A DEEP LEARNING APPROACH TO REDUCE BRAIN CANCER BY DETECTING AND LOCALIZING TUMOR FROM BRAIN MRI IMAGES

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DHAKA, BANGLADESH

SEPTEMBER 2022

APPROVAL

This Project/internship titled **"A Deep Learning Approach to Reduce Brain Cancer by Detecting and Localizing Tumor from Brain MRI Images"**, submitted by Abu Shahed Shah. Md. Nazmul Arefin, ID No: 183-15-12000, S.M. Ishtiaque Ahammed Khan, ID No: 183-15-11988, Mst. Marium Akter, ID No: 183-15-12019 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 12-09-2022.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Nusrat Jahan, Lecturer, 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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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Nusrat Jahan**, **Senior. Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Computer vision and Image processing*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to **Dr. Touhid Bhuiyan**, Professor, and Head, Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

In terms of the neurological system, the brain is fundamental. A brain tumor is a growth or mass of abnormal tissue in the brain. And it's not uncommon for this to prove fatal. When a brain tumor is detected early, it can be treated more quickly and more people can survive. Brain tumors can be spotted on MR scans. However, there are occasions when that just isn't enough. When it comes to medicine, the ability to segment images is crucial. Which may be used to identify malignant brain tumors. However, there are numerous obstacles in the way of image segmentation. One such issue is the vanishing gradient. Which means more time and computing power may be needed to train Deep Convolutional Neural Networks. In order to address the vanishing gradient problem, we present a Deep Convolutional Neural Network (CNN) for fully automatic brain tumor segmentation in MRI data. The suggested method begins with a Resnet-50 classification of brain MRI images to determine the presence or absence of tumor. After that, we compared the two CNN models' degrees of accuracy. After that, we switched to using the U-net structure with the Resnet-50 encoder. And it's yielded spectacular results so far. Resents' skip connections, which serve as gradient superhighways, allow the gradient to travel unimpeded. This characteristic allows gradients to be propagated to higher layers before being attenuated to negligible or zero levels. Our model has been evaluated using the openly accessible LGG segmentation dataset. Our model is used to MRI scans only after they have been preprocessed and enhanced using techniques including rotation, zoom, horizontal and vertical shift, horizontal and vertical shear, and flipping. Results from our proposed technique have shown an accuracy of 99.7 %. As a benchmark, we've also used a model that combines U-net architecture with Inception V3, which has shown accuracy of 99.55%. Since our proposed model yielded better results, we were able to use it to identify and locate the tumor in the brain.

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INTRODUCTION

1.1 Introduction

A Brain tumor is the growth of abnormal cells in a human brain. The tumor first attacks a part of the brain cells and then slowly spreads throughout the cells. After attacking the brain cell, the brain cell is damaged. Brain tumor can be cancerous or non-cancerous. Benign is the non-cancerous and malignant is the cancerous which are the type of brain tumors. The structure of uniformity which is benign tumor do not involve active cells and the structure of non-uniformity which is malignant involve active cells. Benign is classified as primary tumor and malignant is classified as secondary tumor. A primary brain tumor begins in brain cells. on the other hand, secondary brain tumor cancer cell spread into brain from another body part such as lung, breast. Gliomas is called of integral tumor [1]. Basically, gliomas is a brain tumor which can be graded into LGG (Low Grade Gliomas) and HGG (High Grade Gliomas) [2]. HGG is more combative than LGG. In the recent time most of the patients suffered from HGG. When a patient is diagnosed with HGG, their life is at risk. The patients diagnosed with HGG has lower life expectancy than the patients diagnosed with LGG. The life expectancy of patients due to HGG is estimated to be 1 year and their life expectancy due to LGG is about 5 years [3].

Brain tumors are treated based on the age of patients, the type of tumors and the location of tumors. Pictures of brain tumors are captured with MRI (Magnetic Resonance Imaging). It is a difficult work to segment a brain tumor to diagnose by MRI for complex structures and it is time consuming. It is difficult to diagnose damaged tissue from healthy tissue because of the appearance of the tumor, blurred boundaries. We can use automatic brain tumor segmentation in order to solve this problem using MRI images which can identify the type of tumor and the exact location of the effected cell [4].In medical image analysis image segmentation is important component for classifying problem of image pixels in medical sectors. Image segmentation can be partitioned from multiple objects/ segments to a single object. It performs labeling of pixel-level for all image pixels which predicts a single label for the whole image. [5].

In the medical field, U-net is the most important architecture for image segmentation. It has a very fine capturing capability. Naser et al. proposed transfer learning approach where brain tumors can be graded by combining U-net and Vgg16 [6]. Çinar et al. used InceptionV3 as the base for the diagnosis process where removing the last 5 layers. By using this architecture, they got the rate of accuracy 97.2% because of adding 8 new layers [7].

In this paper, we have focused on image segmentation for classifying the tumor from Brain MRI image and identifying the exact location of brain tumors. We have proposed a method of CNNs (Convolutional Neural Network). CNN is used for segmentation of medical image analysis. The proposed method is a combination of U-net architecture with the encoder ResNet-50. First Preprocessing and augmentation have been done on the dataset. Preprocessing is one of the most important techniques which can be improved image quality before proposing method. This work uses preprocessing for removing noise of brain tumors images [8]. Classification has been done with ResNet-50 and Inception-V3 which has shown that ResNet-50 have given better result. The model has been evaluated on the publicly available LGG segmentation dataset. And also, the accuracy of the proposed model has been compared with another architecture which is a combination of U-net and Inception v3.

1.2 Motivation

The main motivation behind our project is to help the people in general. Also, we wanted to use machine learning methods to do so. As a result, we were deciding about how we can help general people with machine learning. Medical sector has huge opportunity in terms of using machine learning to make treatment better. Which can save a lot of lives. We then decided that we will work on medical sectors. Specially with brain tumor. As brain is the most important part of our nervous system. So, it is really vital for our living. Brain tumor is mainly the abnormal growth of brain tissues. Brain tumor can sometimes be fatal. Also, it can cause brain cancer. Which takes many lives away every year. We wanted to save people's lives by detecting brain tumor as earlier as possible because the earlier the brain tumor can be detected the more the patients will have chances of survival. It can also save people from having brain cancer.

Which is fatal and takes many lives every year. Not to mention that it can save the financial situations from getting damaged severely. As treatment of brain cancer is really expensive and most people cannot afford it. Also, if we consider our country, most of the people have middle class family. They cannot afford the expenses for the treatments of brain cancer. As a result, most of the people have premature deaths without even getting any proper treatment. Many automated brain tumor detections have been found over the years. But our goal was to detect brain tumor and its exact location with more precisely with having higher accuracy than the rest of the automated brain detection techniques. After researching many techniques of detecting brain tumor we have come up with our proposed model, "A deep Learning Approach to reduce Brain cancer by Detecting and Localizing of Brain tumor From Brain MRI images".

1.3 Rationale of the Study

Brain tumor is a serious disease. Which takes many lives every year. Also, it causes massive economical damage to the patient and their family. So early detection of Brain tumor is really necessary for increasing the survival rate of the patient also reducing the economical expenses during the treatment. As brain tumor is detected manually using MRI images. Sometimes it can't be detected correctly and quickly. Which can cause massive loss both physically and economically. The goal of our project is to help both the patients and the doctors to detect the exact location of brain tumor more precisely and quickly by using deep convolutional networks. Our plan is to build up a platform where the patients who are diagnosed with brain tumor can easily get their results by using automated brain tumor detection and localization with higher accuracy. The main objectives of our projects are,

- Helping the medical sector by applying automated brain tumor detection and localization techniques in order to have results with better accuracy and get results quicker than manually brain detection techniques.
- Helping the patients and their family by increasing the survival rate by detecting brain tumor as soon as possible and financially as early detection of brain tumor detection will decrease the expenses of the treatment.

- Reducing the risk of brain cancer by detecting brain tumor earlier and start treatment on it as soon as possible.

1.4 Research Questions

Research questions are questions that a study or research project aims to answer in order to build a research study. In the review's judgment, this question is typically answered by the analysis and translation of data. As a result, the following are some key research questions on which this research is centered,

- How can we identify brain tumor?
- What are the types of brain tumors?
- What happens when brain tumor spreads abnormally?
- How does brain tumor cause brain cancer?
- What percentage of people have brain tumor in Bangladesh?
- How can we collect brain tumor data?
- What method can be applied to collect images from people suffering from brain tumor?
- What kind algorithms be used in order to execute our research project?
- How much data is needed to complete our research?
- What kind of device is needed to complete the model?
- How much training data is need to train the model?
- Which domain would better perform in brain tumor classification as machine learning, Deep learning of real-time?
- Are there any proposed methods that exists? If so, then how was it developed and how well does it perform?
- Are there any limitations of the existing proposed models?
- How can we overcome the limitations that exists of the existing proposed models?
- How can we develop our proposed model which can have better accuracy from the existing methods?

1.5 Expected Outcome

The expected outcome of our project is to use deep learning methods to propose a model by training the selected algorithms in order to have better accuracy in terms of detecting brain tumor with its exact location.

- The proposed model will be helpful to detect brain tumor with higher accuracy.
- It will help detecting the exact location of the tumor.
- It will help to increase the chances of survival of the patients.
- It will also help patients financially.
- It will decrease the percentage of brain cancer death rate of this country.

1.6 Project Management and Finance

In order to complete our research, work we had to go to the hospitals as well as the clinics for the purpose to collect data of Brain MRI images with an aim to run and execute our python code in Google Colab to train deferent kind of deep learning algorithms. Intending to classify and segmentation these algorithms were needed. These deep learning algorithms help us to detect brain tumor precisely and location of brain tumor can also be detected. For this purpose, we had visited several hospitals and clinics. As a result, there were some transport costs. Not to mention for the whole covid situation the fairs were higher than usual. We have 3 members in our group. Each of us visited 5 hospitals and clinics in order to collect data. As a result, we were able to visit 15 different hospitals and clinics combined. Estimated visiting the hospitals and clinics were around 2000 taka. But unfortunately, because of the covid situation we couldn’t collect the data from the hospitals and the clinics. As a result, we had to collect our data from publicly available datasets. We have collected our LGG segmentation dataset from Kaggle. Which is an online based platform for data scientists in order to compete in various topics with one another. The algorithms have been executed in python language. And an online based platform named Google Colab has been used. For this reason we had to be connected with the internet. The internet cost was around 1500 taka. Total 3000 taka has been spent.

1.7 Report Layout

There are a total of six parts to this research-based project. There are multiple viewpoints presented throughout the work, each of which is represented by a chapter. Each chapter is broken down into numerous particular subsections that are presented in an easy-to-understand format. Here is a summary of everything can be found in this report:

- **Chapter 1**

  Introduced the effort and discuss its goals, drivers, research questions, and expected outcomes. The topics we have discussed: 1.1 Introduction, 1.2 Motivation, 1.3 Rationale of the Study, 1.4 Research Questions, 1.5 Expected outcome 1.6 Project Management and Finance and 1.7 Report Layout. In the introduction part the tumor types and how it can affect someone's health and financial state. And then how brain tumor can be detected in order to give the patients better chance of aiding from it. In the motivation part the main motivation behind our research work has been discussed. The main objective of our work has been discussed in the Rationale of the study part. The key questions related to our study has been explained on the Research question chapter. The outcome that we've been working on has been described on the expected outcome part. The financial expenses and how the project has been managed properly has been described in the Project Management and Finance. Report layout shows our whole work in chapters.

- **Chapter 2**

  It gives a rundown of previous work completed in this context. The study of the previous work helps to truly understand the work that needs to be done in our research work Later in Chapter 2, we see the implications that result from the authors' decision to set a boundary on this area of study. The following topics we have discussed: 2.1 Preliminaries/Terminologies, 2.2 Related Works, 2.3 Comparative Analysis and Summary ,2.4 Scope of the Problem and 2.5 Challenges.

- **Chapter 3**

  It is relevant to the theoretical discussion of this study. Part of this work involved expanding the statistical methods already in place in order to discuss the theoretical aspect of the research. Deep learning working procedures are also demonstrated in this chapter. Topics are: 3.1 Research Subject and Instrumentation ,3.2 Data Collection Procedure/Dataset Utilized ,3.3 Statistical Analysis ,3.4 Proposed Methodology/Applied Mechanism ,3.4.1 Data Processing,3.4.2 Data Augmentation, 3.4.3 Proposed Methodology, 3.4.4 Classification, 3.4.5 Introduction to Inception V3, 3.4.6 Introduction to ResNet-50, 3.4.7 Image segmentation with Proposed model and 3.5 Implementation Requirements.

- **Chapter 4**

  Gives the results of the experiments, an analysis of the results, and a discussion of the findings. In this section, some experimental images captured along the course of the project's development are presented. 4.1 Experimental Setup, 4.2 Experimental Results & Analysis and 4.3 Discussion has been discussed.

- **Chapter 5**

  Describes regarding reliable to appear in entire venture report after proposal. The chapter concludes with a discussion of the limitations of our work, which may serve as the starting point for future research by others. We have discussed the following topics: 5.1 Impact on Society, 5.2 Impact on Environment, 5.3 Ethical Aspects and 5.4 Sustainability Plan.

- **Chapter 6**

  Presents summary of the study and future works. The following topics we have discussed: 6.1 Summary of the Study, 6.2 Conclusions and 6.3 Implication for Further Study. The summary of the study shows the overall work of our research. In the conclusion we have showed the entire research of ours including the results. In the Implication for Further Study part the further enhancement of our study has been explained.

CHAPTER 2
BACKGROUND

2.1 Preliminaries

Brain is one of the most viable parts of the nervous system. The whole nervous system is mainly controlled by it. Brain tumor has become one of the most common brain diseases in recent years. Many lives are being lost because of this disease as it is one of the reasons of brain cancer. Not only brain tumor can take many lives it also causes huge economical damage of the patient and their families. The mass growth of abnormal tissues in a brain is called brain tumor. It can be fatal which can lead to loss of many lives as well as asset loss. Early detection of brain can increase the chances of survival of a patient. Magnetic Resonance Images are used in order to detect brain tumor. But sometimes it is not sufficient. As it is detected by the doctors. So, there can be human errors which can lead to disaster for the patient and their family. For this reason, automated brain tumor detection has become popular these days. But there might be some limitations of automated brain tumor detection. With this condition we will be moving forward to resolve these issues. Many works have been done in order to resolve the issues of automated brain tumor detection. We have gone through 65 research papers which contains different techniques of brain detection. And found 26 research papers related to our work and reviewed them for better result.

2.2 Related Works

Automated Brain tumor detection has seen some tremendous progress over the years. Not only the speed of detecting brain tumor has been faster but also the accuracy has increased a lot. Yusuf Artan combined two of the successful segmentation algorithms named the LDS and the RW and tested the effectiveness of the method from the Grabcut and Berkeley Segmentation Database and also was compared with the Raw Walker algorithm to assess the performance [9]. Portela et al proposed a method where human specialized inspection is not required nor set of labeled training dataset [10].

The automated brain tumor diagnosis using MRI images has sped up the medical treatments as a result saved a fair amount of time for the diagnosed patients.

In [11] Anurpa Nandi used MRI images as the normal MR image analysis are not suitable for the analysis. K-means clustering was used where some abnormality was shown by the detected tumor. By applying morphological operators and thresholding watershed segmentation tumor cells and healthy cells are separated.

Pereira et al proposed an automated segmentation method on Convolutional Neural Networks (CNN).In their method deeper architectures were allowed. The method was applied on Brats2013 and 2015 datasets which was really faster as the were able to lessen the computation time. It was done by creating and fine tuning each tumor grade's intensity normalization transformation [12]. In [13] Manogaran et al proposed a method which used an approach of upgraded orthogonal gamma distribution based machine learning. With automatic ROI detection the area of brain tumor was calculated. Siar et al detected brain tumor from the Magnetic Resonance images also known as MRI. They used Convolutional Neural Network also known as CNN. The Softmax , Radial Basis Function and Decision Tree (DT) were used to classify the images[14]. By inspecting the brain section during medical screening process Brain cancer can be detected. Magnetic Resonance Imaging(MRI) techniques are considered to record the various sections of the brain and then a three dimensional image can be reconstructed later on. MRI in 3D form is more complex in terms of extracting essential data. That's why most of the brain MRI evaluation techniques are implemented by considering the 2D slices. The authors Proposed a machine learning technique so that the tumor regions can be evaluated easily. The tumor area was classified into low or high grade. In order to do that a machine learning technique was proposed. A sequence of procedures are implemented by the machine learning technique such as pre-processing, post-processing and classification procedures. The Social Group Optimization (SGO) algorithm which is assisted by the Fuzzy-Tsallis thresholding is enhanced the pre-processing. The noise corrupted MRI slices also confirmed the proposed thresholding. The Level-et Segmentation (LSS) to mine the tumor region is implemented by the post-processing. With the segmentation procedures like Active-Contour (ACS) and Chan-vase (CVS) techniques the performance of the LSS is validated. In order to extract the fundamental data of the tumor section and with a statistical test dominating features the authors used Gray level co-occurrence Matrix. Random Forest as well as k-Nearest

Neighbor(KNN) was used to validate the performance. Two class classifier is implemented using Support Vector Machine with Radial Bass Function (SVM-RBF) kernel. The proposed method can achieve an accuracy of>94% [15]. In[16] an automatic MRI brain tumor classification has been presented. Preprocessing, feature extraction, classification and segmentation has been done on BRATS and MICCAI datasets. The images were converted into 3x3 blocks. Before that the noise present on the images were removed. Then features were extracted from the preprocessed images. The authors used K-Nearest Neighbor classifier. Fuzzy C-means clustering algorithm was used to segment the tumor regions.

In recent years the brain tumor detection was way better due to some advanced technologies. Khan et al used deep learning on brats 2015,2017 and 2018 and claimed a new method. Histogram equalization which was based on edge and DCT also known as Discrete cosine transform linear contrast stretching was done. They used CNN also known as Convolutional network models. The model that they used was VGG16 and 19 which was pre-trained and did feature extraction. Transfer learning was also done. For selecting the best features ELM also known as extreme machine learning and a correntropy-based joint learning method was implemented. PLS also known as the partial least square matrix in singular matrix subjected to robust covariant features were fused. In the end to the ELM also known as Extreme machine learning the matrix which was combined was fed [17].

In[18] brain tumors were classified using MRI data analysis in order to help the practitioners. In order to do that they used deep learning methods. VGG19 which was finetuned and k- means clustering was used to classify the MRI images into malignant and benign tumors. The proposed method gave better accuracy than most of the state of the art technologies regarding this.Rehman et al presented an encoder-decoder based model. The model mainly used FE blocks at every encoder stage. Also the model gets a feature map and defined operation is performed by the model which also tries to preserve information. This feature of aggression helps a lot to get better execution of finding brain tumors [19].Various tools for detecting brain tumors have been added over time. Liqiang et al developed a unique network fine-tuning technique based on policy value. The encoder layers, in particular, are fine-tuned to extract latent features, and then a fully linked layer generates policy value. The decoder is then fine-tuned adaptively based on these policy values. They propose an auto policy technique for adaptively fine-tuning the segmentation network. Human intervention was required in prior Transfer Learning approaches to decide which layer in the network needed to be fine-tuned or corrected. The datasets BraTS 2016, BraTS 2017, and BraTS 2018 were utilized in their methodology. They also used a number of experiments to show that their proposed strategy may be used in the medical field [20].

2.3 Comparative Analysis and Summary

In our research, we have proposed a deep learning approach to detect brain tumor more efficiently. In order to achieve our goals, we have proposed a Deep Convolutional Neural Networks (CNNs) for fully automatic brain tumor segmentation in MRI images which can solve the vanishing gradient problem. We have used a publicly available LGG segmentation dataset in order to evaluate our proposed model. The Publicly available LGG segmentation dataset that we have used has been collected from Kaggle. Kaggle is a platform for data scientists for competing with one another on various topics. After collecting the dataset preprocessing and augmentation was done on the dataset. Which increased bot quality and quantity of the dataset. Brain tumor classification has been done in order to classify if there is tumor or not on the MRI images. In order to do so Resnet-50 and Inception v3 have been applied. Comparison between the two algorithms based on their accuracy level has been done. Combining the architecture of U-net and the encoder Resnet-50 Segmentation and localization of the brain tumors has been done. In order to compare the performance level another model combining U-net architecture and Inception v3 has been done. Accuracy level of both of the models has been then compared. The model with better accuracy has been then used to predict the location of the tumor. Accuracy, Precision, Recall and F1-score have also been calculated in order to evaluate our proposed model.

2.4 Scope of the problem

A tumor of the brain is a mass of abnormal tissue that may develop inside the cerebral cortex of a patient. In terms of origin, there are primary and metastatic forms of this disease. Unlike metastatic tumors, which begin elsewhere in the body and travel to the brain, primary tumors begin in brain tissue and grow from there. Depending on their size and location, tumors in the brain may cause a wide range of health complications. Sometimes, tumors may cause pain or other symptoms by pressing on adjacent tissues and organs. Brain tumor also can be severe. Which can take many lives. Not to mention the financial losses that the patient and the patient's family has to face during the treatment. Early detection of brain tumor can increase the chance of survival of the patients. Also, can help with the financial situation of the patient. Automated brain tumor detection can help detecting brain easily and more sufficiently. Machine learning methods can be used in order to do so. We focused on using deep learning methods to detect brain tumor more precisely with higher accuracy. We also focused on solving the problems that we can face in terms of using deep convolutional neural networks. Such as vanishing gradient deficiency. By using our proposed method brain tumor can be detected in earlier periods of treatment. Which can increase the chances of survival of the patient highly.

2.5 Challenges

The main challenge that we faced during our work is collecting the data and processing it. Due to Covid 19 we had difficulties to collect data in person as there were restrictions of visiting the hospitals and the clinics. As a result, we had to collect the data for our project online. Then we had to select the datasets which is suitable for our work. We collected our data from Kaggle. Which is an online platform for data scientists to compete against one another on the selected topics. After collecting the data there came another challenge. As we collected medical MRI images, we had to then process our data into images in order to apply the deep learning methods properly. In order to achieve better quality and higher accuracy we had to motivate ourselves to do the work consistently.

Chapter 3

Research Methodology

3.1 Research Subject and Instrumentation

Automated brain tumor detection has seen remarkable progress in recent years. We have seen many progresses in this sector using deep learning and machine learning methods. Deep convolutional networks algorithm has come long way in terms of detecting brain tumor and localizing its actual position. The aim of our research is to develop a deep learning approach to reduce brain cancer by detecting and localizing of brain tumor from brain MRI images. In order to achieve our goal, we have used deep learning methods. We have used Deep convolutional networks (CNN) such as ResNet-50 and Inception v3 for classifying the brain tumor. For Segmentation we have combined the architecture of U-net with the encoder Resnet-50 also we have combined U-net with Inception v3 for localization of the tumor. Python language has been used with the libraries and packages such as pandas, numpy, matplotlib, matlab. A high configured PC with a high GPU has been used in order to apply the deep learning algorithms smoothly and sufficiently. “Google Colab “which allows to run python codes and it’s libraries has been used in order to train and test our data.

3.2 Data Collection Procedure/Dataset Utilized

Cancer is the most dangerous diseases. Now a days many men and women, including children are diagnoses with different kind of cancer. Increasing rate of cancer is rising worldwide. Brain Cancer is one of them. The main purpose of our research is reducing the Brain cancer by detecting the brain tumor and localizing the brain tumor exact position with the help of deep learning. For our research we needed to collect a huge amount of brain MRI images. As medical related data is confidential so we have to collect it without violating the right of patients. We have visited some hospital and clinic for collecting the data which are allow to use for research purpose. But Suddenly Covid 19 arise in Bangladesh so fast that visiting hospital to collect Brain MRI image data was tough for us. As there were some strong restrictions for anyone who wanted to visit the hospital staff and patients. Actually, those restriction was to prevent covid-

19 spread. For all of this reason, it was so tough for us to collect live data from the hospital and clinic. So, we have researched about the available Brain MRI Dataset on internet. After lot of finding on the internet, we have collected the available Brain MRI image dataset from the Kaggle. We have selected this dataset, because this dataset has around 7858 data. Divided equally into two part which are images and mask. 3929 image and 3929 mask are present in our dataset.

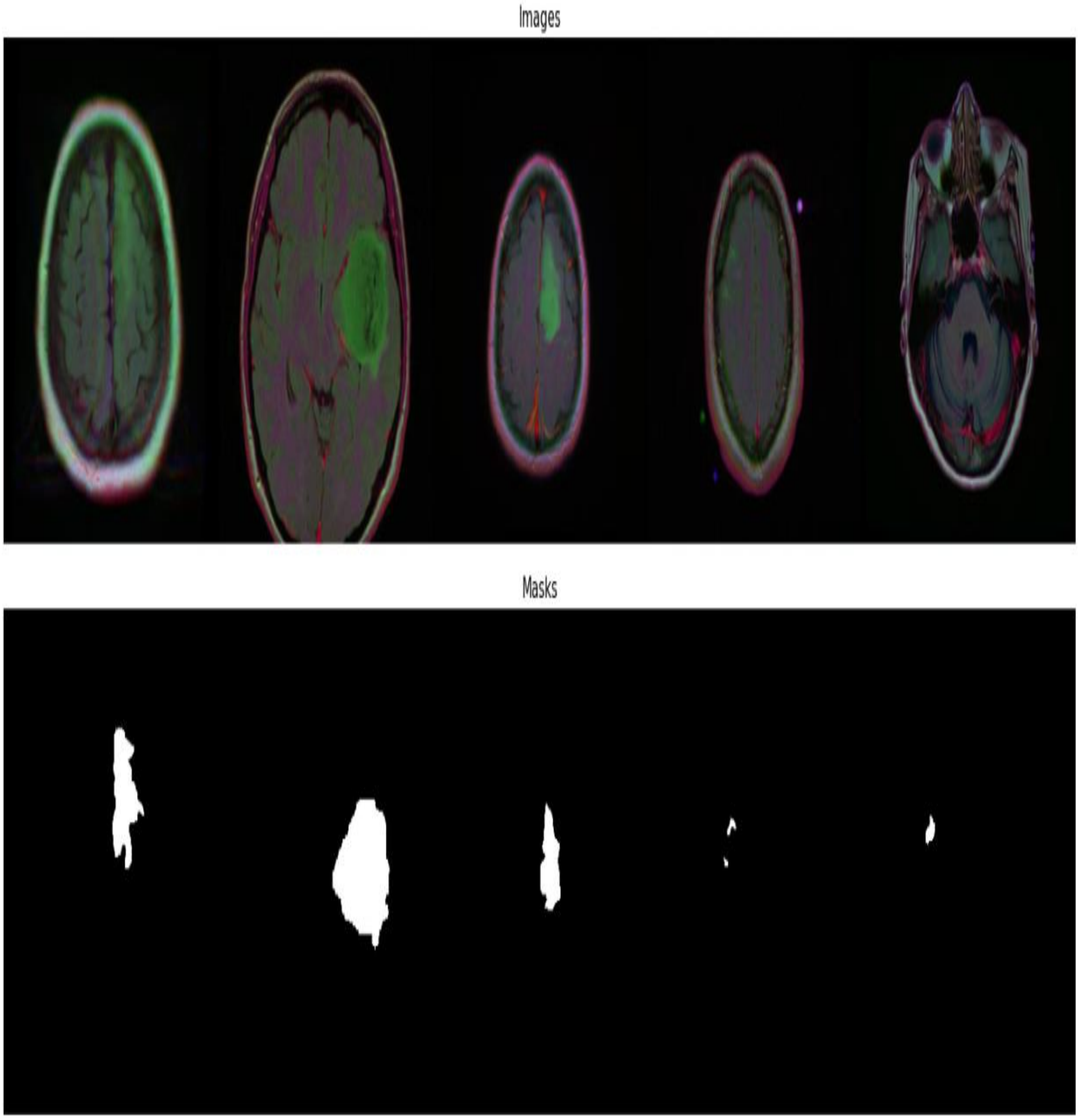

Figure 3.2.1: Some examples of Image and Mask which has tumor.

Examples of combining the Images and Masks which have tumors are shown on the Figure 3.2.1 from our selected dataset

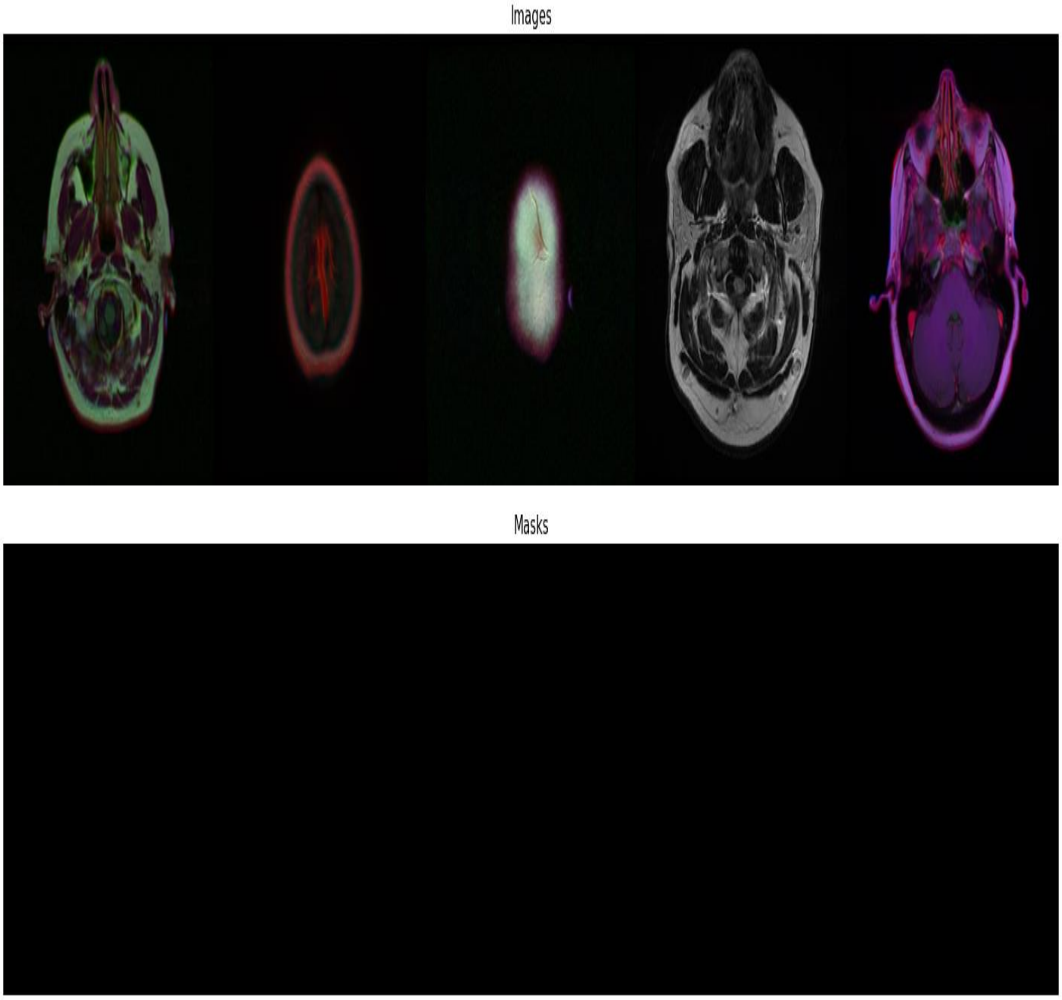

Figure 3.2.2: Some examples of Image and Mask which has No tumor.

We have Combined and visualize the Brain MRI image With Mask from the dataset which has tumor. Figure 3.2.2 shows the output of this visualization. Also Figure 3.2.3 has shown the visualization of MRI images from our dataset containing both Images with Brain tumor and without brain tumor. The masks mainly represent the region where the tumor is. This helps to train algorithms to localization of the brain tumor. Which can identify the exact location of the brain tumor. The exact location can help rectify the speed of the treatment. As a result, the patients can have speedy recovery and also can save the patient from the cancer. As early detection of brain tumor can help in terms of treatment of brain cancer.

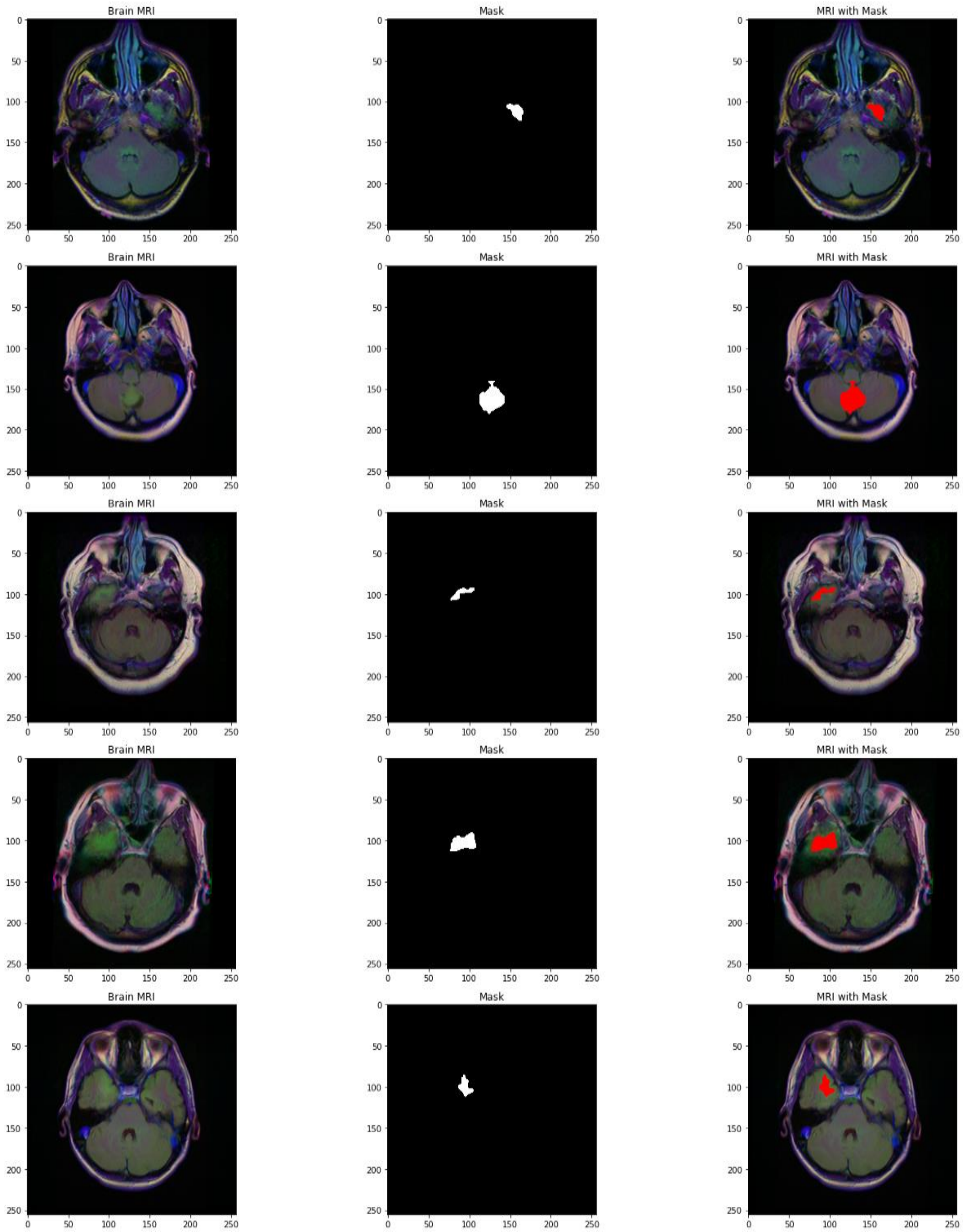

Figure 3.2.3: Visualization of MRI Image with Mask from Our Dataset

3.3 Statistical Analysis:

The accumulated dataset that we have used in our research work has around 7858 data. The dataset is mainly split up equally into two part which are images and mask. 3929 image and 3929 mask are present in our dataset. From the given bellow figure 3.3.1 we can see the image data distribution of dataset. Which are mainly divided into two part named Tumor and No tumor. From this figure we can understand that this Brain MRI image dataset has 2556 image which has no tumor and 1373 image which has tumor.

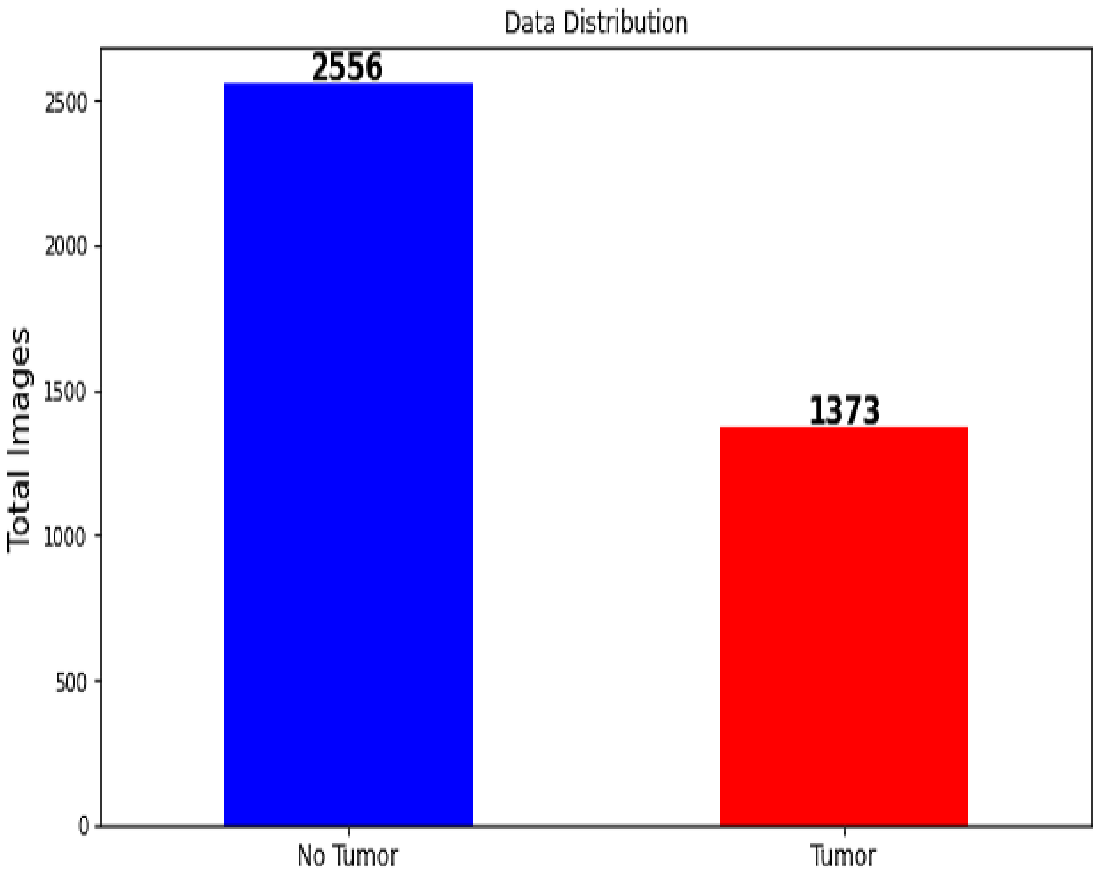

Figure 3.3.1: Data distribution of Brain MRI images in our dataset

The bar chart shown in Figure 3.3.1 shows the data distribution Of Brain MRI images from our dataset. Where 2556 MRI images contain no tumor and 1373 Images contain images. In the course of our research, we have made use of a compiled dataset that contains somewhere around 7858 individual pieces of information. The dataset is primarily divided into two parts, which are referred to as the photos and the mask. Both of these parts are given equal weight. In our collection, there are a total of 3929 images together with 3929 masks. The masks help to measure the accuracy level of a model in order to classify and segment the brain tumor from the MRI images. Which can help to improve the models.

3.4 Proposed Methodology/Applied Mechanism

3.4.1 Data Processing

Data preprocessing is an important step in image processing. It is a critical step in achieving this goal. By performing certain operations on an image prior to further processing, we can often improve its quality and clarity. There are a number of different preprocessing techniques that can be used, depending on the type of image and the desired results. A preprocessing step is done on the MRI images [21] before they are fed into the proposed structure. It is used to generate batches of tensor pictures with real-time data augmentation in the image preparation component of the keras library. keras library's ImageDataGenerator method has the preprocess input parameter set to the appropriate MRI image format for the model. ImageDataGenerator method of keras library does all the necessary preprocessing operations, including cropping, rotation, determining brightness range, flipping the image, and identifying the four rectangular boundary coordinates of cropped image. We also use Gaussian filter to remove the noise from the Brain MRI images.

The equation of Gaussian filter is,

$$G(x, y) = \frac{1}{2\pi\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}} \text{..............................(1)}$$

Here, horizontal and Vertical axis are sequentially defined as x and y, σ is the standard deviation of the equation.

Cropping is the process of selecting a portion of an image to keep and discarding the rest. This can be done for many reasons, such as to focus on a specific subject or to improve the composition of the image. Cropping can also be used to remove unwanted elements from an image or to change its aspect ratio.

Scaling is a process that alters the size of an image or object. This can be done for aesthetic reasons, to improve function, or to fix a flaw. There are several different types of scaling, but they all rely on mathematical formulas to achieve the desired results. The most common type of scaling is linear scaling, which preserves the proportions of an image while increasing or decreasing its size. Other types include angular scaling which changes the shape of an object, radial scaling which enlarges objects from their center, and bitmap interpolation which creates new pixels based on neighboring ones.

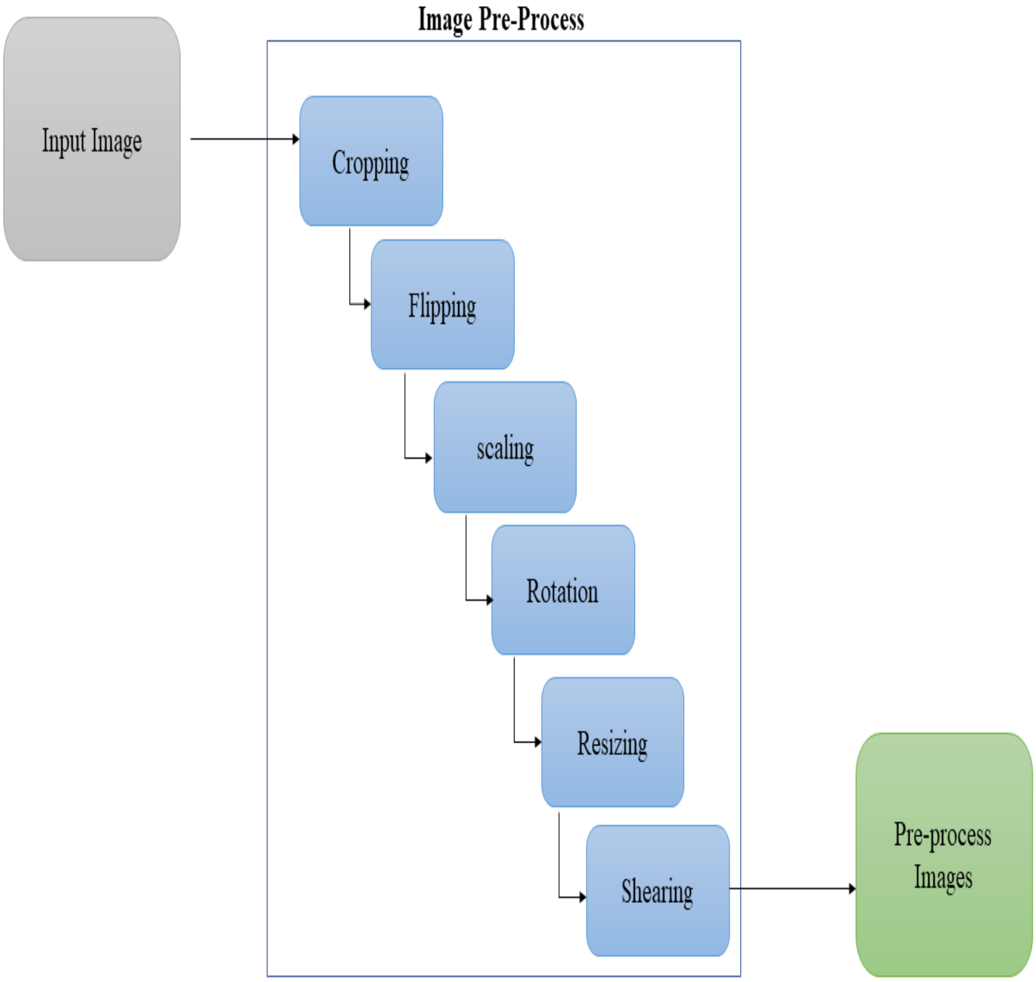

Figure 3.4.1.1: Brain MRI image Pre-Processing

The whole preprocessing process is shown on the Figure 3.4.1.1 above.

3.4.2 Data Augmentation

In most cases, a larger dataset is better for training deep learning (DL) models. The model's efficiency can, however, be improved by adding new data that is already available. Therefore, the efficiency of the model can be improved by employing Data Augmentation. With ImageDataGenerator, we were able to perform Data Augmentation. ImageDataGenerator primarily functions as a batch-based, real-time tensor image data generator. Data is iterated again and over (in batches). This means it can quickly change many images in a set in a very random manner. As a result of the random changes made at the beginning of each epoch, the input image set will be slightly different for each training iteration. The ImageDataGenerator is helpful when additional data collection is neither desirable nor feasible. ImageDataGenerator does not add further epochs to the dataset since it does not grow the dataset by adding new images. It instead provides relatively updated images from a variety of time periods (depending on the configuration). No matter how many epochs pass, it perpetually creates brand-new images. Therefore, slightly different images are used to train the model each time. These augmented images are created dynamically during training and discarded once it is complete. These augmented images are made on the go during training and disposed afterwards. Those enhanced images are gone forever. We would soon hit our storage limit if we kept so many images. The data augmentation methods that have been used By the ImageDataGenerator is given below in the Table 3.4.2.1,

Table 3.4.2.1 Summary of the applied data augmentation methods

Methods	**Range**
Rotation	±20 degree
Zoom	±5%
Horizontal Shift	±10%
Vertical Shift	±10%
Horizontal Shear	±15%
Vertical Shear	±15%
Flip	Horizontal Flip

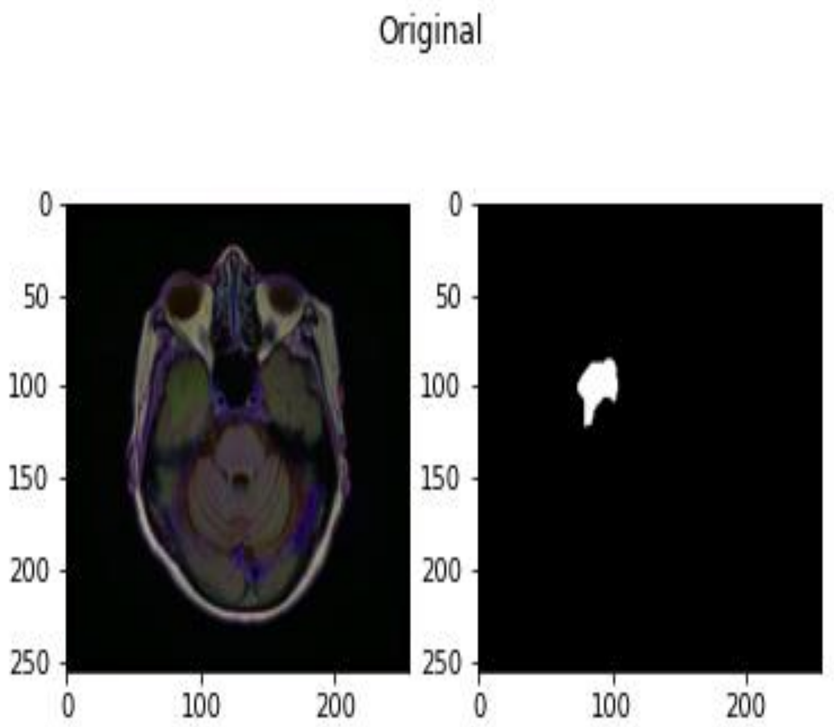

Figure :3.4.2.1 Original Image and Mask before Augmentation

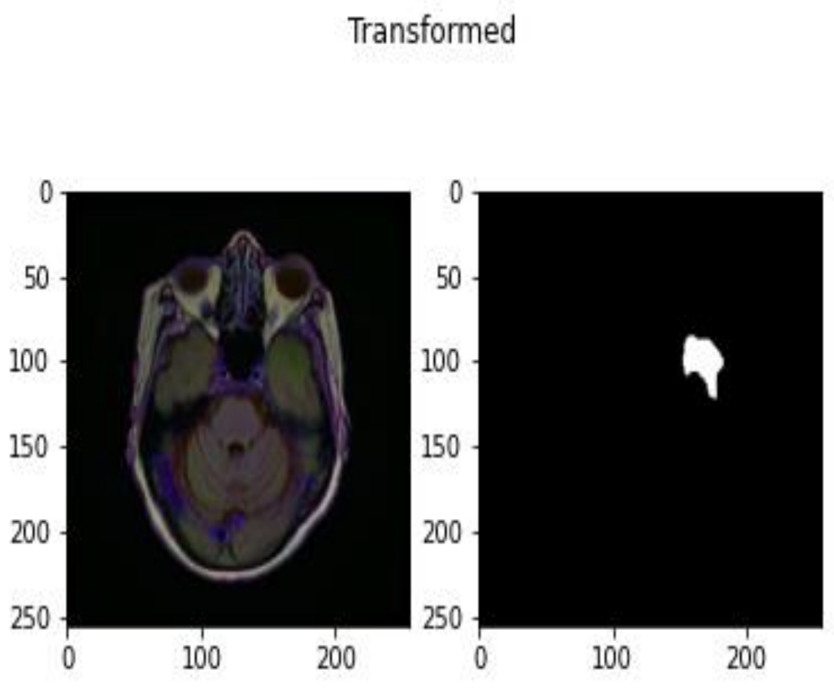

Figure :3.4.2.2 Transformed Flipped Image and Mask After Augmentation

Figure 3.4.2.1 shows the Original Image and mask before augmentation followed by the Figure 3.4.2.2 Shows Image and Mask after augmentation where Flip operation was done.

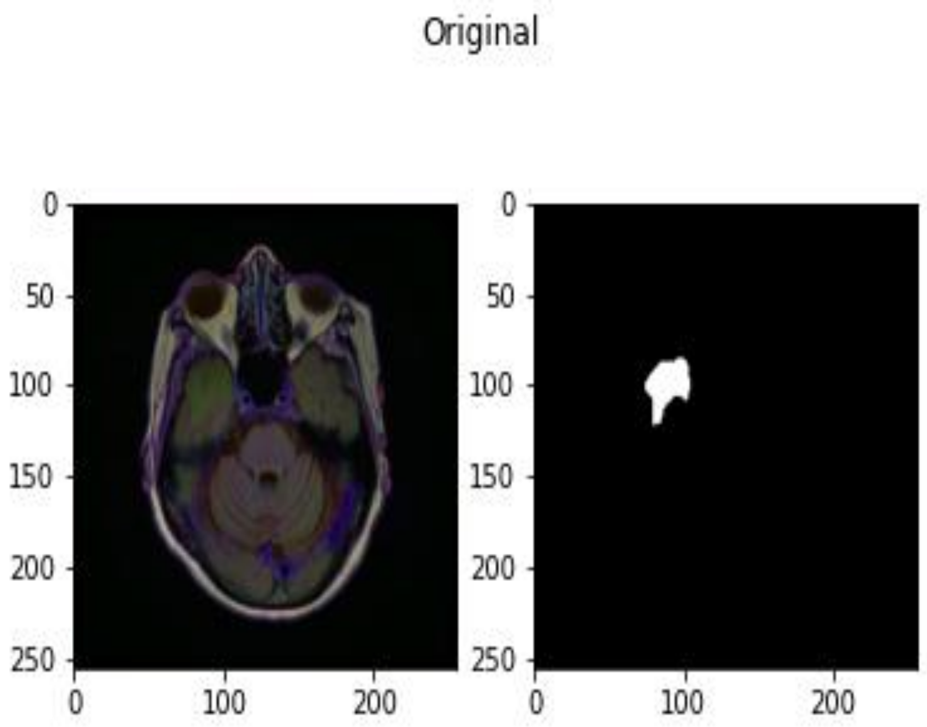

Figure 3.4.2.3: Original Image and Mask before Augmentation

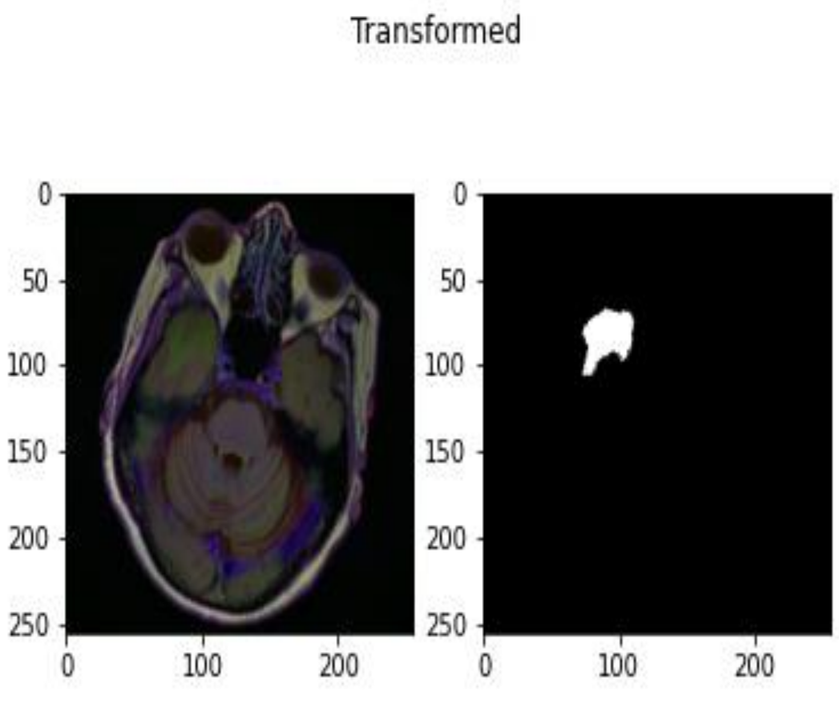

Figure 3.4.2.4: Transformed Rotating Image and Mask After Augmentation

Figure 3.4.2.3 and Figure 3.4.2.4 Shows the before image and mask performing rotation operation as well as after image and mask of performing rotation operation.

3.4.3 Proposed Model

In the model that was developed, the U-net architecture and the ResNet-50 encoder were integrated in order to achieve a higher level of accuracy in the segmentation of brain tumors. Before that classification has been done by two of the models such as ResNet-50 and Inception v3. Then both of the accuracy levels were compared. Preprocessing and augmentation methods has also been applied in order to increase the accuracy of both the classification models and the segmentation models.

The steps that comprised the entirety of our work can be broken down into the following categories:

Step1: The dataset for LGG segmentation that is available to the public was obtained.

Step2: The dataset has been analyzed by means of a data visualization.

Step3: Preprocessing has been carried out using the imageDataGenerator method of the Keras package.

Step4: application of various augmentation techniques, including rotation, zooming, shifting horizontally and vertically, shearing horizontally and vertically, and flipping the image.

Step5: The images obtained from the Brain MRI were classified using Resnet-50 and Inception v3 at this stage.

Step6: Evaluating how accurate each of the CNN models are in comparison to one another.

Step7: Image segmentation has been completed using the suggested model, which included the U-net architecture and the ResNet-50 encoder. Additionally, the proposed model combined the U-net with the Inception v3 network.

Step8: Comparing the two models' degrees of accuracy.

Step9: Prediction.

A flow chart of our Work flow is given below

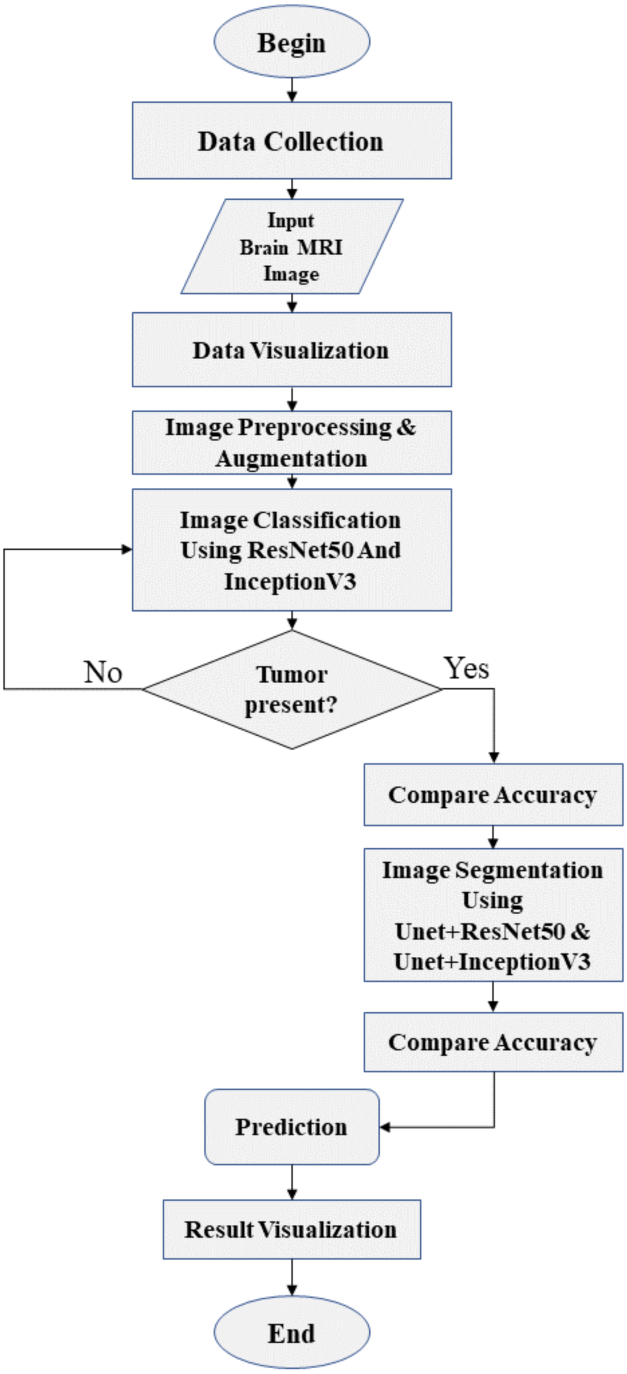

Figure 3.4.3.1: Flow chart of our work flow

Here in Figure 3.4.3.1 shown a flowchart of our work flow where the work flow was described step by step in a flow chart format.

The diagram below shows the full overview of our work,

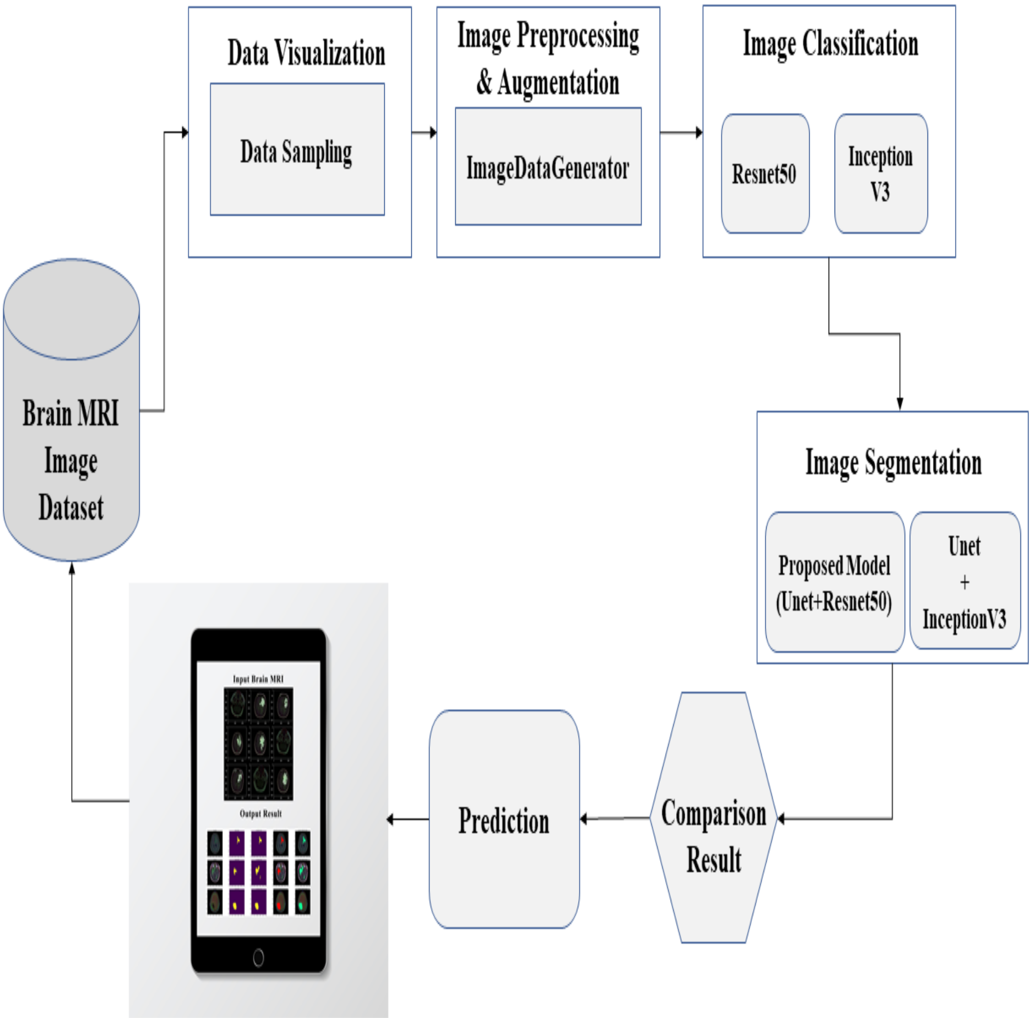

Figure 3.4.3.2: The figure shows the full overview of our work.

Figure 3.4.3.2 has shown the full overview of our work where our entire research work has been described shortly.

3.4.4 Classification

Two CNN models, based on ResNet-50 and Inception-V3, were utilized to classify the MRI images into tumor and non-tumor categories for classification. After that, the two were compared. Algorithm was then chosen based on their performance. For images assessed as nontumorous, the algorithm terminates, whereas images classified as tumorous are sent to the next phase of the architecture.

3.4.5 Introduction to Inception V3

In 2014 Google introduced a network which was a pre-trained network model also known as Google net [22]. With 22 layers, 5M parameters, and filter sizes of 1x1, 3x3, and 5x5, Inception was able to extract features at various scales coupled with maximum pooling. 1x1 filters are used to speed up computations. Inception v3 was introduced by google in 2015 upgrading the inception model [23]. In the Inception v3 model factorization of convolutional layers is used to reduce the number of parameters. Using two 3 x 3 filters instead of the 5 x 5 Convolutional filters to reduce processing without affecting network speed. The 48-layer InceptionV3 model is the most recent iteration. The architecture of Brain tumor classification with Inception v3 is given below in the Figure 3.4.5.1,

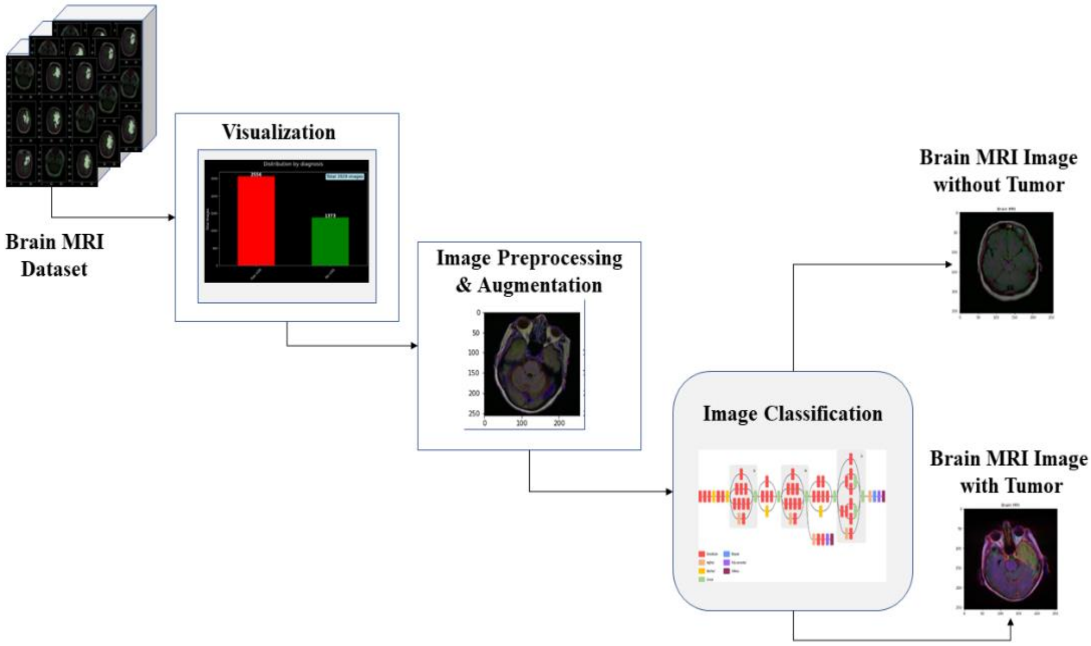

Figure 3.4.5.1: Brain tumor classification with Inception v3

3.4.6 Introduction to ResNet-50

The structure of deep learning-based network is getting deeper as it is evolving [24]. More complex feature pattern extraction can be done by it. But it can cause new problem such as Vanishing gradient problem. It mainly causes during the training process. Due to this problem, it generally takes more power of computational in order to train the deep neural network [25]. The Resents tends to solve this problem. Resnet also known as residual networks is a deep residual network. Which is mainly a subclass of conventional neural network. Resnet50 is mainly conventional network which is 50 layers deep and which can classify pictures into 1000 categories. The learning framework of ResNet is shown in the Figure 3.4.6.1 below,

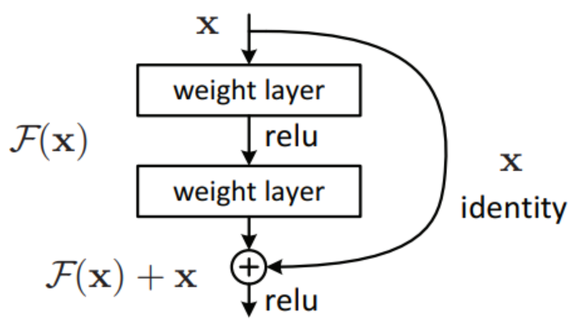

Figure 3.4.6.1: Framework of ResNet

Skip connection is a technique which is used in Residual networks. By skipping some layers in between the ResNet tends to connect activations of a layer to layers which are far. As a result, a residual block is created. ResNets are then made by stacking these blocks with one another. Instead of the underlying layers be learned by the layers the residual mapping is fit by the network. Say, instead of H(x), initial mapping the network fit,

$$F(x) := H(x) - x \; wchich \; gives \; H(x) := F(x) + x \; \ldots\ldots\ldots\ldots\ldots \; (2)$$

The benefit of using this kind of connection skipping is that the layer will be skipped if it hurt the execution of the architecture by the regularization. As a result, the Vanishing gradient problem can be resolved. The architecture of brain tumor classification is given below in the Figure 3.4.6.2,

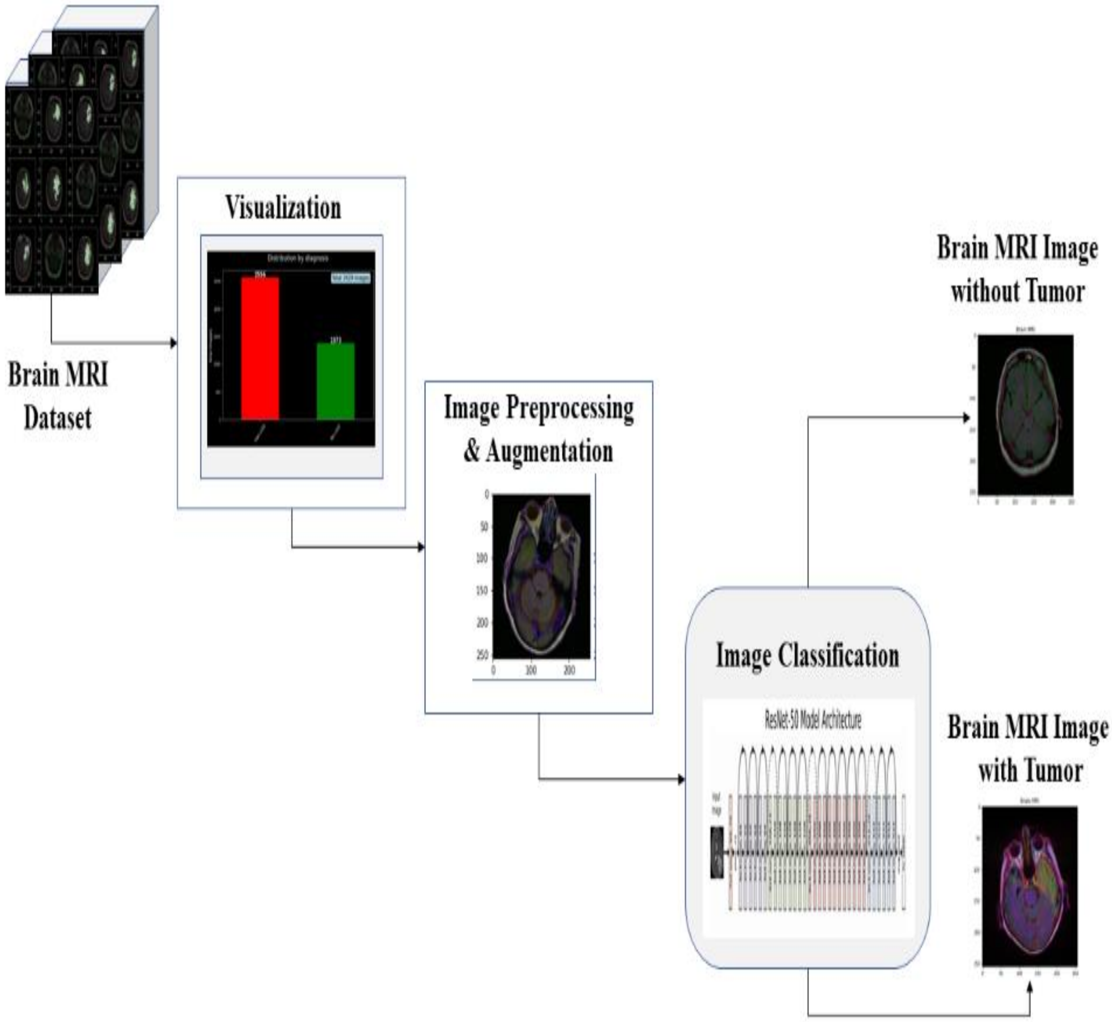

Figure 3.4.6.2: Brain tumor classification with ResNet-50

3.4.7 Image segmentation with Proposed model

It has been a remarkable revolution in the field of deep learning after the invention of U-net. First used for biomedical image segmentation, U-net was originally developed and first deployed. A decoder network follows an encoder network in this system's design. Semantic segmentation is different from classification in that it necessitates both pixel-level discrimination and the ability to project discriminative features learned at different stages of the process onto the pixel space.

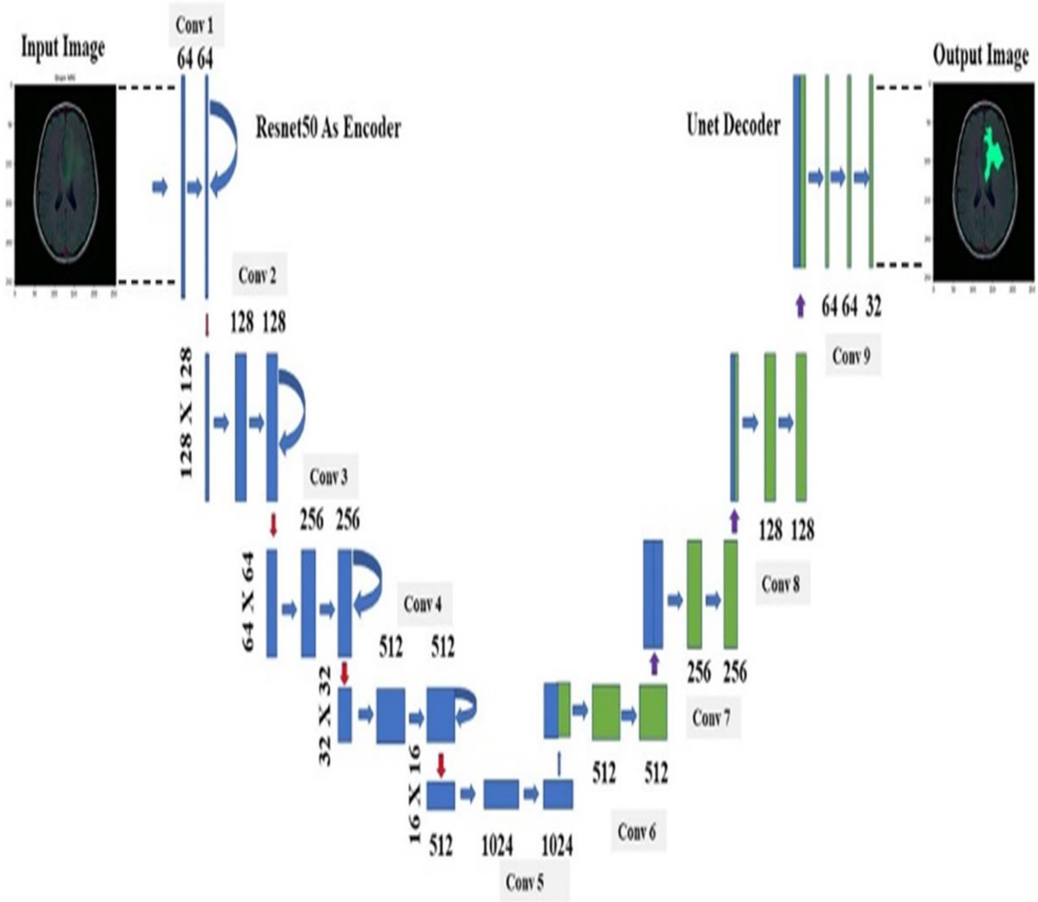

Figure 3.4.7.1: Architecture of the proposed model

1. The encoder is shown as the first half of the architecture diagram (Figure 3.4.7.1**).** We utilized a ResNet-50 encoder and convolution blocks followed by maxpool downsampling to encode the input image into feature representations with varying levels of detail.

2. Following on from the encoder comes the decoder, which can be thought of as the inverse of the encoder. The architecture is complete when the decoder is included. In order to achieve a high level of classification, the encoder needs to learn how to correctly project discriminative features from images of lower resolution onto images of greater resolution. Upsampling and splicing are the

first two steps in the decoder process, which is then followed by the standard convolution steps.

The following Figure 3.4.7.2 shows the summary of the entire work flow of our proposed work. Each of the sections represents the steps that has been implemented throughout our whole research work such as Data set collecting, visualization, Image processing and augmentation as well as Image Classification, Image segmentation and then prediction.

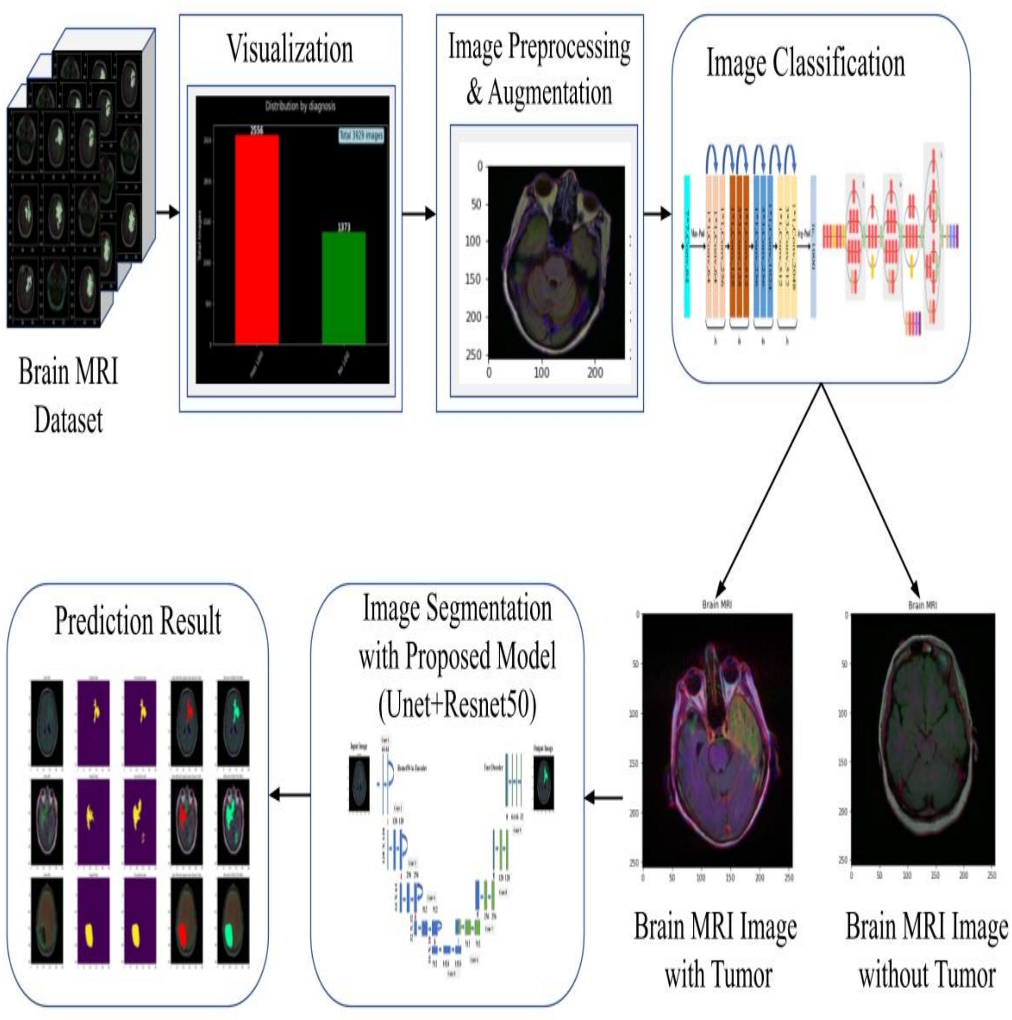

Figure 3.4.7.2: Brain tumor classification and segmentation by our proposed deep learning method

3.5 Implementation Requirements

The deep learning approach calls for the use of a highly capable personal computer that possesses a graphics processing unit (GPU), a significant quantity of random-access memory (RAM), and other components. This is necessary in order to train and evaluate the many types of deep learning models. In the course of our research, we make use of Google Collab on high-configuration computers in order to train and test a range of models, including the model that we have proposed. The following material, which has been given for your convenience, has an explanation of all of the prerequisites for the work that we will be doing on our research.

Used Requirements are:

Hardware Requirements

- CPU having 4.10 GHz
- Core i7 6-core Processor
- 16 GB DDR4 RAM
- 1TB SSD
- I/O device
- 1TB HDD
- 6Gb GeForce GTX 1060 graphics card

Software Requirements

- Operating System – Windows 10
- Image Editor

Developing Tools

- Python Environment
- Google Collab

Chapter 4

Experimental Results and Discussion

4.1 Experimental Setup

In this study, we have worked with Brain MRI image dataset which has a large amount of image data. For Working with this large amount of data we have used a high configuration PC With GPU, as we need this experimental setup to prepare, run and execute our research work. We have trained a lot of models with multiple epochs which takes a lot of time in this research work. To do this, we have used Windows 10 operating system. We know that, at least 4 GB size RAM CPU is indispensable to run the deep learning models. As we have trained a lot of deep learning models, we have used 16 GB RAM size CPU with GPU to run and execute the models properly. In this research work, our used PC has 1 TB SSD, which have been used for storing the Brain MRI Image data. Our whole research coding has been done by using Python programing language. We have used Google Colab to run and execute the python coding to train all the models and develop our proposed deep learning model.

4.2 Experimental Results & Analysis

In this Section, we are discussing about our research analyzing result that we have been earned. Our proposed model has been experimented on Brain MRI images dataset. The publicly available dataset has been collected from Kaggle. Our dataset contains brain MRI images of 110 patients. The data is then split into training, validation and testing. Preprocessing with imageDataGenerator method of Keras library and augmentation techniques such as rotation, zoom, horizontal and vertical shift, both horizontal and vertical shear as well as flipping have been done. 10 epochs with batch size of 16 our models have been trained. After preprocessing and augmentation Brain tumor classification have been done with two CNN models ResNet-50 and Inception v3. Resnet-50 has shown 99.29% accuracy on training data and 95.63% validation data. Inception v3 has shown 99.46% accuracy on training data and 96.56% on validation data. For image segmentation our proposed model which is a combination of U-net architecture and ResNet-50 encoder has shown 99.77% accuracy on test data and 99.63% on validation data. When U-net was used with Inception v3 for segmentation, it showed an accuracy of 99.55% on the training data and 99.49% when used with Inception v3. This was done so that a comparison could be made between the two. The accuracy level on training and validation datasets of classification algorithms is depicted in figures 4.2.1 and 4.2.2, which can be found below,

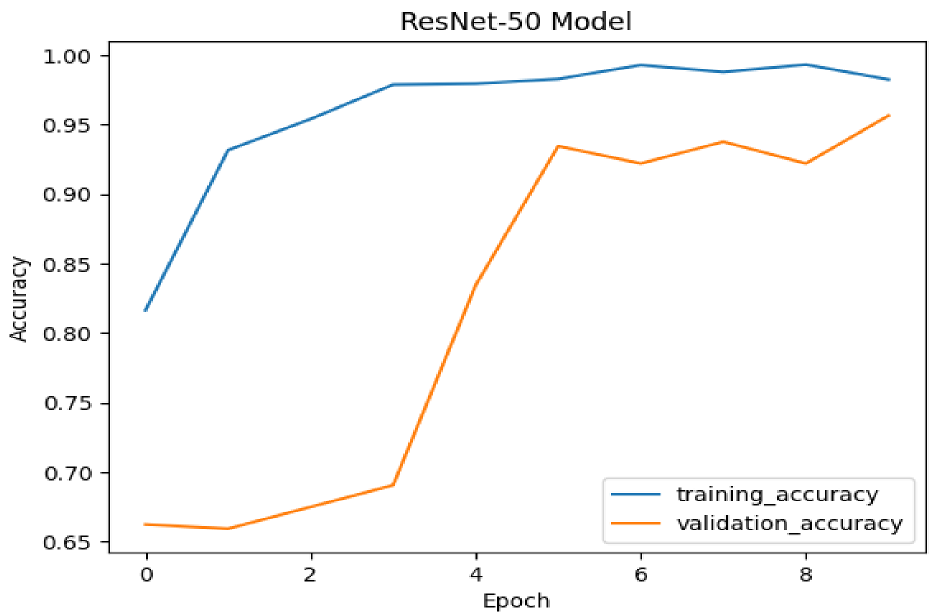

Figure 4.2.1: Accuracy graph of Brain MRI classification by ResNet-50 models.

The following graph, which can be seen in figure 4.2.1, illustrates the degree to which accuracy that is experienced as a result of using the Resnet-50 model. When applied to the data that was used for training, it had an accuracy rate of 99.29%, but when applied to the data that was used for validation, it had an accuracy rate of 95.63%.

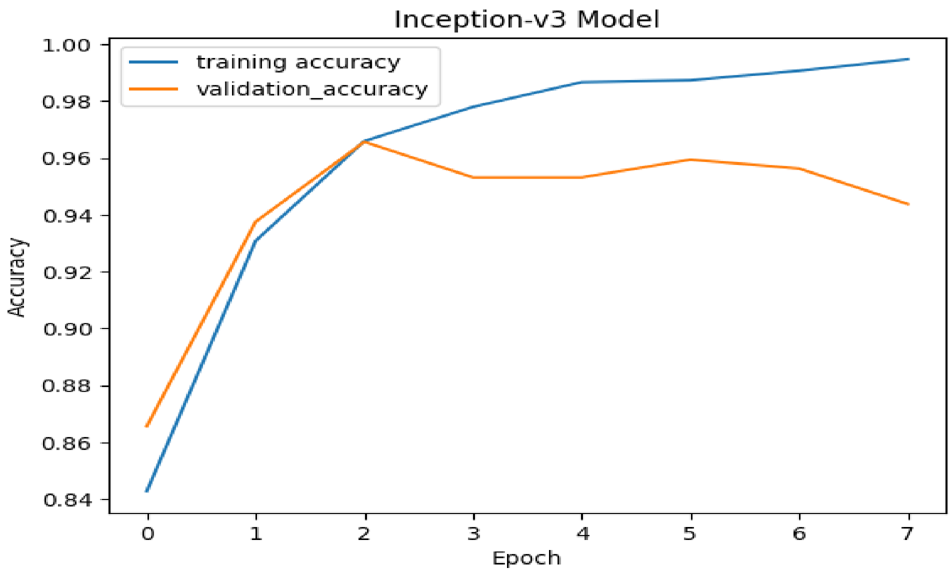

Figure 4.2.2: Accuracy graph of Brain MRI classification by Inception- V3 model

In the Figure 4.2.2 Inception v3 has shown 99.46% accuracy on training data and 96.56%.

The following figures shows the accuracy level on training and validation dataset of Image segmentation methods.

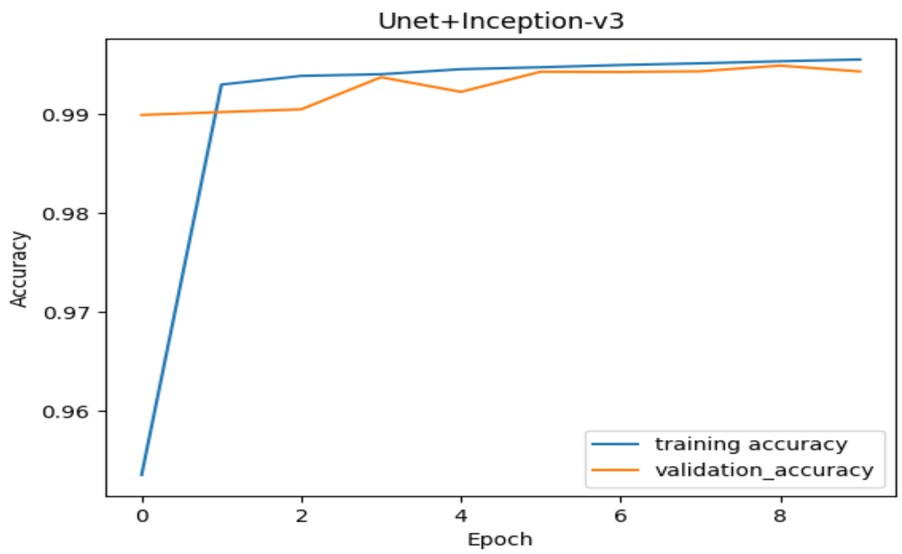

Figure 4.2.3: Accuracy graph of Brain MRI Segmentation by Unet + Inception V3 Model.

Here in Figure 4.2.3 combination of U-net architecture and Inception v3 has shown accuracy on training data 99.55% and accuracy on Inception v3 99.49%

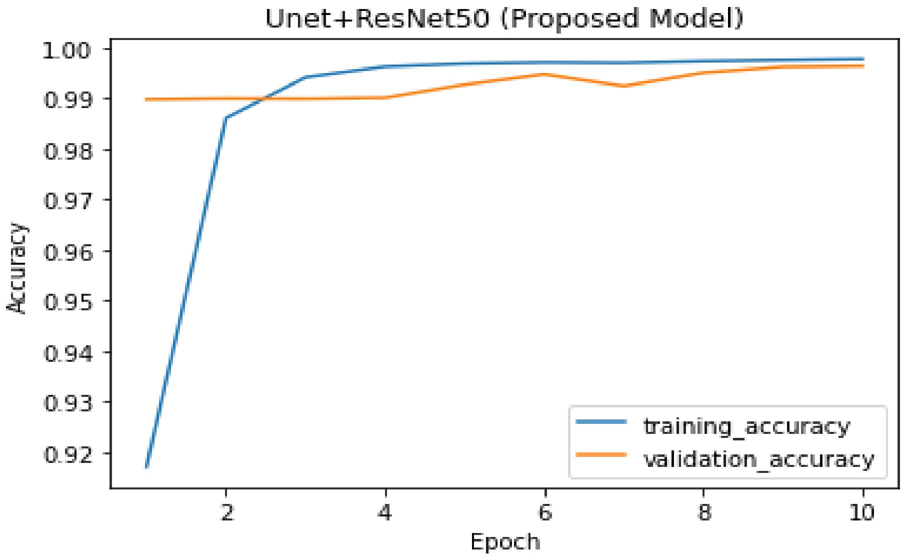

Figure 4.2.4: Accuracy graph of Brain MRI Segmentation by Proposed model (Unet + RestNet-50).

In the Figure 4.2.4 shows 99.77% accuracy on test data and 99.63% on validation data

Accuracy: Classification models may be evaluated by a variety of metrics, one of which is accuracy. The confusion matrix may conveniently be used to calculate the model's accuracy.

$$Accuracy = \frac{(\text{ True Positive+True negative })}{(\text{True Positive+True negative+Flase Positive+False Negative})} \ldots\ldots\ldots\ldots (3)$$

Precision: Random errors have an impact on precision. Precision is a way to convey how close our positive detections are to reality. More relevant results were returned by an algorithm with a high prediction score than those that were incorrect. The model's precision can alternatively be calculated using the formula for the confusion matrix.

$$Precision = \frac{\text{True Positive}}{(\text{True Positive+ Flase Positive})} \ldots\ldots\ldots (4)$$

Recall: Recall is a useful metric for measuring how accurate positive predictions are when compared to the actual data. Recall is a measure of how well a model reproduced the actual data. The formula can be used to figure out how much recall there is,

$$Recall = \frac{\text{True Positive}}{(\text{True Positive+ Flase Negative})} \ldots\ldots\ldots (5)$$

F1-score: A test accuracy is measured using the F1-score in statistical analysis. An average of precision and recall is used to calculate the F1's weighting coefficients. It can be referred to as,

$$F1 - Score = \frac{2\times(\text{Recall} \times\text{Precision})}{(\text{Recall}+\text{Precision})} \ldots\ldots.. (6)$$

Here, Table 4.2.1 represent the True Positive, False positive, True negative and False Negative of RestNet-50 and Inception-V3 which are uses for classifying the brain tumor.

Table 4.2.1 Model classification performance for classification

Model	True Positive	True Negative	False Positive	False Negative
ResNet -50	1363	2538	18	10
Inception-V3	1366	2542	14	7

Table 4.2.2 shows the Evaluation metrics of Brain Tumor Classification with ResNet-50 And Inception-V3. Evaluation metrics shows the results of Accuracy, Precision, Recall and F1-Score of ResNet-50 and inception-V3.

Table 4.2.2 Evaluation metrics for classification

Model	Accuracy	Precision	Recall	F1-Score
ResNet-50	0.9929	0.9869	0.9927	0.9898
Inception-V3	0.9946	0.9898	0.9949	0.9923

Table 4.2.3 represent the True Positive, False positive, True negative and False Negative of RestNet-50 and Inception-V3 which are uses for classifying the brain tumor.

Table 4.2.3 Model classification performance for segmentation

Model	True Positive	True Negative	False Positive	False Negative
Unet+InceptionV3	1367	2544	12	6
Proposed Model	1370	2550	6	3

From Evaluation metrics of Brain tumor segmentation by Unet+ Inception-V3 and our proposed model which is combination of Unet and Encoder of ResNet-50, we have achieved the accuracy, precision, recall and F1-Score. Here Table 4.2.4 shows all of them.

Table 4.2.4: Evaluation metric for segmentation

Model	Accuracy	Precision	Recall	F1-Score
Unet+InceptionV3	0.9955	0.9912	0.9956	0.9934
Proposed Model	0.9977	0.9956	0.9978	0.9967

In deep and machine learning classification, the confusion matrix plays a critical role in monitoring performance. It is one of the most effective methods for speeding up categorization.

In order to better understand the kind of errors that our system produces and the proper actions to take, we may compute a confusion matrix.

Here, Figure 4.2.5 and Figure 4.2.6 shows the Confusion Matrix of ResNet-50 and inception-V3 which has been used for Brain tumor Classification.

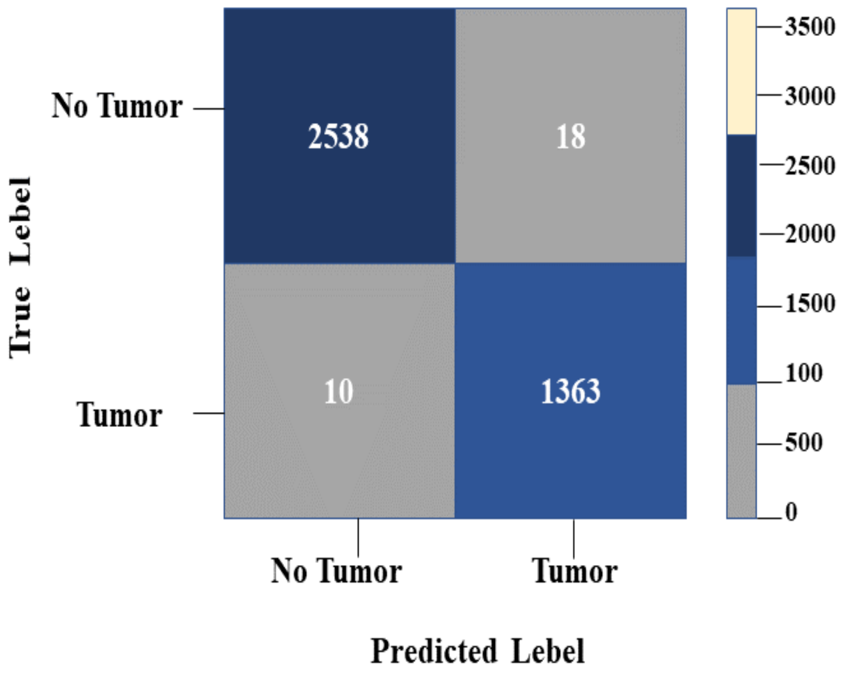

Figure 4.2.5: Confusion Matrix of ResNet-50

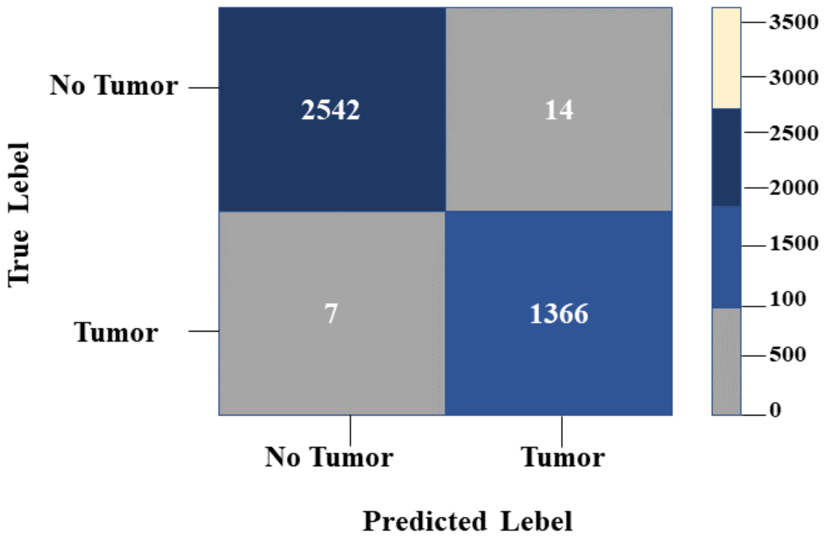

Figure 4.2.6: Confusion Matrix of Inception-V3

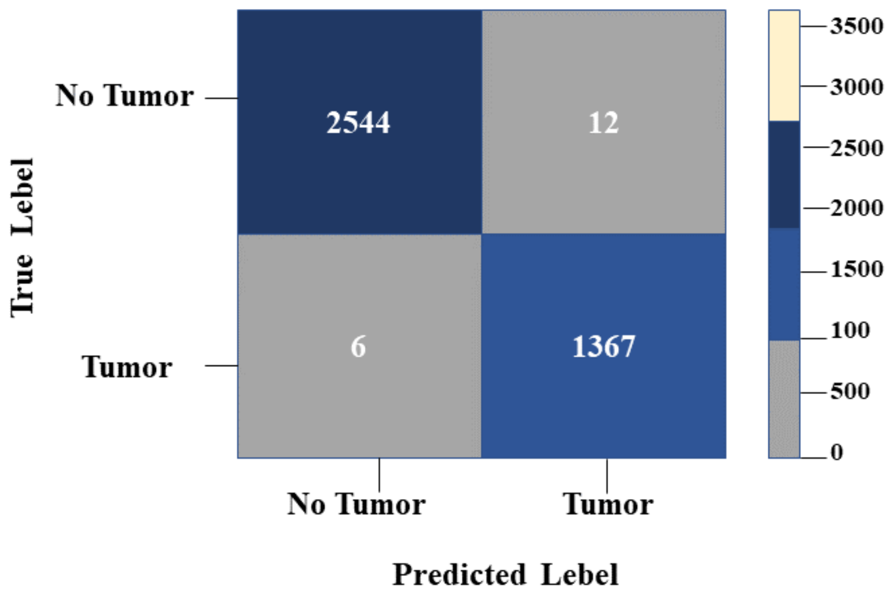

Figure 4.2.7: Confusion Matrix of Unet+InceptionV3

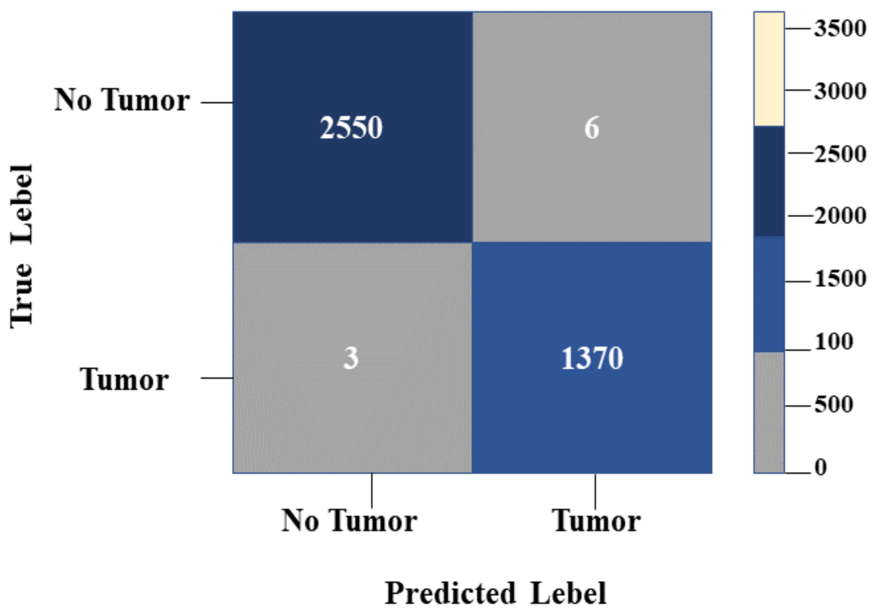

Figure 4.2.8: Confusion Matrix of Proposed Model

Here, in Figure 4.2.5 and Figure 4.2.6 shows the Confusion Matrix of Unet + inception-V3 and our proposed model (Unet+ResNet-50) which has been used for Brain tumor segmentation.

4.3 Discussion

This section examines how our study has been set up for experimental work, how algorithms performed, and what findings such as accuracy, precision, recall, and F1-score we have gotten from our research. Specifically, this section focuses on how our study has been set up for experimental work. In particular, this section focuses on the ratings for accuracy, precision, and recall. Following that, a classification of the brain tumor was performed using Resnet50 and Inception v3 algorithms. After then, there was an evaluation of the degree of precision that was carried out. On the data used for training, Resnet-50 displayed an accuracy of 99.29%, however on the data used for validation, it demonstrated an accuracy of 95.63%. On the data used for training, Inception v3 demonstrated an accuracy of 99.46%, however on the data used for validation, it demonstrated an accuracy of 96.56%. Then, our proposed approach, which is a mix of the encoder Resnet-50 and the U-net architecture, has been utilized for the aim of Brain MRI image segmentation in order to establish the specific location of the tumor. Which led to an outstanding accuracy percentage of 99.73% as a result of the aforementioned. Using the model that was proposed and which we have utilized can help to solve the problem of the disappearing gradient that has been seen. Additionally, we have compared the outcomes of our model to the findings obtained by combining U-net and inception-V3 to see how they compare. It has demonstrated an accuracy level equivalent to 99.55%. The model that was proposed was successful in solving the problem of vanishing gradients, and the accuracy that was reached was 99.77%. In the end, what we discovered was that the model that we had provided shown a higher level of accuracy than the other models.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

Human lives are the most valuable assets someone can have. But sometimes some diseases harms that lives as a result living becomes difficult. Brain tumor is one of them. Brain is one of the most important parts of our body. Every year many patients get diagnosed with brain tumor. And without proper treatment many lives are lost. 83,570 people diagnosed with brain tumor in United States and 18,600 people died. The number becomes much higher when it comes to worldwide. So, brain tumor is one of the biggest threats for the society as it kills thousands each year. Tumors are mainly abnormal cells. Brain tumor is growth of abnormal cells inside brain. To prevent brain tumor treatment from early stage is necessary.

Magnetic resonance imaging is used to detect brain tumor. We have seen many advancements in terms of magnetic resonance imaging. But the method of detecting the disease is still the same as always. The doctors detect the disease manually. As doctors are also human beings there will always be chance of human errors. Not to mention that sometimes late detection of brain tumor can make difference between life and death.

The earlier the tumor can be detected the more the chance of survival the patient has. Again, there are many types of brain tumor present there. A patient can even have multiple types of brain tumors at the same time. So, detecting brain tumor can be very difficult and time consuming if it’s done manually. As a result, the chances of recovery become less for the patient. Our project intends to solve this problem.

Our project mainly is an automated brain tumor detector. Which mainly detects brain tumor through MRI images. The main goal of our project is to detect brain tumor more precisely and quickly than the usual method. Four types of variants of brain tumor can be detected by our project. Such as meningioma, glioma, pituitary.

Three levels of tumor can also be detected by our project. And they are Coronal, Transversal, Sagittal. The features make our project more reliable and more versatile.

The whole project was done using deep learning methods. Our proposed methods gave better results than the previous brain tumor detection methods. Because of that our project detects brain tumor with precision and quickly.

The goal of our project is to help the medical treatment and the society in general. We tend to help the patients and their family. If the brain tumor is not detected earlier it may turn into cancer. Which can cause a family of the patient and the patient him or herself both economically and mentally stress. The brain cancer can cause economical loss as the cancer treatment is very costly. Which can lead to morbidity and premature death. Not to mention the stress the family of the patient has to go through both mentally and economically.

Sometimes the family may lose the only earning members of their family. Which can destroy the family's economical state. These can lead the family members as well as the patient to anxiety, distress and depression. If the brain tumor is not detected earlier the cost of the treatment becomes really expensive also the wastage of the medicine can lead to environmental distress. Thus, how the whole society can be affected by brain tumor.

Our project tends to help in these situations. It accelerates the process of detecting the brain tumor. Which can lead to earlier treatment of the patient. Most of the time earlier treatment helps to recover from the brain tumor. As a result, the patients and their family can lead a healthier and normal life as the rest of us. Thus, how our project impacts on the society.

5.2 Impact on Environment

Brain tumor can be considered as a curse for the mankind. Many years many lives are lost due to this disease. Brain is one of the most important parts of human body. Brain tumor is mainly an abnormal growth of cells. Brain tumor can cause severe brain cancer. Every year many people die due to brain cancer as there is yet no cure to it. So, the solution is to prevent it. But sometimes the task is very difficult.

Most cases the survival rate is much higher if the brain tumor can be detected at its early stage. To do that Magnetic resonance imaging is used. But still the same method is being used to detect a sensitive disease like brain tumor. Most of the time the doctors watching the MRI images the brain tumors are detected. But the doctors are also human beings and we human beings have human errors. Again, sometimes the error can be also be technical. Dim and hazy MRI image can cause confusion. One wrong information can lead to severe loss.

Every year thousands of people are diagnosed with brain tumor worldwide. As a result, thousands of MRI images are used to detect brain tumor. The MRI images that are used are mainly created with plastic. As plastic doesn't decay in the soil. Because of that it causes a great harm to the environment by polluting the soil. Also burning the plastic also does no good as it causes air pollution.

As a result, the wastage of physical MRI images causes a lot of environment pollution. Which can be harmful for the human and the whole eco system. Not to mention the chemical wastage of the medicines that are used to treat the cancer if brain tumor is not detected earlier. Our project intends to solve this problem also. Our project is an automated brain tumor detector where deep learning techniques were used. The main goal of our project is to detect brain tumor automatically with more precision and with more speed than the traditional way of detecting brain tumors.

Our proposed method provides better results than most of the traditional deep learning methods. Four types of variants of brain tumor can be detected by our project. Such as meningioma, glioma, pituitary. Three levels of tumor can also be detected by our project. And they are Coronal, Transversal, Sagittal. The features make our project more reliable and more versatile. As a result, a wide range of brain tumor can be detected by our project. Which makes our project even more sufficient?

As our project uses deep learning methods and is automated need for physical MRI images are less. Which means our project can detect the brain tumor only with the digital data. Which is can making a big impact on the environment. If brain tumor can be detected with our automated method in most of the places there will be less physical MRI images.

As these MRI reports are made out of plastic there will be less usage of plastic. As a result, the soil and the air will be saved. Which can lead to a healthier environment. And a healthier environment means healthier lifestyle of the people living in it. Automated Brain tumor detection technique helps to detect brain tumor detection much faster.

As a result, the patients will receive treatment earlier. Which can be a game changer. Early stages of brain tumor detection mean the patients have much more chances of surviving. As a result, there will be less usage of medicines and other therapies. Which can reduce wastage. Which is also better for both the environment and the patient's economic state. We aim to make the survival rate of brain tumor patients to go higher than before and also aim to make the environment to have better impact by it. And our project really does that. Thus, how our project impacts the environment.

5.3 Ethical Aspects

The purpose of our project is to help in the medical field to detect brain tumor more efficiently and more quickly. As a result, patients will be helped more and more lives will be saved. Because the quicker the brain tumor is detected the more survival chance will be increased. It will also help the patient's financial state and emotional state. The earlier the patient will be recovered the less expenses will be spend also the earlier the patient will be able to go back to his/her earnings. Our project will also be able to help the patients get accurate result. Sometimes wrong outcomes of test can be disastrous. As wrong treatment can bring a lot of complications. Which can also sometimes lead to many diseases. Many crucial financial problems can arise from that. In order to complete our project, we used datasets from public domains. The datasets that we used are LGG segmentation dataset. Which was collected from Kaggle. And the data that are present in the datasets are also collected with consent.

Moreover, our project is also intending to save the patients from scamming too. Sometimes we can see patients gets scammed with false reports. Our project intends to solve the problem as it gives genuine and accurate result.

We also plan to collect real time data from the hospital and medical centers. These values will be more accurate. As accurate datasets will be used so the accuracy of our project will be increased. Because of that we can provide better brain detection techniques which will help the patients more. Thus, all of our works are ethically justified.

5.4 Sustainability Plan

In our research we are using deep learning techniques to Detect tumor. Using Deep learning technologies Our research can help doctor to detect the tumor, find out the actual condition of patients and the level of tumor. Our research not only focus on detecting tumor, but also classify the tumor. Classifying Brain tumor by using different kind of Algorithms, our research will enrich the method of classifying the brain tumor from Brain MRI images. Our research will help the Doctor to easily differentiate the stage of tumor affected patients. If the doctor knows the stage of tumor, they can easily give the appropriate treatment of it. To Sustainability this research, we will collect more data from different kind of datasets. We will also go to the hospital for talking with the doctor and patients. As we know that if we can contact directly with them, then we will have a great chance for getting the real and true data. Which can be more accurate than the Online resource.

We will then merge the data we collected from the hospitals and medical facilities with the datasets that are present on the online sources. As a result, the accuracy of detecting brain tumor will be increased and we will be able to detect brain tumor with more precision and quicker than before. Which can save many lives. When we will be able to save patients by detecting brain tumor more effectively than before and be able to help the doctors as well as the patients with the treatment our project will be sustainable.

CHAPTER 6

CONCLUSION, RECOMMENDATION AND FUTURE WORKS

6.1 Summary of the Study

Brain tumor has become one of the most dangerous diseases nowadays. Brain cancer which is most of the time brain tumor has taken so many lives in recent years. Survival rate of brain cancer within five years is only 34%. As there is no specific treatment for brain cancer the survival rate of patients who are diagnosed with brain cancer is really low. However early detection of brain tumor can increase the chances of survival of the patients. But most of the time detection of brain tumor manually with just MRI images cannot be very sufficient. Also, sometimes it takes more times to detect brain tumor. Which can make treatment for brain detection really late. And late treatment of brain tumor can lessen the survival chance of the patient. Not to mention the financial damage that the patient and the patient's family have to face in the meantime. This is the reason we wanted to help detecting brain tumor and localization automatically. Which can rectify the process of treatment of the patients. To reach our goals we have first researched about how we can make a model that can automatically detect brain tumor. After coming up with a model we have collected a dataset that on which we can train on model. Then we used deep convolutional networks in order to classify the brain tumors. Before that we have applied preprocessing and augmentation methods. For classifying the brain tumor, we have used two algorithms. Resnet-50 and Inception v3 has been used in order to classify the brain tumors. After that we have compared the accuracy levels of the both algorithms. Segmentation was done with combing the architecture of U-net and Resnet-50. Which is our proposed model. Which have given tremendous accuracy level. For comparison we have also combined the architecture of U-net and Inception v3. We have also calculated the accuracy, precision, recall and f1 score of both of the model for comparison. Where we have gotten better score with our proposed model. For that reason, we have also predicted brain tumor with our model. Where have found great success.

6.2 Conclusion

Early brain tumor detection can increase the rate of survival of a patient. Magnetic Resonance Imaging (MRI) has become very popular in terms of brain tumor detection. But sometimes it cannot be very reliable. Image segmentation can be used in order to detect brain tumor more sufficiently. In this work a Deep Convolutional Neural Networks (CNNs) has been introduced combining U-net architecture and Resnet-50 encoder. Which has been tested on the LGG segmentation dataset. First preprocessing with imageDataGenerator method of Keras library and augmentation techniques such as rotation, zoom, horizontal and vertical shift, both horizontal and vertical shear as well as flipping have been done. After that Brain tumor classification has been done with Resnet50 and Inception v3. Then the accuracy level has been compared. For image segmentation our proposed model which is the combination of U-net architecture and the encoder Resnet-50 has been applied after the classification. Which has provided tremendous accuracy of 99.77%. The proposed model that we have used is able to solve the vanishing gradient problem. We have also compared our model with combining U-net and inception-V3. Which has shown the accuracy of 99.55%. We have seen that the accuracy of our proposed model is better compared to another model that we have tested on our dataset. That is why prediction has been done with our proposed model.

6.3 Implication for Further study

Brain MRI scans from other sources will be collected in the future to expand the amount of data. Our dataset can then be used in conjunction with these results for improved accuracy. On datasets like Brats, we can also use our proposed Model since it is publicly available for use. Live data from a variety of hospitals and clinics will be used in our research in the future. As a way to achieve the best classification accuracy, we can use genetic algorithm, simulation annealing, particle swarm optimization, and other techniques [26]. A variety of augmentation methods will be used to identify and locate the tumor in Brain MRI images from different angles.

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