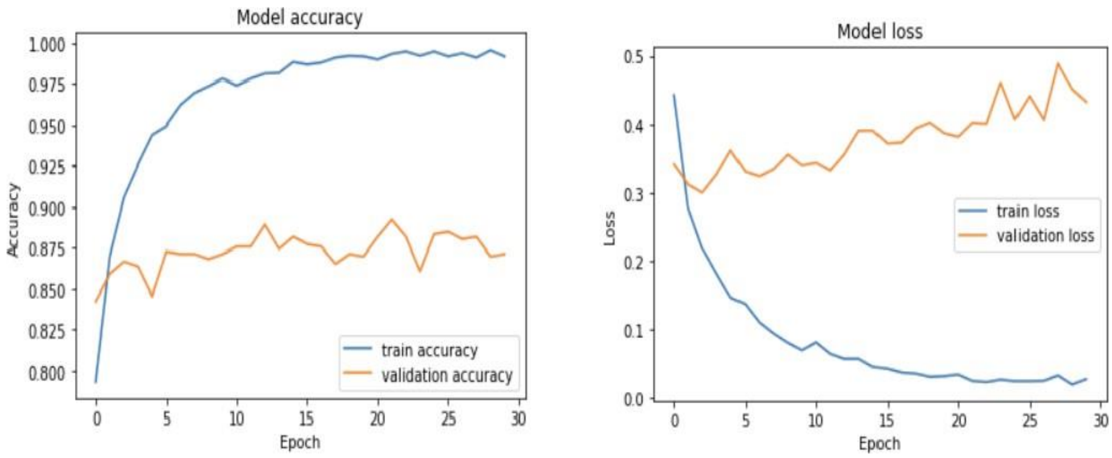

Figure 18 : Accuracy and Loss of EfficientNet

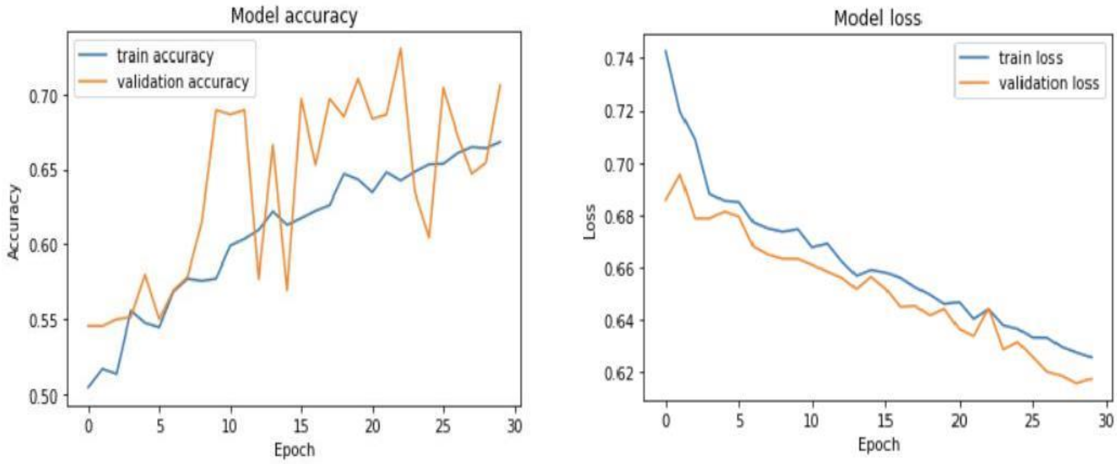

Figure 19 : Accuracy and Loss of ResNet

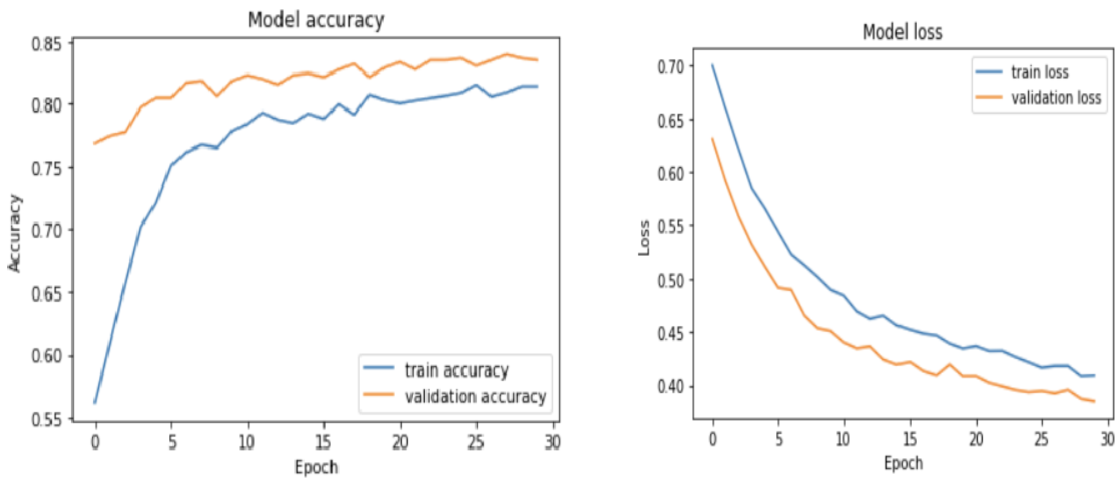

Figure 20 : Accuracy and Loss of VGG 16

After training each model we need to calculate the confusion matrix first in order to calculate other parameters of the models. Confusion matrix is a tabular representation which is used to gain knowledge about the of a machine learning or deep learning model. True Positive, True Negative, False Positive, and False Negative are the values that make up this matrix. The number of cases when the model accurately detected a positive outcome is indicated as True Positive. Similarly, True Negative shows how many times the model properly predicts the negative class. False Positive refers to how many times the model incorrectly predicted the positive class. False Negative denotes an incorrectly projected negative class number. Here, the confusion matrix of different models are shown below :

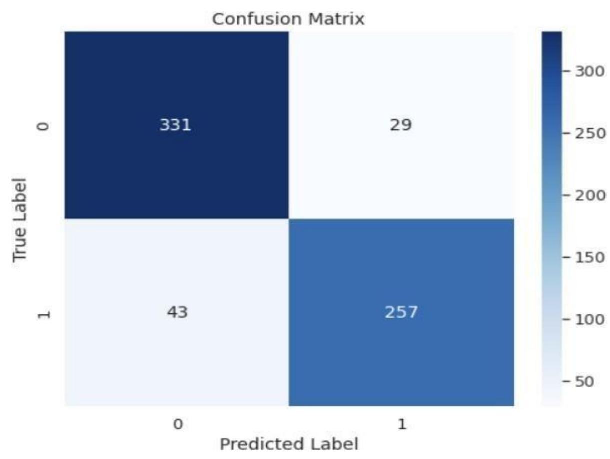

Figure 21 : Confusion Matrix for Xceptron

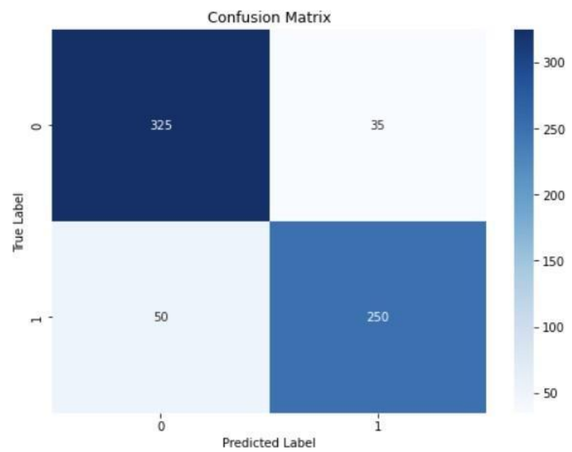

Figure 22 : Confusion Matrix for EfficientNet

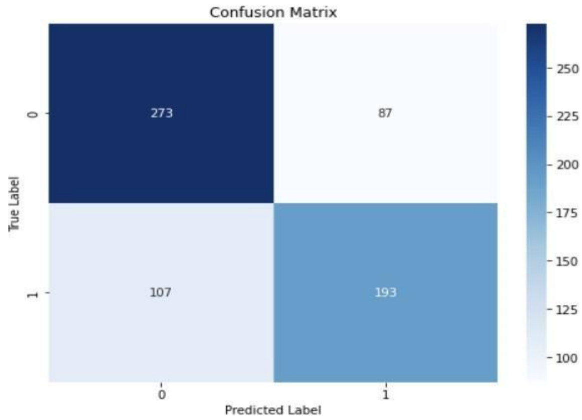

Figure 23 : Confusion Matrix for ResNet

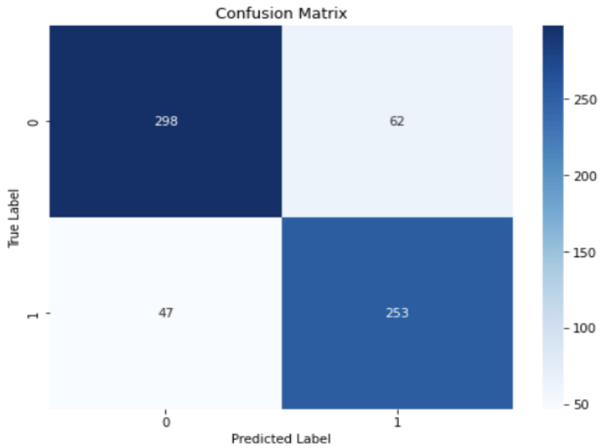

Figure 24 : Confusion Matrix for VGG 16

Confusion Matrix of each deep learning models that are being used in the process. Here top left corner is true positive value, bottom right corner is true negative value, top right corner is true negative value and bottom left corner is false negative values. Hardware specification for running all these four deep learning models: we loaded the dataset. We performed the matrix evaluation on a Kaggle environment with GPU P100, GPU memory used 16 GB, 9 GB RAM.

This study definitely increase the understanding of different deep learning models in the area of skin cancer detection. Every model brings their own unique techniques to counter the problem with vanilla CNN. The scarcity of medical images is another challenge while doing the experiment. These models have definitely overcome that problem as well. Accuracy indicates how many correct prediction have done by the deep learning model. Xcepton has the highest accuracy with 88.6 %. Precision means how many true positive value are correctly predicted by the model. Xceptron has the highest accuracy value with 89.5 %. Recall means how many instances the model predicated true positive from the positive class. Here also the Xceptron have the highest value of 89.0 %. F1 score measures harmonic mean between precision and recall. With the value 0.89 here also Xceptron beats the other models as well. AUC-ROC score signifies how well the model can differentiate between different classes. Here also Xceptron has the highest score with 0.888.

Chapter 5

CONCLUSION AND FUTURE SCOPE

The aforementioned experiments demonstrate the exceptional capabilities of several deep learning models, like as Xception, EfficientNet, ResNet, and VGG-16, in the identification of brain cancer. These Deep learning based models have demonstrated excellent capabilities, rivalling those of field specialists, and offer promise for supporting healthcare professionals in diagnosing brain tumours, especially considering the increased prevalence of skin cancer cases.

In a similar vein, deep learning algorithms have the potential to completely change how skin cancer is found and diagnosed. Methods for effective and prompt detection of skin cancer are desperately needed, as the disease is becoming more commonplace globally. Large datasets of dermoscopic pictures were used to build deep learning models, which have shown attractive results in differentiating between benign and malignant skin diseases.

It is critical that decision-makers in healthcare and policymaking take into account the incorporation of these increasingly complex models into clinical practice for the identification of skin cancer and brain tumours. It is tough to overestimate the possible influence on patient outcomes and the healthcare system as a whole. However, in order to guarantee safety for patients and data privacy, legal and moral problems must also be taken into account. In the future, deep learning may lead to significant breakthroughs in the identification of skin cancer and cerebral tumours. In an effort to improve the interpretability and effectiveness of models. Model development and evaluation in both domains will be accelerated by cooperative efforts to create benchmarking frameworks and collect sizable annotated datasets. Moreover, real-time diagnosis will be possible with the implementation of hardware acceleration devices and useful models, which will result in earlier interventions and better outcome.

In summary, deep learning-based cancer detection has a promising future ahead of it, with an emphasis on improving accuracy, detecting cancers sooner, and developing individualised treatment plans for skin and brain tumours. These crucial areas of healthcare will develop due to ongoing technological advancements, interdisciplinary collaboration, and a dedication to ethical practice. We can transform cancer diagnosis and treatment by utilising deep learning.

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10.1016/j.jid.2020.01.019.

LIST OF PUBLICATIONS

Paper Name	Authors & Co-Authors	Conference Name
A Comparative Study of Deep Learning Models for Brain Tumor Classifications	Tanmoy Das, Dr. Virender Ranga & Prof. Dinesh Kumar Vishwakarma	CONIT 2024
Unveiling The Power of Deep Learning Models for Skin Cancer Detections	Tanmoy Das, Dr. Virender Ranga & Prof. Dinesh Kumar Vishwakarma	ICAC2N 2024

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