Classification of Brain Tumor from MRI Images :A Deep Learning Approach

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APPROVAL

This thesis titled "**Classification of Brain Tumor from MRI Images A Deep Learning Approach: Study**", submitted by **Jahanara Islam (ID:192-35-2858)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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DECLARATION

I hereby declare that I have done this thesis under the supervision of Mr. Md. Khaled Sohel, Assistant Professor, Department of Software Engineering, Daffodil International University. I also declare that this thesis is my original work for the degree of B.Sc. in Software Engineering and that neither the whole work nor any part has been submitted for another degree in this or any other university.

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Abstract

Brain tumors are a significant pathological condition within the field of medicine that poses challenges in terms of accurate diagnosis. In recent times, the utilization of deep learning techniques has been employed to create automated systems aimed at classifying brain tumors based on MRI images. The present study aimed to assess the efficacy of eight distinct deep-learning models in the classification of brain tumors. The models underwent training using a dataset consisting of 4,483 MRI images. Subsequently, their accuracy was assessed by employing a separate set of 1,250 test images. The findings indicated that the MobileNet model exhibited superior performance, achieving an accuracy rate of 99.38%. The remaining models also exhibited strong performance, achieving accuracies within the range of 97.68% to 98.39%. The findings of this study indicate that employing deep learning techniques to automate the classification of brain tumors using MRI images is a promising and advantageous strategy.

Keywords: MRI images; Brain tumor; MobileNet; Deep learning

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CHAPTER 1

INTRODUCTION

Brain tumors are alarming or difficult-to-diagnose medical conditions. One of the most common techniques for screening for brain growth is magnetic resonance imaging (MRI). MRI scans can provide complete brain images, allowing specialists to identify and classify tumors. However, even for experienced radiologists, the interpretation of MRI scans can be complex.

Deep learning has been used in recent years to develop automated systems for classifying brain tumors from MRI images. Deep learning is a method of machine learning that uses artificial neural networks to learn from data. Inspired by the human brain, neural networks can be used to extract complex features from data.

The chapter begins with a brief overview of the research's setting, followed by a statement on the issue. Afterward, the objectives of the thesis, an explanation of the research methodology, and the scope of the thesis are discussed in order.

1.1 Background

Brain tumors are a leading cause of mortality and morbidity, and their diagnosis and treatment necessitate the allocation of substantial resources and sophisticated diagnostic and therapeutic technology. In all geographic areas and SDI (Socio-Demographic Index) quintiles, with the exception of Eastern Europe, the number of incident cases of brain cancer (which is primarily caused by brain tumors) has increased between 1990 and 2016, according to the Global Burden of Diseases, Injuries, and Risk Factors (GBD) Study. However, as SDI increases, the mortality-to-incidence ratio declines, likely as a result of access to early detection and treatment. There are 13 to 15 million cancer patients in Bangladesh, with approximately 2 million newly diagnosed each year, and 1,08 million deaths annually. Head/Neck/Brain tumors account for approximately 2-5% of cases. However, if detected promptly, it is one of the most curable forms of cancer. Therefore, scientists and researchers have been devising sophisticated techniques and methods for brain tumor detection. Doctors prefer MRI over CT for identifying abnormalities in the shape, size, or location of brain tissue, which aids in the detection of tumors. MRI and CT are both widely used for identifying abnormalities in the shape, size, or location of brain tissue, which aids in the detection of tumors. As a result, scientists and researchers have placed a greater emphasis on MRI. When identifying brain tumors from MRI images, conventional examination by physicians is the most common method. However, automated approaches primarily implemented by computer-assisted medical image processing techniques are assisting physicians in detecting brain tumors more and more. Pre-processing, such as augmentation, filter application, segmentation, and feature selection, and post-processing, such as identification or classification, are all parts of the processing of medical images. These steps can be implemented using both conventional machine learning and deep learning techniques. In the conventional approach to machine learning, hand-crafted features are used to obtain results from a test image, and the procedure is quick. In deep learning, models are fine-tuned by selecting the optimal number of layers, activation function, and pooling, and sometimes pre-trained models are incorporated for transfer learning. However, metaheuristic algorithms can be used to improve the classification accuracy in both approaches. In a broader context, this research will examine both conventional and deep learning techniques for identifying brain tumors in MRI images.

1.2 Motivation for the Research

A highly lethal pathological condition referred to as a brain tumor is a leading contributor to mortality, resulting in the demise of 18,990 individuals on a yearly basis. It is estimated that approximately 700,000 individuals residing in the United States are believed to be affected by brain tumors. One of the most formidable diseases that an individual can experience is one that not only impacts the afflicted individual but also has repercussions for their close relations. The process of manually reviewing MRI scans for brain tumors requires a significant investment of time and effort. Magnetic Resonance Imaging (MRI) imaging is an essential modality employed by clinicians for the accurate visualization of the brain's structural characteristics, including tumors, in both two-dimensional (2D) and three-dimensional (3D) formats. Its significance lies in its ability to facilitate the identification and detection of brain tumors. The utilization of automated techniques such as deep learning-based approaches has enabled radiologists to contribute to the mitigation of this formidable illness through efficient diagnosis and classification of brain tumors.

1.3 Problem Statement

Significant research has been devoted to detecting brain lesions using MRI images through machine-learning approaches that acknowledge the accuracy of various emergent image processing methods. The conventional approach to machine learning is quicker than deep learning. On the basis of precision, the deep learning approach is superior to conventional machine learning.

1.4 Research Question

Which deep learning model is the most appropriate for classifying brain tumors?

1.5 Research Objective

Due to their high prevalence and mortality, brain tumors, particularly gliomas, have drawn a lot of attention in recent years. Deep learning models have gained traction as a viable approach to tumor detection that can increase diagnostic precision and lighten the strain on radiologists. Several deep learning models, including Convolutional Neural Networks (CNN), Autoencoder, and Generative Adversarial Networks (GAN), have been suggested for the detection of gliomas. These models have produced encouraging outcomes when it comes to glioma detection using MRI scans. However, it is crucial to assess these models' accuracy, sensitivity, precision, and recall in order to compare their performance. The best model for detecting gliomas from MRI images must be determined through comparative research. Such a study can provide important insights into the benefits and drawbacks of each model, opening the door for the future creation of more accurate and efficient models for the detection of gliomas and other brain tumors.

1.6 Research Scope

To develop a low-cost system that will help the health sector to detect disease from MRI images. In this research, we applied seven convolutional neural network models which are VGG16, VGG19, InceptionV3, Xception, DenseNet121, MobileNet, and ResNet101 for classifying 2 classes.

1.7 Thesis Organization

The context of this work, the problem description, the motivation, the research questions, the research objectives, and the research scope are covered in Chapter 1. The literature study, approach, flaws, and comparison of our work to their work are all included in Chapter 2. The methodology of our research, model design, data collecting, and data pre-processing are all covered in the third chapter. The experiment results of the approach are shown in Chapter 4. We examine the observation, suggestion, limitation, and future work in this concluding chapter.

Chapter 2

Literature Review

2.1 Introduction

This chapter presents a comprehensive review of the pertinent literature that is directly relevant to the present research study. The aim of this study was to develop a theoretical framework for a medical imaging information system that utilizes MRI brain tumor images within the histopathology laboratory. The aforementioned statement was made.

The topic under investigation has been thoroughly examined in accordance with existing research studies. This study also investigates the potential significance of microscopic manual analysis, electronic scanners, and computer-based approaches in histopathology image analysis. This review primarily examines the utilization of currently available electronic scanners, as well as computer-based techniques, in the context of enhancing the analysis of brain tumor tissue in MRI scans. The aim is to compare the accuracy of these approaches with the traditional manual analysis method.

2.2 Previous Work

The utilization of pre-trained models in conjunction with Convolutional Neural Networks (CNNs) exhibits strong potential in the field of image processing.
Five split styles in all were used by the author for training-validation data. However, ResNet50's score of 89.29% was the lowest. This study does a literature evaluation on the MRI diagnostic approach for classifying brain tumors using CNN and Bayesian optimization. It reviews the available deep-learning algorithms for classifying, segmenting, and detecting brain tumors. Additionally, it teaches the idea of Bayesian optimization and how it may be used to pick models and tune hyperparameters. In order to increase the precision and effectiveness of classifying brain tumors, it offers a revolutionary strategy that blends CNN with Bayesian optimization. The research compares the proposed technique to previous methods and assesses it on three datasets.[1]

This paper provides a comprehensive review of the existing literature on the utilization of the synergy-factorized bilinear network, coupled with a dual suppression strategy, for the purpose of classifying brain tumors in magnetic resonance imaging (MRI) scans. This study examines the current approaches utilized in the identification of brain tumors and the associated difficulties encountered, including issues of data imbalance, feature redundancy, and noise interference. The proposed approach introduces a novel technique that employs a synergy-factorized bilinear network for the purpose of extracting high-level features from MRI images. Additionally, a dual suppression strategy is implemented to mitigate the adverse impacts of data imbalance and noise. The efficacy and resilience of the proposed method are evaluated through experimentation on two distinct datasets in this study.[2]

This paper provides a comprehensive review of the existing literature on the explanation-driven deep learning model utilized for predicting the status of brain tumors through the analysis of MRI image data. This paper provides an overview of the existing approaches utilized in the diagnosis of brain tumors, while also discussing the inherent constraints associated with deep learning models, specifically their limited interpretability and explainability. This study presents a novel approach that integrates deep learning and explanation-driven reasoning techniques to deliver precise and transparent predictions regarding the status of brain tumors. The present study assesses the proposed methodology using a dataset comprised of MRI images and subsequently conducts a comparative analysis with alternative methodologies. Additionally, the method offers both qualitative and quantitative analysis of the explanations generated.[3]

In this research on the brain tumor/mass classification framework using magnetic-resonance-imaging-based isolated and developed transfer deep-learning model. It surveys the previous methods for brain tumor/mass detection and classification using MRI images and deep learning techniques. It also discusses the challenges and drawbacks of existing methods, such as low accuracy, high computational cost, and data scarcity. It proposes a novel framework that uses an isolated and developed transfer deep-learning model to classify brain tumor/mass types with high accuracy and low complexity. The paper validates the proposed framework on two datasets and demonstrates its advantages over other methods.[4]

This paper reviews the literature on the classification of gliomas and germinomas of the basal ganglia by transfer learning. It summarizes the previous studies on the use of deep learning and convolutional neural networks for brain tumor diagnosis and segmentation. It also discusses the challenges and limitations of existing methods and proposes a novel approach based on transfer learning with ResNet50. The paper evaluates the performance of the proposed method on two datasets and compares it with other state-of-the-art methods.[5]

In this research a comprehensive analysis of the existing body of literature pertaining to the classification of brain magnetic resonance images into three distinct classes. The classification is achieved through the utilization of an average-pooling convolutional neural network. This paper provides a comprehensive analysis of current approaches utilized in brain MRI classification, highlighting the associated challenges including diminished accuracy, increased dimensionality, and susceptibility to overfitting. The proposed approach introduces a novel technique that utilizes an average-pooling convolutional neural network to decrease the dimensionality of features and enhance the accuracy of classification. The present study assesses the proposed methodology using a dataset comprising brain MRI images and conducts a comparative analysis with alternative methodologies. Additionally, it examines the impact of various parameters on the accuracy of classification.[6]

This study examines the research on deep CNN categorization of brain tumors. It reviews the prior approaches for detecting and segmenting brain tumors using traditional machine learning algorithms and their shortcomings, such as their poor accuracy, high complexity, and reliance on human feature extraction. Neural networks with convolution and deep learning are introduced, along with how they might be used to analyze medical images. It offers a deep CNN model for classifying brain tumors that can accurately and automatically extract information from MRI images. The model is tested on a dataset of photographs of brain tumors in the study, which demonstrates its usefulness and efficiency.[7]

This paper provides a comprehensive review of the existing literature pertaining to the development of a brain tumor classification model that exhibits high precision. The model is primarily based on the utilization of deep transfer learning techniques and the incorporation of stacking concepts. This paper provides an overview of the existing approaches utilized in the diagnosis of brain tumors through the analysis of MRI images and the application of deep learning methodologies. Additionally, it addresses the obstacles encountered in this domain, including issues related to data imbalance, feature extraction, and model selection. This study presents an innovative approach that utilizes deep transfer learning to harness the expertise of pre-trained models and employs stacking to integrate the predictions generated by multiple models. The study assesses the proposed model's performance using a dataset consisting of brain tumor images, demonstrating its notable precision and resilience.[8]

This article examines the research on the use of radiological imaging for brain tumor classification, subtype categorization, and survival prediction. It surveys the existing methods for brain tumor analysis using deep learning techniques and the limitations they have, such as lack of context information, low generalization, and poor interpretability. It introduces a novel method that uses context-aware deep learning to incorporate the spatial and temporal context of radiology images and provide comprehensive and interpretable results. The paper evaluates the proposed method on a dataset of brain tumor images and shows its superiority over other methods.[9]

This paper reviews the literature on brain tumor detection and classification by hybrid CNN-DWA model using MR images. It reviews the previous methods for brain tumor analysis using conventional machine learning techniques and deep learning techniques and the problems they face, such as low accuracy, high complexity, and manual feature extraction. It proposes a novel method that uses a hybrid CNN-DWA model to automatically extract features from MR images and classify brain tumors into four types. The paper evaluates the proposed method on a dataset of brain tumor images and shows its high accuracy and efficiency.[10]

2.3 Conclusion

A wide array of convolutional neural networks is frequently utilized across various applications. The research articles utilized diverse methodologies and approaches. To improve the quality of outcomes, researchers employ various techniques such as data augmentation, feature extraction, and annotation removal. This study utilized a range of methodologies. In order to overcome the aforementioned limitations, we implemented data processing techniques and applied pre-trained convolutional neural network models to our balanced dataset.

Chapter 3

Methodology

3.1 Research Methodology

We have applied VGG16, VGG19, InceptionV3, Xception, DenseNet121, MobileNet, and ResNet101 for this study. Figure 1 shows the working procedure.

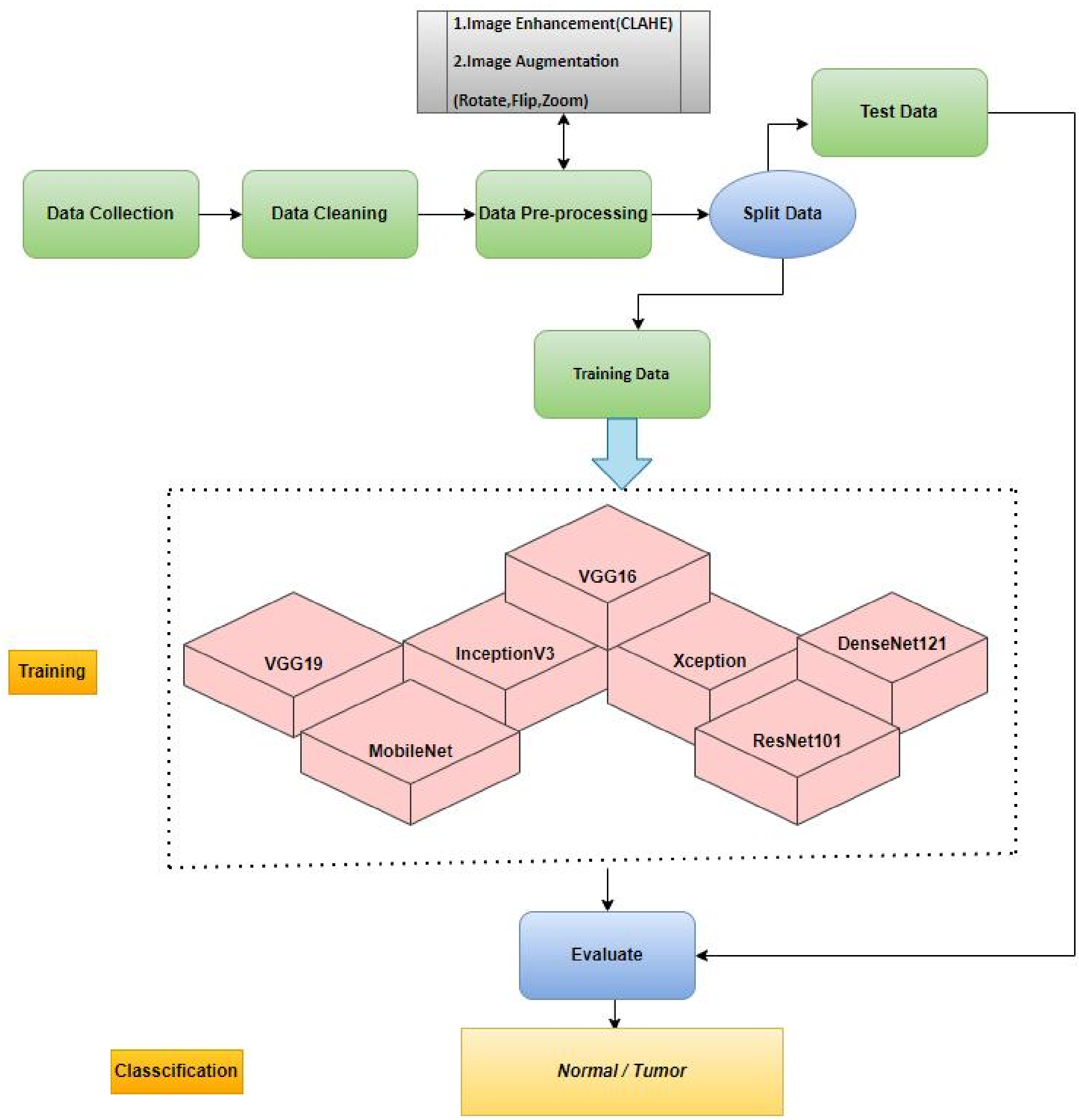

Figure 1: Working Procedure

3.2 Data Collection

Data were collected from various sources for this study. GitHub and Kaggle were the sources of our dataset. Collecting normal, tumor class data from these sources and combining them into a single dataset. There are a total of 5733 images in the dataset. Figure 2 depicts four class-sample pictures of the merged dataset, while Figure 3 depicts the total number of dataset images.

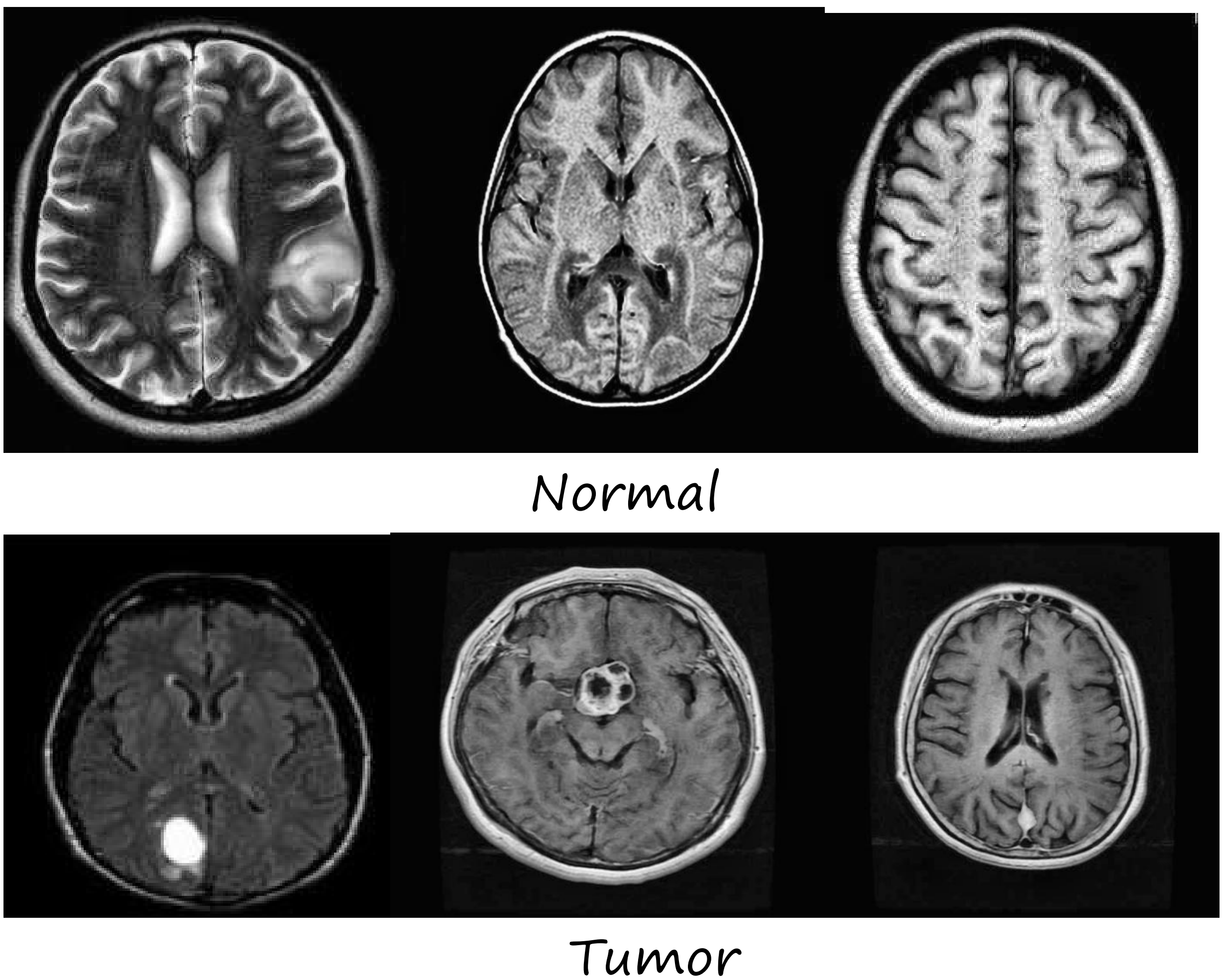

Figure 2: Normal, Tumor sample data

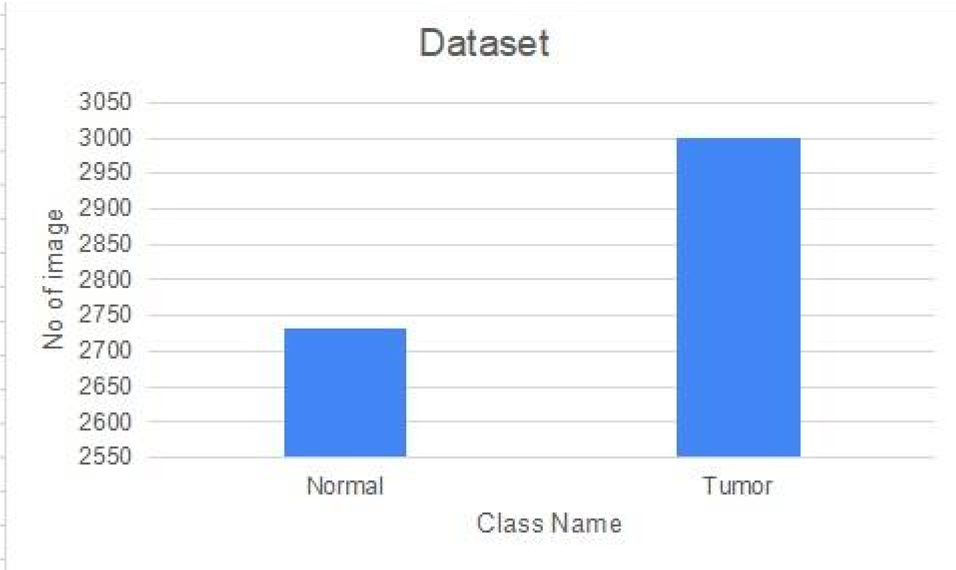

Figure 3: Total Dataset Images

3.3 Data Processing

3.3.1 Image Enhancement (CLAHE)

To enhance the contrast of images we have applied Contrast Limited Adaptive Histogram Equation (CLAHE). CLAHE is a variant of the Adaptive Histogram Equation (AHE). It can amplify the contrast of images. CLAHE is an effective method for low-contrast images. It reduces the false border and removes artificial boundaries neighboring tiles combined with bi-liner interpolation. The output result is shown in Figure 4.

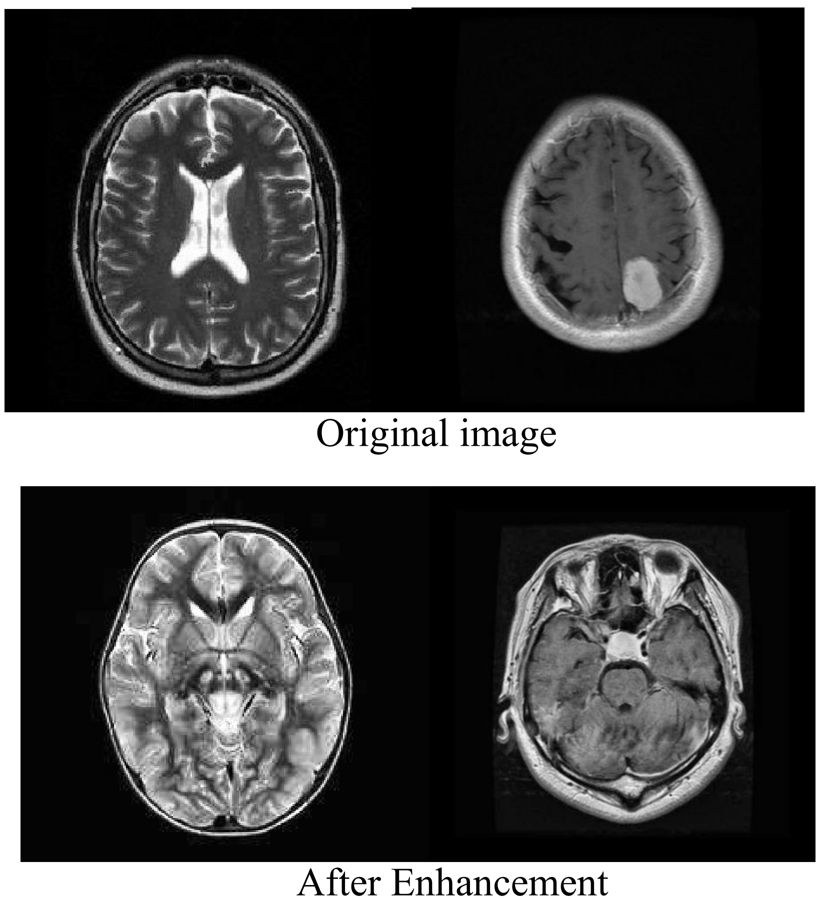

Figure 4: Output after image enhancement.

3.3.2 Image Augmentation

Image augmentation techniques increase the dataset size. It is the process of generating new data from existing data. In this research, we use 3 types of augmentation techniques for increasing the dataset size zooming, flipping, and rotating. This increases the performance of deep learning models. In medical Image processing, MRI data labeling and collecting is a time-consuming process. The augmentation result is shown in Figure 5.

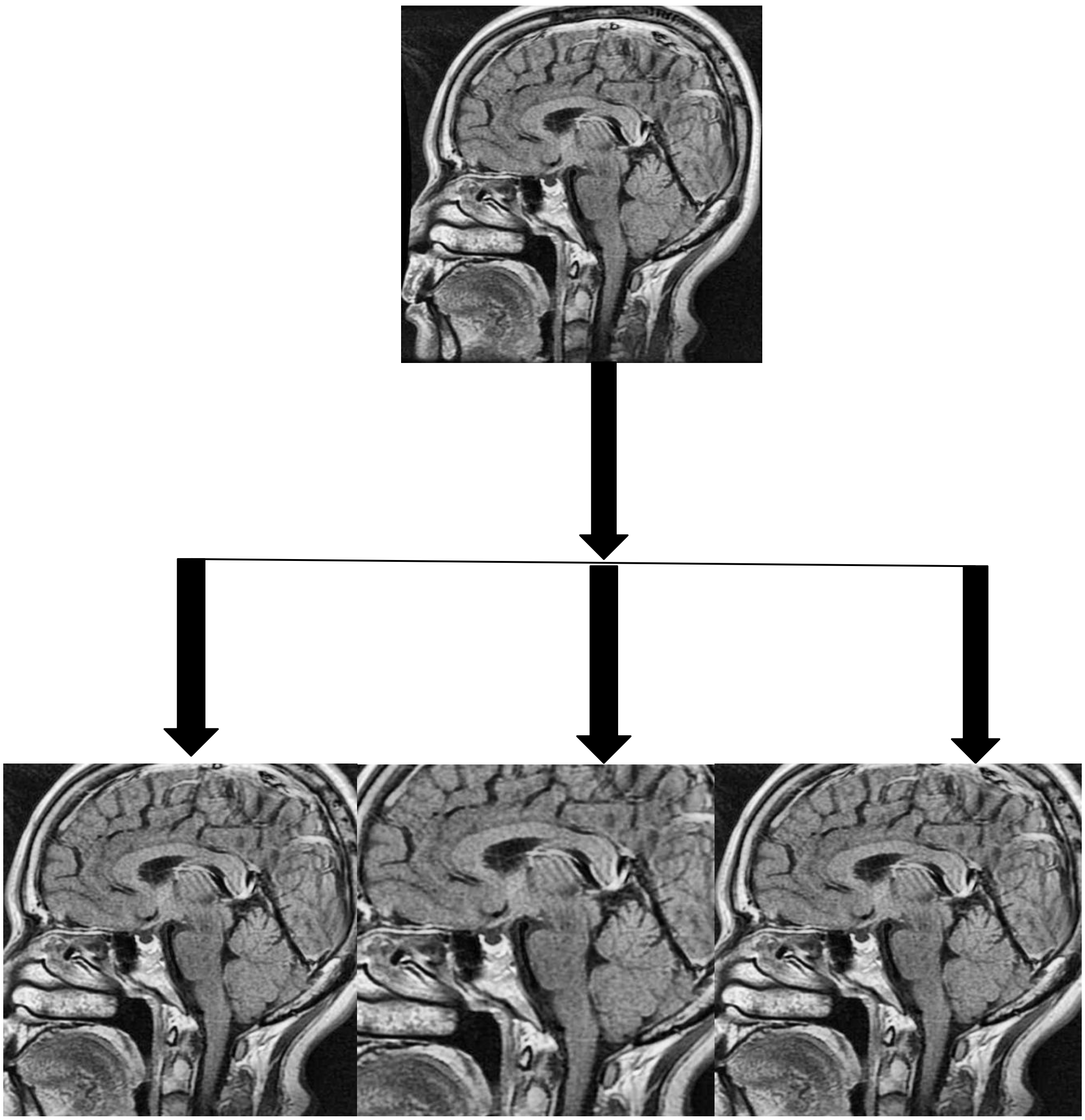

Figure 5: Output of Image Augmentation

3.3.3 Data Normalization

In image processing, the normalization of images changes the values of the pixel intensity. Normalization ensures the input parameter has a similar distribution. This will help train the network faster. The pixel value is from 0 to 255.

3.3.4 Data Resizing

Resizing images is essential to feed deep learning models. The dataset contains various types of images. In this work, we resize it to (224 x 224) pixels.

3.4 Transfer Learning Models

Transfer learning is the process of transferring previously acquired knowledge to new problem-solving situations. In this research, we used 7 pre-trained models for detecting brain tumor illness from chest MRI images. All of these pre-trained models were trained on a large dataset. Extracting features from MRI images by using pre-trained models is a transfer learning technique.

3.4.1 Proposed Model

The objective of this research is to produce adequate classification results utilizing transfer learning models. By hyper tuning VGG16 customized transfer learning model was developed to achieve the highest accuracy among all other pre-trained models. The name of this proposed model is MediNet22.

3.4.2 VGG 16

VGG 16 is a pre-trained model and it was developed by Zisserman and Simonyan in 2014. VGG16 is the improved version of AlexNet. It was trained on a large ImageNet dataset and the collection of images of over a million. VGG16 refers to 16 layers of widgets. VGG16 contains 13 convolutional layers, 5 max-pooling layers, and 3 dense layers. The input layer dimensions are (224, 224, 3).

3.4.3 VGG 19

VGG19 is a convolutional neural network that was developed by Simonyan and Zisserman. It has 19 layers with 16 convolutional layers and 3 fully connected layers. The input sizes of VGG19 are (224, 224, 3). It used (3*3) size of the kernel and 1-pixel size of stride. Spatial padding and max pooling were performed in this network. Max pooling was (2*2) pixel with stride 2. ReLU (Rectified Linear Unit) implemented in VGG19 reduces the computational time and helps to classify better.

3.4.4 InceptionV3

Inception V3 was trained on the ImageNet dataset and it reduces computation power. The input size of inceptionV3 is 299x299x3 and the output size is 8x8x2048. The convolution layer, average pooling, max pooling, concat, dropout, and fully connected layer are used to develop this model. SoftMax was used for loss calculation.

3.4.5 Xception

Xception is 71 layers of a convolutional neural network. The dimension of the input image shape is (299,299). Xception is the improved version of Inception. This model is divided into 3 flows. Entry flow, Middle flow, and exit flow. Start from the entry flow then the middle flow and this repeated 8 times finally show output with the exit flow. Xception architecture shows depth-wise separate convolution and max pooling.

3.4.6 DenseNet121

DenseNet121 resolves the convolutional neural network feed-forward problem and simplifies the connectivity pattern between layers. DenseNet121 has 1 (7x7) convolution, 58 (3x3) convolution, 61 (1x1) convolution, 4 average pooling, and 1 fully connected layer. DenseNet121 allows feature reuse and also requires fewer parameters.

3.4.7 MobileNet

MobileNet has 13 (3x3) Depth wise convolution layers, 1 (3x3) convolution, and 13 (1x1) convolutions. This pre-trained model was trained using the ImageNet dataset. The parameter of MobileNet is 4.2 million.

3.4.8 ResNet101

ResNet101 is 101 layers deep and it was trained on the ImageNet dataset. ResNet101 represents the deep residual network framework. The concept of ResNet101 is residual learning and skip connection. This helps Resnet101 to train much deeper. ResNet101 has zero padding, average pooling, a flattened layer, and a fully connected layer.

3.5 Evaluation Method

In this research, confusion matrices were used for evaluating the result. For model performance evaluation, the confusion matrix is commonly used. In a confusion matrix each column represents the predicted category and each row represents the true attribution of data. For evaluation, a confusion matrix needs true positive, true negative, false positive, and false negative. True positive (TP) is an outcome when the model correctly predicts a positive class. When a model correctly predicts a negative class, it is True Negative (TN). False positive incorrectly predicts positive class and false negative incorrectly predicts negative class.

3.5.1 Accuracy

Accuracy is the ratio between the correctly predicted observation and the total observation. Accuracy is calculated by using Equation 1.

$$Accuracy = \frac{True\ positive + True\ Negative}{True\ positive + True\ Negative + False\ Positive + False\ Negative} \quad \text{---------(1)}$$

3.5.2 Precision

Precision is the ratio between correctly predicted positive observations and total predicted positive observations. Precision is calculated by using Equation 2.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive} = \frac{True\ Positive}{Total\ Predicted\ Positive} \quad \text{-----------(2)}$$

3.5.3 Recall

A recall is the ratio of correctly predicted positive observations to all observations in actual classes. A recall is calculated by using equation 3.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad \text{-----------(3)}$$

$$= \frac{True\ Positive}{Total\ Actual\ Positive}$$

3.5.4 F1 Score

F1 score is the weighted average of Precision and Recall. F1 is more useful than accuracy because it takes both false positives and false negatives values to calculate F1 Score. The F1 formula is given in Equation 4.

$$\text{F1} = 2 \times \frac{Precision * Recall}{Precision + Recall} \qquad \text{-----------(4)}$$

Chapter 4

Result & Discussion

4.1 Introduction

This section gives an overview of the classification report for brain tumors. After gathering the data and doing some preliminary processing, I used a pre-trained model that was previously outlined for the classification approach. This section describes all of the model performances that were utilized.

4.2 Result Discussion

These models' training and validation accuracy, loss, and validation loss graphs are shown once they have been put into use. This study uses VGG16 with a flattened layer, dropout of 0.5, dense layer, and SoftMax as the activation function for 50 epochs. Figure 7 displays the training and validation accuracy graph, as well as the loss and validation loss graph.

The VGG19 model was utilized with a flattened layer and a dropout rate of 0.3. A dense layer was then applied, with the activation function set to SoftMax, and the model was trained for a total of 50 epochs. The graph in Figure 8 displays the accuracy and loss of the model.

InceptionV3 pre-trained model was trained with a merged dataset with 50 epochs and also shown model accuracy and model loss graph in Figure 9.

The Xception model was trained using the same dataset as other pre-trained models; however, it exhibited a higher loss value compared to the other models.
The graph in Figure 10 displays the model's loss and accuracy.

DenseNet121 was trained using a flattened layer, a dropout rate of 0.5, the sigmoid activation function, categorical entropy as the loss function, and the Adam optimizer. The graph depicting the loss and accuracy of the model is presented in Figure 11.

The MobileNet architecture was utilized for the purpose of training, incorporating hyperparameter tuning techniques. The categorical entropy was employed as the loss function, while the optimizer used was rmsprop. The observed validation loss exhibited a significant magnitude. The accuracy graph and loss graph are depicted in Figure 12.

The ResNet101 model was trained on the same dataset without utilizing dropout regularisation and employed the SoftMax activation function. The graph illustrating accuracy and validation is depicted in Figure 13.

4.2.1 VGG16

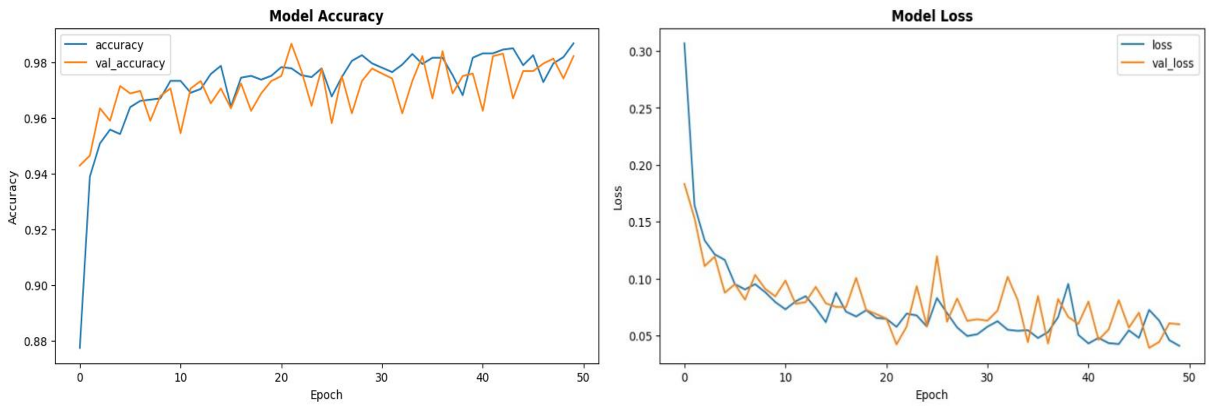

Figure 6: Model Accuracy and Model Loss of VGG16

4.2.2 VGG19

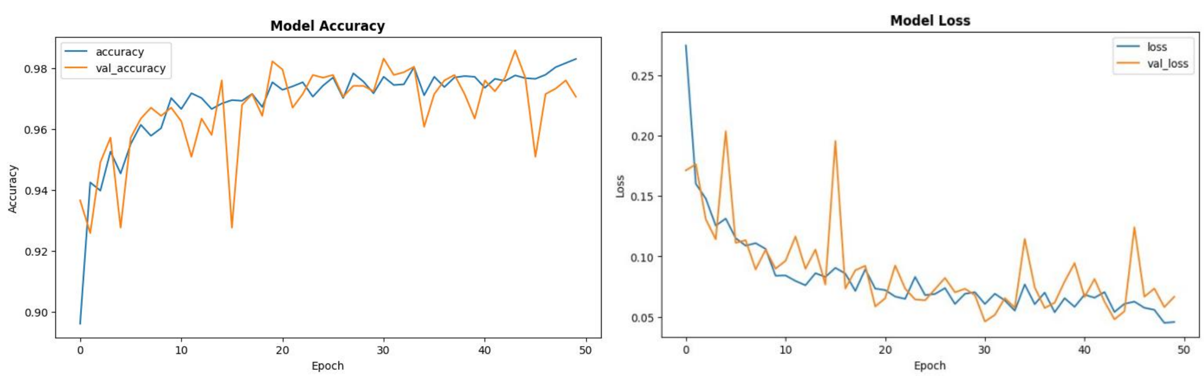

Figure 7: Model Accuracy and Model Loss of VGG19

4.2.3 InceptionV3

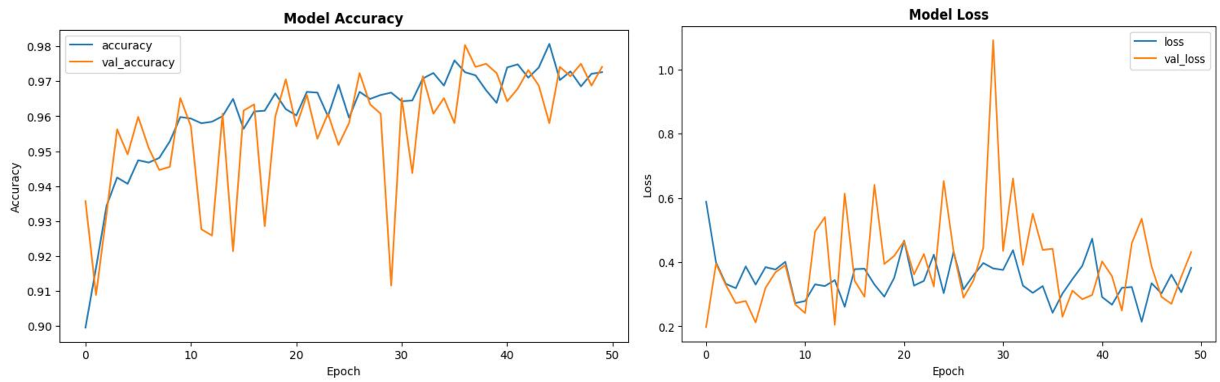

Figure 8: Model Accuracy and Model Loss of InceptionV3

4.2.4 Xception

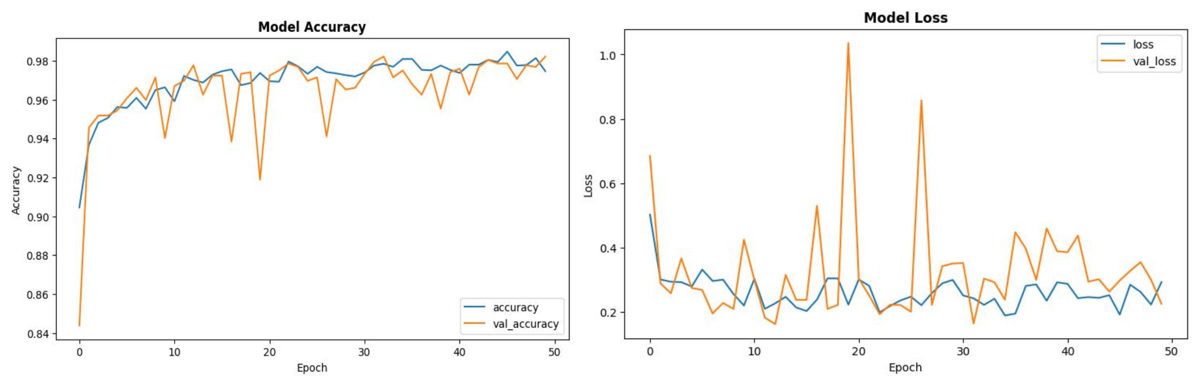

Figure 9: Model Accuracy and Model Loss of Xception

4.2.5 DenseNet121

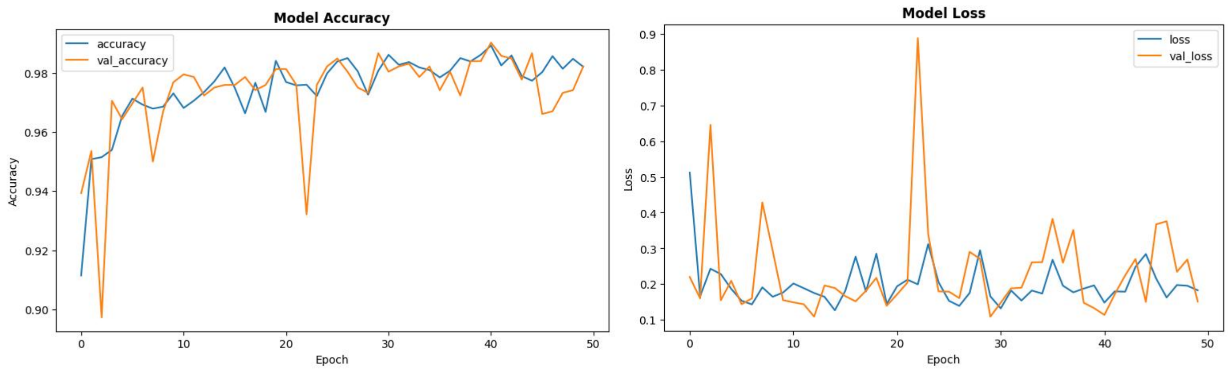

Figure 10: Model Accuracy and Model Loss of DenseNet121

4.2.5 MobileNet

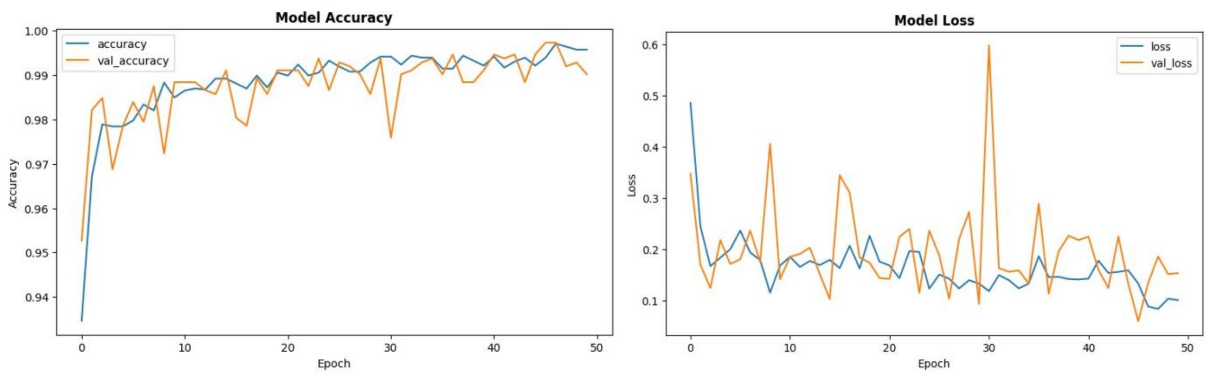

Figure 11: Model Accuracy and Model Loss of MobileNet

4.2.6 ResNet101

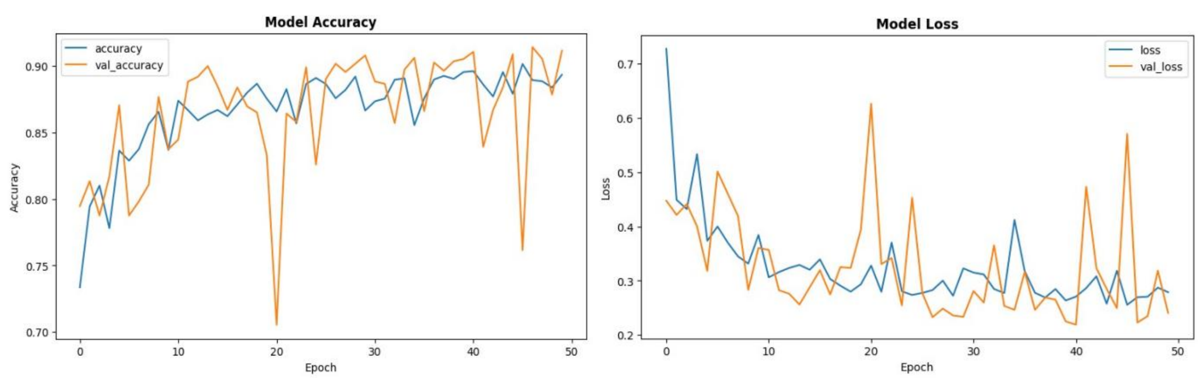

Figure 12: Model Accuracy and Model Loss of ResNet101

In table [1] classification reports of seven pre-trained model has been shown. By analyzing this table, Xception, MobileNet, DenseNet121, ResNet101, InceptionV3, VGG19 and VGG16 accuracy is 99.11%,99.20%,98.39%,91.26%,96.88%, 97.95% and 98.31% respectively.

Model Name	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
VGG16	98.74	98.06	98.40	98.31
VGG19	97.68	99.31	98.49	97.95
Xception	99.02	98.06	98.54	99.11
InceptionV3	98.31	97.09	97.70	96.88
DenseNet121	99.03	98.61	98.82	98.39
MobileNet	99.31	99.86	99.58	99.20
ResNet101	92.62	95.70	94.13	91.26

Table 1: Classification reports of pre-trained models and proposed model

In Figure 14 an accuracy graph is the comparison of accuracy and Confusion matrix results shown in Figure 15.

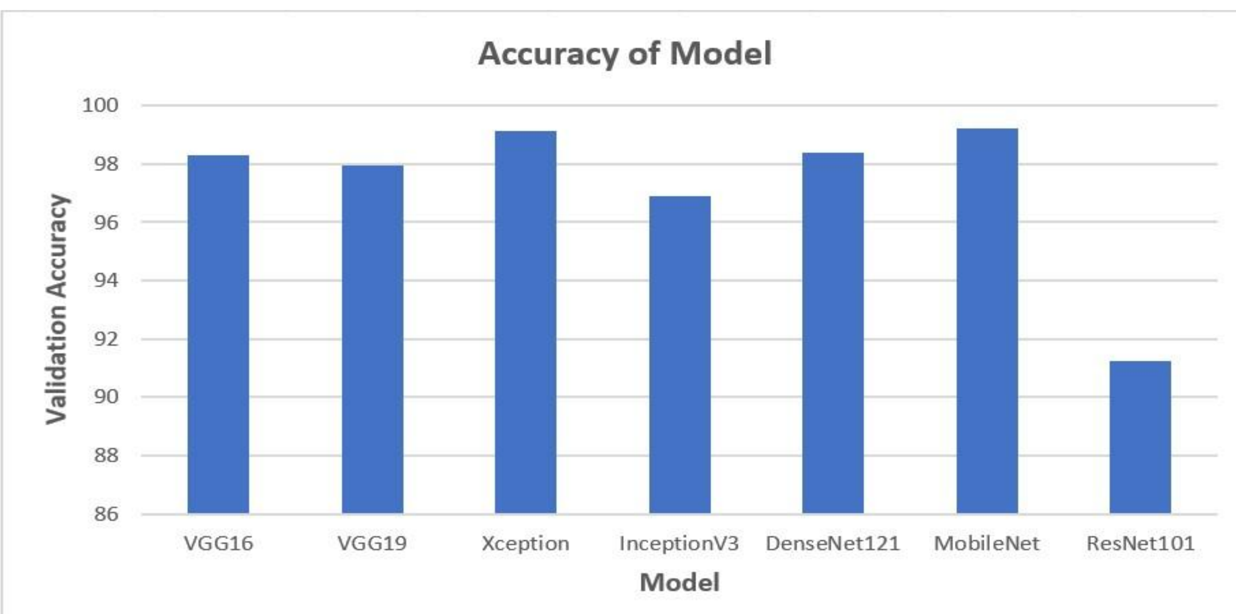

Figure 13: Accuracy of the pre-trained model

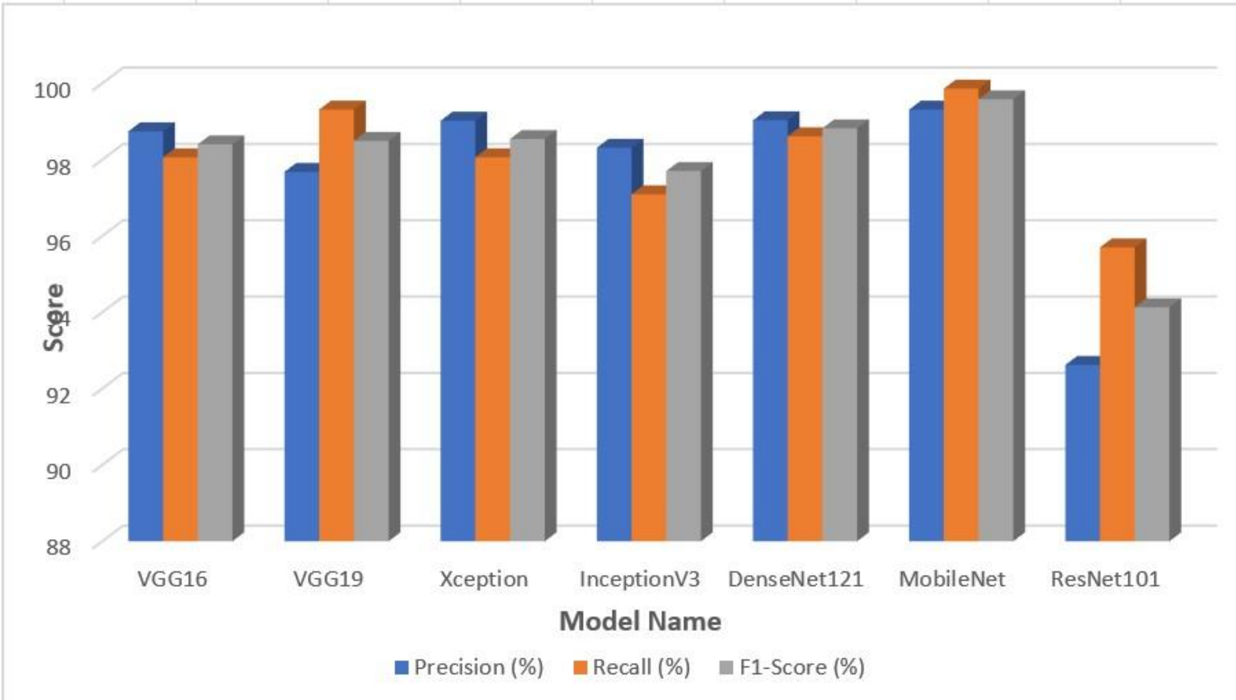

Figure 14: Precision, Recall, F1-Score Comparison of the pre-trained model.

Chapter 5

CONCLUSION & FUTURE WORK

5.1 Conclusion

The purpose of this study is to create a fast tumor identification system that aids neuro-oncologists and neurosurgeons in swiftly analyzing MRI data. Even a skilled neuro-Oncologist finds manually reviewing MRI pictures to be challenging and time-consuming. Additionally, prompt reporting and appropriate treatment will aid patients. Various data processing methods have been used in this study. It was done by removing the picture annotations. Aside from that, picture augmentation and enhancement were applied to improve classification results.
Three different kinds of augmentation techniques were used, which increases the size of the dataset. Seven pre-trained models were applied to this dataset to train them. Comparing these models is shown in this paper. MobileNet has the greatest accuracy and least validation loss among these models. This model's accuracy was 99.20 %.

5.2 Future Works

There is a tonne of room for more research in this area since MRI-based medical image processing for brain tumor investigations has recently drawn attention owing to increasing demand for an effective technique. However, given the research that this individual did
The following actions may be taken: a. A comparison study can be conducted to suggest the best pre-trained model for the second technique (vgg16, which this researcher employed).
b. The authorized medical authority may provide a benchmark dataset so that it may be compared to the current methods.
c. The current study mostly uses 2D data to identify tumor areas. The study could also include 3D data identification procedures.
d. If there is a larger amount of data available, it is possible to grade tumors (partnership with hospitals may make a large volume of data accessible).
e. Using the same set of data, the performance of different techniques may be compared.

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