



NEURAL NETWORK-BASED APPROACH FOR CLASSIFYING BRAIN TUMORS USING MAGNETIC RESONANCE IMAGING

¹Nwobodo-Nzeribe Nnenna Harmony, ²Kwubeghari A.

^{1,2}Department of Computer Engineering, Faculty of Engineering, Enugu State University of Science and Technology, Enugu State, Nigeria.

¹Corresponding Author Email: kwubeghari@gmail.com

This research presents a neural network-based approach for classifying brain tumors using magnetic resonance imaging (MRI). The primary objective is to develop a model capable of accurately detecting different classes of primary brain tumors. Review of relevant literature revealed that no existing solution captures all the primary brain tumor classes comprehensively. To address this gap, data collection was conducted, specifically targeting the primary brain tumor classes, including Medulloblastomas, gliomas, meningiomas, and pituitary adenomas tumors. Additionally, healthy brain tumor data was obtained from the Kaggle repository and integrated with the other classes for feature extraction. The extraction process employed a static and dynamic approach to convert the data into a compact feature vector. The feed-forward neural network algorithm was then trained using the extracted feature vector to generate the brain tumor classification model. The model's performance was evaluated using metrics such as accuracy, precision, and cross entropy through tenfold validation. The average error rate across the iterations was found to be 0.009814, indicating a low rate of misclassification. The average precision and accuracy were both determined to be 96.32%. Furthermore, a comparative analysis of the developed model against other classification approaches revealed an improvement of 3.76%. This suggests that the proposed neural network-based approach is more effective in accurately classifying primary brain tumors compared to existing methods. However, the limitation of the model is the issues of unbalance dataset which may result to classification bias in some cases. However recommendation using data augmentation or Adaboost algorithm can be used to address the probe in future research.

Keywords: Heart Disease; Brain Tumor, Feature Extraction, Feed-forward Neural Network

1. INTRODUCTION

Due to economic reasons, such as poverty, and the high cost of modern hospital treatments, many African regions rely on rural health care centers as an alternative to hospitals for accessible healthcare. However, these medical centers often lack the necessary facilities for diagnosing complex and delicate disease like brain tumors, due to the high cost of diagnostic machines. In cases where some centers do have diagnostic systems, they may lack comprehensive capabilities, which hamper accurate detection of brain tumors. Consequently, the incidence of brain tumor cases continues to rise within African communities, as reported by the Mbi et al. (2017). This

challenge leads to issues such as late detection of brain tumors, misdiagnosis, and an increased risk to individuals within these communities to suffer brain tumor problem.

Another significant problem that arises from this challenge is the potential for human error during the analysis of brain tumor data by radiologists, as decision-making processes are often manual and limited to the interpretation of domain experts. To address these issues, several studies (Lugina et al., 2016; Virupakshappa and Basavaraj, 2018; Selvaraj and Dhanasekeran, 2015; Naveena et al., 2015; Manasavi and Chetan, 2020) have proposed various solutions. These studies have made significant contributions to knowledge by employing techniques such as artificial intelligence and image processing. However, none of these solutions have considered all the primary types of brain tumors. Brain tumors can be classified into two major classes: primary and secondary. Primary tumors originate within the brain, while secondary tumors originate from cancer that has spread to the brain (Camille, 2022). According to Aldape et al. (2019), primary brain tumors are the most devastating and carry high-risk implications if not detected early. Early detection of brain tumors is crucial for ensuring a high survival rate for patients. This paper aims to develop a model that can accurately detect brain tumor data using magnetic resonance imaging (MRI) and artificial intelligence techniques. By leveraging the capabilities of MRI and advanced algorithms, the proposed model intends to improve early detection of brain tumors, enabling timely intervention and improving patient outcomes.

2. LITERATURE REVIEW

Naveena et al. (2015) developed a brain tumor detection system using the back-propagation algorithm, a technique based on artificial neural networks. Their research focused on the detection and classification of brain tumors, achieving an accuracy of 79.02%. While the back-propagation algorithm was effective in this study, further investigations are needed to capture other classes of brain tumor. In Lugina et al.'s (2016) study, a comparative approach was employed to detect and classify brain tumors in MRI images. The researchers utilized region growing, fuzzy symmetric measure, and artificial neural network back-propagation techniques. Among the different artificial intelligence techniques compared, the neural network achieved the best result with an accuracy of 89.72%. This implies that neural network is better than fuzzy logic in solving the brain tumor classification problem. Virupakshappa and Basavaraj (2018) utilized a hybrid approach in their study, combining artificial neural networks and feed-forward back-propagation algorithms for tumor detection and classification. They achieved a notable accuracy rate of 92.56%. While this research demonstrated promising results, further investigations are required to explore other classes of brain tumor, especially the primary type which Aldape et al. (2019) posited is on the rise.

Selvaraj and Dhanasekeran (2015) developed a brain tumor detection system by combining feed-forward neural networks, the k-Nearest Neighbor (k-NN) algorithm, and segmentation-based image processing. The feed-forward neural network achieved an accuracy of 83%, while the k-NN algorithm achieved 67%. The study showcased the potential of these techniques, but there is still a need for further improvements to enhance the accuracy and reliability of the detection system. Meena and Murall (2017) conducted a review and validation of different machine learning algorithms used for brain tumor detection, with a specific focus on magnet resonance images (MRI). The study identified neural network-based clustering as one of the

current trends in the field. However, the authors suggested that further research utilizing machine learning techniques could improve the diagnosis process for brain tumors using MRI.

Muhammad (2018) improved the study on brain tumor diagnosis using MRI by applying gray-scaled segmentation and deep neural networks (DNN). Although the results were promising, however, DNN requires high volume of data, which may not be available at all times, to guarantee unbiased classification success. Parasuraman and Vijay (2019) utilized an ensemble classifier consisting of Extreme Learning Machine (ELM), support vector machine classifier, and Gray Level Co-Occurrence Matrix (GLCM) for brain tumor MRI segmentation and classification. The achieved accuracy was 91.5%, indicating the effectiveness of the approach. However, the researchers acknowledged the potential for further enhancements in the classification process. Neha and Rashmi (2013) developed an automated system for the detection and extraction of brain tumors from MRI images using a fuzzy clustering-based technique. The system achieved an accuracy of 77.5%, which is considered good but still requires improvements to enhance its overall performance. Shahariar et al. (2019) applied template-based K-means and improved fuzzy C-means (TKFCM) clustering algorithms for the automatic detection of brain tumors in MRI images. Although the approach demonstrated success, the authors suggested further improvements using machine learning to enhance the accuracy and reliability of brain tumor detection. Manasavi and Chetan (2020) focused on the application of brain segmentation techniques using edge detection algorithms for the detection of brain tumors from MRI images. The study achieved an accuracy of 61%. However, further research is needed to improve the results and enhance the reliability of the detection system using machine learning.

Sukanta et al. (2017) employed a combination of the watershed algorithm, K-means clustering method, and MATLAB for brain tumor detection from MRI images. The study utilized preprocessing, segmentation, and morphological operation steps to detect brain tumors, achieving a false alarm rate of 17%. The researchers emphasized the need to minimize the false alarm rate through future research and enhancements. Harshini et al. (2019) utilized convolutional neural networks (CNN) and MATLAB for brain tumor detection. The study demonstrated the application of CNN algorithms in MRI images, but the high cost associated with implementing this approach needs to be addressed to ensure wider accessibility and adoption. Sahil and Kalpesh (2015) introduced non-negative matrix factorization (NMF) for brain tumor detection, employing various image segmentation techniques. The study focused on early detection of brain tumors in MRI images, and the researchers recommended further improvement by incorporating artificial neural networks (ANN) into the methodology. Wadhai et al. (2018) employed deep learning techniques, including convolutional neural networks, recurrent neural networks, and fuzzy logic, for the classification of brain MRI images to detect cancer. Although the results were promising, the high cost of implementation remains a challenge that needs to be addressed to ensure wider adoption of these techniques. From the review of literatures, many works have been presented which develop models for the classification of brain tumor, however solution have not been obtained to the researches knowledge which considers all the classes of the primary brain tumor such as Medulloblastomas, gliomas, meningiomas, and pituitary adenomas tumor and develop a model which can classify them. Hence this paper proposes to develop a model which considers these classes of brain tumor and classify, for the correct and early diagnosis of brain tumor.

3. METHODOLOGY

The methodology of this study involved several key steps. To start with, MRI data was collected from Parklane Hospital Enugu, Nigeria, serving as the primary source of data for the study. The collected data included MRI scans of patients with brain tumor cases. Next, the collected MRI data underwent a feature extraction process through static and dynamic extraction techniques to convert the raw MRI data into a more compact feature vector representation. The feed forward neural network was trained using the collected MRI data and the corresponding brain tumor labels to develop a brain tumor detection model. To evaluate the performance of the developed model, an experimental approach was adopted. The model was tested on real-life data from patients to assess its accuracy and effectiveness in detecting brain tumors. The evaluation process involved comparing the model's predictions against the ground truth data to determine its reliability and performance. Furthermore, the developed model underwent a validation process to ensure its generalizability and applicability. The model's performance was tested on additional data from different patients to validate its effectiveness in detecting brain tumors in diverse scenarios.

3.1 DATA COLLECTION

The primary data source for this study was Parklane Hospital Enugu, from which MRI data of patients with primary brain tumor was collected. The sample size consisted of MRI data from 1225 patients under the age of 45 who had brain tumor cases, which spans across the various types of brain tumor. 600 patients provided data for gliomas tumor (which is a type of tumor that arises from the glial cell), 115 patients provided data for meningiomas tumor which is developed around the spinal cord, 200 patients provided data of Medulloblastomas tumor which grows from the cerebellum. 310 patients provided data which of pituitary adenomas tumor which grows from the pituitary gland. Each patient provided 15 samples, resulting in a total of 18375 samples obtained from the hospital. To supplement the primary data, a secondary source was utilized, namely the Kaggle repository, which provided an additional 4,240 MRI samples of healthy tumor. The training dataset used for the study encompassed a total of 22,615 MRI samples containing brain tumors. The distribution of these collected samples is depicted in Figure 3.1, while the corresponding attributes associated with the data can be found in Table 3.1, while the MRI data was reported in figure 1.

Table 1: Data description

S/N	Attributes	Description	Data type
1	Patient ID	This is a unique identifier for each patient health record	String
2	Age	The age of the patient at the time of the MRI scan.	Integer
3	Gender	The gender of the patient (male or female).	String
4	Tumor Location	The specific location of the brain tumor within the brain (e.g., frontal lobe, temporal lobe, etc.).	String
5	Tumor Size	The size or dimensions of the brain tumor, typically measured in millimeters.	Numeric

6	Tumor Type	The classification of the tumor MRI captured which can be either Medulloblastomas, gliomas, meningiomas, healthy tumor or pituitary adenomas tumor.	String
7	Tumor Grade	The grading system used to determine the aggressiveness of the brain tumor	String
8	Image Intensity Values	The pixel intensity values obtained from the MRI images, which represent the different tissue densities and structures within the brain.	Numeric
9	Tumor Characteristics	Features of the brain tumor, such as shape, texture, or presence of necrosis.	String
10	Diagnosis	The category of brain tumor diagnoses such as	Nominal

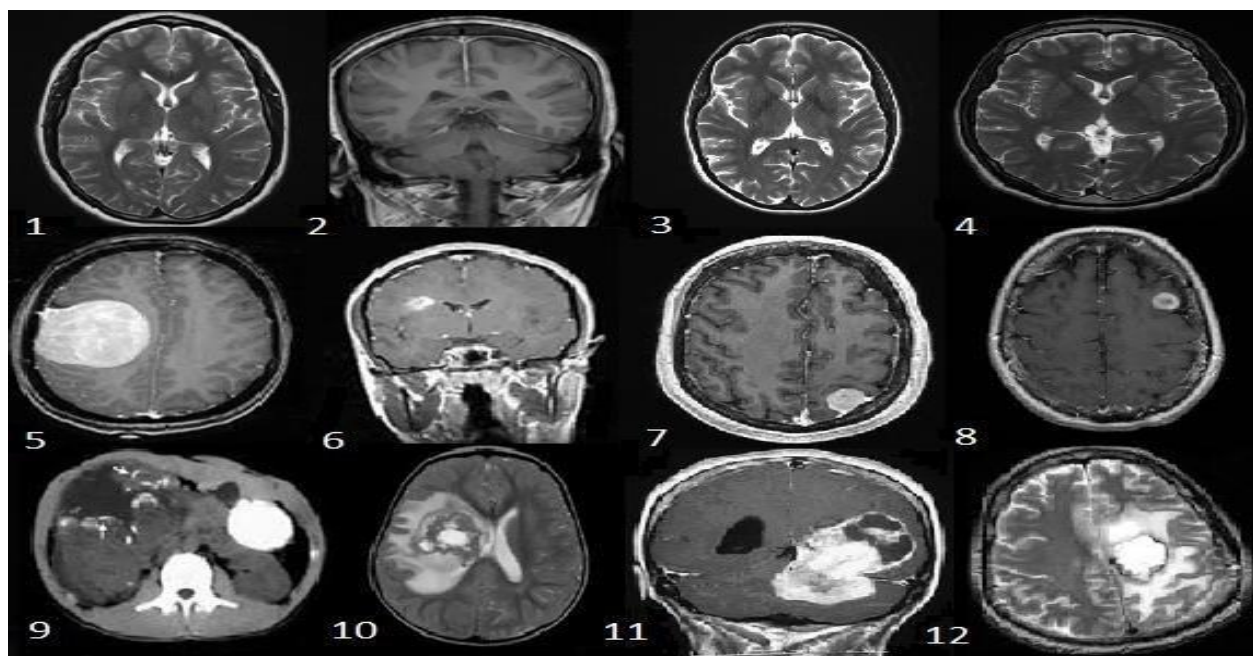


Figure 1: The MRI data

3.2 DATA EXTRACTION

In the study by Saxe and Berlin (2015), a data extraction process was employed to convert the MRI data of brain tumors into a statistically compact feature vector. This process involved utilizing both static and dynamic approaches. The goal of this extraction process was to condense the MRI data into a concise set of features that could be used for training the artificial neural network model developed in the subsequent section. The static approach involved extracting features from the MRI images that remained consistent across the entire dataset. These features could include statistical measures such as mean, standard deviation, or texture descriptors derived from the grayscale intensities of the brain tumor regions. In contrast, the dynamic

approach aimed to capture the temporal or spatial variations within the MRI data. This could involve techniques such as time-series analysis or spatial feature extraction, where changes in the tumor characteristics over time or across different regions of the brain were considered. By applying the static and dynamic approaches, the MRI data was transformed into a compact feature vector that could effectively represent the relevant information for training the artificial neural network model. This feature vector would then serve as the input for the subsequent stages of the study, such as model development, training, and evaluation.

3.3 NEURAL NETWORK MODEL

To train the data, feed forward neural network was adopted from Naveena et al. (2015). The model of the network is defined with the input as (x_n) , weights (w_{nj}) , activation function (θ_j) , and output (o_j) as in figure 2.

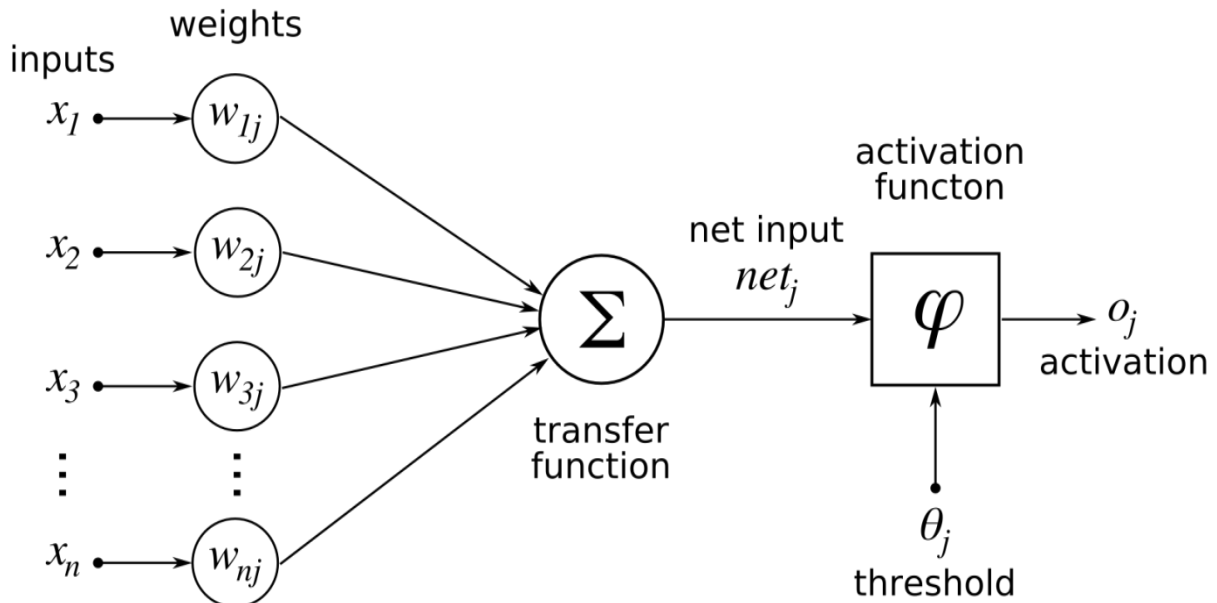


Figure 2: Neural network architecture

The figure 2 was used to model the feed forward neural network with multiple layers, including an input layer, one or more hidden layers, and an output layer. Let's denote the input to the neural network as x_n , where n represents the index of the input. Similarly, the weight connecting the input (x_n) to the neuron in the j th node of the next layer will be denoted as w_{nj} . The input layers which receives the input x_n , from the dataset and propagated forward to the subsequent hidden layers to take the weighted sum of inputs from the previous layer as:

$$z_j = \Sigma(x_n * w_{nj}) \tag{1}$$

After obtaining the weighted sum in equation 1, the neuron applies hyperbolic tangent (tansig) activation function θ_j to introduce non-linearity and produce the output o_j .

$$o_j = \theta_j(z_j) \tag{2}$$

The equation 2 was trained with back-propagation algorithm (Naveena et al., 2015) to learn the feature vectors and then generate the reference classification model which can classify any of the five classes of brain tumor in the output layer as shown in the figure 3;

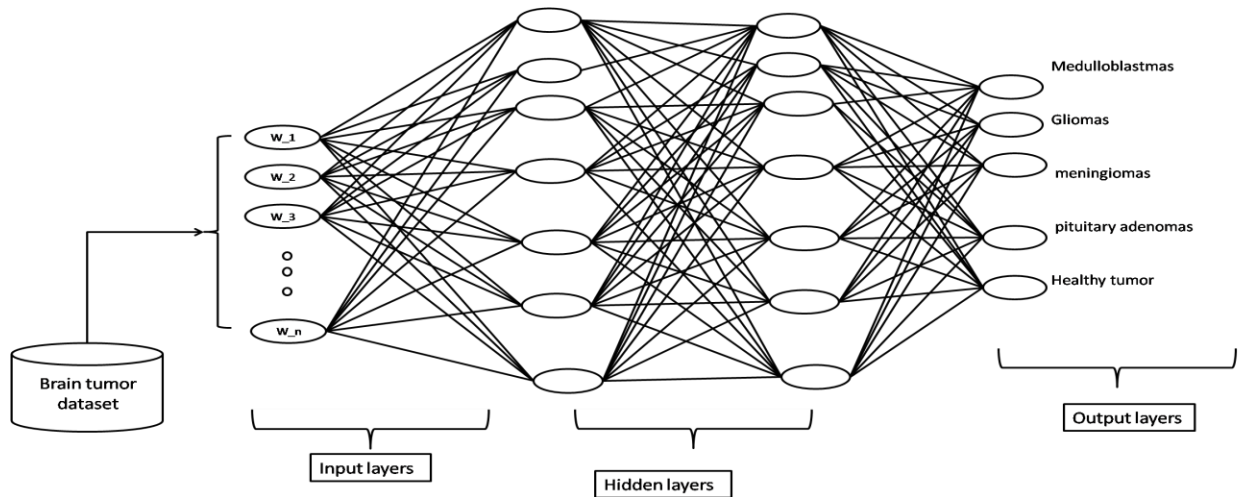


Figure 3: The Feed forward neural network architecture

The figure 4 presents the flow chart of the feed forward neural network training process to generate the classification model for brain tumor. The model was implemented in Matlab using neural network toolbox, which was loaded with the training dataset splitted into training, test and validation sets in the ratio of 70:15:15 and then trained with optimization toolbox (back-propagation algorithm) to generate the classification model for brain tumor detection. During the training, the performance of the model was evaluated at various epoch and then results achieved after validation were reported in the next section.

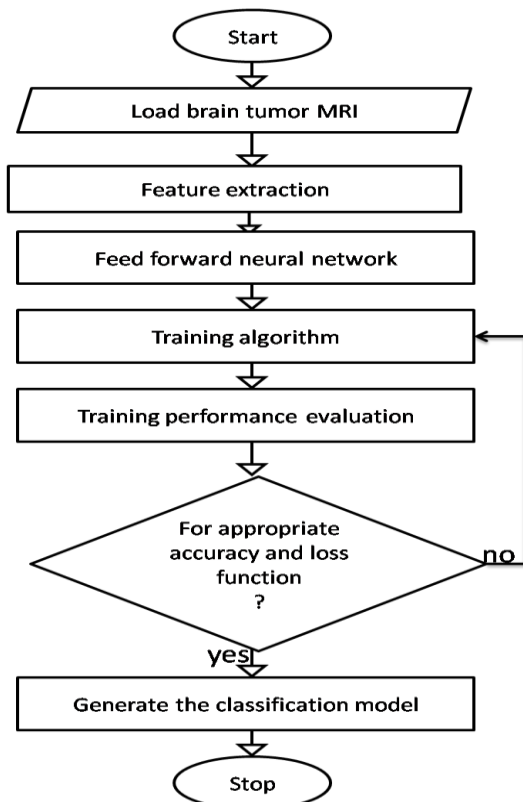


Figure 4: Flow chart of the feed forward neural network training

4. RESULTS AND DISCUSSIONS

This section presented the result of the neural network training for the classification of brain tumor. The training process was evaluated considering cross entropy which was used to measure the error which occurred between the actual value and predicted value during the training process as reported in the figure 5. This was used to quantify the dissimilarity between the predicted probability distribution and the actual distribution of the classes.

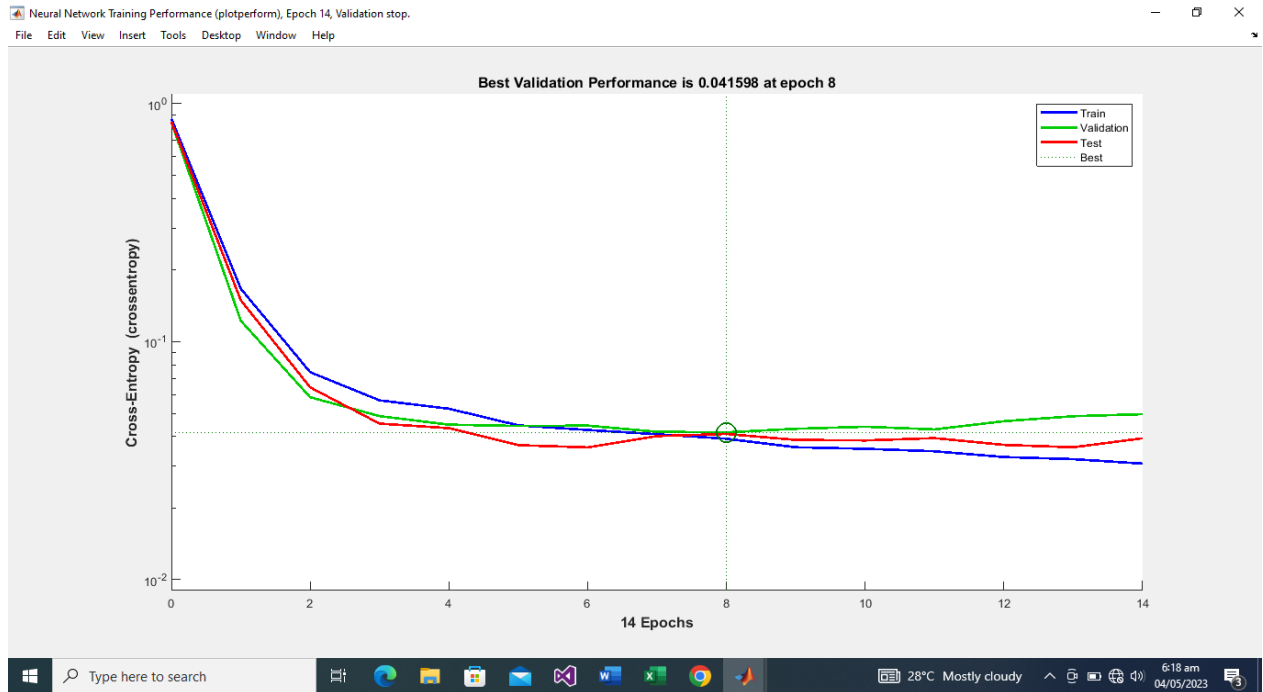


Figure 5: The cross entropy of the brain tumor classification model

From the entropy result in figure 4, the error reported after validation is 0.041566 and at epoch 8. This indicates that, on average, the neural network's predictions are relatively close to the true labels for the given set of brain tumor data at that particular epoch. In addition, it implies that the neural network has learned to make more accurate predictions of brain tumor, leading to a reduced difference between the predicted and true distributions of the classes. The next result utilized confusion matrix to evaluate the brain tumor classification model. The confusion matrix is a table that provides a detailed breakdown of the classification model's predictions and the actual labels for each class of the brain tumor data. It helps to assess the model's performance by showing the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). From this information, various metrics such as precision, accuracy, specificity and sensitivity were reported as in figure 6;

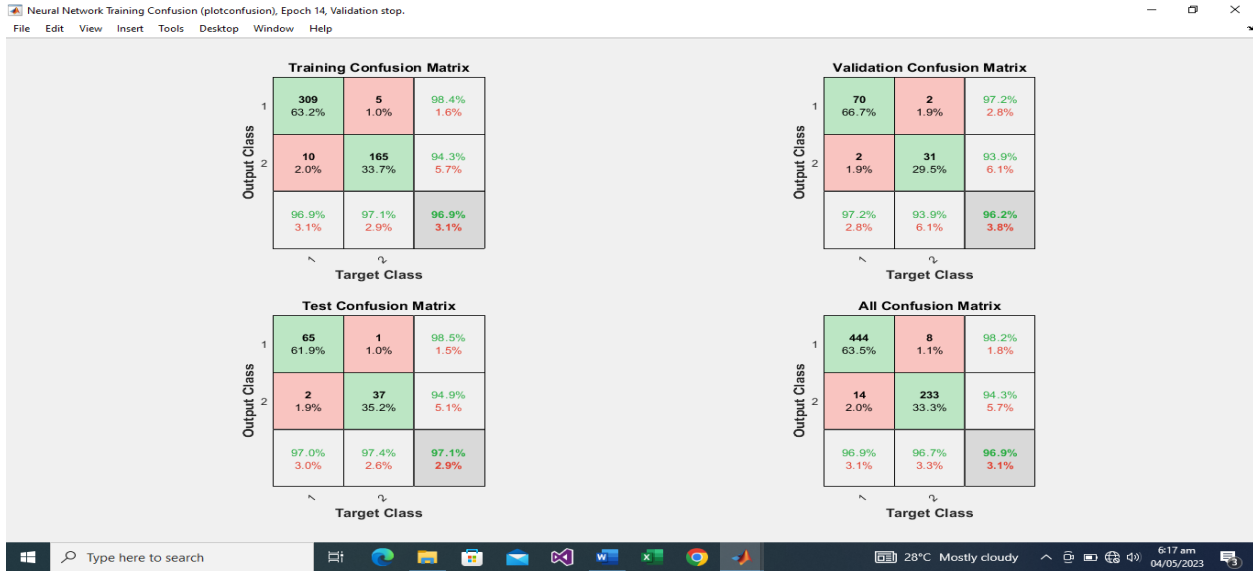


Figure 6: Confusion matrix

The confusion matrix in figure 6 provides a detailed breakdown of the brain tumor classification model's predictions, showing a true positive rate (TP) of 33% and a true negative rate (TN) of 63%. These values indicate that the model correctly identified 33% of the brain tumor cases and 63% of the non-tumor cases, respectively. Furthermore, the confusion matrix reveals a false positive rate (FP) of 1.1% and a false negative rate (FN) of 2%. The false positive rate signifies instances where the model incorrectly classified non-tumor cases as tumor cases, while the false negative rate indicates instances where the model failed to detect the presence of a tumor. The accuracy also reported 96.9%, precision reported 96.9%, sensitivity reported 96.2% and specificity reported 94.3%. While the evaluation parameters reported high scores, it's important to consider the implications of TP and TN. Due to the result recorded which is not very high for both and also considering the delicate nature of the problem under study, it is important to note that the model in some cases may lead to unnecessary treatments, or missed diagnoses. The reason for this was due to the imbalance nature of the dataset collected. However, to address this problem, the tuning of the neural network hyper-parameters or the adoption of data augmentation techniques can be used to generated more artificial dataset and balance the data classes. Ten fold cross validation techniques was used to validate the performance of the classification model developed and the result was reported in table 2.

Table 2: Validation result of the filter with GDA

S/N	Error	Precision (%)	Accuracy (%)
1	0.041566	96.9	96.9
2	0.007574	97.2	97.5
3	0.004575	97.5	96.8
4	0.007764	96.5	97.4
5	0.006587	95.9	94.7
6	0.003566	95.7	95.4
7	0.005686	95.7	94.4

8	0.008424	95.9	95.6
9	0.007835	95.4	94.4
10	0.004566	96.5	95.9
Avg.	0.009814	96.32	0.009814

The table 2 provided displays the results for various performance metrics across multiple iteration evaluation of the classification model. From the result, the average error rate across the iterations is 0.009814, indicating that, on average; the model makes incorrect predictions for approximately 0.98% of the cases. The average precision is 96.32%. Precision represents the percentage of correctly identified positive instances out of all instances predicted as positive. On average, the model correctly identifies approximately 96.32% of the predicted tumor cases. The average accuracy is also 96.32%. Accuracy is the overall percentage of correctly classified instances. In this case, it indicates that, on average, the model correctly classifies brain tumor cases and non-tumor cases with an accuracy rate of 96.32%. These results suggest that, on average, the model performs well in detecting brain tumor cases. It demonstrates a high level of precision and accuracy rates, correctly identifying a significant portion of both tumor and non-tumor cases. The error result further supports the model effectiveness in correctly classifying instances; however, it's important to note that the imbalance classes of the dataset may influence the replication of these results in practical. To further validate the results reported, a comparative analysis with other state of the art algorithms and the new brain tumor classification model was performed and presented in table 3;

Table 3: Comparative Analysis

Author	Technique	Accuracy (%)
Lugina et al.'s (2016)	Fuzzy	89.72
Virupakshappa and Basavaraj (2018)	Artificial neural networks and feed-forward back-propagation algorithms	92.56
Selvaraj and Dhanasekeran (2015)	Forward neural network	83.00
Naveena et al. (2015)	Artificial neural networks	79.02
Manasayvi and Chetan (2020)	Segmentation techniques	61.00
New system	New Feed-forward neural network	96.32

From the result reported, it was observed that the new brain tumor classification model reported better accuracy of 96.32% compare with the closest counterpart in Virupakshappa and Basavaraj (2018) who reported 92.56% with neural network. The percentage improvement achieved is 3.76%. However, the limitation of the new model developed is that the classification result for gliomas and pituitary adenomas tumor classification will be more reliable due to more training

data availability when compared to other brain tumor classes. However to address the problem, data augmentation or Adaboost approach is recommended to ensure equilibrium volume in the data classes.

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