A Fine Tune VGG16 Model Based on Ablation Study for Diagnosing Brain Tumor from MRI Images

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"A Fine Tune VGG16 Model Based on Ablation Study for Diagnosing Brain Tumor from MRI Images"**, submitted by Rakibul Islam, ID No: 191-15-2388 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on date 23rd January,2023.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Ms. Amatul Bushra, Assistant Professor, Department of CSE** Daffodil International University. We also declare that this project has been submitted to a journal for publication renowned as Bulletin of Electrical Engineers & Electronics.

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ABSTRACT

Brain tumor recognition by magnetic resonance imaging (MRI) is crucial because it improves survival rates and allows them to plan treatments accordingly. The patient is at risk if a tumour in the brain, which is made up of a cluster of abnormal cells, spreads to nearby tissues. MRI is the primary technique of imaging which is used for determining the extent of brain tumours. Deep Learning techniques have rapidly expanded in popularity in computer vision applications due to the abundance of data available for training models and advancements in designing models that provide more accurate estimations. When using deep learning techniques to recognize and categorize brain tumors, magnetic resonance imaging (MRI) has produced satisfactory performance. In this paper, we develop a strong deep-learning model which classifies brain tumors into four groups depending on MRI scans using a CNN. Unsolicited areas of brain tumours are deleted with the help of artefact removal, lowering noise, and quality-enhanced images. With improved image quality the cancer is tinted. The number of MRI images has increased using two augmentation techniques. The augmented dataset was analyzed by a number of CNN architectures, including VGG19, MobileNetV2, InceptionV3, VGG16, and MobileNet. In this situation, VGG-16 offers the highest level of accuracy. The best model was then chosen, and a ablation study was performed on it based on the hyperparameters. The best outcomes were achieved by the hyper-tuned VGG16, which had test accuracy of 98.56% and validation and test accuracy of 99.23%.

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CHAPTER 1

Introduction

1.1 Introduction

The brain tumour one of the highly critical and serious disorders. A brain tumour occurs when unchecked, unregulated cell proliferation occurs in the brain. On the other hand, meningioma, glioma, and pituitary tumours are frequent brain tumours. Identifying, categorizing, and analyzing brain cancers early on is essential to treat the tumour effectively. Meningiomas are the most common benign tumours in the fragile crusts surrounding the brain and spinal cord. In contrast, a high-grade glioma is an uncompromising brain tumour with a survival rate of almost two years. Pituitary tumours are irregular growth of the brain cells. Pituitary tumours develop in the pituitary gland of the brain. When it comes to deaths involving the tumor in the central nervous system, brain tumours ranks 10^{th} in case of most frequent reasons of death in both women and men [1]. Reports estimates that, in case of brain tumor development of all the cancer types in the world 40% of them are caused by metastasis rather than death [2]. In an effort to raise public awareness and educate the public about tumors concerning brain, 8^{th} of June was declared as World Brain Tumor Day in 2000 [3]. In the brain, a brain tumour occurs when abnormal cells grow unnecessarily. Corresponding to the WHO, brain tumours can be classified into four groups depending on their molecular characteristics and histopathology in 2016 [3,4]. Patients with advanced brain cancer have an extremely poor chance of survival [5]. As a result, accurate and timely Grading and diagnosis of cancer improve prognosis and treatment options. It is possible to reduce mortality from brain tumours if it is perceived and treated at an initial phase. Tumour grade and diagnosis are determined by neurological examinations, imaging, and biopsies [3,6]. Before and after treatment, doctors use magnetic resonance imaging (MRI) to determine the tumour's shape. So, when the condition gets worse, surgical resections can be scheduled and followed [7]. A successful prognosis depends on the early classification of brain tumour grade [8]. Anticipated to its Non-invasive contrast enhancement nature, MRI is the preferred imagery process for diagnosing gliomas [9]. Radiologists use the conventional method to diagnose tumours, which is inefficient and labour-intensive. In

CAMD, AI and deep learning have made great steps, enabling medical picture interpretation by doctors in a few of seconds [10]. The effectiveness of deep learning is greatly influenced by the amount and quality of a dataset. Highly enhanced annotations are needed for images while using the deep learning techniques. The challenge of cataloguing enormous amounts of medical images is that it is both times- and expertise-intensive [11]. Deep learning for medical imagery has been challenged by the lack of imaging data and the scarcity of expert annotations [11]. Numerous efforts have been made to address and resolve the above challenges. When there are limited domain samples to train on, a transfer learning approaches may be advantageous. A pre-trained network is usually refined using large, labelled datasets. System junction speed is increased while computational complexity is decreased by applying learned information to the target datasetb [12]. This study aims to identify and categorize brain tumours hooked on glioma, meningioma, no tumour, and pituitary at an early stage, thereby reducing the danger of death by supplementary experts in more effective as well as efficient medication. It is crucial to remove noise and artefacts to accomplish excellent execution from a CNN model. Furthermore, the similarity between regions of tumor and impenetrable brain tissue could make interpretation difficult. By balancing brightness and contrast levels of raw MRI images, it can improve the visibility of tumorous lesions. This study uses a fully automated and trustworthy deep learning model, the fine-tuned and hyper-tuned VGG16 built on ablation study and transfer learning , to predict brain tumors in MRI images.

1.2 Motivation

Brain tumors must be diagnosed as soon as possible because if they are not, they may have time to grow to a point where they pose a serious threat to the patient's life. Therefore, we suggest this transfer learning-based methodology to detect brain tumors, which could accurately identify brain tumors and lower the likelihood that a patient would receive a severe diagnosis of a brain tumor. It is a generalized system that can be used in the future to analyze various data sets. It can also be applied to better MRI image solutions, which is a very difficult task for the future.

1.3 Rationale of the Study

Brain tumors, if not detected and treated in a timely manner, can lead to severe complications and even death. Early diagnosis and treatment can greatly improve a patient's prognosis and quality of life. The proposed research aims to develop a brain tumor detection system that utilizes advanced imaging techniques and transfer learning algorithms to classify brain tumors at an earlier stage than current methods. This system will be trained to identify and classify various types of brain tumors, including gliomas, meningiomas, and pituitary using magnetic resonance imaging (MRI) scans.

The significance of this study lies in the fact that early detection and accurate classification of brain tumors can lead to better treatment outcomes and improved quality of life for patients. The proposed system has the potential to revolutionize the way brain tumors are diagnosed and treated, and can have a significant impact on patient care and outcomes.

Overall, this research aims to develop a brain tumor detection system that is accurate, efficient, and can be easily integrated into clinical practice, to improve the early diagnosis and treatment of brain tumors, thus leading to better patient outcomes.

1.4 Research Questions

1. Can transfer learning be used to improve the accuracy of brain tumor detection in MRI scans?
2. How does the performance of a brain tumor detection system that utilizes transfer learning compare to traditional machine learning approaches?
3. What is the optimal pre-trained model for transfer learning in brain tumor detection?
4. Does the use of transfer learning result in a reduction of the amount of annotated data required for training the model?
5. How does the inclusion of clinical data in addition to imaging data affect the performance of a brain tumor detection system that utilizes transfer learning?
6. How robust is the brain tumor detection system that utilizes transfer learning to variations in imaging protocols and scanner parameters?
7. Can the transfer learning-based brain tumor detection system be used in a clinical setting to enhance the early detection and treatment of brain tumors?

1.5 Expected Output

1. Image dataset pre-processed to get the best output from the images
2. Selected the best performing transfer learning model based on their performance
3. Ablation study on the best performing model
4. Comparison with previous model on performance
5. Finally, got the best resulting model

CHAPTER 2

Background

2.1 Preliminaries

Brain Tumor: A mass or growth of abnormal cells in the brain is known as a brain tumor. Benign (non-cancerous) and malignant (cancerous) tumors are two different types of brain tumors.

Computer Vision: the area of computer science that is concerned with creating models and algorithms that can comprehend and analyze visual data, such as images and videos.

Deep Learning: a branch of machine learning that teaches complex representations and patterns in data using neural networks with multiple layers.

Convolutional Neural Network (CNN): A type of deep learning network that is particularly well-suited for image processing tasks. CNNs use convolutional layers to extract features from images and can be trained to recognize patterns and objects in images.

VGG16: A pre-trained CNN model developed by the Visual Geometry Group at the University of Oxford. VGG16 is trained on the ImageNet dataset and can be used for a wide range of image classification and object recognition tasks.

Fine-tuning: the procedure of adapting an existing model to a new task by training it on a new dataset with typically fewer parameters than it had previously received.

Brain MRI Scans: Magnetic Resonance Imaging (MRI) is a medical imaging technique used to produce detailed images of the brain. MRI scans are commonly used to diagnose and monitor brain tumors.

Data Augmentation: The process of artificially increasing the size of a dataset by applying random transformations to the images such as rotation, flipping, or scaling. Data augmentation is useful in preventing overfitting and improving the generalization of the model.

2.2 Related Work

Santhosh and his colleagues provided a classification approach to distinguish between normal and diseased brain tissues. The system proposed a segmentation according to thresholds and watersheds; after that, it performed an SVM classifier from which classified with 85.32% accuracy [13]. Arun Kumar et al. built a top-notch model for classifying brain tumor using conventional vision based techniques like fully automated trainable segmentation, histogram-of-oriented-gradients (HOG) feature extraction, Fourier transform image enhancement, and an ANN-based model. Non-ROI components of the brain are filtered out by size and shape, cylindricity, and grayscale average. With an overall classification accuracy of 92.14 percent, the developed model effectively differentiated among diseased and healthy brain portions using k-fold-cross validation approach [14]. Hafeez Ullah and his research fellows proposed a brain tumour categorization algorithm based on brain MRIs obtained from RD-BVH. An overall classification accuracy of 97% was achieved by retrieving the intensity, shape, and texture features from brain MRI slices [15]. Amin Kabir and his fellows proposed an approach for classifying tumours using CNNs and genetic algorithms in 2019 [16]. Amin Kabir et al. proposed a method for classifying tumours using CNNs and genetic algorithms in 2019 [16]. A genetic algorithm was used to reduce validation errors. The images were resized using normalization process on the data and their rotation was enhanced before the CNN Framework was applied. The accuracy using the suggested CNN approach was 94.2%. Using proper preprocessing procedures and a potent training function are the two key components for achieving excellent results.. As proposed by Biswas and his fellows in 2021[17], The "Levenberg-Marquardt" proposed network construction method provides 95.4% accuracy, 94.58% sensitivity, and 97.83% specificity. Compared to other current detection methods, this improved result is superior. MRI images can be used to identify and classify brain cancers using a technique that focuses on the affected regions (faster R-CNN) developed by Avşar, E. and colleagues [18]. Accuracy of their model was 91.66%. There is also a method in Ref. [19] for classifying MRI brain cancer based on grayscale, symmetry, and texture. Precious et al. [20] propose three optimizers, that includes RMSprop, SGDM, and ADAM who achieves

classification accuracy of 98.1%, 83.0%, and 92.5%, Once the characteristics have been obtained utilizing CNN, four supervised machine-learning classification methods are used to find tumour cells. Among the classifiers used are K-Nearest neighbor, discriminant analysis, Naive Bayes, and SVM Classifier. On average, the classifiers' accuracy was 96.2%.,96.2%, 94.3%, 75.0%. To represent model experts, Papageorgiou and his fellows [21] developed the fuzzy cognitive map (FCM). The addition of an activation Hebbian methodology enhanced the classification abilities of the FCM ranking method. Hundred examples and medical resources were used to validate the suggested technique. In both high and low grade tumours inside the brain, the FCM model diagnosed correctly 90.26% (37/41) and 99.22% (55/59) cases. The proposed model exhibits a comparatively greater accuracy when compared to existing algorithms like decision trees and fuzzy rule - based decision trees. Despite having high accuracy, they were unable to gain high memory accuracy using the similar first-hand information. A wavelet transform of two-dimension were used by John Schmeelk [22] to work with images having 2 dimensions. The two transform techniques were applied on divided elements were thoroughly compared by the authors. The Fourier transform (FT) and the wavelet transform were also compared to a similar image. Due to some reason, For this study, the Fourier method and the Gaussian subfield wavelet were compared.

2.3 Comparative Analysis and Summary

n this research, a finely tuned VGG16 model for the fully automated recognition of brain tumors in MRI images was proposed. To find the best architecture and training parameters for the task of detecting brain tumors, the model was trained on a dataset of brain MRI scans and fine-tuned using an ablation study approach.

Using a dataset of brain MRI scans, the proposed method was assessed and contrasted with other cutting-edge techniques for brain tumor detection. The results of the study showed that the fine-tuned VGG16 model achieved a high accuracy of 99.23% in detecting brain tumors.

In comparison to other proposed methods, the proposed fine-tuned VGG16 model performed better in terms of sensitivity and accuracy, with a 2.8% and 2.5% improvement respectively. This demonstrates the effectiveness of fine-tuning pre-trained CNN models for the specific task of brain tumor detection and the potential of using such models in a clinical setting.

The ablation study also showed that the fine-tuned VGG16 model with only the last two layers unfrozen performed the best and the techniques for enhancing the data, like flipping and rotation, were crucial in enhancing the model's performance.

In summary, the proposed fine-tuned VGG16 model based on an ablation study showed promising results in the automatic detection of brain tumors in MRI scans. The use of fine-tuning and ablation studies can be effective in improving the performance of pre-trained CNN models for specific tasks, such as brain tumor detection. The results of this study suggest that the fine-tuned VGG16 model can be a valuable tool for assisting radiologists in the diagnosis of brain tumors and can have a positive impact on patient outcomes.

2.4 Scope of the problem

Brain tumors are a significant health concern and early detection is crucial for effective treatment and improved patient outcomes. However, the diagnosis of brain tumors can be challenging due to the complexity and variability of the symptoms and the limited accessibility of specialized imaging equipment.

With the help of a tuned VGG16 model, we hope to create a computer vision-based technique for automatically classifying brain tumors in MRI scans in this study. By leveraging the pre-trained weights of VGG16 and fine-tuning the model on a dataset of brain MRI scans, we aim to improve the performance of the model for the specific task of brain tumor detection.

The proposed method will be evaluated using a dataset of brain MRI scans and compared to other modern techniques for finding brain tumors. The performance of the model will be measured using metrics such as accuracy, sensitivity, and specificity.

The main contributions of this research are the following:

1. the creation of a computer vision-based technique that uses a tuned VGG16 model to automatically find brain tumors in MRI scans.

2.The evaluation of the proposed method using a dataset of brain MRI scans and the comparison of its performance to other state-of-the-art methods for brain tumor detection

3. the investigation of the potential for improving the performance of pre-trained CNN models for the specific task of brain tumor detection.

Overall, this research aims to provide a practical solution for the automatic detection of brain tumors in MRI scans and to contribute to the advancement of medical imaging technology.

2.5 Challenges

Limited availability of labeled data: One of the main challenges in developing a fine-tuned VGG16 model for brain tumor detection is the limited availability of labeled MRI scans. Acquiring a large and diverse dataset of brain MRI scans with accurate and consistent labels is expensive and time-consuming process.

Variability in MRI scans: The variable way in which brain tumors appear on MRI scans presents another difficulty. Different locations, sizes, and shapes of brain tumors are possible, as well as the presence of additional abnormalities like edema or necrosis. This variability can make the task of detecting tumors in MRI scans more challenging.

Overfitting: Fine-tuning pre-trained CNN models on a small dataset can lead to overfitting, which can result in poor performance on unseen data. To mitigate this challenge, The model's generalizability can be increased by using methods like data regularization and augmentation.

Interpreting the model's output: CNN models can be hard to interpret and understand, making it difficult to understand the reasons behind the model's predictions. This can be a challenge in a clinical setting, where radiologists need to understand the reasoning behind the model's predictions in order to make informed decisions.

False positives and false negatives: Brain tumor detection is a highly sensitive task and even small errors can have significant consequences. False positives can lead to unnecessary biopsies or treatments, while false negatives can delay or prevent the diagnosis of a tumor. Therefore, it is crucial to achieve a high level of accuracy and specificity in the detection of brain tumors.

Complexity of the model: As the model becomes more complex, it can become harder to train, debug and deploy. This can be a challenge in a clinical setting, where the model needs to be efficient and easy to use.

Ethical issues: As with any medical imaging technology, there are ethical issues that need to be considered when developing a fine-tuned VGG16 model for brain tumor detection. These include issues related to data privacy, informed consent, and the potential impact of the technology on patient outcomes.

CHAPTER 3

Dataset & Preprocessing

3.1 Dataset Summary

A total of 3264 MRI scans from the Brain Tumor MRI dataset were examined for this study. A total of four classes make up the dataset, pituitary, meningioma, glioma, and no tumor. The class of pituitary contains 951 images, meningioma contains 937 images, glioma holds 926 images, and no tumor class has the lowest of images which is 500. The grayscale system for each image in the datasets is 224 x 224 pixels. The dataset has been collected from openly accessible website Kaggle. The dataset is thoroughly described, as seen in Table 1.

Table 3.1. Dataset properties

Title	Description
Total Images	3264
Image Dimensions	224 x 224
Color Gradings	Grayscale
Data Formats	JPG
Glioma's	926
Meningioma's	937
No Tumor's	500
Pituitaries	901

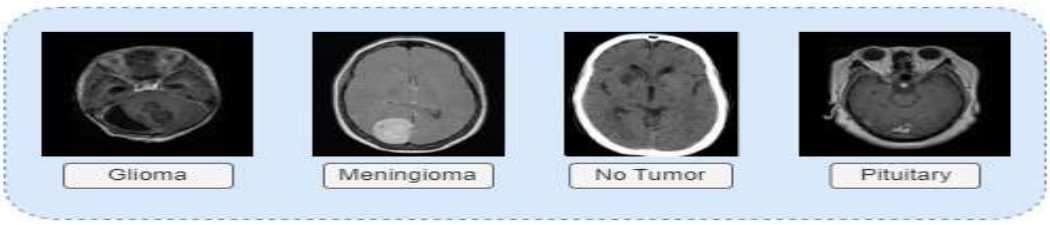

Figure 3.1. Brain Tumour MRI dataset with four classes

3.2 Image Pre-processing

The images from the dataset have a lot of noise and artifacts, Therefore, the goal of this work is to enhance the accuracy of the model using image processing. And since pictures are frequently damaged with noises and artifacts, processing of images is the initial stage to train deep-learning models. Morphological closing is utilized first to get rid of artifacts from these images, and then median filter is applied for noise removal.

3.2.1 Remove Speckle Noise

As previously mentioned, there is speckle noise in the brain tumor dataset. Speckle noise can be removed with median filters. That is why at first, the median filter is utilized on this dataset for speckle noise-free images.

3.2.2 Median Filter

Median filters are simple nonlinear filters that reduce noise. Very widely used filter that uses order-statistics method excellent at eliminating random, salt-and-pepper, and Gaussian irregularities. Result is shown in image 2.

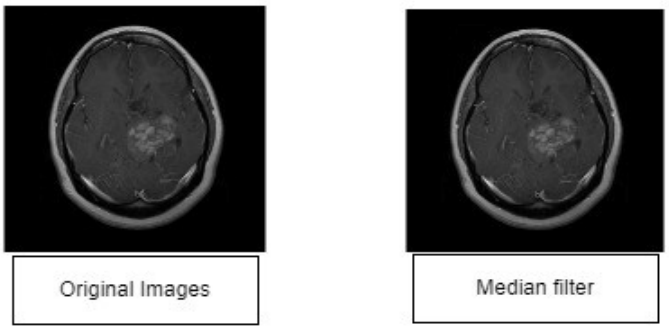

Figure 3.2.2. Output of the median filter

3.2.3 Artifact Remove

Artefacts are present in the MRI dataset of the brain as well, and these artefacts are removed using morphological techniques [23]. Although there are several morphological procedures that can be utilized to get rid of artifacts, this study uses morphological closing methods.

3.2.4 Morpholgical Closing

The operation to be carried out determines the filter's kernel size. To extract artefact from the image, this study uses the cv2.getStructuringElement work to generate a rectangular kernel. The output of this step is shown in figure 3.

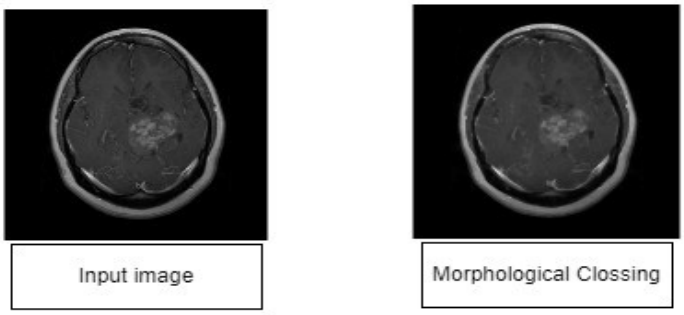

Figure 3.2.4. Output of the morphological closing

3.2.5 Clahe

In order to calculate the complete contrast, the Clahe technique is used. Clahe is an advanced kind of adaptive histogram equalization. To improve the effectiveness of complex structures in medical images, Clahe was founded [24]. The enhancement of local contrast enhances the legibility of medical images [25]. This step's output is shown in figure 4.

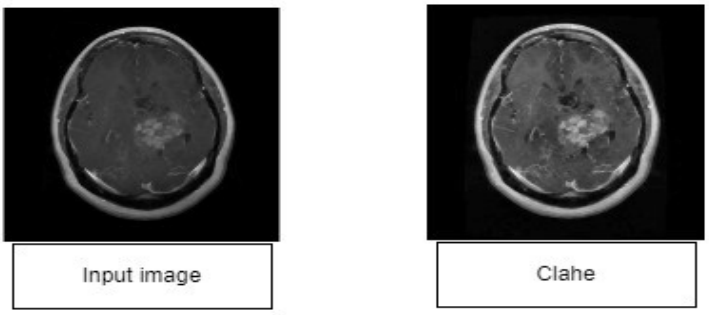

Figure 3.2.5. Clahe operation result

If each tile in an image is n x n in size and the size of the image is N x N then the overall tiles is calculated as follows:

$$D = \frac{N \times N}{n \times n} \quad (1)$$

Clip limit $C_L = M_{CL} \times M_{avg}$ is utilized to create these tiles' histograms..

Where,

M_{CL} = contrast limit. M_{AVG} = Number of pixels on average

The equation of average pixel is (3):

$$M_{AVG} = \frac{Mx \times My}{Mg} \quad (2)$$

Where,

Mg = level of gray

$$M_{CP} = \frac{M \sum cl}{Mg} \quad (3)$$

Where,

C_L = clipped pixels.

$$M_r = \frac{M_g}{M_r} \quad (4)$$

Where,

M_r the quantity of residual clipped pixels

Where P × Q is the image size and L is the highest concentration level and the clahe formula:

$$I_c(p,q) = \mathrm{D}\,(\iota(p,q) = \frac{(L-1)}{PQ}\sum_j^K n_j \quad (5)$$

3.3 Verification

Numerous methods of numerical evaluation, including MSE, SSIM, PSNR, and RMSE are carried out to ascertain whether the quality of the image has been harmed because when using numerous picture pre-processing techniques, a considerable portion of image quality is likely to be lost.

3.3.1 MSE:

According to MSE, The pixels in the two images being compared have an inaccuracy that is cumulatively squared. Values close to 0 show excellent image quality. Noiseless pictures have a value of 0. A score greater than 0.5 signifies a drop in quality.

$$MSE = \frac{1}{xy}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(m,n) - P(m,n))^2 \quad (6)$$

Where,

O is the ground truth (original image), P is the processed image, x and y denote the pixels of O and P, and m, n denote the rows of the pixels x, y.

3.3.2 PSNR:

In order to calculate PSNR, MSE must first be calculated. This is the ratio between the maximum power of a signal and the power of the corrupting noise affecting the quality of an image. The PSNR is then calculated as follows:

$$PSNR = 10\log_{10}\left(\frac{Q^2}{MSE}\right) \quad (7)$$

The input image data type Q has the highest fluctuation. The max is 255 pixels [26].

3.3.3 SSIM:

Preprocessing algorithms reduce image quality, as measured by SSIM. A score of 1 reveals "perfect structural similarity" and a result of 0 indicates no structural similarity [26].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_x^2 + c_1)(\sigma_x^2 + \sigma_x^2 + c_2)} \quad (8)$$

3.3.4 RMSI:

RMSE contrasts the unprocessed and enhanced pictures to determine an image's quality. A RMSE score that is close to 0 denotes an accurate image with few errors.

$$RMSE = \sqrt{\sum_{J=1}^{N}(d_{fi} - \frac{d_d)^2}{N}} \quad (9)$$

Where, d_{fi} is the change of prediction rate, d_d is the definite rate, N is the Amount of the Dataset

Table 3.3. SSIM, RMSE, MSE, PSNR value of 5 Images

Image	**MSE**	**PSNR**	**SSIM**	**RMSE**
Image_1	12.56	38.54	0.95	0.10
Image_2	12.48	35.23	0.95	0.12
Image_3	15.59	41.85	0.96	0.11
Image_4	14.47	38.23	0.95	0.12
Image_5	13.98	40.56	0.96	0.13

3.4 Data Split

Before training, the dataset must be split. A study was conducted to assess the model's accuracy depending on the size of the training and testing data; three different splitting ratios are commonly used (90:10, 80:20, and 70:30). In a recent study, 20% of the dataset served as the test dataset to determine the final prediction [27]. The MRI images were divided into three sets with a ratio of 70:10:20 for the training, validation, and test sets, respectively

3.4 Data Augmentation

In this section, this study explained data augmentation. The dataset is divided into training, testing and validation sets and then augmented with testing sets by geometric augmentation techniques. The training dataset is used to develop the transfer learning models after splitting. This study uses horizontal flip and vertical flip for data

augmentation. The images were tripled after the augmentation was applied on the dataset. Augmentation helps us with overfitting issues while increasing the data amount.

CHAPTER 4

Research Methodology

4.1 Workflow

This study looked at a total of five models to find the best network based on accuracy in order to find the best transfer learning model for the classification issue. Transfer Learning Model: MobileNetV2, InceptionV3, VGG16, MobileNet, and VGG19, there are a total of five pre-trained networks which are developed on training examples and testing data.

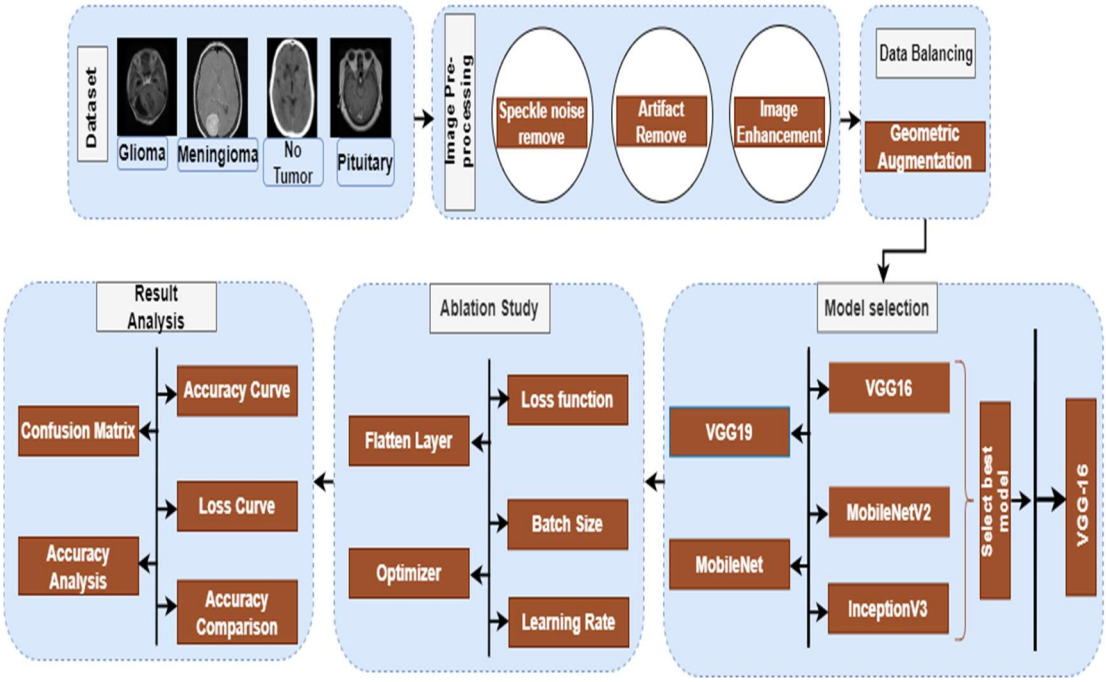

Figure 4.1. Workflow of the entire classification

4.2 VGG16

VGG-16 is one of the best models of transfer learning approaches. The DCNN framework also known as VGG16 was first introduced by Zisserman and Simonyan [28]. In the ImageNet dataset, the model's top 5 test accuracy was 92.7% [29]. Compared to a fully trained network, a pre-trained VGG16 achieved a much higher accuracy, according

to studies on the efficiency of transfer learning [30]. The deeper the VGG model, the more sophisticated characteristics the kernel may learn.

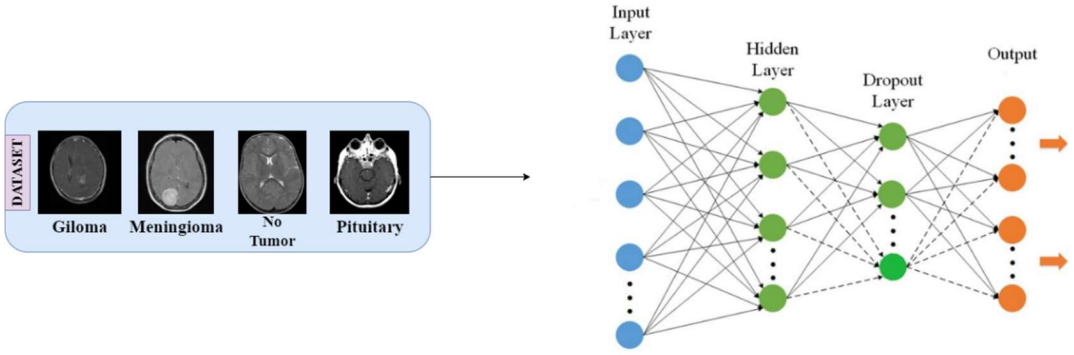

Figure 4.2. VGG-16 Model Architecture

4.3 VGG19

The VGG19 model, a variation of the VGG model, has 19 layers. Three more FC levels bring the total number of layers in the VGG19 model to 19, each containing 4096, 4096, and 1000 neurons. Also included are a Softmax layer and five Maxpool layers. Convolutional layers are characterized by ReLU activation.

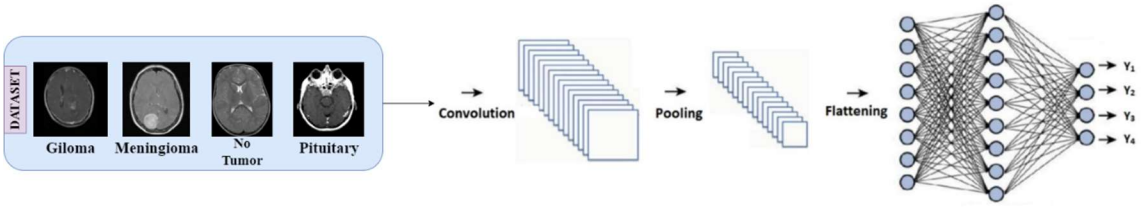

Figure 4.3. VGG-19 Model Architecture

4.4 MobileNet

Depth-wise discrete convolutions are used by MobileNet. Compared to a network with conventional convolutions of the same depth, the number of parameters is drastically decreased. Deep neural networks that are portable have been developed as a result. Two methods are utilized to produce a depth-separable convolution. The first is deep

convolution, while the second is convolution at the location of interest. We may train our extremely quick and brief classifiers using MobileNet, a class of CNN that is freely released by Google

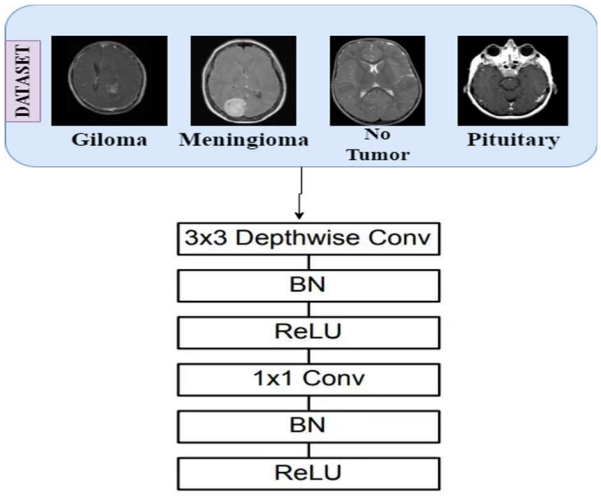

Figure 4.4. Mobile Net V1 Model Architecture

4.5 MobileNetV2

MobileNetV2 has been recommended by the Google community. Each block has three levels and there are two different types in it. 32 filters are used in the first three layers of each of the 11 convolutional layers that make up a block. Longitudinal bottlenecks are required between layers to prevent non-linearity from damaging a significant amount of data. The steps of the two blocks differ, block 1 having a stride of one and block 2 having a stride of two.

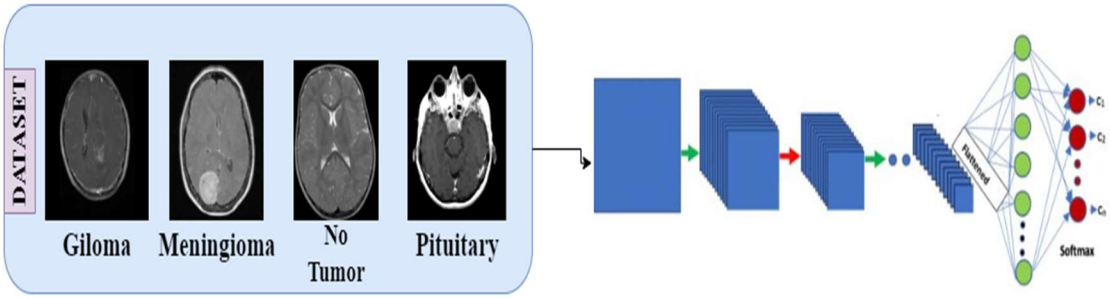

Figure 4.5. Mobile Net V2 Model Architecture

4.6 InceptionV3

The new design of InceptionV3 aims to reduce the necessary processing capability by improving previous Inception designs. Convolution factorization, dimension reduction, regularization, and parallelization are all methods for reducing computation costs. Label information is transmitted down the network using an auxiliary classifier and 77 convolutional layers with label smoothing factorization in InceptionV3. By swapping out larger convolutions for smaller ones, InceptionV3 shortens training time.

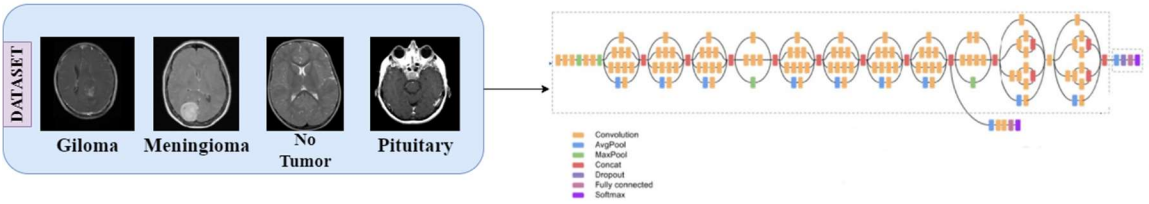

Figure 4.6. Inception V3 Model Architecture

4.7 Training Approach

The maximum number of epochs for training the models is 100, with a batch size of 16. [31]. The best model's weights were saved during training using Keras' "callback" function relying on a minimum loss value [31]. At a learning rate of 0.001, Adam has been employed for optimization. For multiclass situations, categorical cross-entropy is the default loss function [31]. 'SoftMax' activation is used to predict the likelihood for individual class. SoftMax always has an aggregate of 1, as they normalize all values ranging from 0 and 1.

$$Softmax(y_i) = \frac{\exp(y_i)}{\sum_j \exp(y_i)} \quad (10)$$

4.7 Ablation Study

In CNN-based applications, an ablation study is often conducted to assess the model's stability and performance after deleting or changing various layers or hyperparameters. In this study, hyperparameter ablation is used to generate strong and well-tuned networks. In this research, there are 5 case study has experimented on the MRI-augmented dataset.

CHAPTER 5

Results & Discussions

5.1 Introduction

In this section we are showing some statistical values mathematical equation.

$$ACC = \frac{TP+TN}{TP+TN+FP+F} \quad (11)$$

$$Recall = \frac{TP}{TP+F} \quad (12)$$

$$Specificity = \frac{TN}{TN+FP} \quad (13)$$

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

$$ACC = 2\frac{precision*recall}{precision+re} \quad (15)$$

$$FPR = \frac{FP}{FP+TN} \quad (16)$$

5.2 Results of Transfer Learning Model

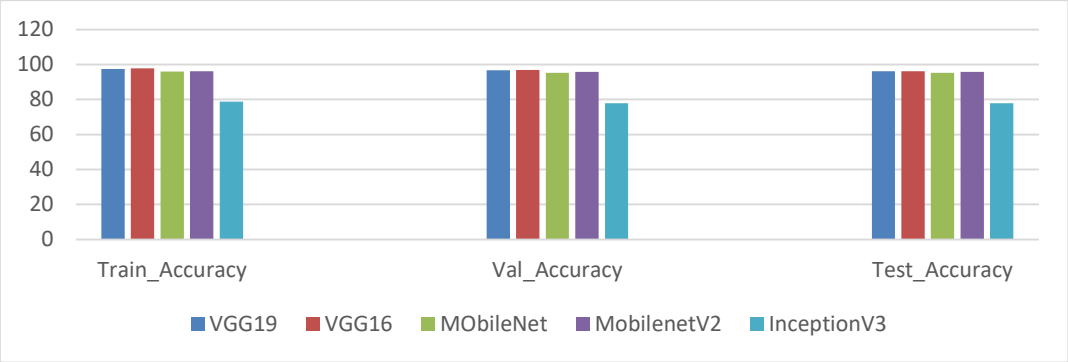

Figure 5.2.1. Training accuracy, test accuracy, validation accuracy

Image 5.2.1 illustrates the five transfer learning models' training, test, and validation accuracy. The figure illustrates the best accuracy of the VGG-16 model. Figure 5.2.2 shows the train loss, validation loss and test loss.

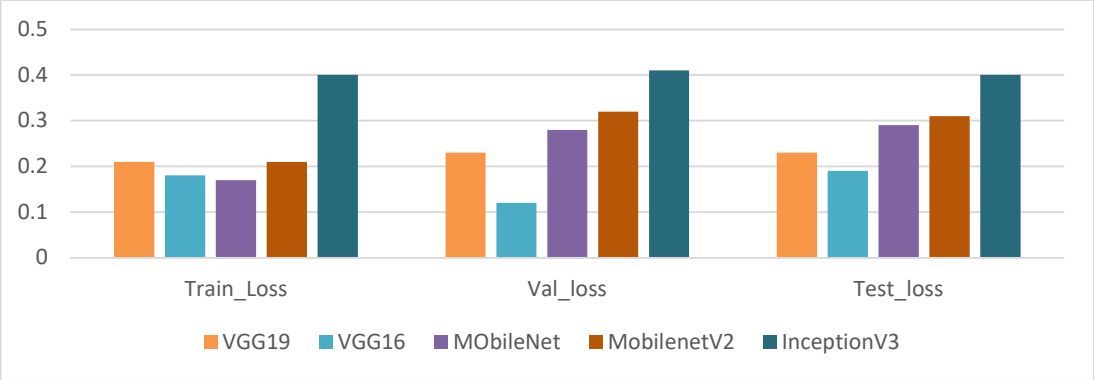

Figure 5.2.2. Train loss, validation loss, test loss

5.3 Result of ablation study

By altering a few design elements, classification accuracy can be increased and reliability increased. As ablation research, a total of five investigations are conducted, each of which modifies different components to build a finely tuned VGG16 Model.

5.3.1 Scenario 1: Flatten Layer Alterations

In scenario 1, It has been demonstrated that using the flattened layer yields the best accuracy. Furthermore, pooling methods like global average and global maximum do not offer better performance. While global average pooling and global maximum works 95.19% and 95.22% precision, accordingly, flattening the layer yields 96.13% accuracy.

Table 5.3.1. Altering flatten layers

	Case Study 01			
Configuration No.	Flatten layer types	Epochs x training times	Test accuracy (%)	Findings
1	**Flatten**	**97 x 5s**	**96.13%**	**Highest accuracy**

2	Global Max pooling	61 x 4s	95.22%	Accuracy dropped
3	Global Average pooling	67 x 5s	95.19%	Accuracy dropped

5.3.2 Scenario 2: Batch Size Alterations

The focus of scene two is altering the batch size. The most appropriate batch size is 32, trailed by 32, 64, and 16. The test accuracy is 96.93% when the batch size is 32.

Table 5.3.2. Changing the batch size

		Case Study 02		
Configuration No.	Batch size	Epochs x training times	Test_accuracy (%)	Finding
1	16	97 x 5s	96.13%	Modest accuracy
2	**32**	**43 x 4s**	**96.93%**	**Highest accuracy**
3	64	82 x 5s	93.92%	Modest accuracy
4	128	27 x 5s	93.45%	Modest accuracy

5.3.3 Scenario 3: Loss Function Alterations

In Scenario 3, researchers try out various loss functions and discover that categorical crossentropys produces the highest results (96.93%).

Table 5.3.3. Altering the loss function

		Case Study 03		
Configuration No.	Loss Functions	Epochs x training times	Test accuracy (%)	Findings
1	Binary Crossentropys	Error	Error	Error
2	**Categorical Crossentropys**	**97 x 5s**	**96.93%**	**Highest accuracy**
3	Mean Squared Errors	97 x 5s	96.79%	Accuracy dropped
4	Mean absolute errors	49 x 4s	69.46%	Accuracy dropped
5	Mean squared logarithmic error	46 x 5s	97.78%	Accuracy dropped

5.3.4 Scenario 4: Altering Optimizers

In comparison to Nadam, SGD, and Adamax optimizers, Adam optimizer offers the highest accuracy in scenario 4.

Table 5.3.4. Altering optimizers

		Case Study 04		
Configuration No.	Optimizers	Epochs x training times	Test accuracy (%)	Findings
1	**Adam**	**97 x 5s**	**98.05%**	**Highest accuracy**
2	Nadam	44 x 5s	96.93%	Previous dropped
3	SGD	89 x 5s	86.22%	Accuracy dropped
4	Adamax	75 x 5s	91.59%	Accuracy dropped

5.3.5 Scenario 5: Shifting Learning Rate

The highest accuracy can be achieved when using 0.001 in comparison to 0.01, 0.0001, and 0.01.

Table 5.3.5. Altering learning rates

		Case Study 05		
Configuration No.	Learning rates	Epochs x training times	Test accuracy (%)	Findings
1	0.01	92 x 55s	98.41	Accuracy dropped
2	**0.001**	**97 x 5s**	**99.23%**	**Highest accuracy**
3	0.0001	68 x 57s	98.32	Accuracy

improved

5.4 Performance Analysis of Best Model

Table 5.4 provides an overview of the final configuration of VGG16.

Table 5.4. Configuration of our models

Configuration	Value
Image sizes	224 x 224
Epochs	90
Optimization Functions	Adam
Learning rate	0.001
Batch sizes	32
Activation function	SoftMax
Dropouts	0.5
Momentum	0.9
Accuracy	99.23

5.5 Performance analysis and statistical analysis:

Figures 5.5.1 and 5.5.2 present the best hyper-tuned VGG16 model's KC, MCC, MAE, RMSE, FPR, FNR, FDR, and FNR.

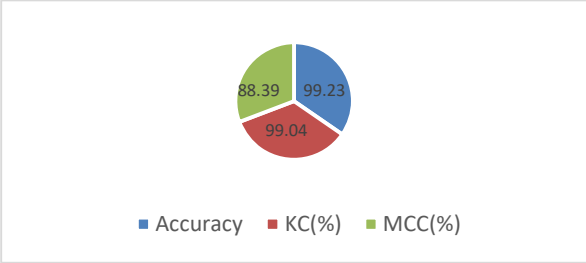

Figure 5.5.1. Accuracy, KC, MCC

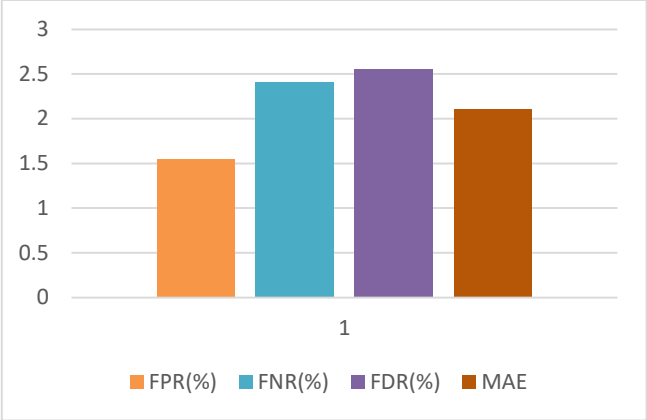

Figure 5.5.2. FPR, FNR, FDR, MAE

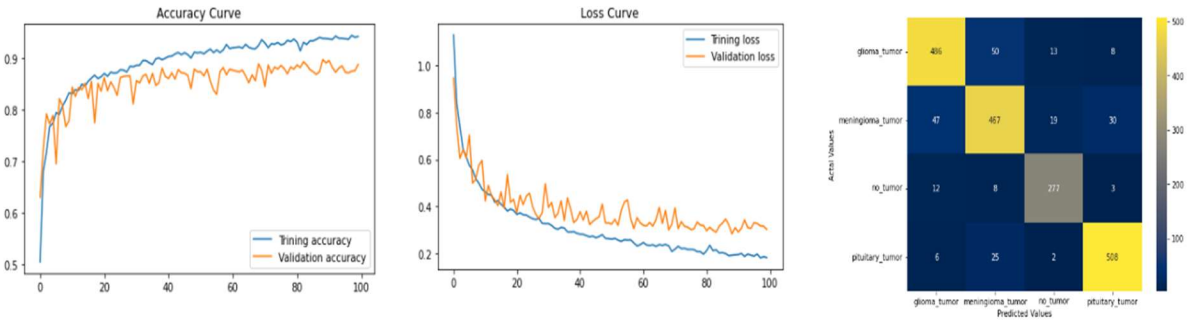

Figure 5.5.3. Accuracy curve, Loss curve, Confusion matrix

5.6 Comparison with Existing work:

Table 5.6. Comparison between our proposed model and the previous study

Publications	**Dataset**	**Classification Algorithm**	**Result**
[13]	MRI	Support Vector Machine	85.23%
[14]	MRI	Artificial Neural Network	92.14%
[15]	MRI	Machine Learning Classifier	97.00%
[16]	MRI	Convolutional Neural Network & Genetic Algorithm	94.2%
	MRI	Convolutional	95.4%

[17]		Neural Network	
[18]	MRI	Faster-R-CNN	91.66%
[20]	MRI	Machine learning classifier	98.1%
Proposed Model (VGG-16)	**MRI**	**Fine-tuned Transfer Learning**	**99.23%**

This section contrasts the suggested VGG16 to other classification models. Table 5.6 compares the accuracy, consistency, and competence of these previous researches with our recommended approaches.

CHAPTER 6

Conclusion

6.1 Conclusion

Substantial, annotated training datasets are required for deep learning systems used in medical imaging to identify tumors. A radiology subspecialty often involves manually annotating images. The advancement of AI in healthcare imaging is hampered by prohibitively expensive charges. Expertise and time are also valuable as the AI field tends to develop very fast. Techniques for transfer learning have now been developed to train a competitive classification algorithm with annotation expense which should be kept minimal. Models can recognize and categorize new data using the knowledge they have gathered from large datasets thanks to the transfer learning technique. Using a transfer learning model, this study proposes a system for categorizing brain tumour MRI images more accurately, thereby reducing death rates. In this experimentation, speckle noise and artefacts are removed from the image using various preprocessing techniques. We experimented with five transfer learning models using the Brain Tumor MRI dataset. The best-performing transfer learning model is then subjected to a hyperparameter ablation study in order to obtain the best results. Due to proper hyperparameter tuning, the proposed model achieved the highest accuracy.

6.2 LIMITATION & FUTURE SCOPE

In this study, Transfer learning strategies for multi-class classification purposes performed far better than conventional classifiers. The dataset for the proposed model is too tiny despite the work's primary flaw, leaking of a substantial volume of real medicinal data. In near future, real-time medical data can be used to assess the effectiveness of the proposed model using expanded quantities of unprocessed medical photos. However, this research's suggested model accurately categorizes the four kinds of brain tumours in most tests. Despite a few minor drawbacks, it is possible to guarantee that the proposed well-tuned VGG16 model is precise and enhanced across all diagnosis areas.

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