Identifying Brain Abnormalities Using Image Processing And CNN Models

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Declaration

It is hereby declared that,

1. The thesis submitted is my/our own original work while completing the degree at BRAC University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material that has been accepted or submitted for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Ethics Statement

Our primary data were collected from different patients' brain MRIs taken at various hospitals. Therefore, the identity of the patients will be kept anonymous, and this data will only be used for this research.

Abstract

In a developing country like Bangladesh, it is tough to detect a brain abnormality, i.e., Pituitary tumor, Glioma, Meningioma, etc., in an early stage and treat them accordingly. In our proposed system, ML(Machine Learning) techniques under supervised learning will allow us to predict the early detection of brain diseases. We will approach by using image processing to separate the abnormal lesions from the normal ones ideally. We'll also use CNN (Convolutional Neural Network) to stratify different brain abnormalities. Especially when it comes to early detection of brain abnormalities, we'll also create image classifiers for stratification without human help by integrating genomic data to give them a better chance of survival through implementing a machine learning approach. This system is focused on any abnormality related to brain activity and helping the victims to recognize it. We have used 3 CNN models: ResNet50, VGG16, Inception V3, and then obtained satisfactory results. Then we also used the augmentation process in the ResNet50, VGG16, and Inception V3 models. Therefore, we got the best accuracy result in the ResNet50 model after augmentation. Our goal is to provide the proposal to the people of Bangladesh a revolutionary system that will give a plan best suited for every individual and increase the chances of survival for neurology patients to a beyond level.

Keywords: Brain abnormality, supervised learning, CNN, ML, revolutionary system, neurology, ResNet50, VGG16, Inception V3, augmentation

Dedication

Our research focuses on people who have lost their precious lives due to brain tumors and various abnormalities in the brain. This work is also a minor contribution to those neurologists who fought against brain tumors to save Bangladeshi patients.

Acknowledgements

We would like to take this opportunity to express our gratitude to our supervisor for his immense help, which enabled us to continue with our thesis work. Without his valuable guidance and continuous feedback, our work could not be completed. We are also truly thankful to our parents, who helped us in various ways to accomplish our research.

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Chapter 1 Introduction

1.1 Introduction

Recently, the use of emerging innovations based on advanced hardware and system architecture has fundamentally changed medical image processing, such as Convolutional Neural Networks(CNN), Machine Learning(ML), Data Augmentation, etc. Medical imaging is used to create a visual representation of human body components for medical analysis and treatment purposes. Though treatment of a brain tumor patient can be convenient, medical imaging systems quite often face technical issues. For illustration, patients' movement during medical tests, instrumental noises, etc. Brain MRI is highly effective for diagnosing abnormalities in the brain such as brain cerebral edema, bruising of brain tissue, different brain tumors, etc. To replicate the images that include the structure inside the body and organs, this approach uses radio wave energy and magnet impulses. However, the identification of brain tumors is very tedious work for any neurologist. Therefore, detecting brain abnormalities and classification is still an enormous challenge in enhancing medical imaging systems.

The brain tumor is one of the most frequent anomalies among the aged and adult people of Bangladesh. Moreover, Cerebral Edema linked to brain tumors is highly prevalent and may occur in and around brain tumors. Hence, a self-activating brain abnormalities detection tool for identifying brain tumors at an early phase is essential for the medical imaging process. Furthermore, different image processing techniques and machine learning algorithms can significantly improve research areas and imply second thoughts on enhancing radiologists' analysis techniques and diagnostic accuracy.

In the Image processing technique a significant phase is image segmentation that identifies a greater image processing stage[1]. In medical imaging systems, the main objective of image segmentation is the processing of images to detect tumors or lesions. However, optimized detection of the tumor or lesion from MRI images often suffers technical barriers using computer-aided testing.

Cancer of the brain and nervous system is a major root of death[2]. Moreover, the World Health Organization(WHO) states that in Bangladesh, brain tumors that are cancerous (malignant) associated with the central nervous system the number of new cases is 1284. Therefore, the total number of deaths is 1144, and 2898 lives have been lost in the past five years as a result of a brain tumor (malignant)[3]. A brain tumor is stated as the formation of abnormal brain cells[4]. There are various categories of tumors in the brain, but the two main types are benign and malignant. Brain tumors begin inside the brain, it can be secondary and alternatively metastatic; Cancer, can begin elsewhere in the body and affect the brain and produce brain tumor in the brain[4]. In Bangladesh, cerebral and malignant brain tumors are common diseases among patients.

Therefore, early detection of brain tumors may be crucial in optimizing diagnosis and increasing the chances of patients' survival rate. However, a large amount of data is generated daily during a medical examination, detecting brain tumors or manually segmenting tumors or lesions takes time. Therefore, the exact stratification of tumor cells from the brain is a very comprehensive task.

This research suggests an effective and competent method for segmenting and detecting the brain tumor without human aid, based on conventional and Convolutional Neural Networks, data augmentation, and image processing techniques.

1.2 Research Problem

Brain abnormalities have various types: pituitary tumor, glioma, Meningioma, stroke & vascular diseases, cancer, schizophrenia, etc. Moreover, there are several hundred types of brain diseases in the world. One of the most significant changes in neurological surgery and medicine is the high-tech imaging techniques to get insight and clarity of the body by MRI, CT-scans, Ultrasounds, etc. Early detection of brain diseases is necessary because symptoms are often not reflected until the last stage. In addition, people who genetically have neurofibromatosis or tuberous sclerosis are more prone to developing brain tumors.Therefore, physicians suggest patients with these symptoms' frequent medical exams and other tests when they are at an early stage to detect cancer so that doctors can monitor and treat them quickly before the tumor growth causes a problem.

After doing an enormous number of researches, it has been found out that in Bangladesh, the detection of tumor, Meningioma, glioma, or other severe brain abnormalities are diagnosed at a very delayed state or a stage where the patients might not get the options of different treatment which would be suitable for those patients.

The late detection causes in decreased survival rate. Though some brain tumor patients receive significant operations to remove the tumor, improper stratification of treatment and medicine has unavoidable side effects. Studies have shown the impacts of medication and therapy have affected other parts of the body for instance, heart disease, damage in neuron cells and many more could be noticed. This is an alarming issue. Another problem that has been specified is that delayed and neglected tests of brain abnormalities in our country have resulted in unsatisfactory patients' treatments, reducing the survival rates. Brain abnormalities and related diseases have no definite cure. Still, if identified at an early stage, patients would have various trial errors during the treatment and would respond to the best one suited for their bodies. Due to the early detection of brain diseases, the survival rate will increase among the patients.

Bangladesh has no efficient platform for the early detection of brain diseases. Hence, the survival rate is low, and well-planned treatment is lacking here. Our proposed image processing research might bring a breakthrough in this situation and to neurological science in Bangladesh.

1.3 Research Objectives

Since Bangladesh is still underdeveloped about the brain abnormality-related issues and specific various critical brain diseases at an early phase is unfeasible, this paper will provide the people of this nation with a perspective and will guide them along the path. Moreover, this paper will focus on the facts related to the MRI(magnetic resonance imaging) images that were still unknown to date. Hence, they will identify the brain issues at an early stage by extracting images from MRI scans and determining the severity level of abnormality.

The objectives of this research are:

1. To thoroughly understand ML and how it works.
2. To identify the techniques that will detect brain abnormalities at an early stage. Moreover, three kinds of brain tumor classifications are as follows: Meningiomas, Gliomas, and Pituitary from MRI images by using the CNN models (VGG16, ResNet50, Inception V3)
3. To improve the performance and models accuracy, data augmentation techniques were implemented. Furthermore, modification of the dataset was made

by doing probability-wise random rotation, enhancing contrast, zoom, flip resizing, etc.

4. To evaluate the model by reflecting the discrepancies of the trained models with the transfer learning models.

5. To provide suggestions regarding models based on performance and demonstrate future work for improvement.

1.4 Thesis Outline

Our research is always striving for the best possible outcome and working spontaneously to achieve our desired goal. Our researchers are always aiming for the betterment of the proposed system. Since Bangladesh is yet to discover the possibilities of the techniques that could bring about a revolutionary change in medical science and expertise, our authors are endeavoring with their utmost efforts to bring it to the people of this country. This study puts light on the path of a developed image processing technique to identify the abnormalities residing in the human brain.

Firstly, in Chapter 1, we have introduced our focal objective of the research. Then, a brief description of our work has been given here for proper understanding.

Secondly, in this segment(Chapter 2), we have given proper identification of similar topics as ours, but there were inadequacies in those papers. Papers cited in the literature review are all working with brain abnormalities, and all are from the same background. We tried to overcome the past endeavors' inadequacies through our research and showed promising and reliable results.

Thirdly, in Chapter 3, we have stated our adapted methodologies and procedures. We have also introduced our dataset and how we processed that dataset. Our dataset contained 3064 brain MRI images divided into 3(three) classes named - Meningioma, glioma, and pituitary tumor.

Fourthly, in chapter 4, we applied CNN models (ResNet50, VGG16, Inception V3) in this dataset. After going through this process, we started our model selection process and selected ResNet50 by judging its test accuracy level. Then we trained our dataset with varying sample sizes and compared it to get the best results. Moreover, we have represented our augmentation process, which has been applied to this Figshare dataset to gain more accuracy in our goal achievement. Finally, we have used our pre-trained CNN models to go through the "without augmentation" and "with augmentation" process and represent the comparison to give light to the best perception.

Fifthly, here in Chapter 5, we have represented the related works by other authors who have used the same Figshare dataset and identified that ours had achieved the best accuracy and results until now. Finally, we have compared our results and theirs in a table form to understand the comparison better.

To conclude, we have stated our goal achievement results, which are gained by the extended and comprehended process. We also shared our interest in doing future work related to this medical research using image processing.

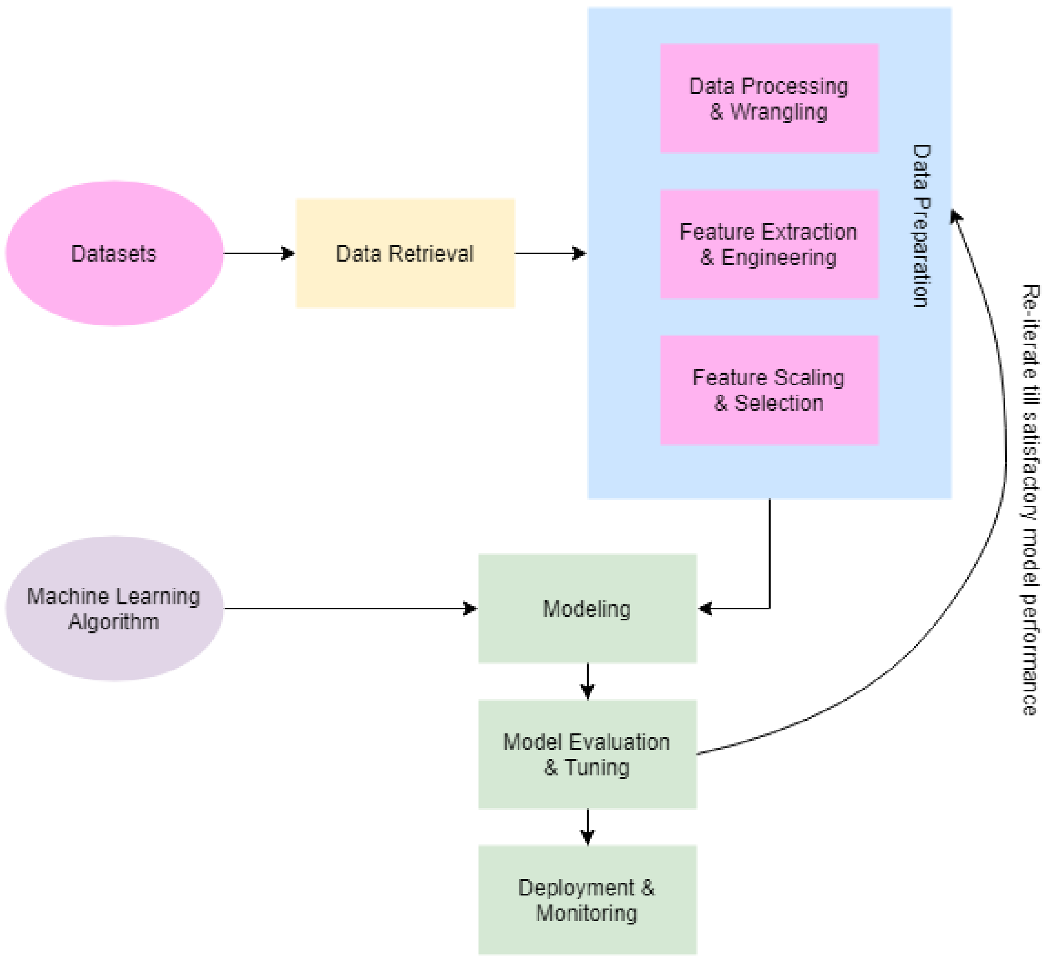

Figure 1.1: Workflow[18]

Chapter 2 Overview

2.1 Literature Review

Medical science in Bangladesh still lacks in various areas. Only digitization of the data and records alone can bring a vast improvement in medical science. However, the hospitals and clinics are still depending on paper works and human analysis to predict disease severity and detect any existing abnormalities. Furthermore, anomalies in the brain are not detected unless a radiologist analyses them, which can often be troublesome. To solve these problems, image processing plays a huge role.

According to [5] MRI is one the best technologies to diagnose brain abnormalities. Using image processing in MRI reports is a very convenient and efficient way to diagnose anomalies in the brain early.

2.1.1 Image processing

Image processing is a term that covers a massive area of Artificial Intelligence. According to [6], image processing starts with a version of grey images and returns another version of grey photos. Then the image will be processed through some vital steps and will operate on the grayscale images to locate abnormalities purposes in the context of measuring differences with the normal ones. In this way, after these steps, the image will be returned with another scale of grey ideas, indicating the brain's abnormal regions.

2.1.2 Image Segmentation

The picture is segmented into relevant areas based on similarity between areas. Image segmentation, coupled with image processing, object recognition and representation, and display of distinct areas of interest, is used in a variety of applications[7]. In medical diagnostics, image segmentation is crucial. Medical photos are often impacted by noise or diffusive borders, or have weak contrasts[8]. Image pre-processing stages can extract noises from medical and these types of images[9]. In image segmentation algorithms, two prior properties are there, which the algorithm works on. Image discontinuity and image similarity are the two types of image discontinuity

[10]. As a result, there are two techniques to segmentation. The intensity of a pixel in a picture is reformatted in the first approach. The second method relies on segmenting a picture into distinct sections. As a result, in several applications, various segmentation techniques are commonly used.

2.2 Related Works

There are various types of proposed work regarding the prediction of brain abnormalities. However, though there are abundant treatment methods regarding brain abnormality, Bangladesh has very scarce research on definite treatment for patient stratification.

To reduce sounds and avoid indistinctness, Weihua Zhu and Ying Shen utilized an anisotropic diffusion filtering algorithm in their research. Image segmentation has also been used to maintain the precise boundaries of MRI images [22].

J. N. Bhandavi and Maya V. Karki employed electroencephalogram (EEG) signals to get the electrical activity of the brain, and a Support Vector Machine (SVM) was employed as a classifier to detect irregularities in their article. Filtering and segmentation were pre-processed, as well as Feature Extraction. As a result, given a dataset for brain anomalies, they were able to attain a better recognition rate [25].

In a separate study, Hak-Seung Kim, Young-Tak Kim, and Dong-Joo Kim assessed HU on CT scans to discriminate between different kinds of injuries by identifying early signs of edema or ischemia. They also constituted a control group. As a result, they may be able to demonstrate the feasibility of assessing edema and anatomical defects in a sample of children who have had a catastrophic brain trauma [26].

In a paper by G. Hemanth [1], M. Janardhan, L. Sujihelen, ML and data mining classification techniques have been used for the early prediction of edema disease. To detect a specific cardiac picture, eliminate noise, and enhance the look quality, picture preprocessing was utilized, which included data cleaning, data transformation, data integration, data resizing, data reduction, Bilateral filtering (Average filtering), and Pixel Based segmentation. The CNN method detects brain tumors with high accuracy [28].

A hierarchy of partition-based extended-FCM and density-based DBSCAN method was employed in a study by Ranjita Chowdhury, Samarpan Dutta, Pinaki Saha, and Diptak Banerjee. The cluster was extracted and DBSCAN was applied to the resulting data. As a result, the Extended-FCM algorithm enabled a novel method of detecting and extracting brain abnormalities from an MRI picture. The method optimizes in a fewer number of iterations and requires much less time for each iteration than its traditional version. The use of density-based clustering in the extraction of ROI has proven to be extremely beneficial [31].

Dr. M.Karnan suggested three strategies for detecting brain cancers in a work by N. Nandha and Gopal, including Hierarchical Self-Organizing Map with Fuzzy C-Means, Genetic Algorithm with Fuzzy C-Means, and Ant Colony Optimization with Fuzzy C-Means. The pixel and position accuracy are calculated for 120 for each technique's performance analysis. Images from an MRI scanner. When the accuracy of the brain tumor segmentation procedure is compared to existing approaches, it is found to be superior [5].

In their study, Omneya Attallah and his study team correctly classified fetal brain disorders using photos of various fetal GA. The precision is acceptable. Segmentation, Enhancement, Feature Extraction, and Classification are the four phases of the suggested technique. The algorithms employed are linear discriminant analysis (LDA), support vector machine (SVM), K-nearest neighbor (KNN), and Ensemble Subspace Discriminates classifiers [20].

Sofiane proposed a research in which they used a Deep Learning Network and CNN to detect brain disorders. The K-Means algorithm and CNN Deep Learning Network are used to propose an automatic and supervised MRI brain abnormalities detection methodology based on raw brain MRI images. The proposed methodology successfully detects brain abnormalities with 95 percent accuracy, according to the obtained findings of brain abnormalities detection [22].

The photos used in this study were collected from the Centers of Biomedical Research Excellence (COBRE) database, thanks to a paper by M. Latha and G. Kavitha. Using multiplicative intrinsic component optimization, the original pictures are treated to simultaneous bias correction and segmentation. The feature area recovered from the ventricle appears to be significant, suggesting that it could be useful in the identification of Schizophrenic patients [23].

Manisha, B. Radhakrishnan, and L. Padma Suresh used a variety of approaches to detect brain anomalies in their publications. The efficacy and accuracy of brain tumor treatment have improved as a result of this study. To get to this point, they used a variety of methods. First, the image was pre-processed to remove any discrepancies, and then the image was smoothed using a median filter. They've also developed a method for determining threshold values based on standard deviation, which results in an intensity map. They used this to compute the average intensity of pixels above the standard deviation. The tumor will be segmented from the original MRI images using this computed mild intensity as the threshold value. The intensity value that is greater than or equal to the determined threshold value is set to 255, and the intensity value that is less than 0 is set to 0. The Sobel edge detector was utilized to determine the border of the tumor region in these parts of the aberrant region, which is a tumor [29].

Yanshuai Tu, Chengfeng Wen, Wen Zhang, Jianfeng Wu used brain structural MRI biomarkers to assess Alzheimer's disease progression and intervention effects in their paper. For brain morphometry analysis, an unique isometry invariant shape descriptor was developed. The Beltrami coefficient shape descriptor is calculated using a global area-preserving mapping from the cortical surface to the unit sphere. Furthermore, a study of average shape descriptors is consistent with previous AD research that identified medial temporal lobe volume as an important AD imaging biomarker. For feature dimension reduction, an unique patch-based spherical sparse coding approach is used. Finally, support vector machine (SVM) classifiers are used. All of these methods have proven to be effective in detecting the severity of Alzheimer's disease [30].

Next, Bradford A. Moffat and his colleagues published a report in which they employed diffusion MRI as a biomarker for early treatment response prediction in brain cancer patients. For correlation with clinical response, they employed water diffusion values computed and shown as a functional diffusion map (fDM). Finally, utilizing the T2 pretreatment, MRI images were spatially co-registered. The treatment of individuals with brain tumors has greatly improved because to these treatments [32].

Rohit Kempanna Atyali and Shivchandra R Khot's work has aided in the early detection of brain cancer and the provision of suitable therapies. The report also aided the radiologist, a physician, in detecting cancer tumors that were worrisome, improving the accuracy, sensitivity, and speed of cancer detection. They employed a variety of methods to get at the final outcome. The approaches used to identify malignant tissues by image fusion were Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) based fusion to multi-modality medical images [33].

Hardeep Kaur and Jyoti Rani published another study that successfully and precisely altered the brightness of photographs. LRE, ARE, and CLARE are also useful for enhancing picture brightness. Because LRE is a more time-consuming approach, CLARE is preferable. CLARE is a tool for enhancing picture contrast and removing noise, however it still has a tendency to noise. Histogram Equalization (HE), Local Histogram Equalization (LHE), and Adaptive Histogram Equalization are approaches for improving MRI image contrast (AHE). Adaptive Histogram Equalization with Contrast Limits (CLARE) [34].

Kandasami and her colleagues write in a similar study that their study presents a Neuro-fuzzy based method for classification and deblocking of anomalies from brain fMRI. Feature deblocking, categorization, and conflict detection are the three primary steps of the project. The crucial data that drives categorization is evaluated during the feature deblocking step. To diagnose the picture class, texture and Wavelet characteristics are employed as discriminating characteristics. Using a feed forward Backpropagation neural network, the classification phase distinguishes between normal and abnormal fMRI slices. After that, feature extraction and comparison with ground truth data are performed on the classified aberrant photos [27].

Another work by Arjon Turnip, K. Dwi Esti, Artha I. Simbolon, Teddy Hidayat, and Firman F. Wirakusumah offered a novel study approach for determining which part of the brain was most influenced by its functionality; the EEG-P300 capability and latency were assessed [24].

Chenjie Ge, Irene Yu-Hua Gu, Asgeir Store Jakola, and Jie Yang published research proposing a training technique to improve glioma classification performance, where GAN enhanced imaging is employed to pre-train the usage of refined training utilizing actual brain MRIs. Furthermore, the method was proved by testing and comparisons of classificatory gliomas. Inter-modality imaging was also used to suggest a brain image enhancer (GAN). TCGA was evaluated on an accessible data collection of 167 participants for IDH genotypes (mutation or wild-type). The suggested strategy was validated by test results from two experimental settings, which showed that employing mixed reality and more data, it was possible to enhance Glioma classification performance (test accuracy 81.03%, with 2.57% improvement) [35].

In a publication, Changhee Han and his colleagues suggested a GAN-based DA that works in two phases to produce and modify brain MR images with and without tumors: Multistage picture noise, progressive GAN development (PGGANs). GAN generates 256 realistic and varied pictures; (ii) a Multimodal Unsupervised Image-to-Image Translation (MUNIT), which combines GENs/Variational AutoEncoders or SimGAN with a DA-focused loss and refines the texture and form of the PG-GAN produced pictures to make them seem like the real thing. A high-resolution MR image generating system uses GAN to produce realistic pictures. The findings suggest that our two-phase GAN-based DA, when paired with conventional DA, can significantly outperform conventional DA alone in terms of tumor identification (i.e., enhanced sensitivity of 93.67 percent to 97.48 percent) and other medical imaging tasks [36].

A GAN (MSG-GAN) multi-scale gradient is used to construct meningioma-like MRI images in a work by S Deepak and P M Ameer. The synthesized pictures are used as the training material for a multi-class brain tumor issue in a deeper concussion neural network.The analysis is made on the images from the coronal view of the figshare database and the performance of the classifier was improved in terms of balance accuracy [37].

Similarly in a paper by Shikar Rajcomar, Anban W. Pillay, and Edgar Jembere Studied that both types of problems are prominent when the brain tumor detection is based on MRS data. Hence, proposed a different method to solve these challenges by merging samples in one class with those in the same and other classes to develop a profound neural network to distill particularly representative training examples and increase training data.They showed that this technology significantly improves performance so that with just a few thousand workouts, our method can achieve human-expert precision [38].

The paper by Shikar Rajcomar, Anban W. Pillay, and Edgar Jembere In this paper, presented a method for determining the most efficient amplification techniques to be combined in the machine pipeline. They proposed that only two pipeline increases should be used, followed by the advanced offline technique followed by a simple online technique. This approach is validated through the application of datasets with class imbalances and small sizes to two medical image problems.The first problem with binary classification with brain tumor data and the latter with the white blood cell dataset with multi-color classification. There are reports of a comprehensive experiment with around 170 different augmentation method combinations. Experimental results show a 15% and 11% increase in accuracy of validation over no increase and a 2% better increase than one increase [39].

Chapter 3 Data collection and Data Classification

3.1 Methodology

Our implemented system model comprises four components: data collection, data pre-processing, features learning, and data classification. Figure 3.1 displays the entire architecture of the machine and shows all elements. The following subsections describe all subsystems(modules).

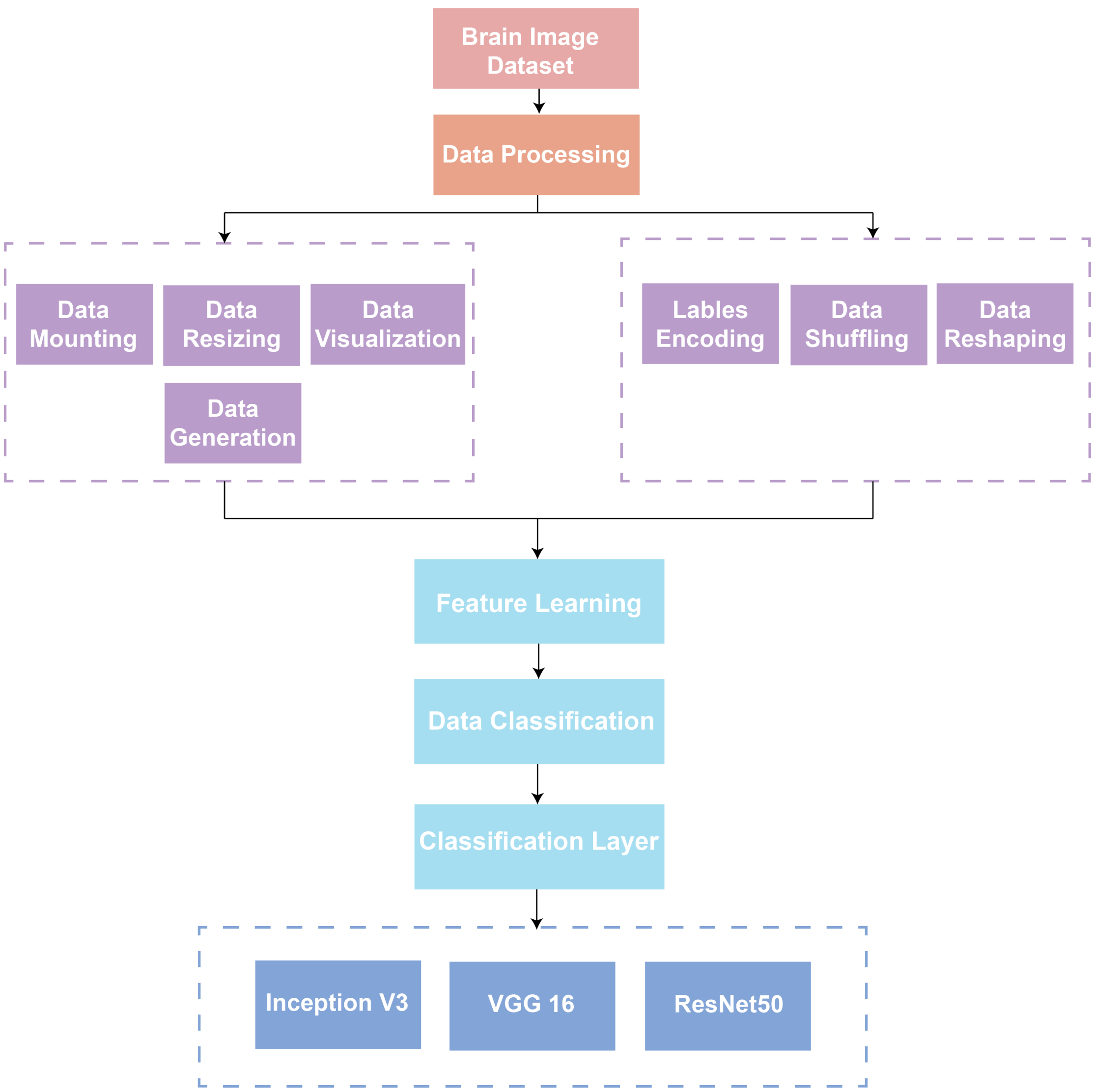

Figure 3.1: Structural outline of the proposed methodology

3.2 Dataset Collection

The Figshare dataset is readily accessible[11]. It was widely applied to enhance the performance of brain tumor classification[12], and using Adaptive Spatial Pooling and Fisher Vector; brain tumors were retrieved[13]. The dataset contains 3064 collections of MRI images from 233 patients with brain tumors. Here, the photos are T1-weighted (contrast-enhanced). Meningioma, glioma, and pituitary tumor were the most prevalent types of brain tumors found in the patients. This includes 1426 glioma-related brain MRI images of 89 patients, 708 meningioma images from 82 patients and 930 pituitary tumor images from 62 patients. This information is formatted in Matlab (.mat file). The images are 256 x 256 pixels in size. The data collection of MRI images was pre-processed as follows (Figure 3.2). Because of the repository file size limit, we split the entire dataset into 4 subsets and archived it into 4.zip files with 766 slices each.zip file[13].

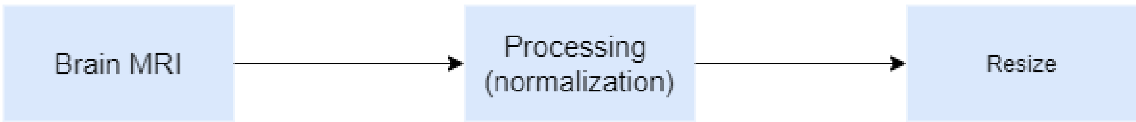

Figure 3.2: Data pre-processing step

3.3 Data Processing

The pre-processing data concept typically refers to all transformations done in raw data before the profound learning module is processed. For example, training a convolutional neural network on raw pictures is likely to lead to poor classification. This study carried out a sequence of seven pre-processing operations before it was fed to the next ResNet50, VGG16, Inception V3 module (as shown at the second level in Figure [3.1]).

3.3.1 Data Mounting

On the Windows operating system, this stage serves as a virtual machine, similar to a USB drive, to install a Google Drive account (DGA) for searching and accessing the drive at the Google Co-laboratory. Our Figshare dataset has been imported into a directory and then extracted it (known as a master) on the Google drive, and used the Python/glob library, which includes data handling including framing, reading and writing between data in-mémoire and format structures, and accessing the data into Co-Lab. We also have access to the Figshare dataset in the Python/Glop library.

3.3.2 Data Resizing

This phase is needed to remove redundancies in input data that mostly add to that same network's computation time without making significant changes. With the support of Python/Keras, this is done on pre-processing. As a consequence of wearing multiple image sizes, we are able to finish with an image size of 256x256, with a practical compute complexity preserving image readability.

3.3.3 Data Encoding

This phase is implemented to convert categorical data into a format values that our deep learning predictive models can comprehend.Label encoding method was used to assign for every value to one column in a single group, that is, the class 'Meningioma,' the value '1' was added, the value '2' was given to 'Glioma,' the value '3' was given to the category 'Pituitary tumor'. With the Python/sklearn.preprocessing library, pre-processing was done.

3.3.4 Data Shuffling

In this step, the data samples in the training data set are re-divided to guarantee that any sample of the data causes an unbiased transformation in the model. With Python/keras. pre-processing library is achieved.

3.3.5 Data Visualisation

This step is required to sample and assess the input data in order to assure the accessibility of the input pictures by displaying some sample sizes of the training dataset using 2D models associated with the new pixel dimensions. Python/tensorflow and the Python/numpy libraries can be used to do this.

3.3.6 Data Generation

This step is used to create batches of tensor image data with real-time data augmentation. The data would be repeated over for both research and training (in batches). At this step, batch normalization is combined with picture plotting for sample normalized pictures and encoded labels. This is accomplished using the

Python/tensorflow, Python/keras.preprocessing, and Python/matplotlib packages.

3.3.7 Data Reshaping

This step can be used to manipulate the layers of input ResNet50, VGG16, and Inception V3 to fit the input structure for our pre-processed data set image width 224 and image height 224, NoChannels=3. The Python/keras libraries can be used to do this.

3.4 Data Classification

Classification of data is an important mechanism in which large datasets may be divided into groups for judgments, pattern detection and other purposes. A classification layer uses the fully implemented layer which calculates the loss of entropy for problems of multi-class classification for each other. Python/keras.layers, Python/keras.models and Python/keras/optimizers may be used.

The proposed models for the files are described in table 3.1 and attached to the appendix.

File Name	Description
Performance and Explainability analysis subject to varying sample size and augmentations..ipynb	In google colab, after importing the necessary libraries we first extracted the image data, converted into .mat extension and scanned through the .mat files. Then image data was labeled and trained as a model. For training out of 3064 Brain MRI images 2452 images are used for training purposes. After training, the three classes meningioma, pituitary tumor, glioma were visualized and a total 612 files were used for validation. Via transfer learning, the datasets were trained using the models and then checked the loss and accuracy of each model.

Table 3.1: Proposed Models' Description

Chapter 4 CNN Model Selection and Implementation Analysis

4.1 CNN Model

Deep neural networks are classified by CNN in general. In deep learning we usually learn various types of networks and one of the types is "convolutional neural network". This method is used to analyse visual representations, image segmentation, object detection and so on. After doing the analysis, the models provide results. The accuracy of these results depend upon the variety of CNN models that are being used. In the proposed system, three CNN models have been used and the accuracy of the results are provided according to the comparison that have been made among them.The basic CNN architecture comprises of 5 layers of CNN. They are:

- Pooling Layer
- Convolutional Layer
- Dropout
- Activation Functions
- Fully Connected Layer

Convolutional layers, pooling layers, and fully connected(FC) layers are the three types of layers in a CNN. When these layers are stacked, a CNN architecture is created. In addition to these three layers, the dropout layer and activation function are defined in addition to two other important parameters.

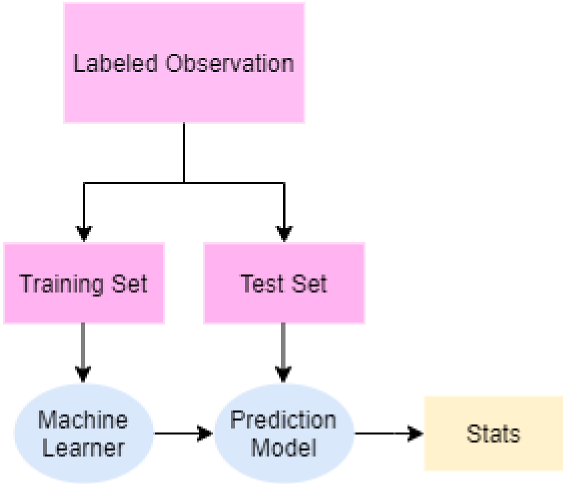

Figure 4.1: Supervised learning

4.1.1 ResNet50

According to [14], ResNet50 is one of the convolutional neural networks. It consists of 50 layers. Moreover, it can contain vast pre-trained images. Afterward, it classifies the images and trains the given input dataset. The network's picture input size is 224/224 pixels. [16] said ResNet50 is one of the best models as a backbone of many computer vision tasks. This model has five phases, each comprising a three-layer convolutional block and a three-layer identity block. Over 23 million parameters make up the ResNet50.

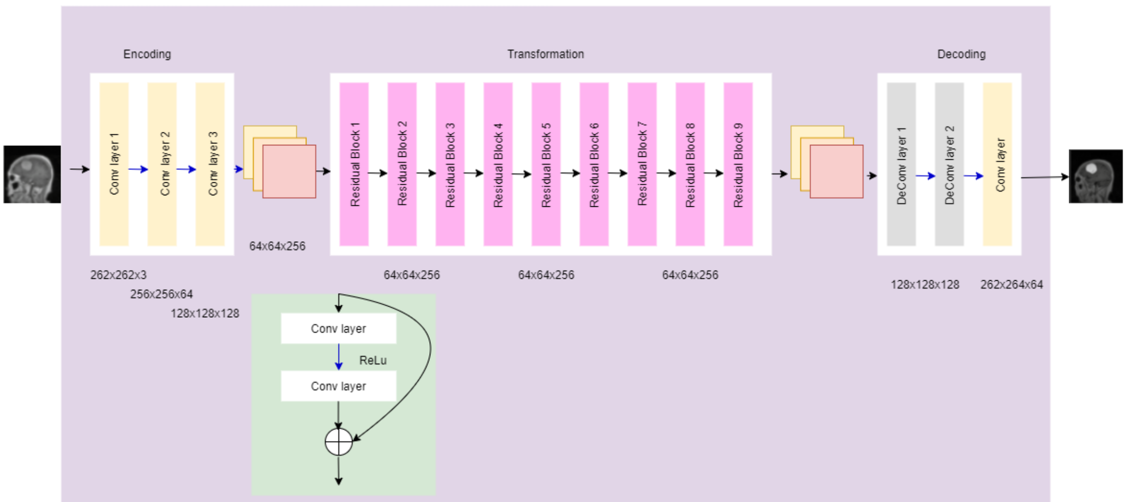

Figure 4.2: ResNet50 Model.[19]

4.1.2 VGG16

According to [15], VGG16 is a CNN model, having the depth of 16 layers and the image size for the VGG16 input layer is 224X224.[17] Here,224 x 224 RGB image is fixed size(input to cov1 layer). Between the stack of convolutional layers, the images are passed. Moreover, filters are applied with a minimal receptive field: 3x3 to capture the notion. In the max pools and elements, there are five layers of spatial pooling following some of the conv (all the conv. layers are not followed by the max-pooling). Max pools are created using a 2/2 pixel window with Phase 2[17].

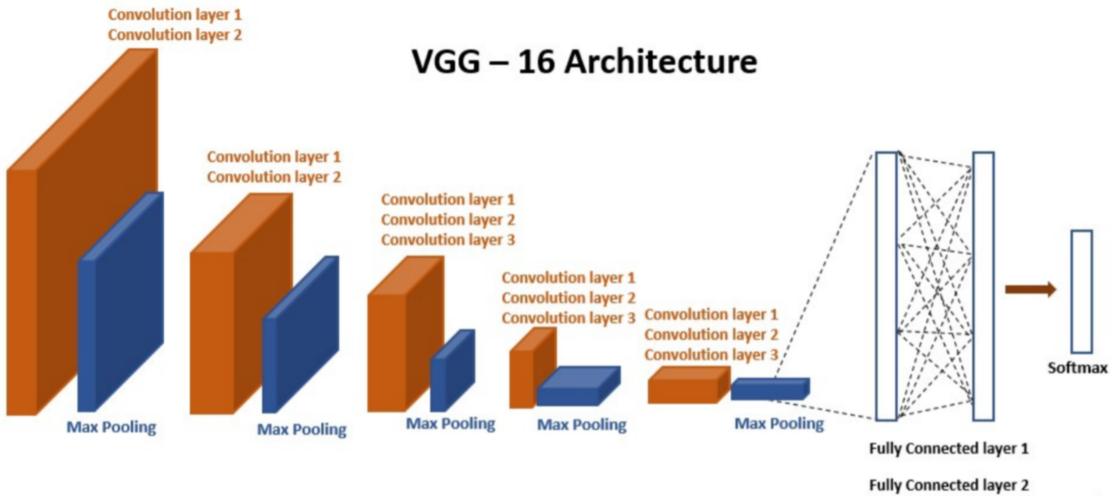

Figure 4.3: VGG16 Architecture

4.1.3 Inception V3

On the ImageNet dataset, Inception V3 is a commonly used image recognition model that has been demonstrated to achieve higher than 78.1 percent accuracy. The convolutional neural network is 48 layers deep. Inception Networks (GoogLeNet/Inception V1) have proven to be more computationally efficient compared to VGGNet. VGGNet is cost-effective and efficient in terms of the quantity of network parameters generated. If there are any enhancements to be made to the Inception Network, care must be taken to ensure that the computational advantages are not jeopardized. As a result of the intricacy of the new network's effectiveness, adapting an Emergence network to numerous use cases becomes difficult. In an Inception V3 model, several ways to simplify the network have been presented to reduce the limitations for easier model adaptation. Factorized convolutions, regularization, dimension reduction, and parallelism are some of the approaches used [21].

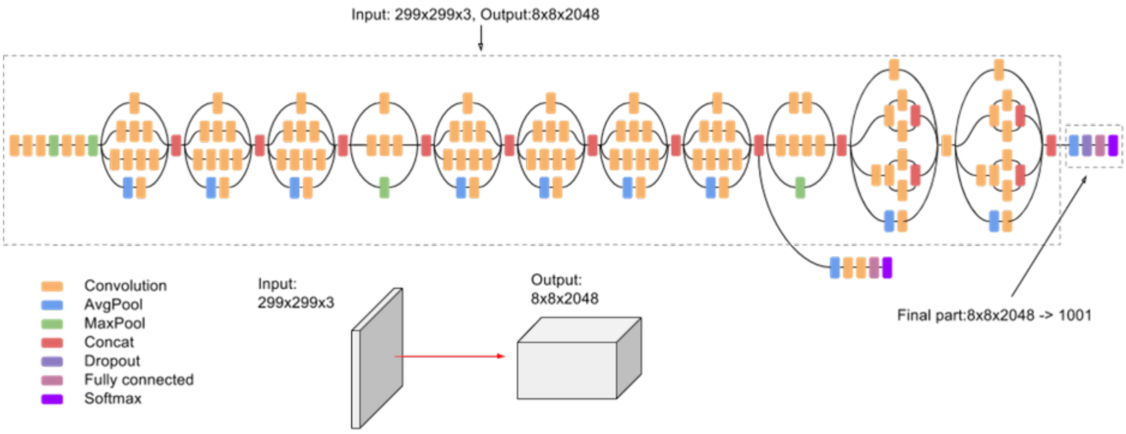

Figure 4.4: Inception V3 Architecture

In our system we have used Inception V3 instead of Inception V1 or V2 since this is the most updated one and the one with the least error rate according to Szegedy [14][15]. In the table below a small comparison is given.

Inception V1	Inception V2	Inception V3
Increases numbers of units and shielding.	Removes dropout, reduces weight, randomises training examples more efficiently.	Trained much faster than other models of Inception.
Error rate is 6.67%	Error rate is 4.82%	Error rate is 3.5%

Table 4.1: Comparison Between Inception

4.1.4 Transfer Learning Method

Transfer learning means that the knowledge gained through one problem is used in other problems as a reference to achieve solutions. Transfer learning models are pre-trained, and we used this model in our desired system to achieve our desired goal. Some of the pre-trained CNN models are: GoogleNet, AlexNet, VGG16, VGG19, Inception V3, Inception V2, Inception V1, ResNet18, ResNet50, ResNet150 etc. These models contain thousands of classes and millions of training images which are tested and validated on thousands of test images. Moreover, they are all being compared with one another in terms of accuracy to provide people the best desired results for their proposed system. These models use images as an input, then label them and produce probabilities of the best category. In our proposed system, we used a FigShare MRI dataset as the input. We classified three types of tumors from this dataset and then used the models ResNet50, VGG16, and Inception V3 to train our dataset. After training, we found the accuracy percentage of each model. Here the output results are the representation of the kind of tumor. Figure[4.5] provides a brief illustration.

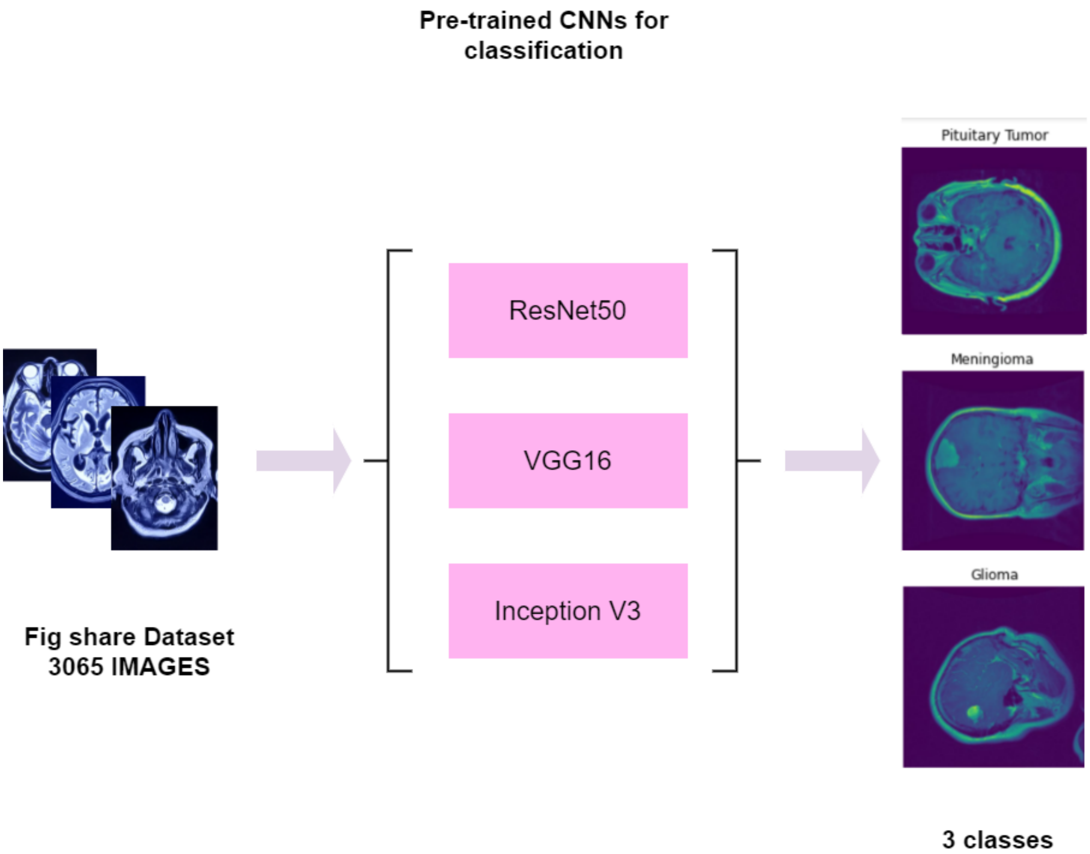

Figure 4.5: Pre-trained CNNs

4.2 Comparison between different CNNs architectures for image analysis

The CNN architecture consists of numerous filters/kernels which comprise trainable parameters. CNN models can detect features like shapes, edges, and other specific entities from a given image dataset in terms of object detection. In medical image analysis with the application of different CNN models such as VGG16, ResNet18, ResNet50, ResNet150, Inception V3, Inception V2, Inception V1, VGG19, GoogleNet, AlexNet, etc. the proposed model can efficiency train and reflect a given image into a highly abstract representation. We have ResNet50, Inception V3, and VGG16 in our proposed approach. Table 4.2 [17] shows the discrepancy between the architectures regarding layers, error rate, dataset, task, etc.

Discrepancy Between Three CNN Architectures				
CNN Architecture	No Of Layers	Top 5% Error Rate	Our Training Dataset	Tasks
ResNet50	152 layers	3.57%	Figshare Dataset	Classification and Object Detection
VGG16	41 layers	8.8%	Figshare Dataset	Classification and Object Detection
Inception V3	48 layers	4.2%	Figshare Dataset	Classification and Object Detection

Table 4.2: Discrepancy Between Three CNN Architectures

4.2.1 Selection of ResNet50

After Training ResNet50 model, In order to measure the performance the accuracy results in 92.65%. In VGG16 and inception V3 the accuracy reflected was 90.69% and 82.68% respectively. Then we used the three transfer learning models to go through the augmentation process and found out that "ResNet50" showed highest accuracy. Therefore, we have used the ResNet50 model for the data augmentation process.

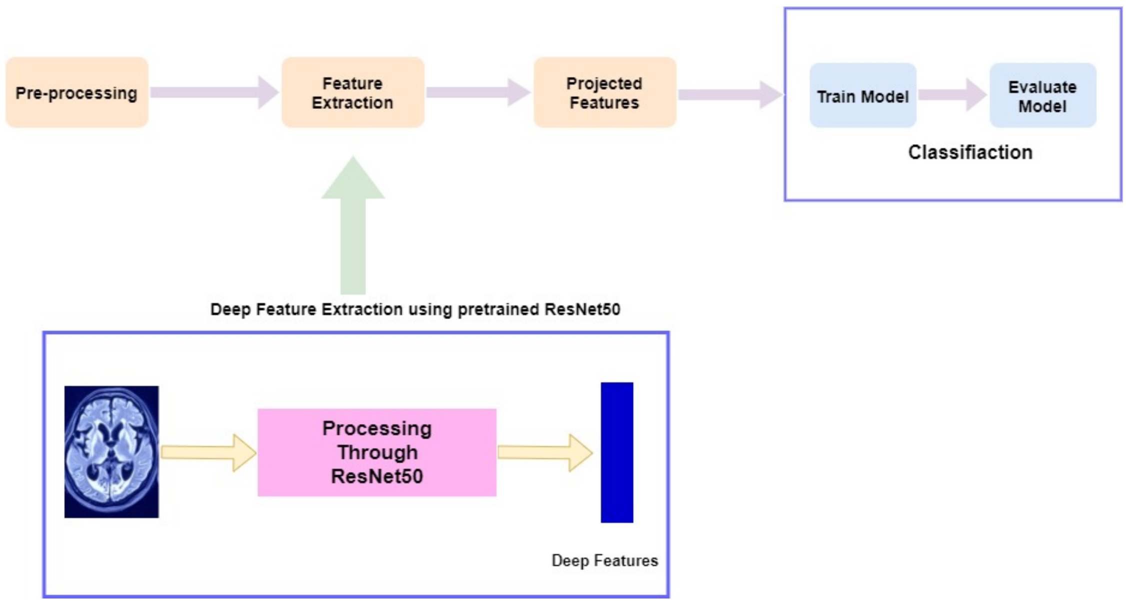

Figure 4.6: ResNet For Detecting Brain Tumors

4.3 Training Data with varying sample size

In our proposed system, the concept is to extract 50% of the dataset in terms of training and observe the progress and get accuracy according to it. For illustration, it has been found that 3064 files belong to the three classes and used 1532 files for training. The percentage of the dataset has been increased gradually to train the system. Figure 4.7 shows that the dataset used in ResNet50 gives more accuracy than our simple trained dataset. A comparison has been shown to get a clear idea of the models used in the system. After using 50%, then 60%, 70%, 80% and 90% has been used respectively. In addition, 20% has been used on the dataset of the validation set. Hence approximately 612 files have been used for the validation process. Validation is used to measure and to assess the model's performance. Metrics on the set of validation will provide estimation regarding the quality of the model. According to the figure plotting, the highest accuracy has been gained through 80% since it is the highest accuracy peak.

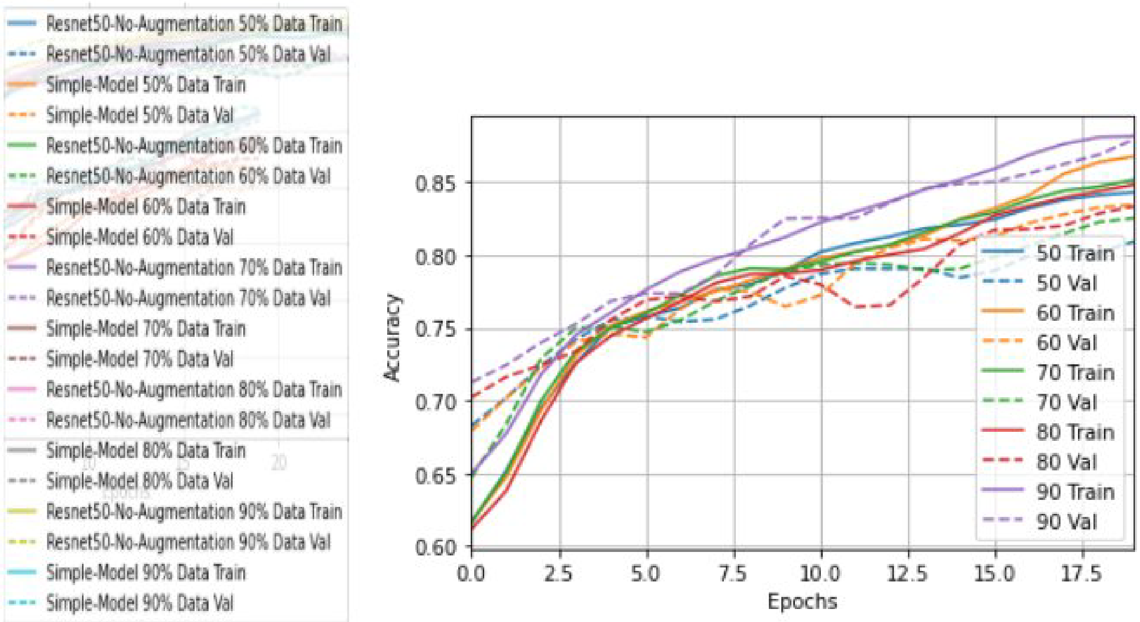

Figure 4.7: Varied Sample Size

Chapter 5 Comparison of Augmented Models

5.1 Augmentation

Data augmentation, also known as assumed regularization, is a prominent strategy for improving the generalization capabilities of deep neural networks [40]. Image augmentation is a process or technique where the images can be artificially manipulated through editing the trained dataset. Augmentation of images is utilised in building CNN models. Moreover, augmentation of images enables us to predict more accurate results in our trained CNN model. Generally, data augmentation increases the size of the dataset [41] and represents variability in the dataset instead of significantly collecting new data. It also helps to reduce oversize and process every image in a distinctive way. Our dataset may contain images taken under specific conditions, but we may fall short in a variety of conditions. In this case, the modified/augmented data aids in dealing with such circumstances. The FigShare dataset has been used in our proposed system, and this dataset has gone through the augmentation process. Here, ResNet50 has been selected to go through this process since this CNN model has given the most accuracy in our system.

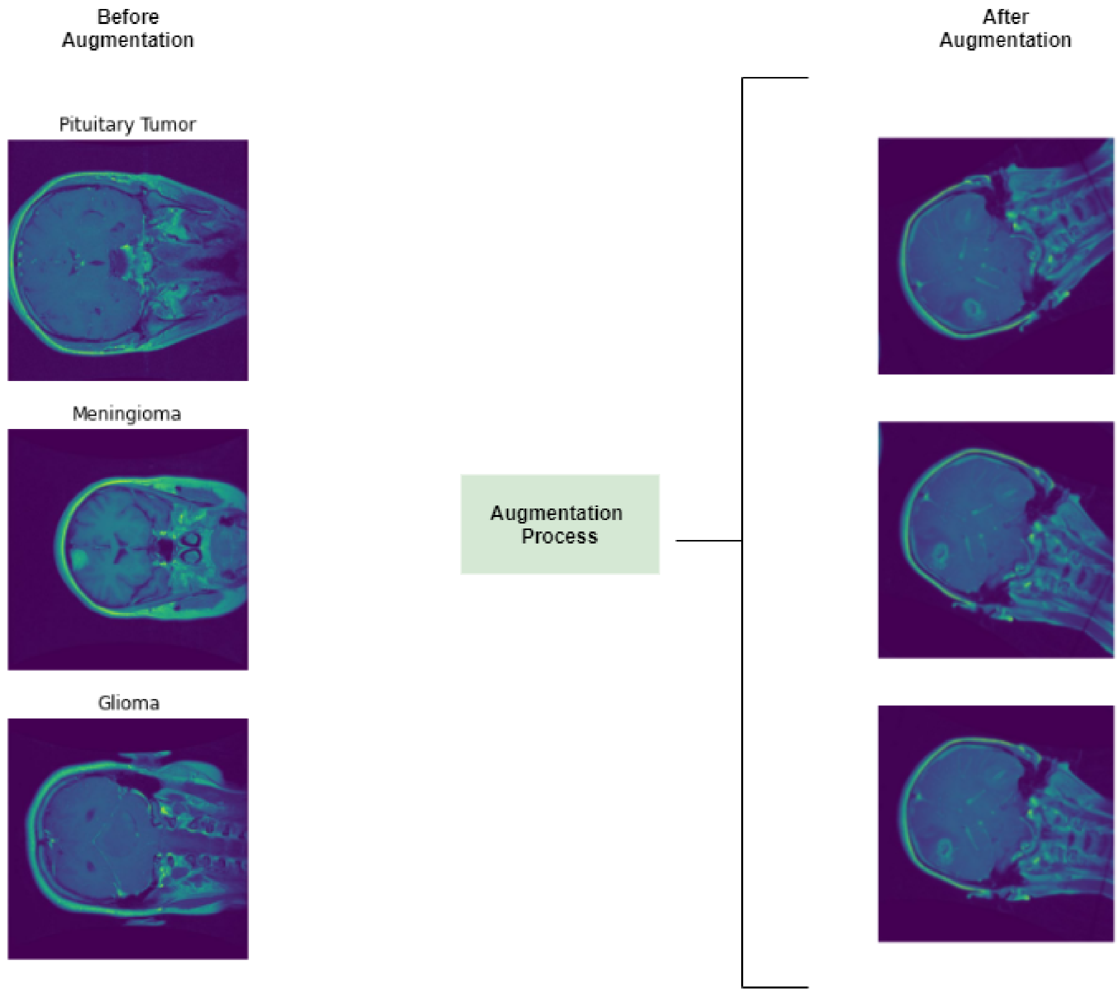

Figure 5.1: Augmentation

5.1.1 Without Augmentation

In our proposed system, a generic comparison of the accuracies between the Simple model and pre-trained transfer learning models "ResNet50", "VGG16", "Inception V3" were represented. Our suggested models were trained using the dataset and they compared the accuracy between the two models to evaluate the discrepancy. In the validation set, To train the dataset, which was passed forward and backward through the neural network, the epochs were set to 25 and at the 25th accuracy, the validation accuracy resulted in 93.95%. Therefore, the "ResNet50" model reflected better accuracy than the simple model.

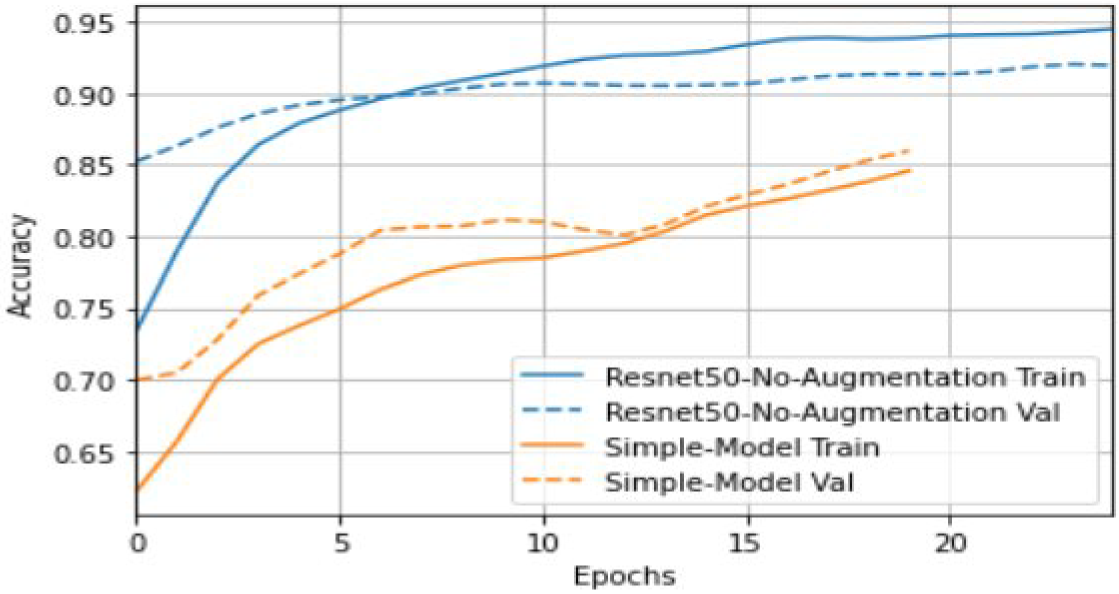

Figure 5.2: Without Augmentation

5.1.2 With Augmentation

In the proposed system, the datasets were augmented and then trained again with transfer learning models "ResNet50", "VGG16", "Inception V3" to get the accuracy from augmented data. The augmentations were done considering different aspects and probability wise. Such as random zoom, rotate, flip, crop and resizing of the images. Then the augmentations showed promising results of the accuracy. After this, the accuracy results were compared to non-augmented transfer learning models trial accuracy. In the figure 5.3, it is vividly visible that the "ResNet50" model showed more accuracy after applying the augmentation technique than the other model.

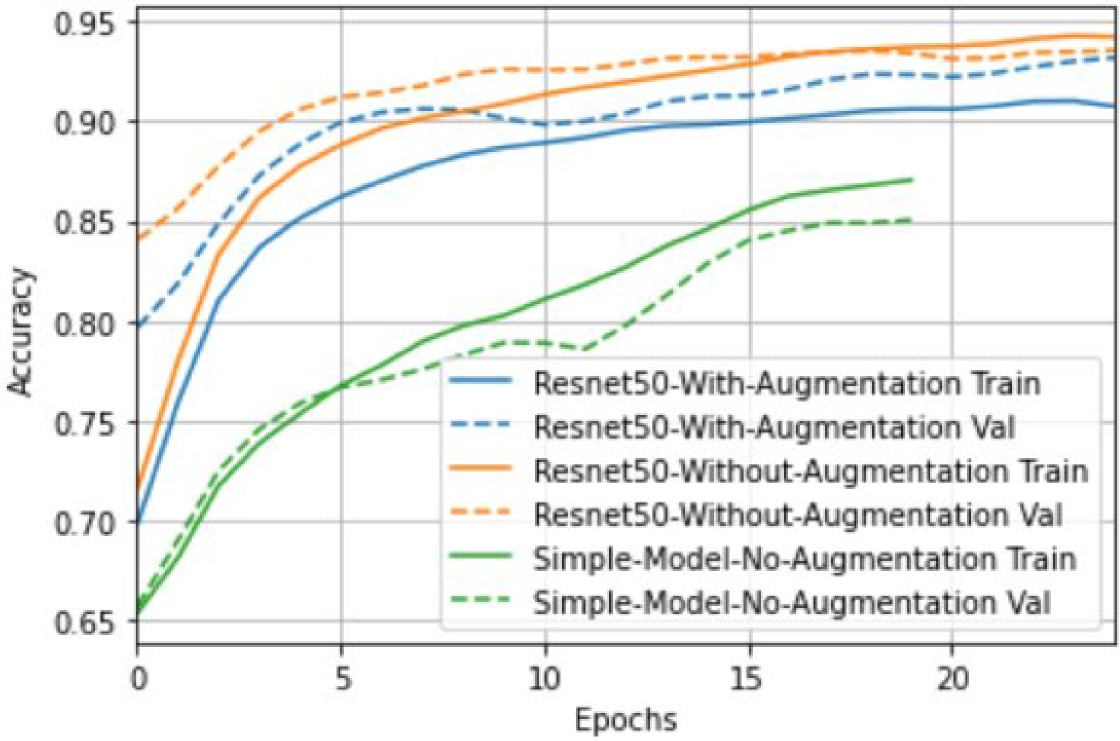

Figure 5.3: With Augmentation

5.2 Probability-wise augmentation

We have used 6 types of augmentation in our proposed system, using different parameters and then found the most optimal result. The parameters are random flip(horizontal), random rotation, random zoom, random contrast, random crop.

Augmentations	Parameters
Augmentation 1	Random Flip("horizontal"), Random Rotation (0.1), Random Zoom (0.1)
Augmentation 2	Random Zoom (0.1), Random Contrast (0.02)
Augmentation 3	Random Flip("horizontal"), Random Contrast (0.01)
Augmentation 4	Random Flip("horizontal"), Random Rotation (0.1)
Augmentation 5	Random Flip("horizontal"), Random Rotation (0.1), Random Zoom (0.1), Random Contrast (0.01)
Augmentation 6	Random Flip("horizontal"), Random Crop (240, 240)

Figure 5.4: Different augmentations with parameters

5.3 Implementation and Results

The implementation of the proposed model for brain detection of abnormalities is defined in this section. Using Google Collaboratory, the model was introduced and tested. The model's implementation consists of several phases; pre-processing of input data, CNN, classification and checking. Pre-processing of input data is a stage for qualifying the brain tumor dataset to be used as an input to the detection process for anomalies. The key model used for identification is CNN.

This chapter also includes the outcomes of the proposed model's implementation for detecting anomalies in the brain. To run the test, Google Collaboratory uses part of unclassified input data and obtains the result.

5.3.1 Implementation

We used a "Random" Python package with a probability function to build a total of six augmentations utilizing three CNN models, namely VGG16, ResNet50, and Inception V3. In a single instance, CNN models were used to train each of the augmentations using 25 epochs. We obtained the outcomes of training accuracy, training loss, validation accuracy, and validation loss after training with each enhanced dataset.

5.3.2 Prediction of stratification accuracy

Classification accuracy refers to the ability to accurately predict and presume the value of a predicted attribute for new data. As a result, one criterion for evaluating classification models is accuracy[16]. The following is the formal definition of accuracy [16]:

Accuracy =Number of Correct Predictions/Total Number of Predictions

Figure 5.5: Formula of Accuracy

After training the networks in this section, the test images are classified, and overall classification accuracy is estimated. In terms of binary classification accuracy, the calculation is based on true /false notation.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \times 100$$

Here, TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Illustration for the outcomes will be as following:

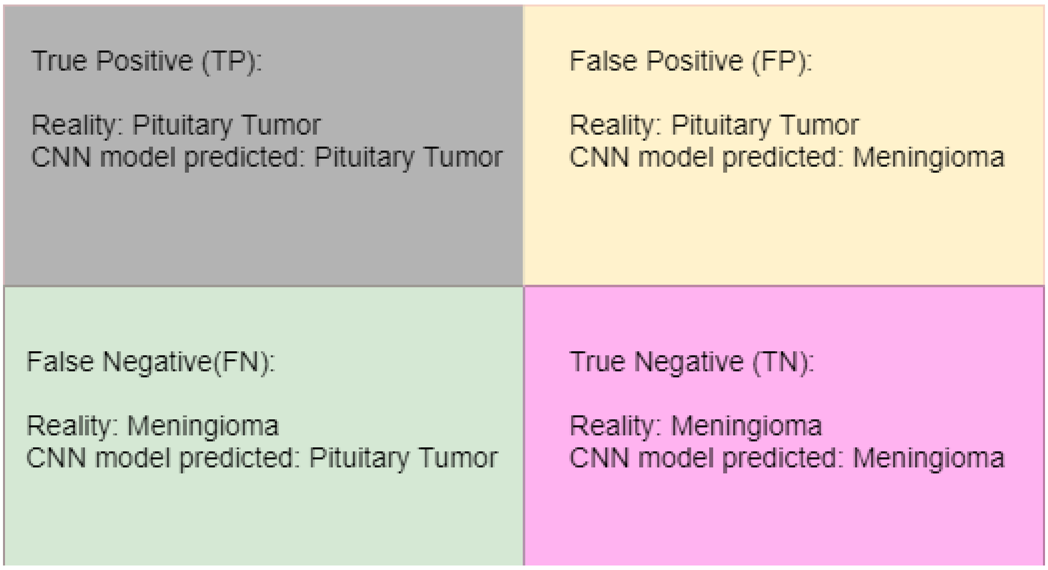

Figure 5.6: Classification Accuracy Prediction

5.4 Comparison of Augmented Models

Tables 5.1, 5.2, 5.3 depicts information regarding the discrepancies between the Augmented models(VGG16, ResNet50, Inception V3). The Augmentation was performed probability wise and we represented the models along with the accuracies. At 90% ResNet50 had the highest accuracy among the models.

VGG16

	Aug 1	Aug 2	Aug 3	Aug 4	Aug 5	Aug 6
Sampling Rate	Training Accuracy | Validation Accuracy					
40% (1226)	0.8730 | 0.8627	0.8754 | 0.8840	0.8916 | 0.8856	0.8901 | 0.8840	0.8893 | 0.8856	0.8873 | 0.8693
50% (1532)	0.9135 | 0.8905	0.9018 | 0.8709	0.8841 | 0.8758	0.9147 | 0.8873	0.8905 | 0.8758	0.8952 | 0.8758
60% (1839)	0.9005 | 0.8791	0.8993 | 0.8791	0.8991 | 0.8905	0.9032 | 0.8954	0.8922 | 0.8856	0.9008 | 0.8856
70% (2145)	0.8917 | 0.8954	0.8937 | 0.8938	0.9128 | 0.8873	0.8834 | 0.8938	0.8925 | 0.8709	0.9075 | 0.8840
80% (2452)	0.8941 | 0.8873	0.8984 | 0.8954	0.8859 | 0.8840	0.9129 | 0.8709	0.8941 | 0.8840	0.8813 | 0.8905
90% (2758)	0.8924 | 0.9265	0.8982 | 0.9085	0.8897 | 0.9150	0.8997 | 0.9216	0.9063 | 0.9297	0.9140 | 0.9150

Table 5.1: Accuracy Table of VGG16 after Augmentation

ResNet50

Sampling Rate	Aug 1	Aug 2	Aug 3	Aug 4	Aug 5	Aug 6
	Training Accuracy | Validation Accuracy					
40% (1226)	0.9541 | 0.8873	0.9434 | 0.8971	0.9379 | 0.8873	0.9439 | 0.8840	0.9458 | 0.8938	0.9463 | 0.8905
50% (1532)	0.9445 | 0.9020	0.9376 | 0.9036	0.9471 | 0.9101	0.9444 | 0.8873	0.9522 | 0.8938	0.9378 | 0.9003
60% (1839)	0.9461 | 0.9232	0.9579 | 0.9020	0.9556 | 0.9167	0.9468 | 0.9216	0.9570 | 0.9183	0.9510 | 0.9150
70% (2145)	0.9449 | 0.9199	0.9425 | 0.9036	0.9473 | 0.9069	0.9482 | 0.9069	0.9402 | 0.9167	0.9499 | 0.9134
80% (2452)	0.9452 | 0.9199	0.9474 | 0.9297	0.9458 | 0.9134	0.9505 | 0.9330	0.9471 | 0.9248	0.9378 | 0.9134
90% (2758)	0.9430 | 0.9379	0.9361 | 0.9444	0.9490 | 0.9444	0.9389 | 0.9477	0.9435 | 0.9510	0.9433 | 0.9428

Table 5.2: Accuracy Table of ResNet50 after Augmentation

InceptionV3

Sampling Rate	Aug 1	Aug 2	Aug 3	Aug 4	Aug 5	Aug 6
	Training Accuracy | Validation Accuracy					
40% (1226)	0.7622 | 0.7876	0.7925 | 0.7908	0.7940 | 0.8023	0.7858 | 0.7908	0.7989 | 0.8023	0.8072 | 0.8154
50% (1532)	0.7963 | 0.8023	0.7771 | 0.7859	0.7974 | 0.7369	0.8103 | 0.7925	0.8061 | 0.7925	0.8287 | 0.7859
60% (1839)	0.8038 | 0.8154	0.8164 | 0.8219	0.7875 | 0.8072	0.7645 | 0.7631	0.7637 | 0.7843	0.7903 | 0.7990
70% (2145)	0.7834 | 0.8105	0.7987 | 0.8170	0.8100 | 0.8203	0.7716 | 0.7435	0.7827 | 0.8056	0.7841 | 0.8170
80% (2452)	0.8095 | 0.8154	0.8075 | 0.8023	0.7954 | 0.8137	0.7935 | 0.8056	0.8037 | 0.7974	0.8187 | 0.8219
90% (2758)	0.7933 | 0.8333	0.8176 | 0.8497	0.7789 | 0.8546	0.8199 | 0.6062	0.8090 | 0.8137	0.8045 | 0.8546

Table 5.3: Accuracy Table of Inception V3 after Augmentation

5.4.1 Results

After running the model using Google Collaboratory, results after using ResNet50, VGG16, Inception V3 models are obtained. After training and feeding data in these models, each model showed a certain amount of accuracy. 3064 files belonging to 3 classes have been found and 2452 files have been trained which covers about 80%.

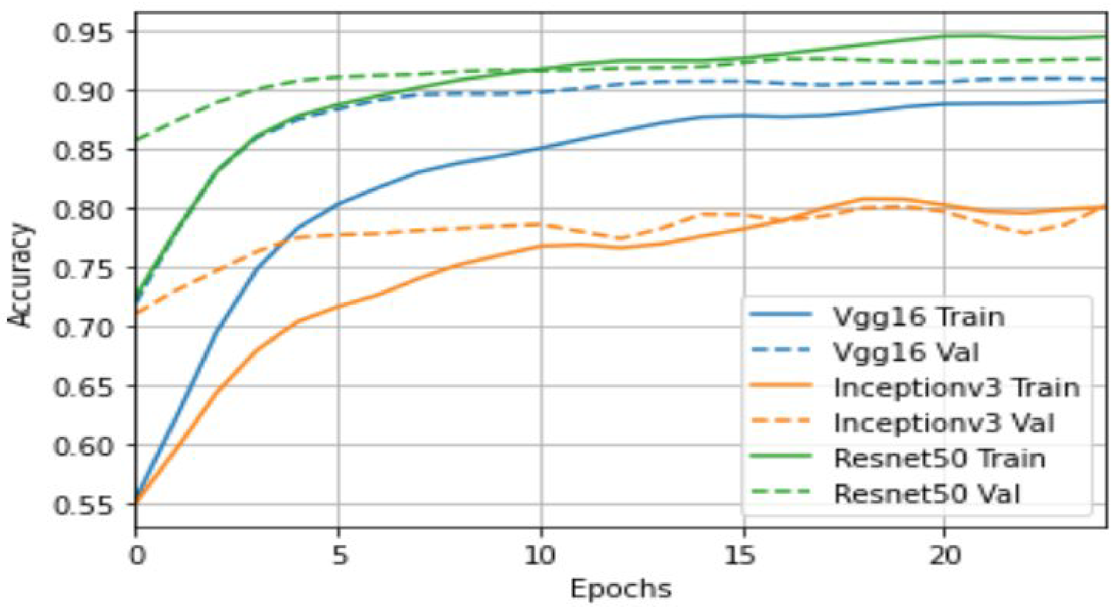

Figure 5.7: Comparison of Accuracy Graph

After running the dataset on ResNet50, VGG16, Inception V3 the accuracy rate which have been found are as follows: 92.65%, 90.69%, 82.68%. The above chart is based on the accuracy rate of the models which are used in the brain tumor dataset in Google Collaboratory.

5.4.2 Best Augmentation

In the data augmentation part, probability wise augmentation was performed and the number of augmentation was 6. After analysing the overall augmentation, the observation states that at augmentation 4, both the VGG16 and ResNet50 model provided the best augmentation. Furthermore, at augmentation 6, the Inception V3 model produced better augmentation results than the other 5 augmentations. For all three models, the epoch count was 25 and the train-validation splits were 80:20. It is quite visible that ResNet50 outperformed the other two models in terms of training and validation accuracy, producing 95.05% and 93.30%, respectively. Thus, among the three models, ResNet50 produced the best accuracy results. The following table depicts information regarding accuracy analysis.

Model	Number of parameters	Number of epochs	Train-Validation Split	Best Augmentation	Training Accuracy	Validation Accuracy
VGG16	138.36M	25	80:20	Aug 4	0.9129	0.8709
ResNet50	25.56M	25	80:20	Aug 4	0.9505	0.9330
Inception V3	23.83M	25	80:20	Aug 6	0.8187	0.8219

Table 5.4: Accuracy Analysis

Chapter 6 Conclusion & Future Works

Our proposed paper reflects the advantage of using deep learning features in models to identify brain tumors. Two different strategies have been evaluated experimentally. First, the proposed system classifies categories of brain tumors (three categorisations) using the brain-MRI dataset from figshare. Moreover, the concept of deep transfer learning was used in three pre-trained architectures for brain MRI image classification and trained for several epochs.

Medical science has been developed in Bangladesh, but people, especially patients, face many dilemmas while facing reports from tests given beforehand. Typically radiologists are assigned to analyse the reports but the given image processing technique can predict and analyze the report with a high accuracy rate. Furthermore, it will take a lot less time than that of a radiologist. Thus, the research represents an attempt to cut human resources and budget, which can be invested in improving the medical science of Bangladesh. Furthermore, this early identification of brain abnormalities can save time and utilize it in treating the patient at an early stage to prevent the severity of the case. Anomalies detection has always been a significant issue, but it can be handled very efficiently due to the given solution.

In the future, we will explore and apply CNN architecture to predict early brain cancer. In addition, we will analyze and identify best suited treatment for brain cancer patients early to enhance the survival rate of brain cancer patients. Furthermore, we would apply our system to stratify medical images from various scans, such as CT scans, Bone densitometry (DEXA), Ultrasound, Thermal Imaging etc. Furthermore, we will explore other body organs for CT scans to detect complications in the body. Lastly, we will also emphasize the impact of the number of epochs related to the performance of the CNN classifications.

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