A COMPREHENSIVE STUDY ON BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK AND TRANSFER LEARNING

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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 titled **"A COMPREHENSIVE STUDY ON BRAIN TUMOR CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK AND TRANSFER LEARNING"**, submitted by Mehadi Gani Rafe, ID No: 201-15-3674 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 **January 26, 2024**.

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DECLARATION

I hereby declare that, this project has been done by us under the supervision of **Narayan Ranjan Chakraborty, Associate Professor and Associate Head , Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Brain Tumor is a life threatning disease in the world . Estimated 100,000 people affect by brain tumor per year. Significant effect exist in the health condition, life expectancy, patients' family members and the society. Brain tumor patients need efficient and treatment for saving their life. Brain tumor patients suffer from memory problem, personality changes and sickness. Only 5-10% people have family history of brain tumor while others doesn't have. Brain tumor mostly happen in older adult people. But also some brain tumors are common in childrens. Brain tumor not only affect in body but also it affects in mental health. There are nine in ten people heavily affect in depression and mental problems. Therefore, fast and rapidly detection and classification of the brain tumor is essentially important. With important help of technologies now a days medical treatment can go real far. So, trying to train a model with deep learning techniques will be highly helpful. Deep learning Convolutional Neural Networks are efficiently helpful to train a model for classification of brain tumors. So, This study is conducted on the brain tumor patients. All the data collected from various sources. There are 8000 mri image data and in this dataset. A total of six DL algorithms those are use those are MobileNet, Xception, InceptionV3, Resnet50, CNN1 and VGG19 . And also calculate precision, f1 score and recall and their results are compared. Among this algorithms MobileNet give highest accuracy that is 92% .

Keywords—Brain tumor, MRI, MobileNet.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Brain tumor refers to a mass of abnormal brain cells which can be developed anyplace within the brain or the skull . Brain tumor can occur in various locations, including the skull based, sinuses , nasal cavity ,brainstem, and others[11] . There are 120 different types of tumors which depends in the tissue[12]. Brain Tumor is a dangerous disease , and patients' overall health codition become affected by this. Brain tumor is affecting 100,000 people per year. In 2020, the dangerous primary brain tumor and spinal cord tumor afftected 308,102 people [13] . It is essential to diagnose and classify the brain tumor early, so that the patient can receive timely and appropriate treatment. Hence, the detection and also classification of the brain tumors are ongoing research topics in bio-medical engineering. Brain tumors can fall into either the benign or malignant category, on the basis of abnormality of brain cells[14]. The benign brain tumors are not cancerous by far, on other hand malignant tumors are and they spread quickly and cause harm. Most freaquent and common brain tumors are gliomas, glial cells are the root of these brain tumors. They are graded as I, II, III, or IV, based on the risk factors and effects. Another common brain tumor is meningioma, which develops in the central nervous system. One of the category which is pituitary tumors rooted from pituitary glands, these control the hormones[15] . By computer technology progression which automated the detection and also classification fully is boon for the making decisions accurately and also fast by experts. The diagnosis rate gradually improve which also save time. Using the brain tumor classification became a trending research topic. Convolutional Neural Network or CNN is one of the popular among all the models out there due to the high performance and also the flexibility. The model called CNN performs extract the features and also the classification using numorous trainable layers, which are possible to be adjusted based on the results. Based on these factors, we used the pretrained models which are MobileNet, Xception, InceptionV3, Resnet50, VGG19, which are CNN architectures, to identify and also classify of brain tumors into four distinguished types: these are called meningioma , glioma, no tumor, and the pituitary tumor. We have used variety of the MRI images consist of the brain tumors in the datasets of ours, because of their quality are high and also they do not emit the radiation[16]. I use the Unet architecture to segment the tumor and determine its structure, shape, and size.

1.2 Motivation

In recent years, the deep learning models are extensively being utilized on the classification of the patients with brain tumor disease. The CNN architecture is the most popular among all of these models, because of it gives high performance and flexibility. The model which is CNN uses multiple trainable layers to perform feature extraction and classification, which can be adjusted based on the results. Based on these factors, I use the pretrained MobileNet, Xception, InceptionV3, VGG19, ResNet50 architecture to classify brain tumors. MOBILENET achieved the best accuracy. We used a dataset which consists brain tumor MRI images, because their quality are high and do not emit radiation.

1.3 Rational of the Study

A The investigation of applying Convolutional Neural Network (CNN) algorithms in the brain tumors classification are great significance according to realms about medical imaging and healthcare. The motivation for this study lies in the potential to transform the whole system of diagnosis and the treatment of the disorders related to brain. Beginning first with intricate nature of brain tumors images necessitates sophisticated computational methods for precise and efficient analysis. CNNs, well-suited for tasks involving image recognition, provide a robust framework for autonomously learning complex patterns and features within medical images, thereby enhancing diagnostic accuracy. Moreover, the integration of algorithms related to the deep learning in the task of classification of the brain tumors which has potential to significantly diminish reliance on manual interpretation. Automated systems based on CNNs can rapidly process extensive medical data, expediting the diagnostic process and enabling healthcare professionals to concentrate more on treatment planning and patient care. Additionally, the use of CNNs facilitates the extraction of hierarchical features from medical images, enabling the algorithm to discern subtle nuances that might pose challenges for human observers. This capability to capture nuanced information enhances the sensitivity and specificity of tumor classification, potentially leading to earlier detection and intervention.

The adaptability of CNNs is evident in their ability to accommodate numerous imaging modalities, for instance magnetic resonance imaging (MRI) and also the computed tomography (CT) scans., makes them versatile tools for integrating multi-modal data. This comprehensive approach offers a deeper understanding of tumor characteristics, thereby assisting in the development of personalized treatment strategies.

Furthermore, ongoing advancements in deep learning methodologies, including transfer learning and ensemble techniques, further enhance the potential of CNNs in the classification of brain tumors. The ability to transfer knowledge from pre-trained models on large datasets ensures improved generalization and performance, even when dealing with limited labeled images. Ultimately, integrating CNNs into the deep learning models for the classification of brain tumors not only enhances diagnostic accuracy but also plays a necessarily crucial role in advancing of the development of more efficient and also reliable tools for healthcare professionals. This research holds the potential to significantly impact patient outcomes by enabling earlier detection, precise characterization, and the formulation of tailored treatment plans within the field of neuro-oncology.

1.4 Research Questions

- What does the term "brain tumor" refer to?
- In what ways can brain tumors pose a threat to life?
- How do technologies aided by computer effectively aid professionals of medical sector in the detecting and classifying of the brain tumors?
- What makes the automated detection and automated classification of brain tumors significant?

1.5 Expected Output

To detect tumors early, we need to classify them by their types and classes. I used the pretrained MobileNet, Xception, InceptionV3, VGG19, ResNet50 and our created CNN1 architectures to classify brain tumors. MOBILENET outperformed of all the other models. We used a datasets for each task. The dataset has the four tumor types of tymors: these are: glioma , meningioma , no tumor , and the pituitary tumor . We expect that, the model will successfully classifying them correctly.

1.6 Report Layout

- The initial chapter provides an introduction encompassing the motivation, justification for the study, research inquiries, and expected results.
- Chapter two explores the background study, encompassing related literature, comparative analysis, summary, the extent of the existing problem, and associated the challenges related.
- In the the chapter third, a comprehensive overview of the research methodology is presented, covering aspects such as the subject related to research and the instrumentation , methodology for the collection of data , statistical analysis , the approach proposed , and also the prerequisites for the implementation.
- In the fourth chapter, a comprehensive exploration of experimental results and discussion is presented here. The chapter covers the experimental setup, findings, and analysis, followed by an elaborate discussion.
- In the fifth chapter, the discussion revolves around the societal and environmental impact, ethical considerations, and a plan for sustainability..
- In the fifth chapter, a comprehensive overview is provided, encompassing the summary, conclusions, recommendations, and implications for future work.
- Chapter six explain the reference

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

Chapter two presents the major aspects about the previous research on related topic and outlines of the problem and challenges that we face while our work.

2.2 Related Works

Detection while brain tumor and categorization is a vital topic for early diagnosis of tumors. Many studies have explored this topic using deep neural networks, which have shown great performance in identifying brain tumors. Some of the research works that use deep CNN architecture are noteworthy and deserve to be mentioned. There some impressive GAN based research works as well on this topic. Here are some other brief summaries about them.

Ismael et al. used two different methods for feature extraction: 2D DWT and 2D Gabor extraction. They obtained statistical features from these methods and fed them to a standard neural network that was trained by backpropagation. The network has the capability to categorize the three distinct types of tumors: meningioma, glioma, and pituitary tumors [17].

Sultan et al. introduced a technique that employed a CNN architecture to classify MRI images of life-threatening brain tumors into three categories: meningioma, glioma, and pituitary tumor. Additionally, the method could differentiate between various grades of gliomas, including grade II, grade III, and grade IV [18]. Nevertheless, the effectiveness of this method required evaluation through a more extensive dataset of MRI images.

Naceur et al. created deep learning models named 2CNet, 3CNet, and EnsembleNet.. They employed a proprietary training method to construct a self-learning complex incremental convolutional neural network [19].. The model which called a model that combines the technologies 2CNet and 3Cnet and uses which is ensemble learning . The model needs to get tested on the datasets with large-scale to validate its performance.

Havaei et al. presented a new method in their paper which uses CNN architecture Their convolutional neural network (CNN) architecture incorporates binary paths, enabling the extraction of both local features from MRI brain tumor images and global features from their context [20] . The output that is CNN based, which while fed back in CNN , is used to train the architecture with a two-phase training method. The architecture, however, needs to be evaluated on large datasets to handle a large number of MRI images.

Cheng et al. opted to use the tumor portion as the Region of Interest (ROI) for enhancement rather than focusing solely on the tumor region. This decision was based on the understanding that the surrounding tumor tissues can provide additional information related to the tumor. They split the ROI to ring-shaped subregions in order to preserve the information of spatial. They employed GLCM (Gray Level Co-occurrence Matrix), intensity histograms, and Bag-of-Words (BoW) methods for feature extraction. They also utilized Support Vector Machine (SVM) with the Histogram Intersection Kernel (HIK) to classify three types of tumors: meningioma, glioma, and pituitary tumors [21].

In another study by Cheng et al., they employed a Content-Based Image Retrieval (CBIR) approach to identify brain tumors from T1-CE MRI images. They enhanced the tumor portion with the aim of using it as the Region of Interest (ROI), incorporating information from the surrounding tumor tissue. They divided the ROI into small regions on the basis on intensity orders, using the adaptive spatial pooling approach. They applied the Fisher Vector technique to aggregate the local features of each subregion., which were extracted as raw image patches from each subregion [22].

Milica M. Badza and Marko C. Barjaktarovic proposed a novel and straightforward CNN method. They used two databases and a four kind of evaluating strategy and a two kind of 10 cross validation approaches . They evaluated the model on both original and augmented images, employing a 10-fold cross-validation for both subject-wise and record-wise based approaches [23]. The record-wise based cross-validation yielded the best results when combined with augmented images. The technique did not require any pre-processing and utilized all MRI images.Pashaei et al. developed a method that used CNN to extract brain tumor features and then used KELM (Kernel Extreme Learning

Machines) to classify the features which are into three of types of tumors: these are pituitary tumors, glioma and meningioma [24].

Mohsen et al. employed deep neural network classifiers in conjunction with Principal Component Analysis (PCA) and They utilized discrete wavelet transform and classifications to categorize brain tumors into four specific groups: normal, sarcoma, glioblastoma, and metastatic bronchogenic carcinoma [25]. The main architecture of that method was similar to the traditional convolutional neural networks or CNN, but that had better accuracy results.

Ahmet Cinar and Muhammed Yildirim used ResNet50 architecture, a CNN architecture, in order to classification of brain tumors. They modified the algorithm called ResNet50 architecture by replacing which last 5 layers with 10 layers. Their modified architecture could only classify brain tumors in a binary way [26].

Divya Kumari suggested a machine learning-based approach for predicting alcohol misuse[12]. The model incorporated two distinct Artificial Neural Network (ANN) modules, denoted as ANN-D and ANN-C. After implementing ANN-D on the amassed data, they proceeded to utilize ANN-C for individuals who had participated in alcohol consumption.The UCI machine learning database served as the source of their data and the total record is 1885 and also the feature are 12 . To ascertain if someone used alcohol or not, ANN-D was utilized, and to ascertain when an alcoholic was drinking, ANN-C was employed. The evaluation of this model focused on precision, where ANN-D exhibited a precision rate of 98.7%, while ANN-C showcased a precision rate of 49.1%.

Afshar et al. employed a capsule network to overcome the limitations of CNN. This was done to address issues such as losing features active at a specific location during the subsampling of layers and obtaining poor training results, especially when working with small datasets [27]. To enhance accuracy, segmented tumor regions were sent to the CapsNet technology, despite the time-consuming nature of this process.Afshar et al. also created a CapsNet that used whole-brain MRI as input without segmenting the tumor. It could keep of the spatial information [28] . However, it also showed the coarse of tumor boundary to focus more on the main target.

Halimeh Siar and Mohammad Teshnehlab used convolutional neural networks to detect brain tumors and MS (Multiple Sclerosis) at the same time [29].

Tahir et al demonstrated how difference of the combinations of noise deduction, enhancement of contrast , preprocessing techniques for edge enhancement could also improve the results of the techniques segmentation and classification on several datasets. They conducted binary classification tests using Support Vector Machine (SVM) and the Otsu technique for pixel-based image segmentation [30].

Sharif et al. employed the Inception v3 architecture which was pre-trained, for feature extraction. They integrated the obtained features with DRLBP (Dominate Rotate LBP) to enhance texture analysis. They They applied the PSO (Particle Swarm Optimizer) algorithm to enhance feature vectors, and utilized a softmax. [31].

Swati et al . block-wise used VGG16 networks based on transfer learning. The model did not need much preprocessing and did not use handcrafted features [32]. The outcomes of the model were compared with results from both deep learning and traditional machine learning approaches.

Sajjad et al Introduced an approach for categorizing multiple graded brain tumors by employing a brain tumor segmentation method and an extensive augmentation of data strategy..

They employed a CNN model to generate segments of the brain tumor. They applied eight different data augmentation techniques, encompassing various geometric transformations and noise invariances., were employed to enhance the segmented data due to the limited scale of the datasets . They utilized the pre-trained VGG19 architecture to process the data for classification[33].

Noreen et al. created two separate multi-level architectures by employing the Inception-v3 and DenseNet201 architectures... They concatenated features from different modules of these pre-trained architectures and sent them to the softmax layer for classification. They could not use fine-tuned techniques on pre-trained architecture in their proposed model [34].

Chelghoum et al. used a small scale dataset to study several pre-trained CNNs. They utilized nine pre-trained CNN architectures, which included AlexNet, ResNet18, ResNet50, VGG16, VGG19, SENet, GoogleNet, ResNet101, and Inception-ResNet-v2, for comparative analysis within the framework of transfer learning [35].

Togacer et al. incorporated advanced techniques, such as Recursive Feature Elimination (RFE), the hypercolumn method, and Support Vector Machine (SVM) with pre-trained VGG16 and AlexNet architectures to attain superior classification performance.. The proposed model merged from the fully connected layers deep features of these two architectures to leverage their generalization capabilities [36] . The proposed model could only be used for the binary classifying ; anyway, it needed a large dataset to classify different tumors, which could be a difficult and time-consuming task.

Ghassemi et al. modified a pre-trained CNN network within a GAN model to serve as a classifier for brain tumor classification. They also introduced a deep CNN as the discriminator to detect generated fake images produced by the generative model [37]. However, limitations of GAN prevented them from using certain effective architectures as the discriminator since they required a larger input size than the MRI input-sized images in the proposed model, which was 64 × 64.

Rezaei et al. created a conditional Generative Adversarial Network (cGAN) approach to segment distinct subregions, encompassing the total tumor area, core tumor area, and augmenting tumor area, assigning different labels to each. This segmentation was employed for predicting the number of days a patient survived after tumor detection. The model included a loss function designed to enhance performance on previously unseen data [38].

The study by Chelghoum et al . The study conducted a comparative analysis in the realm of transfer learning on a small-scale dataset by employing various pre-trained CNNs. For this purpose,
They employed nine pre-trained CNN architectures, which included AlexNet, ResNet18, ResNet50, VGG16, VGG19, SENet, GoogleNet, ResNet101, and Inception-ResNet-v2 [35].

According to Togacer et al., achieving high classification performance involves integrating state-of-the-art techniques such as Recursive Feature Elimination (RFE), the hypercolumn method, and Support Vector Machine (SVM) with pre-trained VGG16 and AlexNet architectures. The proposed model leverages the generalization capabilities of these two architectures by combining deep characteristics generated from their fully connected layers [36]. It's important to note that the suggested model is designed exclusively for binary classification. To extend its application to categorizing various tumors, a substantial dataset must be fed into the model, which can pose challenges and be a time-consuming operation.

. Ghassemi et al. presented a GAN model in which a pre-trained CNN network is fine-tuned to act as a classifier for brain tumor classification. At the same time, a deep CNN serves as the discriminator to recognize generated fake images produced by the generative model [37]. The suggested model encounters limitations associated with GAN restrictions, restricting the use of certain effective architectures as the discriminator due to the requirement for a larger input size. In this instance, the MRI input size in the proposed model was limited to 64 × 64.

2.3 Comparative Analysis

Table 2.1: Comparative analysis

SL	Author name	Use of algorithms	Description	Best accuracy
01	Wang, F., Jiang, W., Zhang, W.,	3D CNN (DenseNet and ResNet)	Brain tumor segmentation	86.2% (Dice Score)
02	Wu, Z., Yang, D., Zhou, Y., et al.	Multi-Scale Attention U-Net	Glioblastoma and segmentation	88.5% (Dice Score
03	Sharma, N., Liu, X., Kumar, V., e t al.	CNN-SVM hybrid	Classification	89.2%

04	Chen, W., Li, W., Jiang, H., et al.	Attention-based U-Net	segmentation	87.1% (Dice Score)
05	Wang, S., Wang, S., Huang, W., et al.	Hybrid Attention Network	segmentation	85.9% (Dice Score)
06	Roy, S., Khan, A., Das, D., et al.	VGG16, ResNet, Alex Net	Detection and classification	87.5% (Classification)
07	Zhao, X., He , J., Tang , Y. , et al.	Zhao, X., He , J., Tang, Y. , et al.	segmentation	85.7% (Dice Score)
08	Sun, M., Zhou, T., Cheng, S., et al.	Cascaded Deep Learning Framework	segmentation	88.3% (Dice Score)
09	Zhou, Y., Wu, Z., Yang, D., et al.	Multi-Scale Hybrid Network	Segmentation and classification	86.5% (Dice Score), 89.8% (Classification)
10	Sun, X., Yang, X., Sun, J., et al.	Combined Network with Spatial-Temporal Attention	segmentation	89.1% (Dice Score)

2.4 Scope of the problem

Majority of the published studies primarily concentrated on the classifying tumors into the two or three categories. different kinds or also in a binary way. The pretrained MobileNet, Xception, InceptionV3, Resnet50 , CNN1 , VGG19 models are used to classify tumors which are of these types: these are glioma , meningioma , no tumor, pituitary tumor . Our study presents a paradigm change by giving sophisticated classification models priority. The idea that strong classification might produce useful information without segmentation is what drives this departure from traditional segmentation-centric approaches. Currently existing models perform satisfactory with small datasets to classifying various tumors, but also performance drops as dataset size also grows . The dataset size has been increased to improve performance and address the issue which is a limited kind of which dataset.

2.5 Challenges

There various category of Brain tumors. As we know there are more than 120 different types, and most of them are deadly. [12]. We used the pretrained MobileNet, Xception, InceptionV3, Resnet50 , CNN1 , VGG19 models to classify tumors into four classes only. We could not classify other types of brain tumors because we did not have datasets with other types.

Also, the available datasets have few images. The classification brain tumors which essential to know the class of the brain tumor . To classification, we need a dataset with brain MRI images to train the model. Such datasets are hard to find, not to mention datasets for classification for other types of tumors. Therefore, we have to do manual dataset to create a dataset for classification, which is exhausting and time-consuming.

CHAPTER 3

RESEARCH METHOD

3.1 Introduction

In this section it is providing the oversight of collected datasets employed related in the study, outlines the procedures for data preprocessing, including techniques such as dataset augmentation, normalization, and splitting. It also discusses the classification model architectures and briefly elucidates the functioning of these classification models.

3.2 Research subject

My research about treatment of brain tumor. The main subject to do this is to detect the category of the tumor to diagnose the disease early and helpful for patient to avoid risky situations.

3.3 Data Collection Procedure

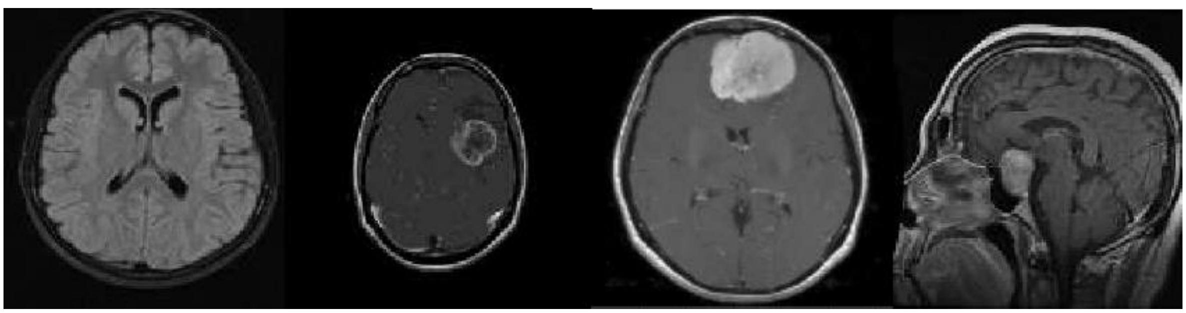
In my research on classifying brain tumors, I utilized a dataset containing 8000 brain MRI images, aiming to categorize four tumor types: which are : glioma, meningioma, no tumor,, pituitary tumor[1]. The dataset which, sourced from both a medical center and Kaggle, is a compilation of the Figshare, Br35H, and SARTAJ datasets. It comprises three main directories for training, testing, and validation, each containing four subfolders corresponding to the tumor types.

To ensure model evaluation, we split the dataset in the three sets - The data was divided into training, testing, and validation sets, utilizing the ratio which is 70-15-15, respectively. Training set consists total of 5600 image sets , 1400 images in each tumor type (no tumor, glioma, meningioma, pituitary tumor). The testing and validation sets each contain 1200 images, distributed in the same manner across the four tumor types.

The Figshare Dataset, a part of our compilation, Constituting are 3064 T1-weighted contrast- enhanced MRI images collected from 233 brain tumor patients, the dataset includes of meningioma(708 slices), glioma(1426 slices), and pituitary tumor(930 slices) [3]. Additionally, the SARTAJ dataset which provides 3264 MRI brain images encompassing of meningioma, glioma, no tumor, pituitary tumor [4]. Furthermore, the Br35H dataset, integrated with SARTAJ, contributes 1500 MRI images with no tumor instances [5]. I also collected 200 mri brain tumor images from our local hospital. From those we have 50 images for glioma, 50 for meningioma, 50 for no tumor, 50 for pituitary tumor.

3.3.1 Format of Dataset

All MRI pictures in the consolidated dataset are in JPG format, and their sizes vary. To guarantee proper categorization of brain tumours, all images must be rescaled to a uniform dimension. The four groups of brain MRI tumours that are used for classification



are shown in Figure 3.1.

(i) No Tumor . (ii) Glioma . (iii) Meningioma . (iv) The Pituitary Tumor .

Figure 3.1 : The mri images of brain tumor sample for example: these are (i)Glioma , (ii) No tumor , (iii) Meningioma , (iv) Pituitary Tumor .

3.4 Data preprocessing

I utilized a dataset consisting of 8000 brain tumor images for my CNN-based project. The dataset which was divided into the three distinguished training , testing, and validation sets. After the data collection phase, I addressed preprocessing tasks such as handling null values. The dataset comprises both numerical and categorical data, with the latter transformed into a numeric format using a label encoder.

For training testing and validation data, a 70-15-15 split was implemented. five algorithms were employed, and accuracy along with confusion matrices, classification were calculated for each. Additionally, the process of resizing and augmenting the initial classification dataset is also discussed in this section.

3.4.1 Resize

There are 8000 different-dimensional MRI brain pictures in the categorization dataset. The photos were resized to 224 by 224 height and weight in order to the facilitate of the classification..

3.4.2 Augmentation

Augmenting the data enhances the models' performance and outcomes of the deep learning models with introducing diverse and new instances into the training, testing, and validation of datasets. Under the guidance of our supervisor of the project and using data gathered from various sources, we generated a total of 8000 augmented images. The augmentation process involved implementing modifications like rotation (rotation_range: 40), width shifting (Width shift_range =0.2), height shifting (Height shift_range: 0.2), shear (Shear range: 0.2), and zooming (Zoom range: 0.2) to create novel images.

To maintain dataset balance, we allocated these augmented images into three sets—training, testing, and validation—following a 70-15-15 ratio. Each training set consists of 1400 MRI images, while both the testing and validation sets include 300 images each.

The dataset encompasses three directories, each containing four distinct tumor types: these are: meningioma , glioma, no tumor, and the pituitary tumor. Although there are variety in the number of photos within the three folders which are training, testing, and validation folders, achieving balance in each folder of both directories is crucial for classification. To ensure this balance while preserving the characteristics, of the brain tumors in MRI images which have a variety of augmentation techniques including many techniques like rotation, width shifting, height shifting, zooming, and horizontal flipping. The enrolled augmentation technique is depicted in Figure 3.3.

Table 3.1: Total images post-augmentation

Tumor Classes	Training	Testing	validation	Number of the Images
No Tumor	1400	300	300	2000
Glioma	1400	300	300	2000
Meningioma	1400	300	300	2000
Pituitary Tumor	1400	300	300	2000
Total no. of augmented images in the dataset				8000

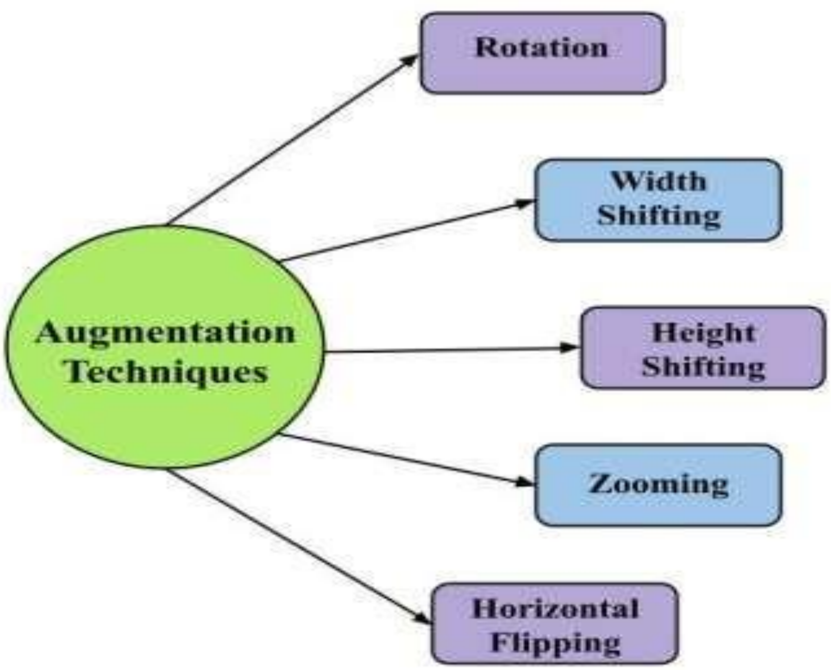


Figure 3.2: augmented technique.

3.4.3 Normalization

Image dataset normalisation entails scaling and centereding pixel values. To get pixel values into the range [0, 1], divide them by the maximum allowable value (e.g., 255). Normalisation is applied to each colour channel separately in colour images. Mean and standard deviation normalisation can also be conducted across the dataset by subtracting of the mean and dividing by the standard of the deviation. Normalisation parameters are being calculated on training dataset and uniformly applied to both training and test data. This preprocessing step is critical for improved training convergence and generalisation performance of machine learning models . After doing successful augmentation we normalized the newly created dataset with the help of our supervisor.

3.5 Statistical Analysis

I have 8000 data . We implemented different different algorithms in this model. The statistical graphs are included.

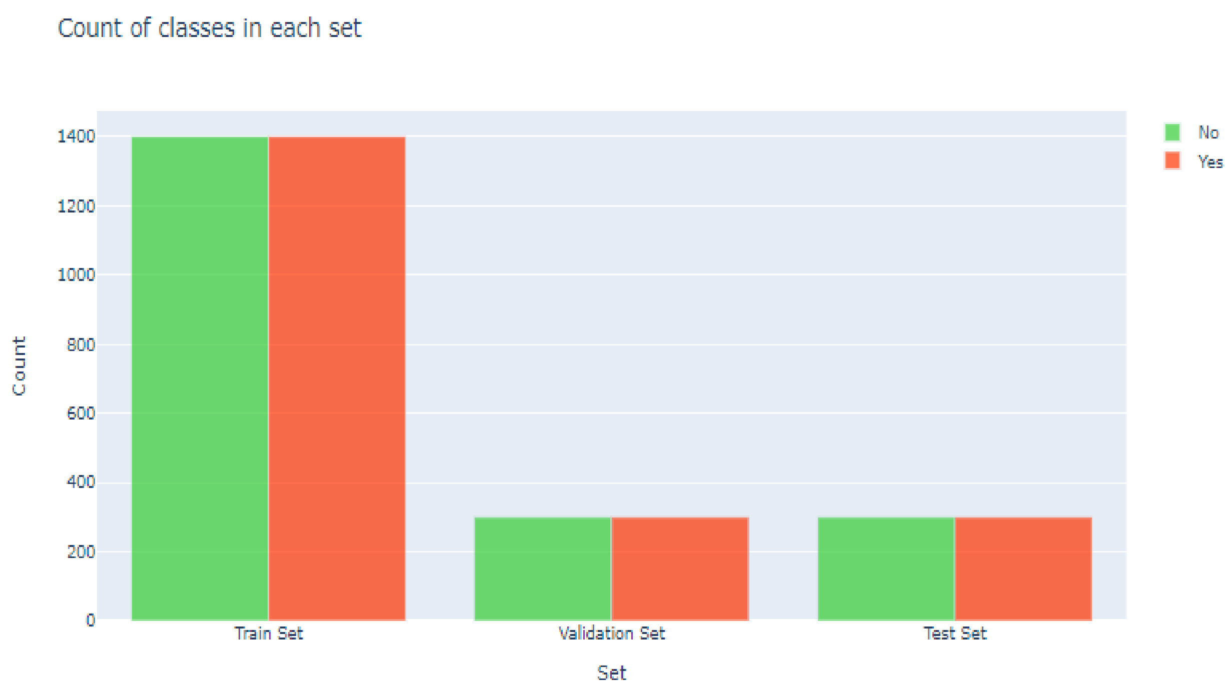


Figure 3.3: Count of classes of each set.

Data count in training set:

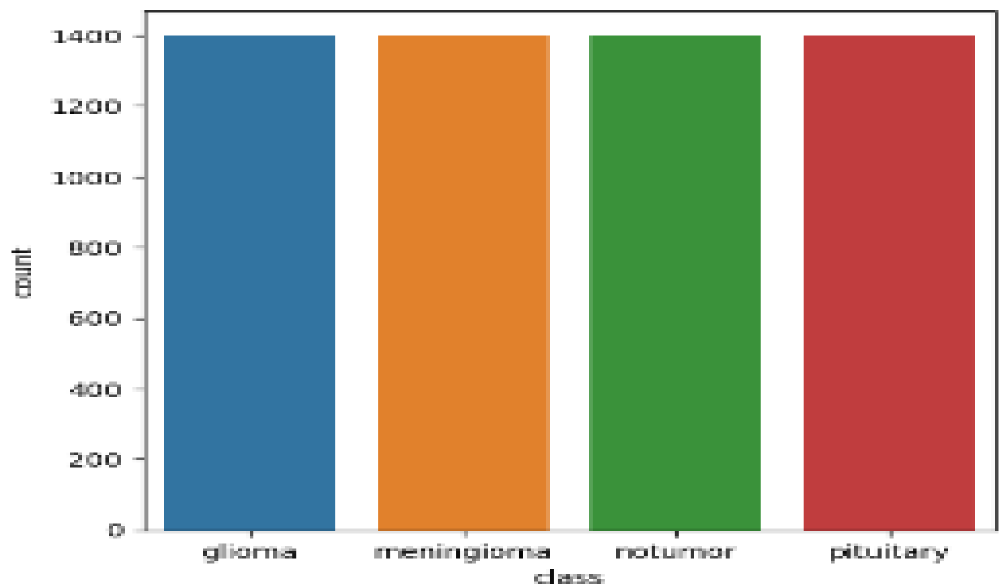


Figure 3.4: data count in training set.

Data count in testing set:

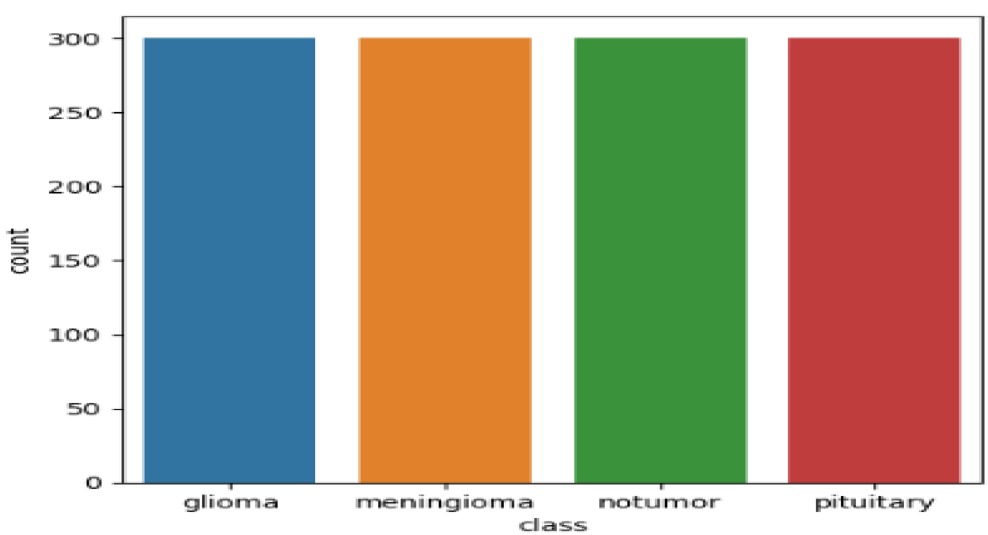


Figure 3.5: data count in testing set.

Data count in validation set:

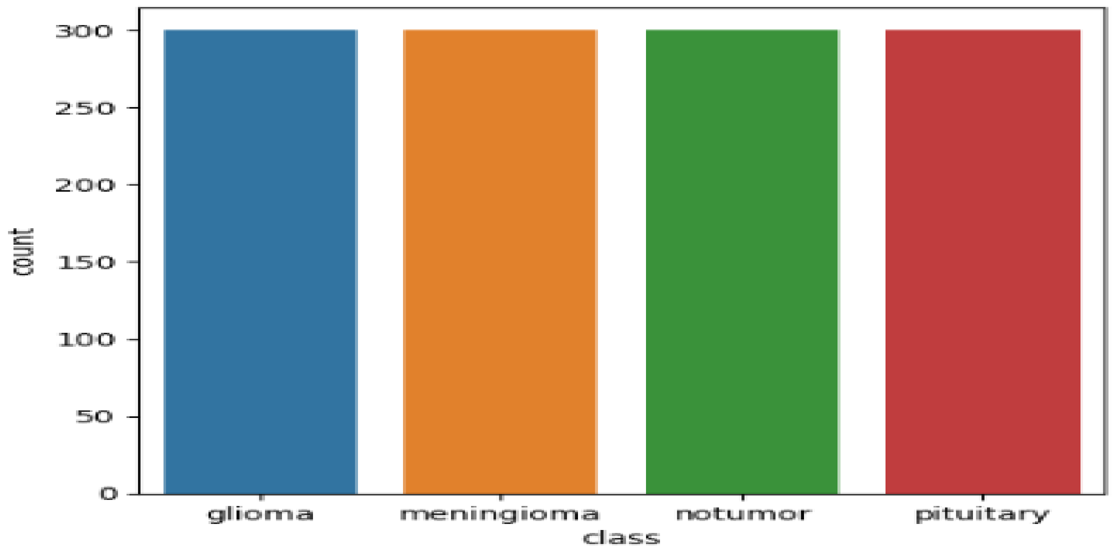


Figure3.6: data count in validation set

3.6 Proposed Methodology

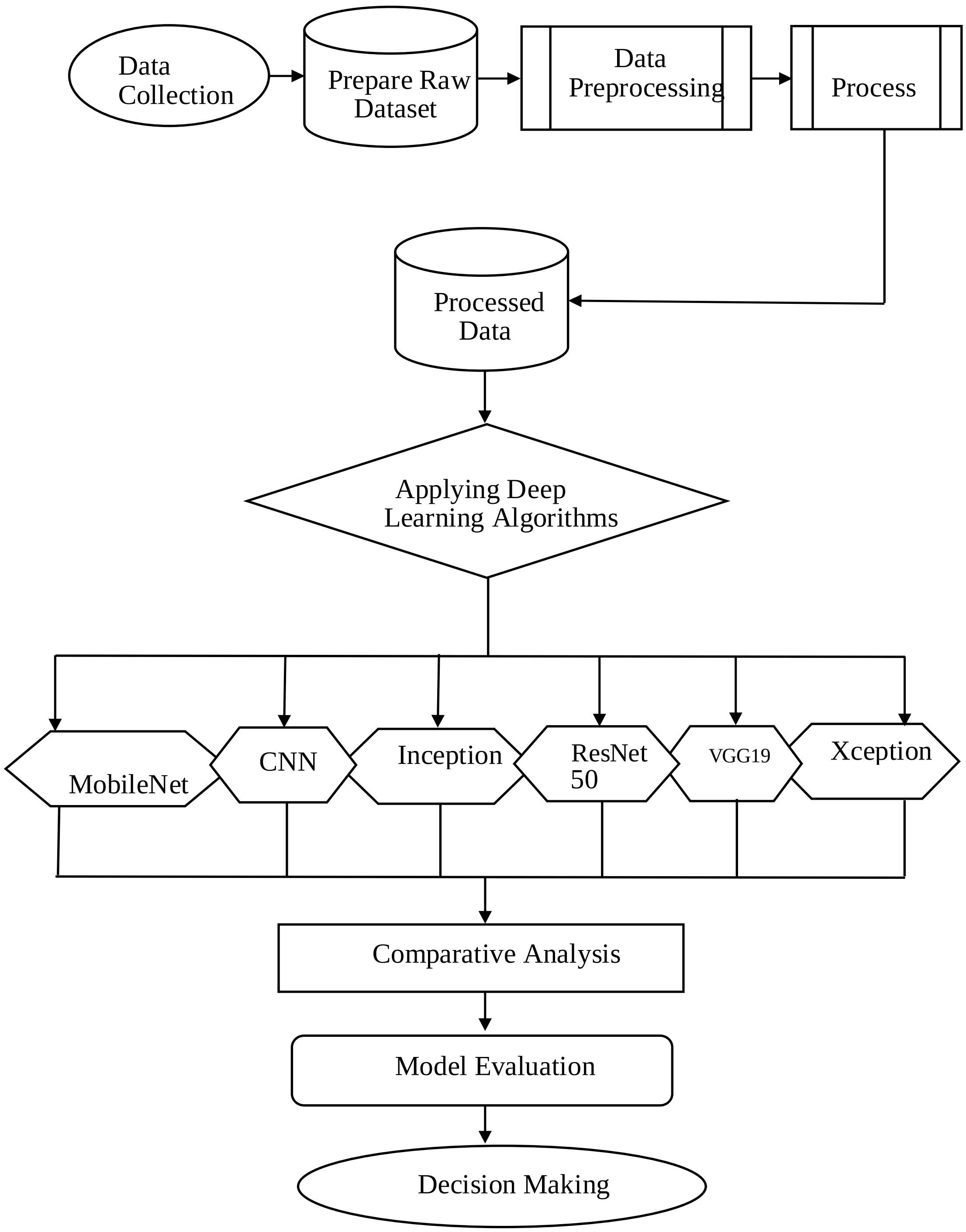


Figure 3.7: steps of methodology.

3.7 Implementation requirements

- Intel core i3 12 gen-intel 4000 graphics
- RAM 8Gb
- Open source Anaconda
- Jupyter notebook
- Python 3.9
- Windows 10

Within this chapter, it gives a summary about the entire system and explains how tumours are found, and categorised.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

In the prior chapter, I delved the dataset and also outlined of the steps involved within the processing the dataset. There are 8000 images in our dataset. To segregate data for training, testing and validation we designated 70% for training , 15% for testing , 15% for validation and algorithms are MobileNet, Xception, InceptionV3, Resnet50 , CNN1 , VGG19. After that we use five algorithms and calculate accuracy, confusion matrix for each algorithms.

4.2 Experiment Result

I employed five transfer-learning algorithms and conducted a comparative evaluation for each, gauging their effectiveness using metrics such as accuracy, confusion matrix, precision, recall, F1.

4.2.1 MobileNet

MobileNet, designed for efficiency, is trained on diverse datasets, including ImageNet. It utilizes depthwise separable convolutions to reduce computational complexity, making it suitable for real-time applications on mobile and edge devices. In this algorithm we have run 25 epochs and get 92% accuracy. This model classified brain tumor correctly in the confusion matrix, the precision, recall and f1 stands at for glioma 0.91 , 0.99 , 0.94 ,for meningioma 0.95 ,0.74 ,0.83, for no tumor 0.98 ,0.95 ,0.97 , for the pituitary tumor 0.86,1.0,0.92.

```
Classification Report:
              precision    recall  f1-score   support

      glioma       0.91      0.99      0.94       300
  meningioma       0.95      0.74      0.83       300
     notumor       0.98      0.95      0.97       300
   pituitary       0.86      1.00      0.92       300

    accuracy                           0.92      1200
   macro avg       0.92      0.92      0.92      1200
weighted avg       0.92      0.92      0.92      1200

AUC-ROC for glioma: 0.9982
AUC-ROC for meningioma: 0.9832
AUC-ROC for notumor: 0.9975
AUC-ROC for pituitary: 0.9960
Average AUC-ROC across classes: 0.9937
```

Figure 4.1: Classification Report MobileNet

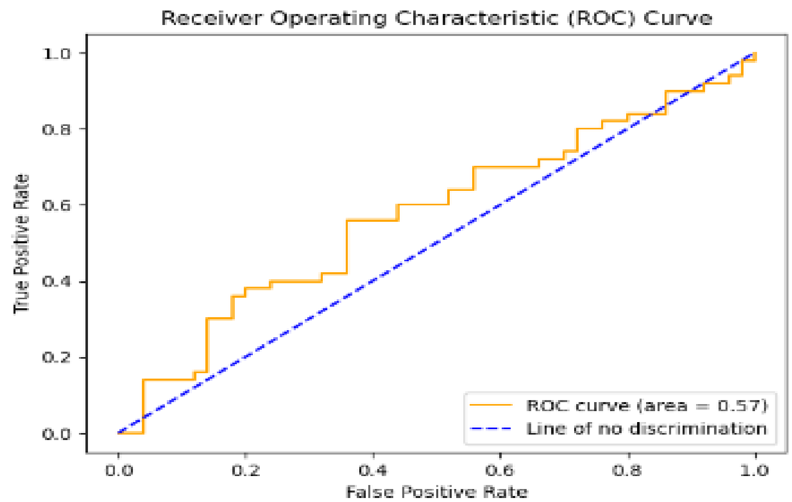


Figure 4.2: ROC curve MobileNet

4.2.2 Xception

Trained on large datasets, Xception extends the Inception architecture with depthwise separable convolutions. This approach captures complex features effectively, making Xception a powerful model for image classification tasks. In this algorithm get 89% accuracy. We ran 20 epochs in this model to train the model.The confusion matrix yielded a precision , recall and f1 for glioma 0.90 , 0.97 and 0.94 , for meningioma 0.88,0.71,0.79, for notumor 0.95,0.92,0.94, for pituitary 0.83,0.96,0.89.

Classification Report:

	precision	recall	f1-score	support
glioma	0.90	0.97	0.94	300
meningioma	0.88	0.71	0.79	300
notumor	0.95	0.92	0.94	300
pituitary	0.83	0.96	0.89	300
accuracy			0.89	1200
macro avg	0.89	0.89	0.89	1200
weighted avg	0.89	0.89	0.89	1200

AUC-ROC for glioma: 0.9950
AUC-ROC for meningioma: 0.9584
AUC-ROC for notumor: 0.9938
AUC-ROC for pituitary: 0.9880
Average AUC-ROC across classes: 0.9838

Figure 4.3: Classification Report Xception

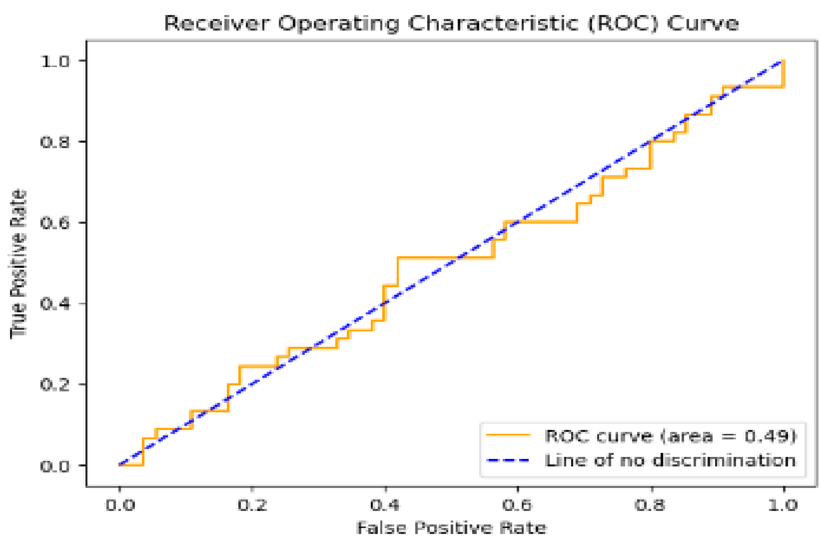


Figure 4.4: ROC curve Xception

4.2.3 InceptionV3

Known for its effectiveness in image classification and trained on ImageNet, InceptionV3 employs multiple parallel convolutional pathways. This architecture enhances feature extraction by incorporating various convolutional filter sizes and pooling operations. After running 15 epochs I get the testing accuracy that is 87%. The confusion matrix for glioma exhibited a precision of 0.85 , a recall of 0.95 , and an F1 score of 0.90 . Similarly, for meningioma, the precision derived from the confusion matrix was 0.80, accompanied by a recall of 0.75 and an F1 score of 0.78 . Confusion matrix yielded a precision, recall and f1 for notumor 0.95,0.90,0.92, for pituitary 0.86,0.87,0,87.

Classification Report:

	precision	recall	f1-score	support
glioma	0.85	0.95	0.90	300
meningioma	0.80	0.75	0.78	300
notumor	0.95	0.90	0.92	300
pituitary	0.86	0.87	0.87	300
accuracy			0.87	1200
macro avg	0.87	0.87	0.87	1200
weighted avg	0.87	0.87	0.87	1200

AUC-ROC for glioma: 0.9906
AUC-ROC for meningioma: 0.9473
AUC-ROC for notumor: 0.9890
AUC-ROC for pituitary: 0.9829
Average AUC-ROC across classes: 0.9775

Figure 4.5: Classification report InceptionV3.

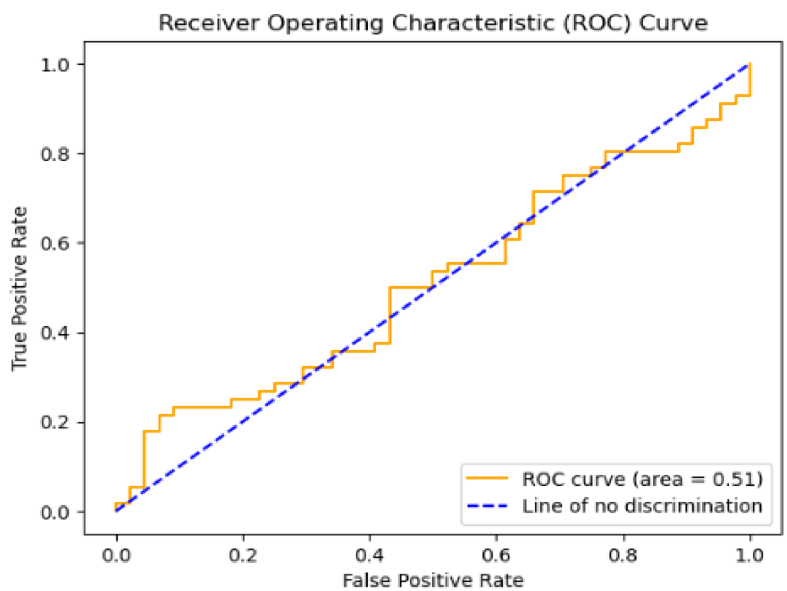


Figure 4.6: ROC curve InceptionV3

4.2.4 ResNet

Trained on ImageNet, ResNet addresses vanishing gradient issues in deep networks. Introducing skip connections and residual blocks, ResNet enables the training of very deep networks without degradation in performance. Its architecture with residual connections allows for smoother gradient flow, contributing to its success in various computer vision tasks. A testing dataset we used which is only 15% of the total data get the 88% accuracy . I ran 10 epochs in this model. For glioma the precision obtained from the confusion matrix is 0.84, with a recall of 0.93 and a f1 of 0.89, for meningioma confusion matrix precision is 0.86,0.65,0.75, for notumor 0.98,0.94,0.96, for pituitary 0.83,0.98,0.90.

```
Classification Report:
              precision    recall  f1-score   support

      glioma       0.84      0.93      0.89       300
  meningioma       0.87      0.65      0.75       300
     notumor       0.98      0.94      0.96       300
   pituitary       0.83      0.98      0.90       300

    accuracy                           0.88      1200
   macro avg       0.88      0.88      0.87      1200
weighted avg       0.88      0.88      0.87      1200

AUC-ROC for glioma: 0.9890
AUC-ROC for meningioma: 0.9577
AUC-ROC for notumor: 0.9955
AUC-ROC for pituitary: 0.9900
Average AUC-ROC across classes: 0.9830
```

Figure 4.7: Confusion matrix of Resnet50

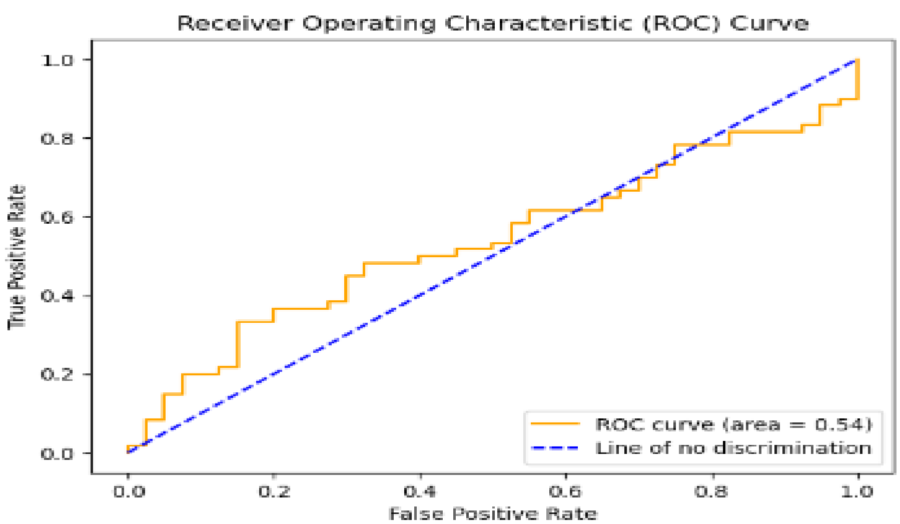


Figure 4.8: ROC curve Resnet50

4.2.5 CNN1

The Convolutional Neural Networks(CNNs) are a technique of deep neural networks designed to do image processing tasks. Utilizing the convolutional layers, CNNs are automatically learn hierarchical features from the input data and making them particularly effective for the tasks like the image recognition and the object detection. With layers for feature extraction, spatial reduction, and decision-making, CNNs simulate human visual processing and have achieved remarkable success in computer vision applications. "cnn1" likely denotes a specific CNN model tailored for a particular task or dataset, showcasing the versatility and power of CNNs in artificial intelligence. I got the accuracy 70%. We ran 10 epochs here. For glioma the precision from the confusion matrix stood at 0.66, with a recall of 0.72 and an F1 score of 0.69 . For meningioma, the precision from the confusion matrix is 0.62, with a recall of 0.44 and an F1 score of 0.52 . For notumor precision 0.82 , recall 0.87 , f1 score 0.85 . And for pituitary, precision 0.69 , recall 0.78, f1 score 0.73 .

```
Classification Report:
              precision    recall  f1-score   support

      glioma       0.66      0.72      0.69       300
  meningioma       0.62      0.44      0.52       300
     notumor       0.82      0.87      0.85       300
   pituitary       0.69      0.78      0.73       300

    accuracy                           0.70      1200
   macro avg       0.70      0.70      0.70      1200
weighted avg       0.70      0.70      0.70      1200

AUC-ROC for glioma: 0.8908
AUC-ROC for meningioma: 0.7842
AUC-ROC for notumor: 0.9648
AUC-ROC for pituitary: 0.9196
Average AUC-ROC across classes: 0.8899
```

Figure 4.9: Classification report CNN1 .

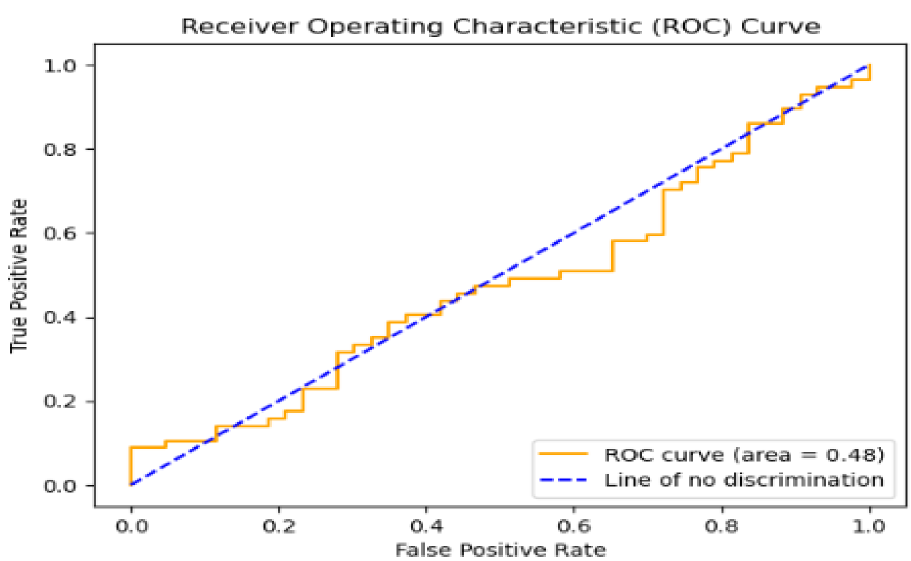


Figure 4.10: ROC curve CNN1

4.2.6 VGG19

Part of the VGG family of models, VGG19 is trained on the ImageNet dataset. With a simple and uniform architecture, it uses 3x3 convolutional kernels throughout its 19-layer design, proving effective in image classification tasks. I got the accuracy 87%. I ran 10 epochs here. For glioma the precision from the confusion matrix stood at 0.90, with a recall of 0.94 and an F1 score of 0.92 . For meningioma, the precision from the confusion matrix is 0.84, with a recall of 0.68 and an F1 score of 0.75. For notumor precision 0.94 , recall 0.91 , f1 score 0.92 . And for pituitary , precision 0.82 , recall 0.97 , f1 score 0.89 .

```
Classification Report:
              precision    recall  f1-score   support

      glioma       0.90      0.94      0.92       300
  meningioma       0.84      0.68      0.75       300
     notumor       0.94      0.91      0.92       300
   pituitary       0.82      0.97      0.89       300

    accuracy                           0.87      1200
   macro avg       0.87      0.87      0.87      1200
weighted avg       0.87      0.87      0.87      1200

AUC-ROC for glioma: 0.9901
AUC-ROC for meningioma: 0.9383
AUC-ROC for notumor: 0.9888
AUC-ROC for pituitary: 0.9822
Average AUC-ROC across classes: 0.9748
```

Figure 4.11: Classification report VGG19 .

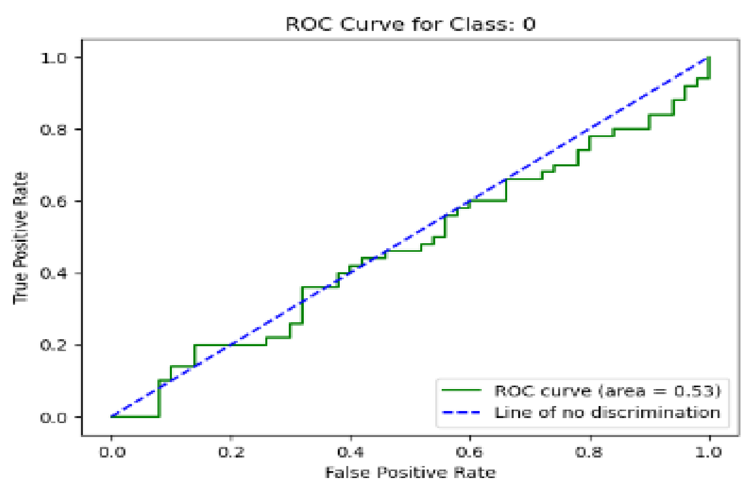


Figure 4.12: ROC curve VGG19 .

All confusion matrix:

MobileNet:

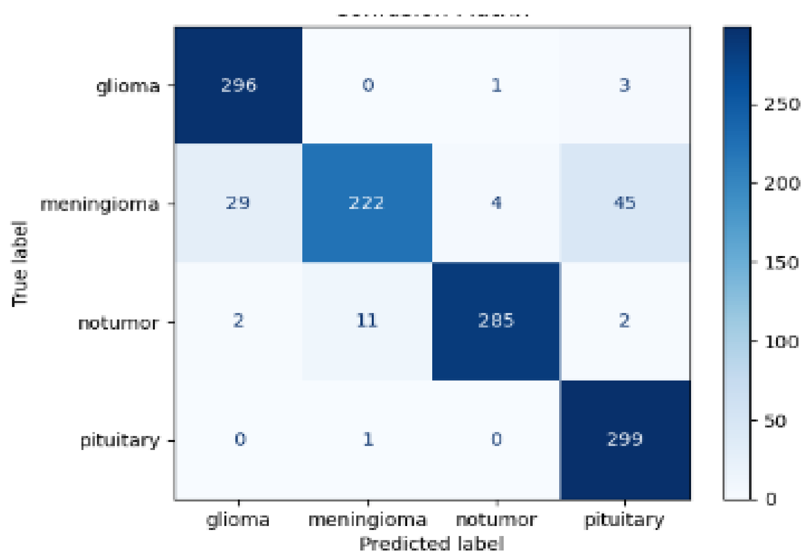


Figure 4.13: MobileNet confusion matrix

Xception:

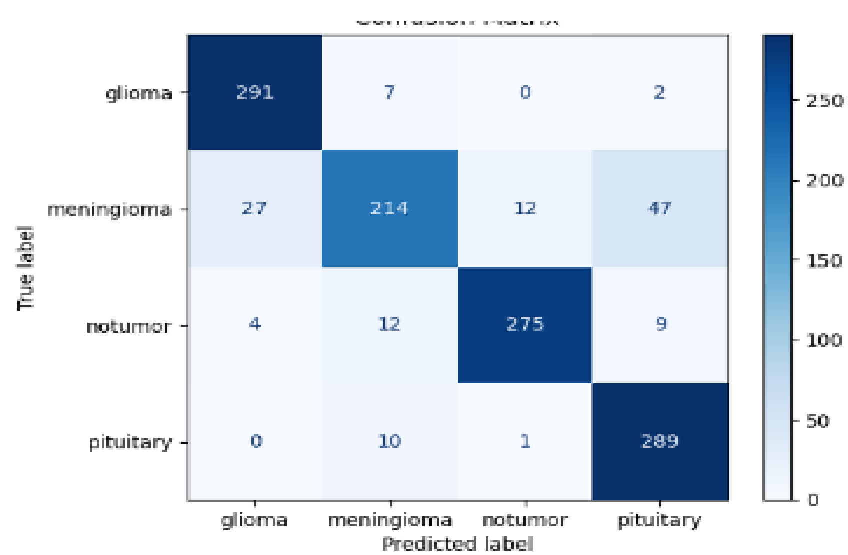


Figure 4.14: Xception confusion matrix

InceptionV3:

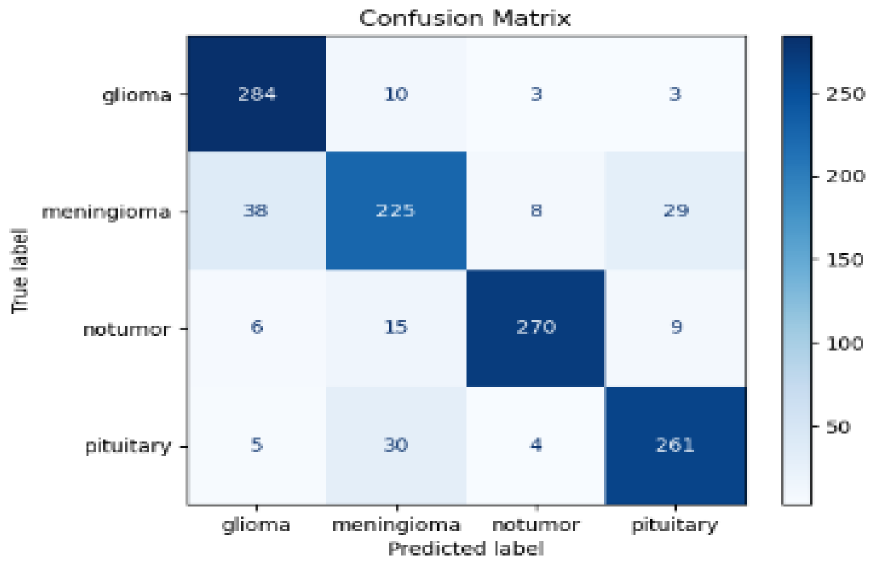


Figure 4.15: InceptionV3 confusion matrix

Resnet50:

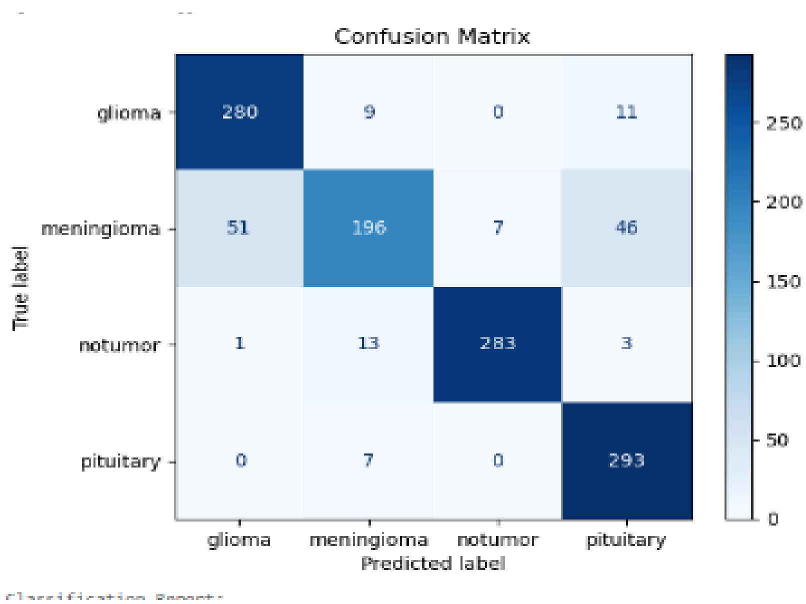


Figure 4.16: Resnet50 confusion matrix

CNN1:

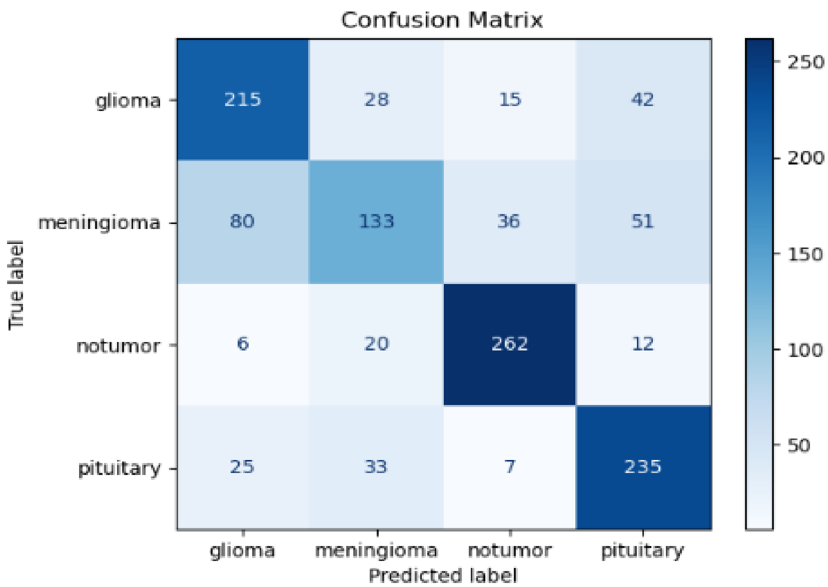


Figure 4.17: CNN1 confusion matrix

VGG19:

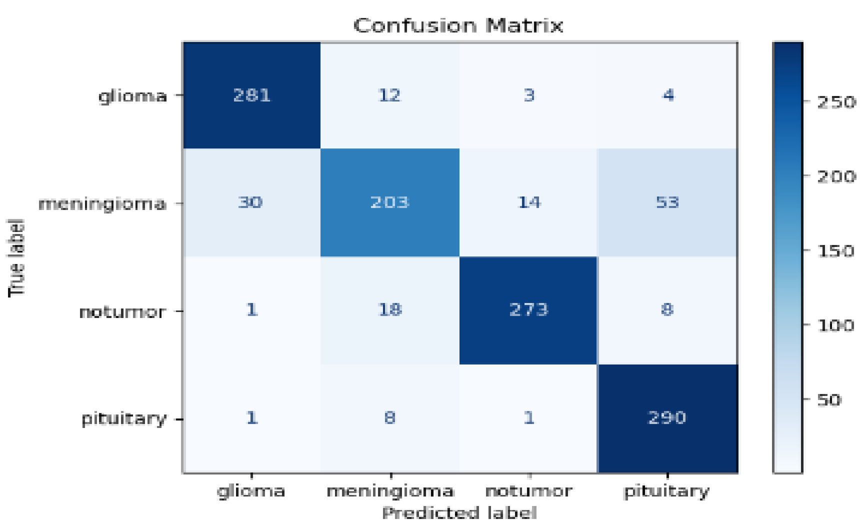


Figure 4.18: VGG19 confusion matrix.

In this part we can see comparison between all six algorithms those are MobileNet, Xception, InceptionV3, Resnet50 , CNN1 , VGG19.

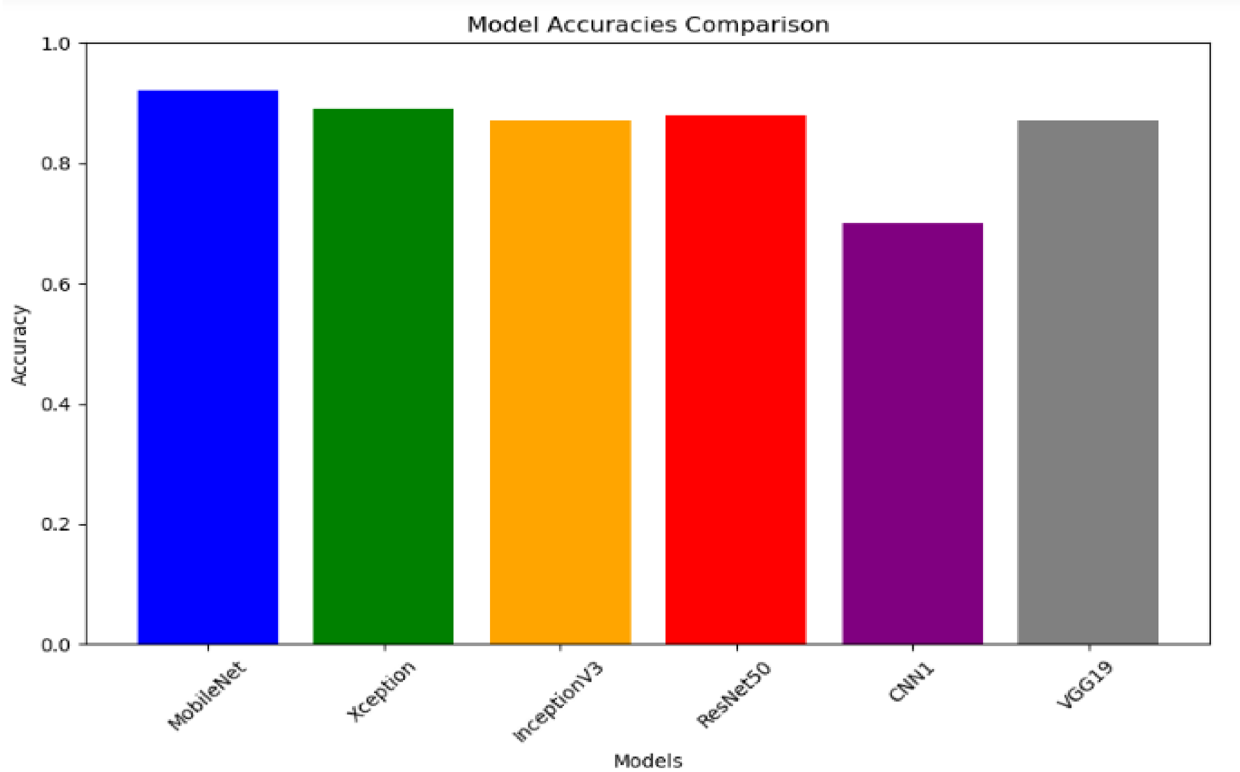


Figure 4.19: Accuracy comparison of all models.

Accuracy , Macro avg and weighted avg of the precision , recall , F1 of each algorithm:

Table 4.1: Algorithms performance evaluation

Algorithm	**Accuracy**	**Precision**	**Recall**	***F*1**	**No of epochs**
MobileNet	92	M. avg 92 W.avg 92	M. avg 92 W.avg 92	M. avg 92 W.avg 92	25
Xception	89	M. avg 89 W.avg 89	M. avg 89 W.avg 89	M. avg 89 W.avg 89	25
InceptionV3	87	M. avg 87	M. avg 87	M. avg 87	25

		W.avg 87	W.avg 87	W.avg 87	
Resnet50	88	M. avg 88 W.avg 88	M. avg 88 W.avg 88	M. avg 87 W.avg 87	25
CNN1	70	M. avg 70 W.avg 70	M. avg 70 W.avg 70	M. avg 70 W.avg 70	25
VGG19	87	M. avg 88 W.avg 88	M. avg 88 W.avg 88	M. avg 88 W.avg 88	25

4.3 Comparative Analysis

I ran five algorithms and train-test-validation split is 75:15:15. Total data is 8000.

Table 4.2: comparative analysis.

Work	Fact	Done	Best algorithm	Best accuracy
This work	Brain tumor classification	classification	MobileNet	92%
Machiraju Jaya Lakshmi and S. Nagaraja Rao	Brain tumor classification	Classification	Random Forest	89%
M. Mzoughi et al	Brain tumor classification	classification	Logistic Regression	91.8%
Kumar, Nitish et al.	Brain tumor classification	classification	CNN	89.2%

Lee, Seungjin et al.	Brain tumor classification	classification	CNN	88.5%

4.4 Discussion

This thesis done by F1 score, ROC curve, accuracy, recall, and precision. The evolution model equations and their purpose are also covered here. MobileNet algorithm show the highest accuracy with 92% also precision, recall and F1 92%. It is ultimately determined that the MobileNet technique yields the best results for our classification model of brain tumor .

In this chapter, it provides a comprehensive exploration of the overall performance of our classification models.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

Application of the advanced technologies like the algorithms of the deep learning models for brain tumor classification brings about a transformative impact on society. It improves diagnostic accuracy, enabling earlier detection and intervention, ultimately enhancing treatment outcomes and potentially saving lives. This not only streamlines healthcare processes but also allows for more personalized patient care. The societal benefits extend to resource optimization in healthcare systems, contributing to improved overall efficiency and public health. In essence, these advancements represent a significant stride towards a future where healthcare is more accurate, efficient, and tailored, positively impacting both individuals and society at large.

5.2 Impact on Environment

The environmental impact of advanced brain tumor classification technologies is complex. While the focus is on healthcare benefits, the incresing computational power and the energy requirements of complex algorithms, such as algorithms like deep learning models which must be considered. The manufacturing and the disposal of electronic components in medical imaging devices contribute to electronic waste concerns, requiring responsible recycling. Continuous operation of computational systems may increase energy consumption and carbon footprint. However, more accurate diagnoses could potentially reduce unnecessary medical procedures, partially offsetting the environmental impact. Balancing improved healthcare outcomes with environmental considerations is crucial for a comprehensive evaluation of brain tumor classification's impact that on the environment.

5.3 Ethical Aspects

Ethical considerations in brain tumor classification involve crucial aspects of privacy, informed consent, and transparency. Collection and use of patient data for deep learning algorithms must prioritize privacy standards. Transparent development and implementation of these algorithms, integral to medical decisions, are vital. Scrutiny of algorithmic bias is necessary to prevent disparities in healthcare delivery. Balancing technological advancements with human empathy is essential to avoid dehumanization in patient care. Responsible disclosure of algorithmic limitations maintains trust. Ensuring equitable access to diagnostic technologies is crucial to prevent healthcare disparities. Ongoing ethical reflection and guideline adaptation are imperative as brain tumor classification technologies advance, aligning with principles of beneficence, justice, and respect for individuals.

5.4 Sustainability Plan

Creating a sustainable plan for brain tumor classification with transfer learning involves assessing computational resources, optimizing energy efficiency, and prioritizing ethical data use. Data governance, including robust anonymization and compliance with privacy regulations, is crucial for patient confidentiality. Collaboration and knowledge-sharing through open-source initiatives are key for progress and transparency. Establishing education programs for healthcare professionals ensures seamless integration of transfer learning technologies. Continuous monitoring of algorithmic performance, energy efficiency, and ethical considerations, along with stakeholder feedback, guides ongoing refinement. This holistic approach, spanning technological, ethical, and educational aspects, ensures the responsible and enduring deployment of transfer learning in medical imaging and healthcare.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the study

Brain tumors are deadly disease. Many people are dying for brain tumor per year which is alarming. Through our models, I could train six deep learning models which are used to classify brain tumor images. There are 8000 data in this model and all data collected from various sources. Established data from 8000 images. I aspire that our research will leave a positive imprint and prove beneficial for health system. The investigation sought to formulate a model for classifying brain tumor. I implement Deep Learning model that can I can classify tumor of a patients. In this paper there are 5 algorithms used.

6.2 Conclusion

I am classifying a patient’s brain tumor with the help of modern technologies like the models of deep learning model. So we need data . I collected data from various sources . I established 8000 data . For raw data we need to preprocessing our dataset . I use augmentation, labeling, normalization techniques to preprocessing our dataset . After process dataset we implement five deep learning models. Those are : MobileNet, Xception, InceptionV3, Resnet50 , CNN1 , VGG19 and train-test-validation ratio is 75-15-15. I also measure f1-score , recall, precision. MobileNet give us highest accuracy that is 92% .

6.3 Implication for further study

This research is bound by certain restrictions. If I could use more data, the model will be more better trained . I collected 8000 data but there are more way to increase data for betterment of the model. If I collected more data it will be more beneficial. Another limitation is if I could classify more variety of brain tumors, that would be more betterment of our model.

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