University of Essex
Department of Mathematical Sciences

MA981: DISSERTATION

Brain Tumour Classification Using Image Processing

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Abstract

A Brain Tumour is a growth of a group of unstructured tissues in the human brain that can be cancerous or non-cancerous and can lead to the loss of human life. According to cancerresearchuk.org official data, only 12 percent of individuals survived brain Tumours between 2013 to 2017. The mortality rate of patients suffering from tumours is also increasing each year. Brain Tumours can be classified by both human and advanced machine learning methods, which are increasingly used daily in modern medical practices to avoid errors in assessing the type of tumours which was a major concern while treating a patient against it. Brain Tumour Classification using image processing techniques is considered the most interesting and strenuous task when it comes to medical image processing techniques. The medical image processing technique is a growing field in the medical domain as it is proven to be more efficient than the manual techniques used to detect tumours and other types of cancer. In a very traditional manual approach, the accuracy of predicting the type of brain tumour was proving to be more and more inaccurate because of the nature of tumours, and the similarity of cancer-causing tumours structure with the normal tissues of the brain. In this paper, we have obtained a dataset containing 3064 Magnetic Resonance Imaging (MRI) images from 233 patients with three kinds of brain tumours: meningioma, glioma, and pituitary tumour, and compared different algorithms which can efficiently detect the types of tumours and in the case of normal tissue. We have used both modern classifiers like Convolutional Neural Networks (CNN) and Extreme Gradient Boosted Decision Trees (XGBoost) which were implemented using Python packages such as Keras and Tensorflow. While comparing these classifiers, we can conclude that XG Boost classifiers are more accurate for image processing techniques than the Convolutional Neural Networks (CNN) algorithm. In our work, Extreme Gradient Boosted Decision trees (XGBoost) gained the highest accuracy at 99.45 percent and successfully classified the images into 3 categories: Glioma Tumour, Meningioma Tumour, and Pituitary Tumour. The main aim of this paper is to devise the perfect method for the segmentation and classification of tumours based on the behaviour and structure of those tissues.

CHAPTER 1

Introduction

1.1 What is Brain Tumour?

Brain Tumour is considered the most complex disease to treat in the human body due to the complexity of the Neural network inside the brain.[3] Detecting brain tumours and devising methods to classify the tumour is proving to be a very exigent field in medical science. The human brain is considered the most complex structure in the human body due to the presence of the whole nervous system in the brain. It is considered the smartest organ of the whole body because it controls and operates the whole body.[10] The human brain consists of 3 parts: Fore Brain, Mid Brain and Hind Brain. Types of cells found inside the brain are Neurons and Galilean Cells and the Expansion of these cells results in a Brain Tumour. Brain Tumours are classified depending on their size, density, and shape where they are situated inside the brain which is a very complex structure.[3] Due to this if there is a manual detection of the tumour it results in a lot of errors and mistakes as it is very difficult to classify the tumour from the images we get from X-ray and MRI images as they are most of the time blurry. Brain Tumours can be cancerous (Malignant) and lead to the death of human life and they can be non-cancerous(benign) which are less harmful to the Human body. Malignant Brain Tumours can be further classified into 3 types: Glioma Tumour, Meningioma Tumour, and Pituitary Tumour. [figure 1] These types of Malignant Brain tumours tend to grow more rapidly in the brain than the Benign type of Tumours which can mostly be successfully removed using surgeries.

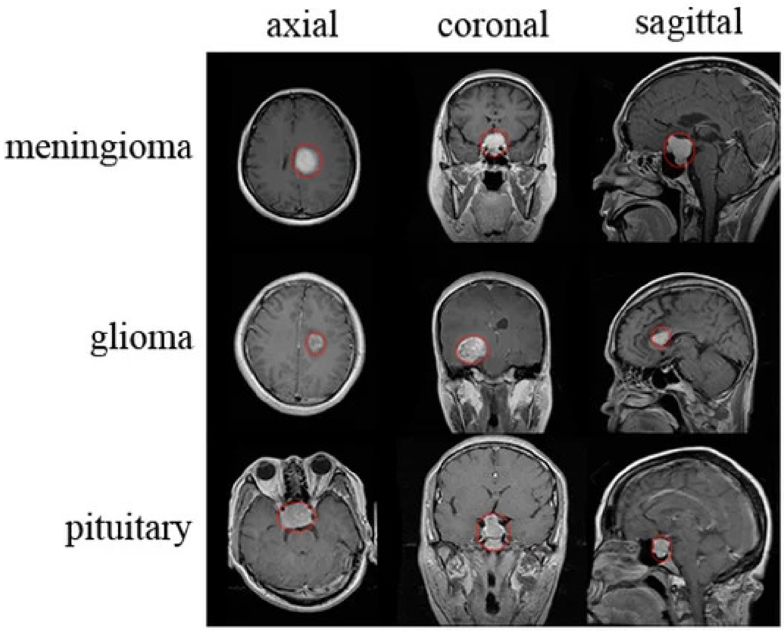

Figure 1.1: Types of Brain Tumours and their structure

1.2 Types of Brain Tumours

According to a survey done by John Hopkins Medicine, 33 percent of the brain tumours detected in the brain are related to Glioma type. This type of tumour occurs in the glial cells, forms a part of the normal tissues, and grows inside them. Gliomas are also known as intra axial brain Tumours since they grow within the glial cells. Gliomas are considered the deadliest cancerous tumours because they grow inside such areas of the brain which are difficult to remove even with the help of complex surgeries and they can be proved very hard to remove because of surrounding neurons present inside the brain. Gliomas can be further classified into Astrocytoma, Brain stem gliomas, Ependymomas, oligo-astrocytoma, Oligodendrogliomas, and Optic pathway gliomas. Common symptoms found in glioblastoma are Headaches, Seizures, Personality changes, Numbness etc. Chemotherapies are mostly recommended as a possible treatment for treating gliomas.[5] A Meningioma tumour is a type of tumour which directly affects and attacks the Central nervous system (CNS) of the parts of the brain and spinal cord. These are the most common types of tumours occurring in patients. Meningioma tumour behaviour is completely different from glioma tumours and it is treatable at lower stages. Meningioma is classified into three grades namely Grade 1, Grade 2, and Grade 3. Surgery can be used to remove the Meningioma tissue at every grade of this cancer. In the case of Grade 2 and Grade 3, there is a chance of relapse and it can result in the re-growth of the tumour which will be treated again with the help of surgery. The growth of Meningioma tumours is very slow compared to Glioma tumours but at a later stage, it can be proven deadly for the patients that is the reason that it should be treated and detected as early as possible. Large exposures to radiation and the development of cancer-causing cells within the normal tissues are the primary causes of Meningioma cancer. The common cause of this type of tumour is normally the formation of genetic tissues which can later be developed into cancerous tissue. Meningioma symptoms vary from individual to individual but the most common symptoms are confusion, seizures, loss of hearing, and vision changes. [6] Pituitary Tumours as the name suggests are tumours that grow in the pituitary glands in the brain. It is a very small gland which is situated at the back of the brain. Pituitary Tumours are mostly non-cancerous (benign) and their growth is normally very slow compared to the other types of tumours. Pituitary Gland is mostly responsible to make hormones in the body and then it gets supplied to other organs of the body. A tumour in this gland can lead to the gland becoming slow in its process of creating hormones and also supplying those hormones to other organs and parts of the human body. Pituitary Tumours are symptomless and they dont cause any serious bodily harm to any other organs or the spinal cord. Around 25 percent of the people in the world are predicted to have pituitary tumours without them even knowing about it and they normally can be detected using medical imaging techniques. If the pituitary tumours are increased in size, they will lead to serious vision complications as they press towards the optic nerve situated in the brain which leads to loss of vision. A pituitary tumour can be further classified into four types namely Non-functional adenomas, Prolactin-producing tumours, ACTH-producing tumours, and Growth hormone-producing tumours. [7] The most common symptoms involved with these types of tumours are rapid increase in weight, Extra growth hormones, Deepened voice, Snoring etc. Radiosurgery and Tissue removal surgeries are mostly used to treat these types of tumours or different kinds of medicines can be suggested by doctors which can lead to less formation of hormones in the human body which stops the overgrowth of certain parts and glands of the body. Magnetic Resonance Images (MRI) are the most common ways to detect Pituitary Tumours, however, they can also be detected using blood and urine samples and getting them tested in a laboratory.[7] Benign tumours are normal tissues in the brain cells and they dont grow towards other parts of the brain which is why they are considered non-cancerous. Benign

Tumours normally do not cause any problems in the functioning of the brain and other parts of the body as opposed to other types of tumours. They generally are left untreated by the Doctors even after they are detected in the MRI images because they are not responsible for causing any bodily harm and they dont behave as cancer tissues which are formed in Glioma and Meningioma Tumours.

1.3 Image Segmentation

Image segmentation is a crucial step in image processing. The primary objective of image segmentation in the field of medical image processing is to detect tumours or lesions. A core problem is to increase the sensitivity and specificity of lesions. Pre-processing includes conversion to greyscale, noise reduction and removal, and image reconstruction and enhancement. A greyscale image is usually called black and white but it is not true. The intensity of the image is 1 or 0 and it has two shades only black and white. After converting the image into greyscale, it removes the excess noise. There are two types of filters; once is low-end frequency is passed then it allows the high-end to pass. It helps in flatten or sharpen the images. When the image is flattened, the noise gets blurred but when it is sharpened the noise of the image increases. This noise of the image has to be clipped before processing otherwise it can alter the accuracy of the image processing.

1.4 Traditional Algorithms used for the classification of Tumours

Manual methods in the detection of brain tumours were proving to be error-prone because of the similarity between the structure of normal tissue and Cancer-causing tissues. In the 1900s Doctors were using Microscopical methods for the classification of Tumours However it was very difficult to understand the behavioural patterns and structure of Tumours and their similarity to the normal tissues of the brain.[9] To overcome these Anomalies in traditional medical science, Deep Learning (DL) and Machine Learning (ML) methods were implemented which were efficient in medical Image processing tasks like classification and segmentation.[11] These methods replaced traditional algorithms like Logistic Regression, Random Forest Classifier and K-Nearest neighbours as shown in figure 2 Two-Tier Classification Techniques are used to bring out the automation accuracy of the models. Self-organising maps (SOM) and K-nearest neighbour (KNN) are the simplest techniques used as they are very efficient and less time-consuming computationally. Figure 2 [8]. K-NN is a type of classification which depends on distance for classification and if the features represent vastly different scales and then it normalizes which affects the accuracy level dramatically. The set of classes also called neighbours have to be known for classification and regression. A popular distance metric called Euclidean Distance is used for measuring the distance metric for continuous variables and Hamming distance for categorical variables. The degradation of the classifier occurs when the data is noisy and has irrelevant features. [12] Modified K-Means along with mean shift segmentation help in pre-processing the MRI images. The computation time of K-Means is less and different segments can be obtained by comparing factors with the anatomy of the brain. Support Vector Machine (SVM) transforms high dimensional data for better optimization.The accuracy of K-nearest neighbours is quite good but not the best when compared to more modern and versatile algorithms like Convolutional neural network (CNN) which is based on a Deep Learning algorithm that boosts the accuracy of the model and can train the image dataset in a much better and efficient way possible. Convolutional Neural Networks (CNN) uses image segmentation and augmentation methods which pre-processes the data very efficiently and remove the excess noise and blur from the images. To improve the training and testing accuracy done in Convolutional Neural Networks (CNN) and to boost the accuracy of the model gradient boosters are used as a parallel machine learning algorithm. XG Boost Classifier is the most commonly used gradient booster in medical image processing.[8]

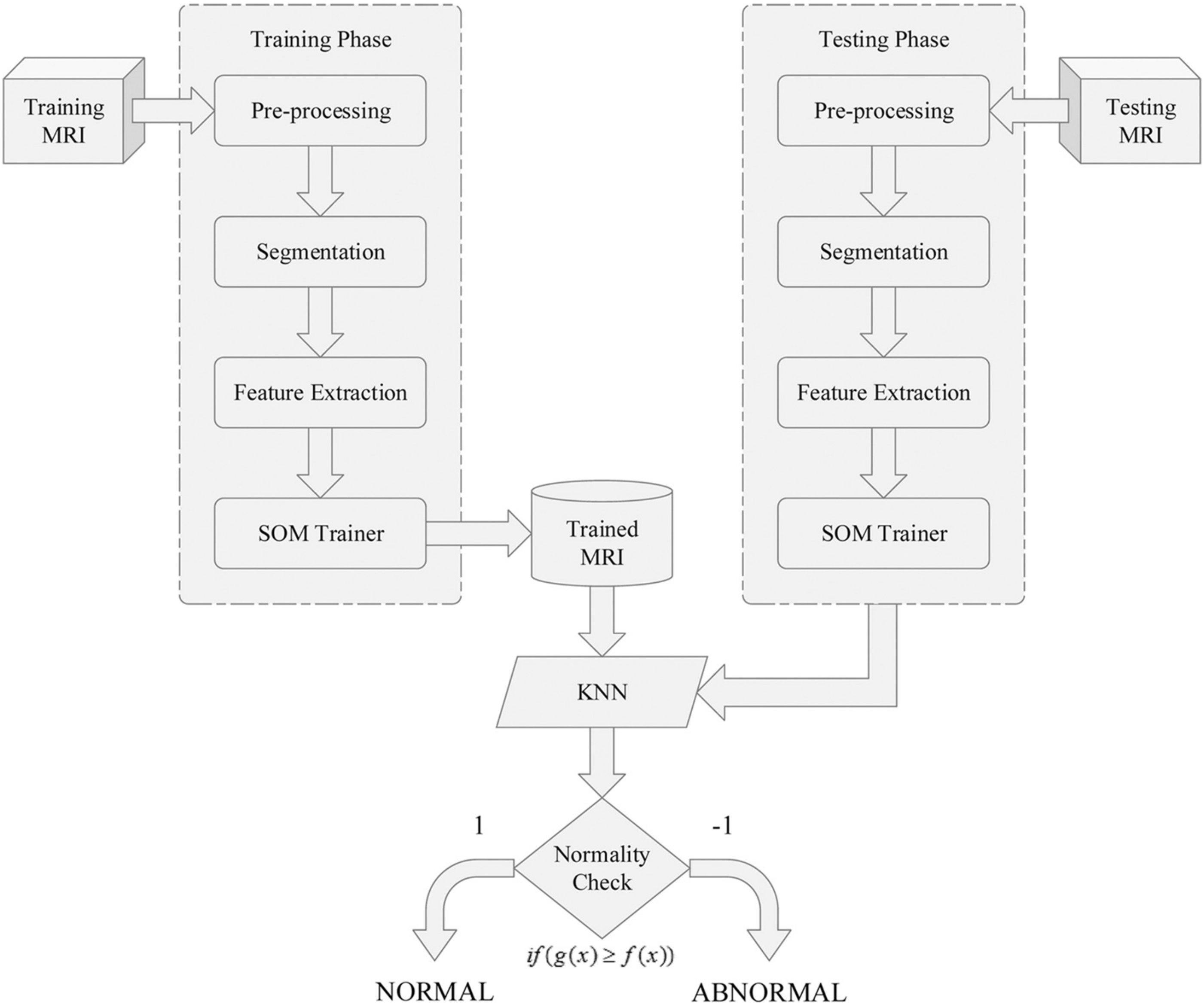

Figure 1.2: Two Tier Classification using SOM and KNN.

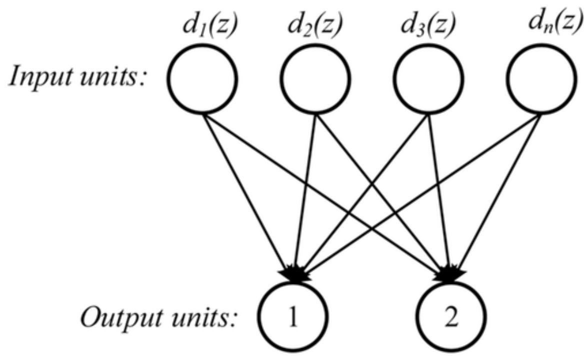

Figure 1.3: SOM Architecture

1.5 Objective and Motivation

The objective of my research was to find and compare two of the best algorithms which can detect the type of Brain Tumours (Glioma, Meningioma, Pituitary). In this paper, we have used Convolutional Neural Networks (CNN) and XGBoost Classifier Algorithms using Image Processing techniques like Keras and Tensorflow as opposed to traditional K-Nearest Neighbour (KNN), Logistic Regression and Random Forest Classifiers which proved to have less accuracy scores as compared to the methods used by us. We have used image processing techniques to work on the Dataset consisting of 3064 Magnetic Resonance Imaging (MRI) images obtained from 233 patients. The main motivation behind working on this project is to classify and detect the type of brain tumours accurately with the help of modern Machine Learning and Deep learning techniques which can prove useful to the field of medical science. Brain Tumours can be treated and increase the rate of living of patients for up to more than 5 years but this is possible only if the Tumours are detected at the correct time. Right now the Highest number of Deaths happening in the world is because of the illness in the Central nervous system of the body and particularly brain Tumours. Therefore we need to devise an automatic method that can take the MRI Images and Automatically Segment whether the Image is a Tumour or not. This will be immensely popular in the Medical Science field and will serve as a major contribution towards Medical Science. Some countries in the world where technology is not so advanced still use the traditional approach to solve this problem as they cannot afford automation machines due to High Computing Power, So my aim is to devise a method that consumes low computing power so that everyone can have access to this technology and mortality rate will decrease compared to last 5 years.

CHAPTER 2

Literature Survey

Bahadure N. B. et al [26] is the one who had proposed the SVM, BWT (Berkeley wavelet transformation), and brain Tumour identification system. The skull stripping algorithm was heavily used so that only other parts of the brain are visible except the skull. BWT is an image segmentation method used which had a classification accuracy of 96.51 percent. Abdel-Maksoud and other authors [27] presented K-Means Clustering (KMC) and Fuzzy C-Means Clustering (FCM) which is considered a novel segmentation technique. Their hybrid model takes very much less time to run so it is very efficient. Pathak K. et al. [29] used the watershed algorithm to solve the the problem of CNN algorithm. They inputted images in the form of normal and brain with tumours as well. The authors of [30] proposed a method based on CNN and a Genetic Algorithm(GA) which was used to do segmentation of brain tumours based on images. GA was originally used here to find the best CNN functions and Architecture. Their CNN model has 94.2 percent Accuracy. Authors [31] have used an ensemble classifier for Brain tumour segmentation and MRI Images processing. Feature extraction has been done with the help of clustering and GLCM. Begum S.S. et.al. [32] have mentioned a brain tumour classification technique which is based on RNN and statistical techniques. An oppositional gravitational algorithm (OGSA) was developed by them that removes the significant features. An adaptive neuro-fuzzy classifier was used in the classification and feature selection for the Brain Tumour segmentation. It gained an accuracy of 85.83 percent.

CHAPTER 3

Methodology

In the proposed methodology in this project, we have applied two algorithms for the segmentation and detection of Brain tumours. The first algorithm for segmenting the tumour is Convolutional Neural Network (CNN) which is used on the training and testing data we received and the second algorithm is XGBoost Classifier which is used to boost the accuracy of the Model which is used in CNN.

3.1 Dataset

Finding and working on an image dataset is a very complex part of any Data Science Project where image processing is being used. These dataset samples are quite huge and need a lot of pre-processing techniques. The dataset was carefully chosen from Kaggle for this project as it contains a good sample of 233 patients having different types of Brain tumours and comprises 3064 images in Mat format. Mat files are images which were compressed in MATLAB and MATLAB is used in formatting the dataset and they can be directly used without consuming too much memory on the system. Images in the dataset are T1-weighted contrast-enhanced images which contain 3 types of Tumour images: meningioma (708 slices), Glioma (1426 slices), and Pituitary tumour (930 slices). Due to the huge file size of the images, it was split into 4 subsets of archives and five-fold cross-validation was also provided. To initialise, the use of the Dataset we used the Pymatreader which uses efficient ways to read and compile the Mat files as the mat files were split into 4 subsets and we need to combine them all into a single file and read them for Data pre-processing.

3.2 Packages and their applications in the project

In this Project, we have employed packages like Pandas, NumPy, Matplotlib, Tensorflow, and Math Packages. Pandas is a package highly used in data science which is used when you want to access and modify the dataset. Except this Pandas gives you a lot of great features which can be used to analyse data. [17] Pandas library also provides the flexibility to merge the dataset which we have used in this project as our whole dataset was scattered into 4 parts. We have also used the size mutability feature of the pandas library. Labelling is the key feature of the pandas library and it is heavily used in our dataset. We have saved our model in HDF5 format using pandas and it gives us flexibility in store and space saving as you can access that model and run it from any other notebook as well. NumPy is another package which brings on board functions of C programming and Fortran to Python. Its applications are not just limited to image processing but it is also used in audio processing, Quantum Computing, Mathematical Analysis, Chemistry, and Geographical Analyses as well. The NumPy package is easier to learn and use as it mostly has Matrix transformation functions preloaded. Matrix Reshaping can also be done using the NumPy package and it has almost all the functions related to matrices which are created in image processing. That it can also perform sorting, Input output, and discrete Fourier transformations on the matrix. Basic statistical operations and Basic Mathematics can also be done using the NumPy Package. [18] . Matplotlib is the most important package which is used by every data scientist in this world. These libraries are used to create Interactive histograms and plots which are used to analyse the data efficiently. They can also create colourful and animated plots which are highly used by a data scientist to represent their work on a dataset. In our project, Brain Tumour Transformations performed are plotted using Matplotlib Package and It improves the readability of the data. [19] Tensorflow is a Highly-regarded industry-standard Python Library which has applications in Machine Learning and Deep Learning Algorithms. Tensorflow is a free-to-use and open-source library so it can also be modified according to the needs of the data scientist working on it.[21] Tensorflow provides a very diversified form of tools and resources which can be used to train and test a model. It works on arrays to form algorithms based on Deep learning techniques which cater to the heavy computational needs of the developer. TensorFlow allows users to create a Dataflow graph which helps in the efficient building of algorithms in Machine learning. Tensorflow can be opened on Cloud and local machines as well and can work with the help of heavy CPUs and GPUs as well as some Deep Learning Training requires a high amount of computational power to run on. Tensorflow is also heavily used in the field of AI particularly when it comes to Image Detection and Segmentation which is used in this project. Since Neural Networks algorithms are used in our project Keras library is used in our project which enables us to train neural networks Model. It gives you the functionality to efficiently perform tasks related to the CNN Model.[21] It has building blocks which are based on layers, activation functions, and optimizers. It also allows the Normalisation of image datasets which is required while working on a medical image dataset. Keras is implemented using the Tensorflow package and it already comes pre-installed in the Tensorflow library allowing us to easily call and implement the library. It ensures flexibility, High computational power and Storage friendly working on Image and Audio datasets. [21] Math Library uses Mathematical functions in python which easily gives us the flexibility to perform mathematical equations and solve those problems related to mathematics. Trigonometric functions are used in our dataset using the Math library in Python and it is efficient in removing mathematical errors which we perform manually during the working of the datasets. Math library is free and easy to use and it gives us the option to modify the functions and resources available in the library.

3.3 Data Pre-processing

Data Pre-processing means getting your data ready before fitting any model or algorithm into the data. Data pre-processing is very important before running any Exploratory Data analysis and algorithm because almost all generated Datasets contain noise or distortion that needs to be removed for the accuracy of results. Since here we are working with an image dataset we need to prepare the dataset using image processing methods and do training and testing. The first step that we did in this project is we made a class which reads the whole mat file and puts labels in the images based on the types of tumours that is Glioma Tumour, Meningioma Tumour and Pituitary Tumour.

3.3.1 Data Augmentation

There are a lot of Data Normalisation techniques available that are useful in removing noise from the data that can be further used in CNN and Deep Learning Models. These methods include Dropout methods, Batch Normalization, Transfer Learning, One-shot and Zero-short learning. Out of all these methods, Data augmentation is considered the best method for Image processing as it removes the possibility of overfitting the model from the root. [13] This is because Data Augmentation is using a technique known as Data warping. Data warping is used in such a way that the originality of those images is always preserved and also their labelling is preserved. Data warping is used if you want to apply rotations, and geometric or colour transformations to your Image dataset. This technique is often the best one to make your images noise-free, improving the lighting conditions, improving the viewpoint, and making them blur-free to improve the quality of Images, Background, and scaling of the images. After correction of all these anomalies from your images, one can observe that the overall performance of the model being run on these will increase and will provide very accurate results.[13] This accuracy keeps on increasing as your dataset increases in size and it will work on every pixel to make those images clearer. In this research, Data warping is more sensible and accurate because there are magnetic Resonance Images (MRI) and it is the best method used for medical imaging purposes. Random Cropping, Image flipping and Space augmentations are very common and basic methods of Data augmentation that show signs of accuracy. These types of basic geometrical transformations remove many invariances or anomalies from the dataset and help us have clean images to do our training on. The types of Basic Data Augmentation techniques used by us in this paper are Geometric Transformations, Flipping, Color space, Cropping, Rotation, and Noise injections. These methods preserve the labels of the image dataset and at the same time make it very easy to work on. The safety of the data is of utmost importance while doing these transformations on the data. Non-label preservation of the data can result in a poor accuracy score of our dataset and it will result in poor training and testing of our dataset. This could prove a very expensive process as the authenticity of data will be lost. Rather than doing a Vertical axis flipping, Horizontal axis Flipping is recommended for the type of images we are using here, the MAT images. Brain Tumour images are not based on text recognition so we can use the flipping method without the loss of any labels in the dataset. Colour space is another method used in our

Image dataset as it improves the colour quality of our images and changes the colour of our MRI images to Gray-scale, making detecting and segmentation of tumours pretty easy for the training. An image can be converted into grayscale by isolating that matrix and then adding 2 matrices to it from some other colour channels.[13] Cropping of images is a very excellent method for image datasets having mixed dimensions. Sometimes when you take the image dataset the images have different heights, widths and lengths. Random cropping can also be used as part of the Image cropping procedure which will drastically reduce the size of the input but it will successfully preserve the spatial dimensions of the images hence reducing the label loss and giving better accuracy to the training model. Rotation data augmentation is done either on the horizontal axis or vertical axis and it is rotated between 1Â° and 360Â° but we cannot rotate the image drastically here as it is going to not preserve the data label. The translation segmentation is used to shift the data left and right it proves useful and this is done to avoid positional bias in our data.[13] Noise Injection as the name suggests injects a matrix into the image dataset to increase the clarity of the image and adds noise to your images to ensure the images are clear and ready to be trained on. These methods are defined in our main class Brain tumour and Data augmentation is defined as a function in our class made. This ensures that during training the model we can call the class and run the data augmentation as shown in figure 4.

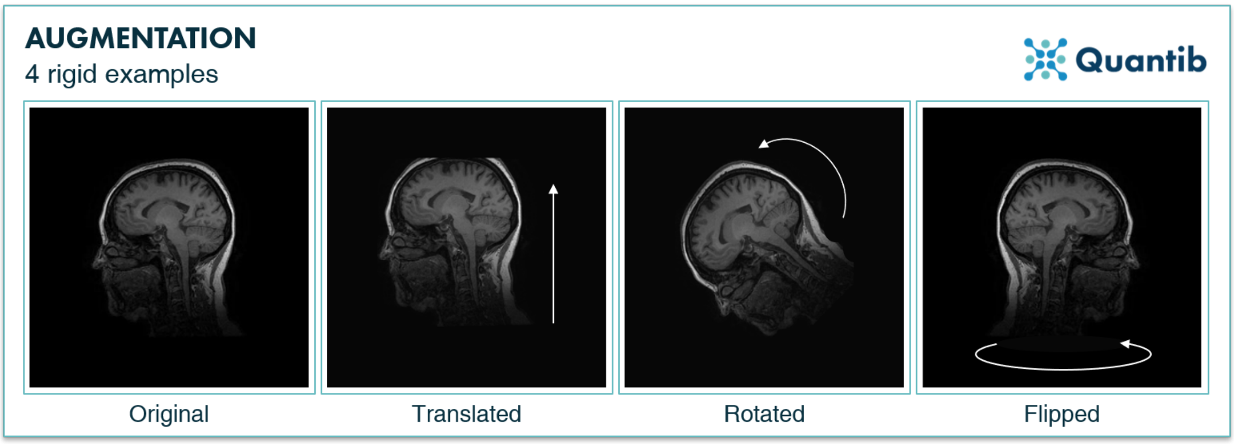

Figure 3.1: Data Augmentation Methods.

3.3.2 Batch Normalisation

Batch normalization is a part of pre-processing which is done to normalize the features and variables in the dataset. It transforms all the data to zero mean and adds unit variance to it. Batch Normalisation is because when there is an input layer there is a loss of learning accuracy to minimize this loss in learning Batch Normalisation is used to normalise the Training model which helps in giving us better accuracy of the training model without the loss of layers in the model.

3.4 Modelling Methods Implemented

In this dataset, we have applied Convolutional Neural Networks (CNN) and Extreme Gradient Boosted Decision Trees (XGBoost) over the Convolutional neural networks (CNN) to increase the accuracy of the model. The journey to looking for the correct modelling technique to achieve the right accuracy was very interesting after choosing the dataset. Many research papers which we can find on google have devised various methodologies to approach the problem of Brain Tumour Segmentation. Some of the traditional methods include Support Vector Machines (SVM), Decision Tree Classifier, Random Forest Classifiers (RFC) and K-nearest neighbours (KNN) but these all methods proved to be less efficient when compared to Modern Modelling techniques like Convolutional Neural Networks (CNN).

3.4.1 Convolutional Neural Networks (CNN)

Modern-day developers are highly recommending and using Convolution Neural networks (CNN) in fields like image processing and pattern recognition. This is due to the efficiency of the convolutional neural networks to reduce the number of parameters used in Artificial Neural Networks (ANNs). [14] This method enables developers to work on huge datasets and solve the problems faced in these datasets which was a highly lacking factor in the classic Artificial Neural Networks (ANNs) methods. If one takes the example of facial recognition which is highly used in the technical industry nowadays, here ANNs require a very precise location of the faces but in the case of CNN that drawback was removed as it doesnt always require the precise location of the face and it can detect the faces from every angle possible. Another Plus point of using Convolutional Neural Networks in our paper is it uses multiple layers to propagate images for example it uses detects the image in the first layer and the second layer relies on edge detection and then goes to the shaper and blurry layers. So because of this layering, CNN is considered one the best Models to use for image processing.

$f(x) = \max(0,x)$

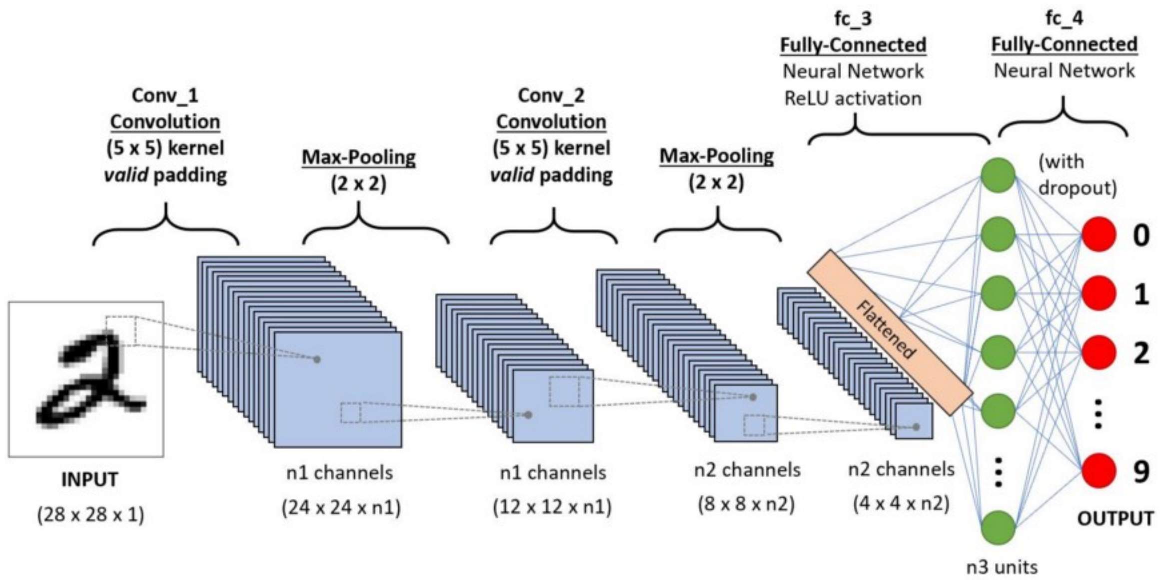

Figure 3.2: Convolutional Neural Networks

Convolutional Layer

The convolution Layer is used as a Generalized Linear Model (GLM). This enhances the representation ability of our MRI images which is implemented in our data. This is a basic layer of CNN used for abstraction purposes in which the latent components are inseparable. [15]

Dilated Convolution Layer

The dilated CNN layer has been used on our MRI images to patch one hyper-parameter to our convolutional layer by inserting zeros between our filtered elements. Dilated CNN is a technique which expands the input by inserting holes which means it skips the pixels to cover a larger area of our images.[16] (l-1) parameters are skipped in the kernels so maximum input will be covered without the use of pooling. The main aim of applying these in our Tumour dataset is to cover more information about the structure of tumours, which in turn helps in segmenting the types of tumours. 1-Dilated CNN offers a more field view of the image with less computational power and input. [16] This method doesnt spoil the order of the dataset and inputs it in the same order provided by the developer.

Pooling

Pooling is a very important concept used in Convolutional neural networks (CNN). It lowers the computational power used in the Convolutional layers.[15] In the concept of pooling, Lp pooling provides better generalisation as compared to other types of pooling in convolutional neural networks. Mixed pooling is known as the combination of max pooling and average pooling. Mixed pooling is implemented when you want to stay safe from an overfitting model. It addresses a very common problem when it comes to Data science algorithms. When we are training a dataset, the major problem is Overfitting if the model is overfitted it gives very inaccurate results which we want to avoid. Spectral pooling is used to preserve more and more information by reducing the distribution of dimensionality by cropping the input of the frequency. This method is efficient with the help of Matrix truncation and it helps to reduce the computational costs while running the CNN Model while employing the FFTs for Convolutional layers. Spatial Pyramid Pooling is done to generate fixed-length representations of the images regardless of their input sizes this helps us to train the model efficiently. This is different and much more efficient than the other pooling functions as it increases the accuracy of our model. In the formula below nh is the height of the feature map, nw is the width of the feature map, nc is the number of channels in the feature map, f is the size of the filter, and s is the stride length.[28]

(nh - f + 1) s x (nw - f + 1)s x nc

Rectified linear unit (ReLU)

Rectified linear unit (ReLU) is a negative function that cuts off the negative part to absolute zero and it retains the positive part. ReLU works better than most of the functions and is the most optimum way to deal with our image datasets like MRI images. Different types of ReLU functions which are used in the dataset are Leaky ReLU, Parametric ReLU, and Randomized ReLU. In our type of problem, Randomized ReLU is the best suited and we have successfully implemented that in the CNN Layer. As we are going to use the CNN model to improve the accuracy of testing in Extreme gradient-boosted Decision Trees (XGBoost) Randomized ReLU function is better to work with and it gives us optimum results compared to other functions of ReLU. As the name suggests, Randomized ReLU creates random variants of samples in the data and uniformly distributes them among the training data to ensure that the testing goes smoothly and efficiently. [15]

Global Average Pooling Layer 2-D

The Global Average Pooling (GAP) layer is an improved version of the CNN-GAP method. It is used when too many parameters are connected in the traditional CNN. It is similar to the Max Pooling operation in the traditional CNN model. It is a special rectangular matrix which is different from the Max Pooling operation but the operations are pretty similar to the standard Max Pooling Operation. The working of the GAP layer is it considers the size of the output feature map before the GAP operation h x k. Several Average pooling filters are created first then the GAP filters are the same as the output feature map. [20]

Softmax

Softmax Layer is used as a classification function widely used in pattern and image recognition problems. It is used to convert the output of the Global Average Pooling Layer to a precise result with a probability distribution. Softmax layer is used to normalise our result as it is in 1-D array form. The softmax layer converts the output into a 1-D vector form to make it readable for the model which we are using to fit the algorithm precisely. This gives us high accuracy of the model we are trying to run. [20]

3.4.2 Extreme Gradient Boosted Decision Trees (XGBoost)

Extreme Gradient Boosted Decision Trees (XGBoost) is a tree-boosting algorithm and it is efficient in providing accuracy for desired models with a larger learning database. This method is used to improve the previous decision trees in the next tree-based structure making it a very optimised structure to exist. Decision Trees are sometimes prone to making the model overfitted thats when XGBoost is used to make feature tuning and improve the accuracy with the help of achieving low variance and low bias. These features of the XGBoost Algorithm make it a good choice for our Project Brain Tumour Classification. Here we are using XGBoost as an algorithm that boosts accuracy over the fitted model of CNN because both CNN and

XGBoost have Multispectral Data as we are performing Softmax. The flow chart on how the XGBoost model works is shown below. Features of XGBoost include Regularised learning, Gradient tree Boosting, Shrinkage and Column Subsampling. Regularised learning is used in avoiding the overfitting of the algorithm. It helps to smooth the weights to improve accuracy. Gradient tree boosting helps in the optimization in an additive manner. XGBoost has a faster execution speed than other algorithms. The Model performance of XGBoost is also more efficient than other algorithms. Block Compression and Block Sharding are used in XGBoost. Time complexity analysis is also done by XGboost as it is very important for model accuracy. XGBoost also relies on the GlobalAveragePooling2D Model which is defined in 2.4.1.5 above and due to this layer, it doesnt overfit as you can see in figure 6.[22]

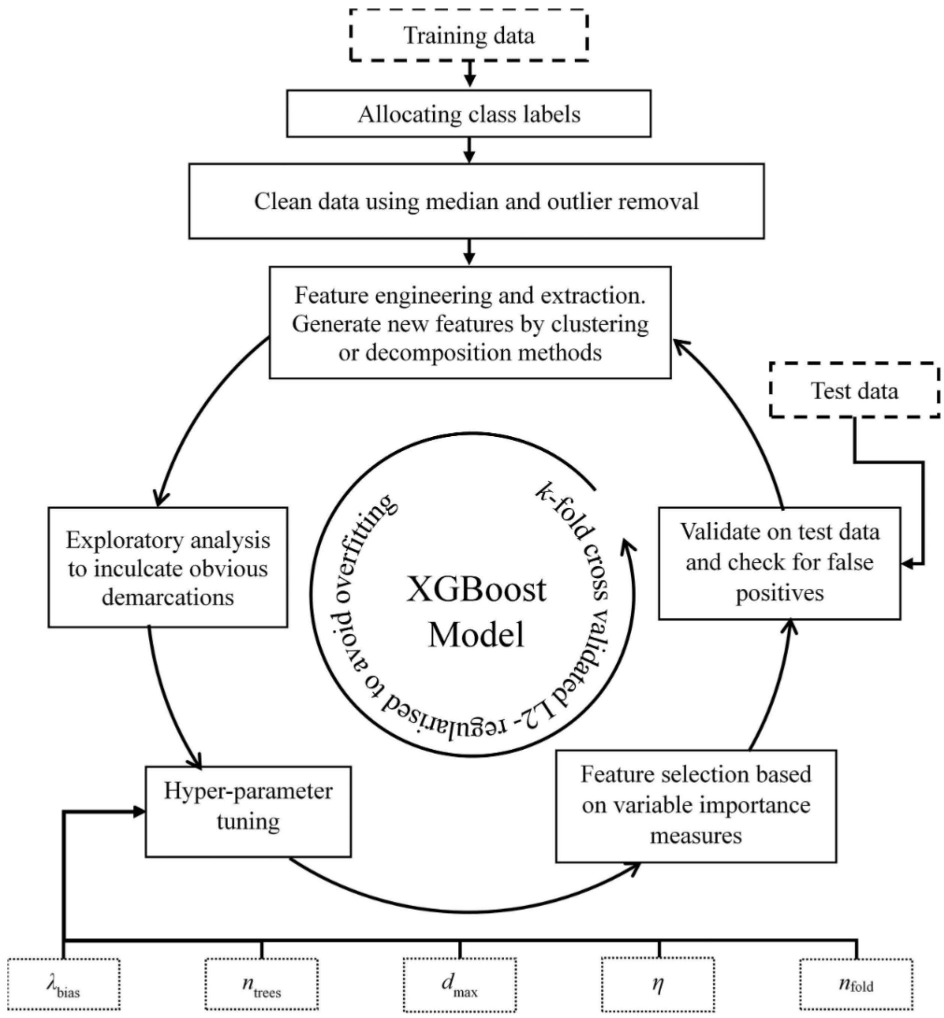

Figure 3.3: Extreme Gradient Boosted Decision Trees

3.5 Implementation of Convolutional Neural Networks (CNN) and Extreme Gradient Boosted Decision trees (XGBoost)

- We imported the libraries that we are going to use for the dataset. We have loaded libraries like Pandas, NumPy, Matplotlib, Pymatreader and Tensorflow.
- We have used the Dataset which is split into 4 archives(.zip) files and loaded the dataset using the Pymatreader, we used to Read functions to read the image data which contains 3064 Magnetic Resonance Images (MRI).
- We have split the data into 4 parts for better to make a better structure of images and it will be easy to use the images from there on.
- Next, we created a Class named Brain Tumour which we are going to use for further processes of dealing with the data. In the class Brain Tumour we are going to define functions to Resize and Reshape the data into arrays, perform Data augmentation by creating a data augmentation function, perform the train-test split of the data and define a function containing the model into it. In Simple words, we are creating a single class and defining functions inside it to perform all the operations of CNN within that class and using that same class in the Extreme Gradient Boosted Decision Trees (XGBoost) as well.
- In Class Brain Tumour we have defined the variables epoch, optimizer, loss, batch size and the dataset folder as well which we created by unzipping MRI images.
- Since the images are not labelled with the type of Tumour it contains, we are going to label the images with the help of classes. We have 3 types of Tumour labels which are assigned to the images: meningioma, glioma, and pituitary.
- We defined a function named collect feature labels and we patched both the images and label files into one file to assign labels to the images.
- In the same function, we used resizing using the cv2 package to resize the images into the ideal size we want and we also converted the images variable into a float datatype.

- Using the colour function in cv2 we converted all the images colour to a gray colour scale.
- Data augmentation is done to the dataset by performing steps like rotation and flipping (Horizontal and Vertical).
- Augmented images of both dataset images and labelled images are then reshaped using the np function as they are in the arrays. Reshaping is done because we want our dataset in a 2-D array.
- The variable containing the labels array is then converted into a categorical variable.
- Then we perform the train test split of the data while merging the data and labels and then splitting them randomly.
- In the compile function, we have compiled the data and used the optimiser for better accuracy.
- In the Function Model, we have called both the train and test data (self) and we have used the Dropout method, GlobalAveragePooling2D and also SoftMax activation techniques using the Tensorflow package and Keras library to improve the accuracy of the algorithms.
- We have also loaded the weights file which will be further used in Extreme Gradient Boosted Decision Trees (XGBoost) in the same Model function in Class Brain tumour.
- To run the model, we have created a variable called Brain Tumour obj and then called the class Brain Tumour with 25 epochs, brain tumour dataset and category crossentropy loss type.
- Category cross entropy is a loss function which is used with Softmax in our model which will train on the CNN model as a multi class classification.
- Now we collected Feature labels from our newly created variable Brain Tumour obj and plotted some data images for checking whether the flipping and transformation are done efficiently or not.

- Finally, we called the model, compile and fit which were created in a single class above and completed the training of the Convolutional Neural networks (CNN) model with 25 Epochs.
- Epochs were completed with the Convolutional Layer and ReLU.
- We used the testing features to gain our accuracy for the CNN Model.
- The CNN model obtained was saved in a file with the extension as brain tumour model.h5 as the same model will be used in XGBoost.
- Brain tumour model.h5 was assigned a variable for using it in XGBoost and it was read successfully.
- Then we used that variable and also loaded some weights and used GlobalAveragePooling2D as a layer we ran the XGBoost
- Now we have created a variable known as X train features and put the previous model data inside which will be used for training the model for XGBoost and we are again using it with the help of a multiclass softmax function.
- Also, we have created an X test feature variable to do feature testing for gaining the accuracy of the Extreme Gradient Boosted Decision trees XGBoost model.

CHAPTER 4

Results

In the above project, we have successfully implemented 2 algorithms Convolutional Neural Networks (CNN) and Extreme Gradient Boosted Decision Trees (XGBoost) which are successfully performing Brain Tumour Classification using Image Processing and Classifying our dataset into 3 Types of Tumour Meningioma Tumour, Glioma Tumour and Pituitary Tumour. We have implemented the project using the 3064 Image dataset of various kinds of tumours. As this is an image dataset, we already know that there is no Exploratory Data analysis that can be done on the dataset. For example, we cannot compare the features and variables using histograms, plots, graphs, line charts, and scatterplots. The results are in the form of plots which show the successful processing of images.

4.1 Plot showing types of images in the dataset

As shown in the figure 4.1, we have successfully loaded the image dataset and also performed Data augmentation on the dataset as it clearly shows that we have already merged the Labels.

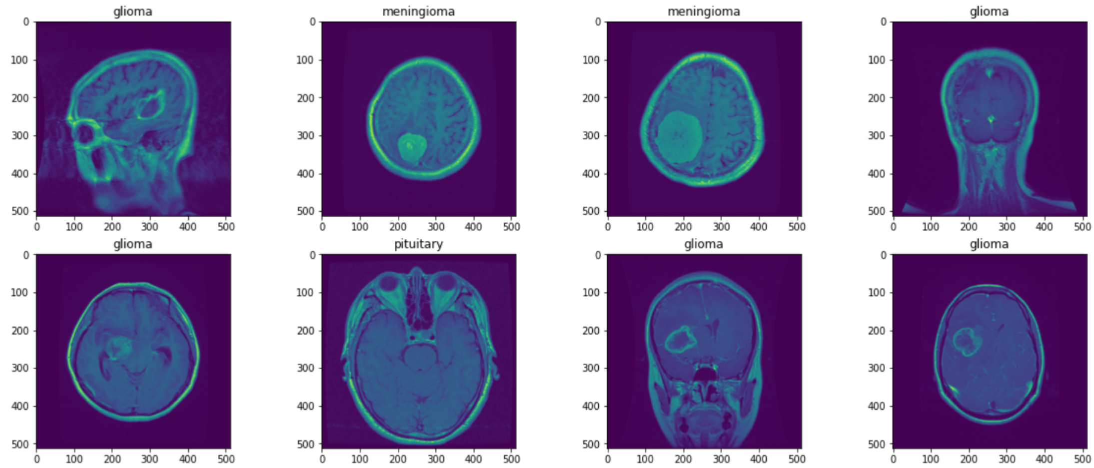

Figure 4.1: Plots of the image dataset

4.2 Plot showing the collection of feature labels and using RGB colour as Grayscale.

As we can see above in the figure 4.2, We converted the color of the images above to grayscale colour and we have also done data augmentation and cleared some noise from the images which further enhances the quality of the images.

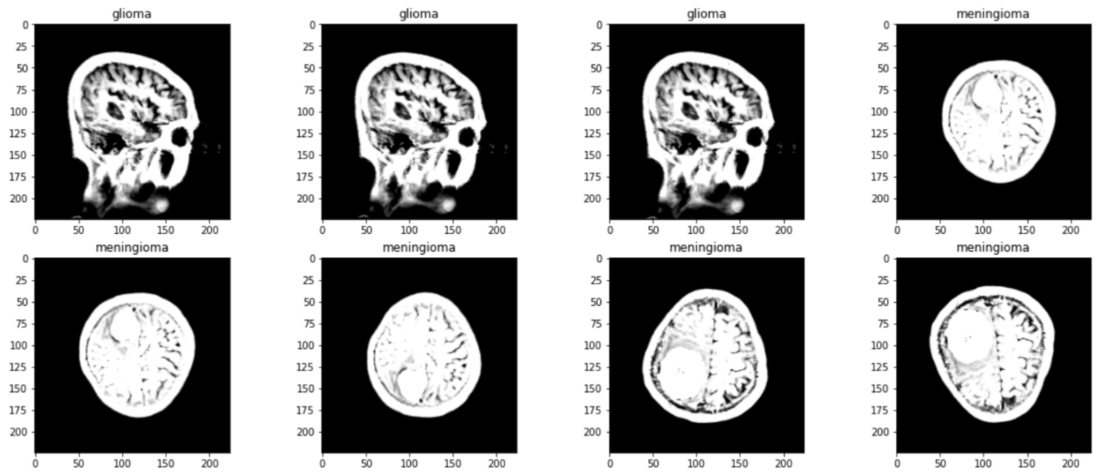

Figure 4.2: Plots of Grayscale Images

4.3 Plot showing Images after performing Image augmentation

In the above figure 4.3, we can see that Image augmentation has been performed in which you can see reshaping and minor rotations have been performed to improve and position of inner layers of the images which will be later on beneficial for the algorithms to have better accuracy.

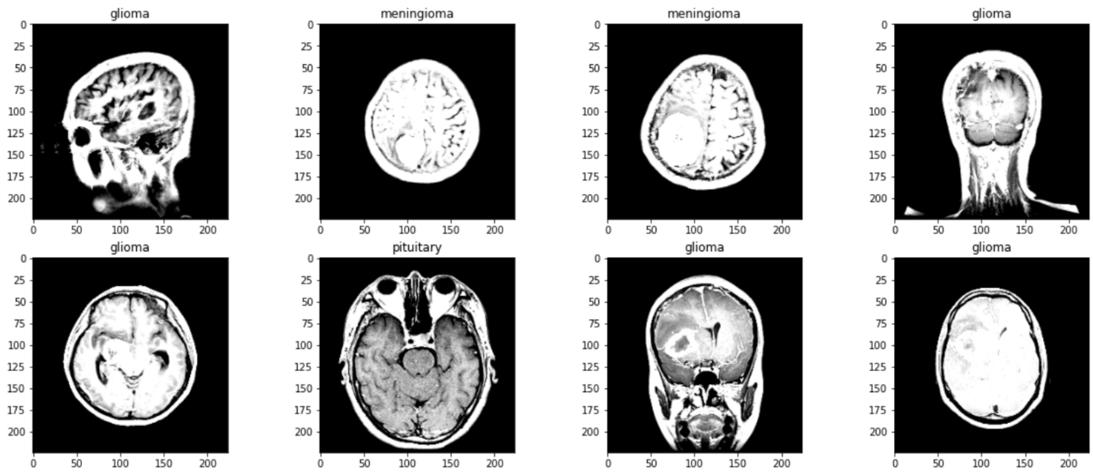

Figure 4.3: Plots of after image augmentation

4.4 Legend plot showing a comparison between Loss-Validation Loss and Accuracy-validation Accuracy

The above figures 4.4 and 4.5 gives you an overview of the validation loss-loss and validation accuracy-accuracy comparisons in which you can see the distribution of validation loss-loss and validation accuracy-accuracy when we were training the data during the runtime of our whole 25 epochs. Here you can also check the data was never overfitted as the validation accuracy and accuracy as the epochs were well within 100 percent level and also the behaviour was stable after it reached the desired level while training the data. Also, we can see that the validation loss and loss are almost and the same level and decreasing constantly as the validation accuracy is increasing. This shows us the Data is well-trained using the CNN algorithm.

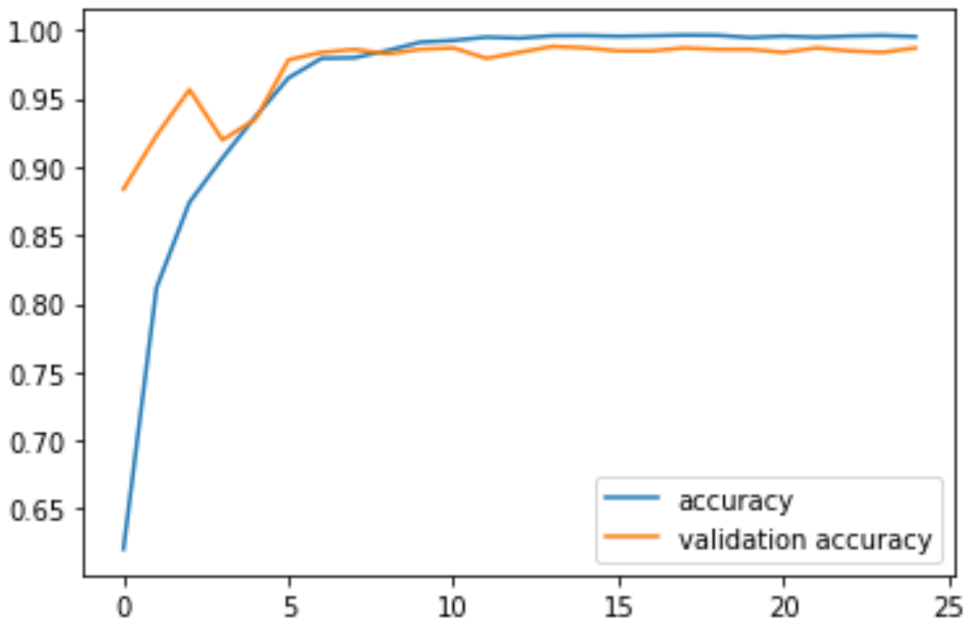

Figure 4.4: Comparison between validation accuracy-accuracy

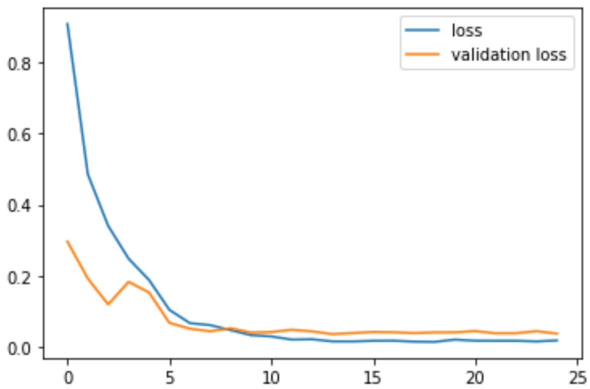

Figure 4.5: Comparison between validation loss-loss

4.5 Convolutional Neural Network (CNN) Confusion Matrix and Accuracy

In the Figure above we can see that, we have successfully implemented the CNN algorithm. As you can see that the accuracy score of the CNN model is 98.6 percent. Hence, we can say that we have successfully trained and tested the data. Our main aim in this project was to improve the accuracy of the Convolutional Neural Networks (CNN) and find the best algorithm based on Deep learning and Machine learning methods. This is why we applied Extreme Gradient Boosted Decision trees (XGBoost) after this to check whether it is giving a better accuracy than the Convolutional neural network or not.

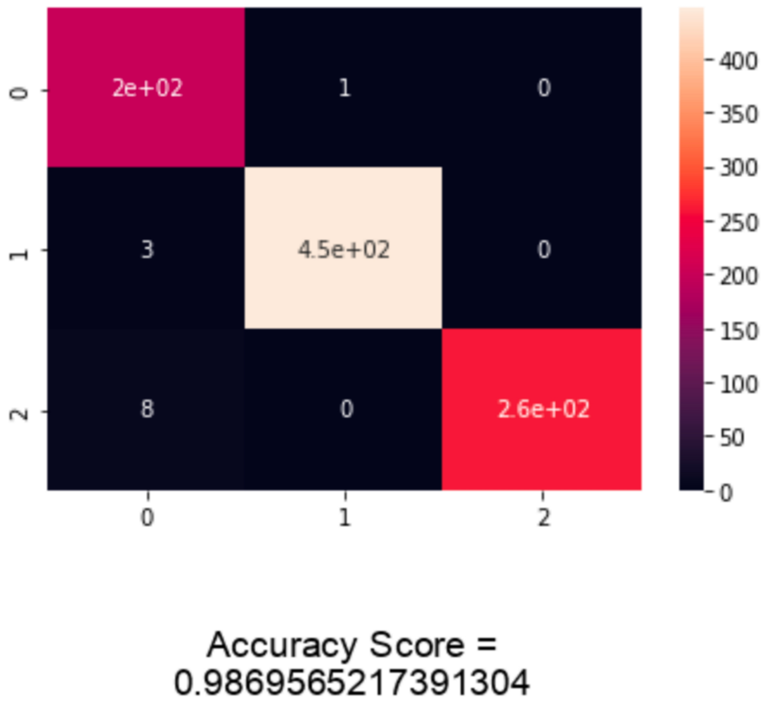

Figure 4.6: Convolutional Neural Network Accuracy score

4.6 Extreme Gradient Boosted Decision Trees (XGBoost) Confusion Matrix and Accuracy

As you can see from the Figure below, after applying the Extreme Gradient Boosted Decision trees (XGBoost) over the layer of CNN with the addition of GlobalAveragePooling2D our Accuracy has now been Boosted or increased to 99.45 percent which is a staggering change over the previous model and also XGBoost is the most efficient while working on an Image Dataset.

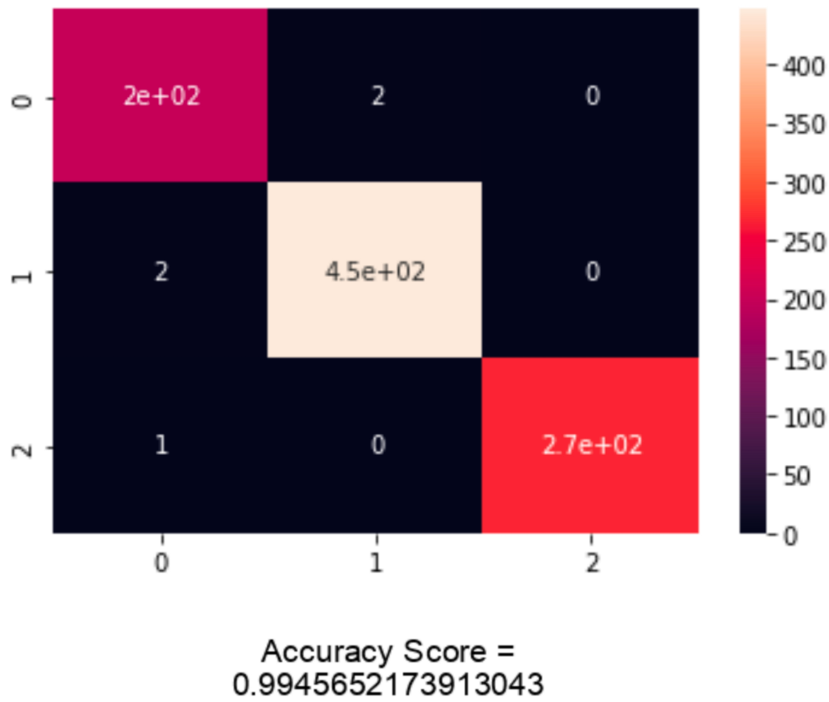

Figure 4.7: Extreme Gradient Boosted Decision Tree Accuracy Score

CHAPTER 5

Conclusions

Our objective behind doing this project was to compare two of the best modern-day algorithms based on Deep Learning and to find the best method which can segment and detect Brain tumours in an individual accurately and automatically. The motivation behind taking up this project was to help contribute towards a noble cause for the betterment of patients who die from tumours because they are not detected on time and also to help medical science devise a better algorithm for segmenting different types of Brain tumours. Our dataset has data from 233 patients and 3064 MRI Images in it. We were successfully able to devise the algorithm with the perfect accuracy score of 99.4 percentage over the traditional methods which showed less accuracy in solving such serious problems. Additionally, this technique uses modern-day Neural network and Machine learning algorithms and improves it to provide more accuracy. Also, we were able to establish that this method has very less consumption of computational power over the traditional methods. The Challenge that we faced during this whole project was while implementing the Extreme Gradient Boosted Decision trees (XGBoost) on the original dataset we received containing .jpeg files where it creating an n-dimensional array and reducing that array to a 1-D array was resulting in a heavy loss of pixels for the images as it was getting scattered. Then while researching and surfing through more and more research papers and particularly Kaggle we found this Dataset with MAT files which were the perfect MRI images and also were perfect to work on.

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