JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

BRAIN TUMOR DETECTION USING ARTIFICIAL NEURAL NETWORK

Nura Abba Muhammad, Mustapha Ismail, Suleiman Salihu Jauro,
Department of Computer Science, Gombe State University, Nigeria.

Abstract

Brain tumors are abnormal growths or masses of brain cells that can develop from brain tissue or spread to other parts of the body. Diagnosis of brain tumors involves medical history evaluation, physical examination, imaging tests, and biopsy. In this study, an artificial neural network (ANN) model specifically Convolutional Neural Network (CNN) model was developed for brain tumor detection. The model was trained using a dataset of brain tumor images and evaluated using various performance metrics and has achieved high accuracy, precision, recall, and F1-score. The image preprocessing was done using TensorFlow (keras) to resize, augment the data and normalize it before feeding to the model. The feature extraction was performed using ReLU and then the extracted features were fed into the CNN model developed to detect whether there is tumor or not. The model successfully classifies both positive and negative cases, with detection accuracy of 0.9849, precision of 0.9846, recall data of 0.9828, and an F1-score of 0.9837. The confusion matrix analysis confirmed the model's performance, revealing low false positives and false negatives. These findings suggest that the CNN model holds promise as a valuable tool for assisting medical professionals in early detection of brain tumors.

Keywords: Brain tumor, benign, malignant and MRI

1.0 Introduction

The Brain is one of the most extremely complicated organs inside the human body that works with an extremely huge number of cells. Brain tumors increment when there is an unregulated division of cells that frames a sporadic. Brain tumor is one of the most deadly types of cancer infections. It has its high effects because it is very close to the main neuronal motor of the human being where every small defect can cost a lot. In recent years, both children and adults have lost their lives to brain tumors, one of the most terrible types of cancer [1]. Radiologists' interpretation and processing of MRI images takes a lot of time and is prone to inaccuracy [2]. Cancers that are mostly found in other places of the body that have spread can also cause brain tumors to enlarge [3]. The region of the tumor, the type of tissue it formed, its malignant or benign nature, and other factors all play a role in how a brain tumor is classified [4]. Tumors come in two different varieties: malignant and benign. A malignant tumor, on the other hand, is a particularly aggressive tumor that spreads from one place to another. A benign tumor is a slow-growing tumor that does not penetrate neighboring organs. The World Health Organization (WHO) assigns a brain tumor a grade between I and IV. While tumors in categories III and IV are always malignant and have a worse prognosis, cancers in categories I and II are thought to be slow-growing [5].

Thus, it is important to develop model that will aid in the early detection or alarming the possibility of the existence of brain tumor. It is a fact that early detection increases significantly the possibility of saving the life of patients by curing the disease. The treatments of cancer have greatly developed in recent times, especially in the early stages of infection. Possibilities of survival are very high for the patients receiving early treatments compared to the patients that don't have this prospect in the early stages of sickness.

According to [6], they proposed using a Decision tree algorithm and Multilayer Perceptron MLP algorithm to develop a model of early detection of brain tumor in order to save patients lives. They were able to come up with an accuracy of 95% but they were faced with some challenges such as predictions not smooth or continuous and their model also suffer from over fitting problems. In another study [7], they presented a method of brain tumor detection using ANN. They uses different dataset of Modalities T1 and T2 of MR Images and the model they developed achieved an accuracy of 88%.The challenges they faced was that their dataset contains different modalities of MR images which increase the recognition difficulty for ANN.

2.0 Literature review

Brain tumor detection is a critical task in medical imaging, as early and accurate diagnosis plays a crucial role in determining the appropriate treatment plan and improving patient outcomes. This research discusses problems related to the brain tumor detections, reviewed some research works, identified their gaps and attempt to overcome their limitations. There are several brain tumor detection techniques that include traditional approach, machine learning and deep learning techniques.

2.1 Traditional Methods of Brain Tumor Detection

The main non-invasive methods for brain tumor diagnosis and assessment are brain imaging like computed tomography (CT), positron emission tomography (PET) and magnetic resonance imaging (MRI) scans [8]. Image content-based retrieval is a growing research area focusing on texture information in digital libraries and multimedia databases. Gabor wavelet features are proposed for texture analysis, with superior pattern retrieval accuracy compared to other multi resolution features [9]. Magnetic Resonance Imagining (MRI) is broadly used for detecting tumor and diagnosing various tissues abnormalities.

There are several traditional methods of brain tumor detection such as CT scan, MRI scan, PET scan, and biopsy [8]. The table below shows the different traditional methods of brain tumor detection with their description and limitation:

2.2 Machine Learning Approaches for Brain Tumor Detection

Machine learning is a subfield of artificial intelligence that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions without explicit programming. It involves studying mathematical and statistical techniques that allow machines to automatically learn and improve from experience or data. Machine learning algorithms learn from data by identifying patterns, relationships, and statistical properties within the data. There are several types of machine learning, including supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and model training and evaluation. In unsupervised learning, patterns are found in unlabeled data, supervised learning involves the computer learning from labeled data. Reinforcement learning involves an agent learning through contact with an environment and receiving rewards or punishments based on its behaviors, whereas semi-supervised learning incorporates labeled and unlabeled data [10].

In [11] described overfitting, where models perform well on training data but do not generalize to new data, is a frequent problem in machine learning. To avoid overfitting and enhance generalization, regularization approaches like L1 and L2 regularization, dropout, or early stopping are used.

Machine learning is used in a wide range of industries, including autonomous vehicles, healthcare, finance, natural language processing, recommendation systems, and picture and audio recognition. It has the ability to streamline decision-making procedures, automate difficult operations, and draw conclusions from big datasets [12].

2.2.1 Literature reviews on machine learning techniques

In [13] studied computer aided system for brain tumor detection and segmentation. In this paper brain tumor segmentation and detection is done using MR images. The proposed method enhanced the MR image and segments the tumor using global thresholding. False segmented pixels are the removed using morphological operations and applying windowing technique. The final brain tumor detected image is obtained by applying the tumor mask on dilated MR image. Results and experiments show that their propose technique accurately identifies and segments the brain tumor in MR images. It encounters some challenges such as it is a difficult task to segment brain tumor in an automatic computerized system as it involves pathology, physics related to MRI along with intensity and shape analysis of MRI image. The major issue with brain tumor segmentation is that the tumor varies in form of shape, size, location and image intensities. According to [14] whose work reported in Brain Tumor Detection based on Multi-parameter MRI Image Analysis that the aim for their work is to segment a tumor in a brain. This will make the surgeon able to see the tumor and ease the treatment. Watershed segmentation based algorithm was used for detection of tumor in 2D and in 3D. MATLAB and 3D Slicer was used to create the 3D image. It is clear two results that tumor can be segmented out from the MRI image data set very efficiently and effectively and 3D image can be visualized in MATLAB environment. After visualizing it becomes very easy to calculate the tumor dimensions. The main limitation was that the method was semi-automatic. In another study [15] uses K-means clustering technique. K-means clustering is a crucial technique in pixel-based methods, making it more practical and suitable for biomedical image segmentation. They focuses on selecting appropriate features from brain images for clustering, achieving good segmentation results while maintaining low computational complexity. The color space transformation function is essential for image processing systems, minimizing overhead. The proposed image tracking method maintains efficiency in magnetic resonance brain tumors and helps pathologists distinguish exact lesion sizes and regions.

According to [16] described that the human body is composed of many types of cells. Divide in an orderly manner and form some new cells. These new cells help to keep the human body healthy and properly working. When some cells lose their capability to control their growth, they grow without any order. According to a report published by central brain tumor registry of the United States, approximately 39,550 people were diagnosed with benign and malignant brain tumors in 2002. Another study [17] proposed a fully automated method for detection and segmentation of the abnormal tissue associated with brain tumor (tumor core and oedema) from Fluid Attenuated Inversion Recovery (FLAIR) Magnetic Resonance Imaging (MRI). They use a method based on super pixel technique and classification of each super pixel. A number of novel image features including intensity-based, Gabor textons, fractal analysis and curvatures are calculated from each super pixel within the entire brain area in FLAIR MRI to ensure a robust classification. Extremely randomized trees (ERT) classifier is compared with support vector machine (SVM) to classify each super pixel into tumor and non-tumor. The proposed method was evaluated on two datasets: Clinical dataset: 19 MRI FLAIR images of patients with gliomas of grade II to IV, and BRATS 2012 dataset. The experimental results demonstrate the high detection and segmentation performance of the proposed method using ERT classifier.

To take use of the potential of quantum correlations, [18] suggested a quantum fully self neural network (QFS-Net) network using qubits/three states of quantum for segmentation of the brain lesions. In supervised QINN networks, the cutting-edge quantum back-propagation method is swapped out for an innovative qubit-based counter-propagation method in the QFS-Net. Iterative quantum states can spread through the network's layers using this technique. Study [19] describes a new MAS (Multi-atlas segmentation) framework for MR tumor brain images. In essence, MAS creates a new brain picture for segmentation by recording and merging label data from many normal brain atlases. Although the majority of its frames are for normal brain imaging, tumor brain images continue to be a challenging worry for it. At the first level of the MAS framework, a new low-rank method is being used to retrieve the recovered picture of the normal brain from the MR tumor brain image by using the information from the normal brain atlas. The image is recovered without tumor interference in the following stage by registering normal brain atlases.

The table below shows the summary of various machine learning techniques including the dataset used, accuracy and drawbacks.

table 1: a survey of various machine learning techniques

Author	Dataset	Methodology	Accuracy	Drawbacks
Amin *et al.* [20]	BraTs 2013 &BraTs 2015	Weiner Filter, PF Clustering & Gray level thresholding		Gliomas are infiltrative due to fuzzy borders, hence it is more difficult to segment the tumor.
George *et al.* [6]	Human MR images	C4.5 Decision tree algorithm and Multilayer Perceptron MLP algorithm	95%	Predictions are not smooth or continuous. Having Overfitting problems
Pareek *et al.*, [21]	150 T1-weight MRI scans	KSVM	97%	Not suitable for large dataset and does not perform very well when the dataset has more noise
Ayadi *et al.*, [22]	MRI	SVM and K-fold cross-validation	90.27%	Target classes are overlapping. It also under

				perform at times.
Arif *et al.*, [23]	MRI Images	Berkeley's wavelet transformation (BWT)	98.5%	Overfitting and Underfitting

2.3 Related reviews on Deep Learning Techniques

A study [24] developed a method for choosing the optimal CNN features for classification, called feature selection. Their method enhances the contrast of the original MRI images and applies a saliency-based strategy for tumor diagnosis. Later, the deep features are extracted using TL and the inception CNN model. The best of them are chosen using the PSO approach after the CNN features and DRLBP characteristics have been combined. The tests used a series of BraTS datasets and achieved higher accuracy. Another study [25] had proposed as a technique to remove brain tumor from 2D Magnetic Resonance Brain Images (MRI). They used a real-time dataset with various tumor sizes, locations, forms, and image intensities for the experimental study. Fuzzy C-Means clustering algorithm, followed by conventional classifiers and Convolutional neural network were also visited. They adopted six traditional classifiers in the scikit-learn-implemented traditional classifier part: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naive Bayes, and Random Forest. They go for Convolutional Neural Network (CNN), which is constructed using Keras and Tensor flow, because it performs better than the conventional ones. The accuracy CNN achieved in their study was 97.87%, which is impressive. ANN-based tumor classification and an automatic model-based segmentation utilizing MRI data were reported. They use model-based segmentation to extract ROI, which is then used to generate textural descriptors. Through the use of ANN, the retrieved textural descriptors were recognized and improved performance for 200 MRI cases according to [26].

In another study [27] proposed a system that uses computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network. Brain Cancer Detection and Classification System has been designed and developed. The proposed system efficiently classifies the input MRI brain tumor images. The tumor is extracted from the MRI brain images by using mentioned techniques/ methods. The extracted tumor image is further classified on ANN classifier in this way. The Classification of MRI brain cancer images are also successfully implemented by using artificial neural networks. The future work can be carried out to improve the classification accuracy by extracting more features and increasing the training data set. In [28] introduced a deep learning model for segmenting various brain modalities. They build a hybrid CNN model to extract the local and contextual information of tumors using MRI datasets for this goal. The overfitting issue is then resolved and sent to the feed-forward NN for training. Overall, throughout the validation, the given approach produced a superior precision rate on a few chosen BRATS series. Another study by [29] had proposed a modified Probabilistic Neural Network (PNN) model to carry out an automated brain tumor classification using MRI-scans. The segmentation of brain tumors in magnetic resonance images (MRI) is a challenging and difficult task. They applied a modified image segmentation techniques on MRI scan images in order to detect brain tumors. Experiments are conducted on various real-world datasets and the results concluded that the proposed algorithm yield good results when compared with the other classifiers. The results revealed that the proposed hybrid approach is accurate, fast and robust. It has a limitation that classification accuracy results are different for different datasets. According to [30] by combining concepts from convolutionary neural networks (ConvNet) and short-term memory (LSTM), a deep learning model for segmenting brain tumors has been suggested. The class-weighting notion is added after preprocessing in order to address the concerns with class inequality. The BraTS 2018 benchmark dataset was used for the studies, and ConvNet provided a single accuracy score (exactitude) of 75% while an LSTM-based network generated 80%, resulting in a combined accuracy of 82.29%.

In [31] they developed a method for detecting multigraded brain cancers in MRI images using a deep neural network (DNN) design. A pretrained CNN is employed for training on recently acquired segmented pictures, and the retrieved tumors utilizing deep learning are further boosted by data augmentation. Later, the validation is conducted using the original stored datasets as well as the enhanced datasets, and a considerable change in accuracy is noted. In another study [32] developed a method for choosing the optimal CNN features for classification, called feature selection. Their method enhances the contrast of the original MRI images and applies a saliency-based strategy for tumor diagnosis. Later, the deep features are extracted using TL and the inception CNN model. The best of them are chosen using the PSO approach after the CNN features and DRLBP characteristics have been combined. The tests used a series of BraTS datasets and achieved higher accuracy. According to [33] recommended that primary malignant brain tumors are among the most dreadful types of cancer, because of the dismal prognosis. The most frequent primary brain tumors in adults are primary central nervous system lymphomas and gliomas, which account for almost 80% of malignant cases. They presented fully automatic brain tumor detection and segmentation method using the U-Net based deep convolution networks. In their work, they proposed and created U-Net based completely Convolutional networks for tackling the Brain cancer division issue. This load of three examinations presently positioned on the highest point of the Imps challenge. They classified the Dice Likeness Coefficient (DSC) for HGG, LGG and consolidated cases. They utilized a far reaching information increase conspire that contains inflexible or relative based twisting, yet in addition incorporates magnificence and flexible expression based change. In a study [25] had proposed as a technique to remove brain tumor from 2D Magnetic Resonance Brain Images (MRI). They used a real-time dataset with various tumor sizes, locations, forms, and image intensities for the experimental study. Fuzzy C-Means clustering algorithm, followed by conventional classifiers and Convolutional neural network were also visited. They adopted six traditional classifiers in the scikit-learn-implemented traditional classifier part: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naive Bayes, and Random Forest. They go for Convolutional Neural Network (CNN), which is constructed using Keras and Tensor flow, because it performs better than the conventional ones. The accuracy CNN achieved in their study was 97.87%, which is impressive. According to [34], the authors analyze brain MRI images to detect tumors and classify them into three categories: meningioma, glioma, and pituitary. The authors also compare and implement enhanced machine learning algorithms for early detection and classification of brain tumors. The dataset includes two types of brain MRI images with and without tumors. Nine machine learning algorithms, including SVM, Logistic Regression, KNN, Naïve Bayes, Decision Tree, Random Forest, XGBoost, and Stochastic Gradient Descent, were used. The Gradient Boosting classifier outperformed all other algorithms, with an accuracy of 92.4%, recall of 94.4%, precision of 85%, F1-score of 89.5%, AUC-ROC of 97.2%, and AUC-PR of 91.4%. The multi-class classification problem involved four machine learning algorithms, including SVM, KNN, Random Forest, and XGBoost. The XGBoost classifier outperformed all other algorithms in terms of accuracy, precision, recall, and F1-score. In another study [35], presents a deep convolutional neural network (DCNN) for diagnosing brain tumors from MR images. The model outperforms conventional methods in the test dataset, with a 96% accuracy rate. The model's precision-recall score is 0.93, Cohen's Kappa 0.91, and AUC 0.95, making it useful for clinical experts to confirm a patient's brain tumor and accelerate treatment. The primary objective of this study is to enhance the accuracy and efficiency of brain tumor detection and classification compared to traditional methods. The DCNN model demonstrated remarkable performance when tested on a dataset, outperforming conventional techniques with an impressive 96% accuracy rate. The model achieved an overall classification accuracy of 96%, precision of 0.93, sensitivity of 1.00, and F1-score of 0.97. Its efficiency was improved through preprocessing procedures. The proposed framework could be used for early detection of brain tumors and could expand with 3D brain scans in the future.

2.4 Neural Network

Neural networks are very fast and precise because after training, the processing, optimization, and time-consuming calculations are no longer required. The network's outputs are generated directly from the provided inputs. The network is built by teaching it how the specific system behaves with each of the inputs. There are various network types that have been implemented for various applications. Neural networks are used in engineering, weather and financial market forecasting, oil price forecasting, business, and medical fields. They have the ability and power to generalize various problems [36].

The human brain is a complex structure with billions of nerves interconnected, making it faster and more powerful than any computer. It performs parallel processing tasks, such as recognizing and memorizing images, with minimal effort and processing time. Each neuron is connected to millions of other neurons, allowing for efficient data exchange. The main components of a biological neuron include cell body (Soma), dendrites, synapse weights, and axon, which transmit information to surrounding neurons.

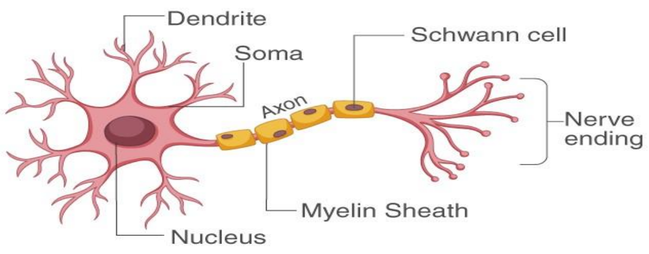

figure1: biological neuron structure

Complex challenges such as motion detection and recognition are made possible by the brain's excellent decision-making abilities. Using training and learning methods, scientists have constructed artificial networks that imitate the function and structure of the brain.

Brain-Inspired Artificial Intelligence: In designing intelligent systems, artificial intelligence (AI) researchers have long been inspired by the structure and function of the brain. Deep learning models, in particular, are aimed to emulate the interconnected structure and learning mechanisms observed in the brain. The goal of this method, known as biomimicry, is to mimic the brain's ability to process information, learn from experience, and make judgments [37].

2.4.1 Deep Learning Techniques

Deep learning techniques have revolutionized various domains, including computer vision, natural language processing, and speech recognition. Deep neural networks (DNNs) are a type of artificial neural network (ANN) with many layers of interconnected nodes (neurons). These neural networks can learn complex patterns and hierarchical representations from data. There are several deep learning techniques such as Convolutional Neural Network, Recurrent Neural Network (RNN), Generative Adversarial Networks (GANs), Transformer Networks and many more.

2.4.2 Architecture of Convolutional Neural Network

The architecture of a Convolutional Neural Network (CNN) typically consists of several layers, each serving a specific purpose in the image processing and feature extraction process according to [12]:

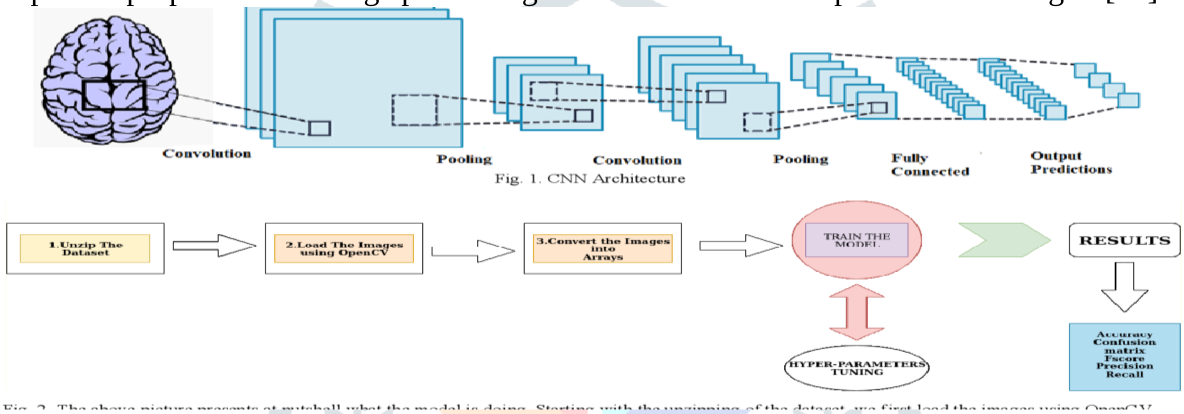

figure 2: architecture of convolutional neural network

The input layer accepts the input image and passes it to the subsequent levels. The dimensions of the input image define the size of the input layer. Convolutional layers are the foundation of CNNs. They are made up of several convolutional filters that move through the input image, conducting element-wise multiplications and aggregating the results into feature maps. Each filter recognizes a distinct feature or pattern in the image. As it scans the input with respect to its dimensions, it employs filters that execute convolution processes. The filter size and stride are two of its hyper parameters. The resulting output is known as a feature map or an activation map. Following each convolutional layer, an activation function (such as ReLU, or Rectified Linear Unit) is applied element-by-element to bring non-linearity into the network and permit modeling complex data interactions. POOL is a down sampling technique that is often used after a convolution layer that performs some spatial invariance. Pooling layers assist in reducing the spatial dimensions of feature maps while retaining the most relevant features. Max pooling is a popular pooling method in which the greatest value inside a feature map region is chosen as the representative value for that region. Max and average pooling, in particular, are types of pooling that take the maximum and average value, respectively. Fully connected layers, also known as dense layers, turn the output of convolutional and pooling layers into a one-dimensional feature vector. These layers are generally employed for jobs requiring high-level reasoning and classification. The size and number of completely connected layers are determined by the problem's complexity and desired model depth. It operates on a flattened input where each input is connected to all neurons.

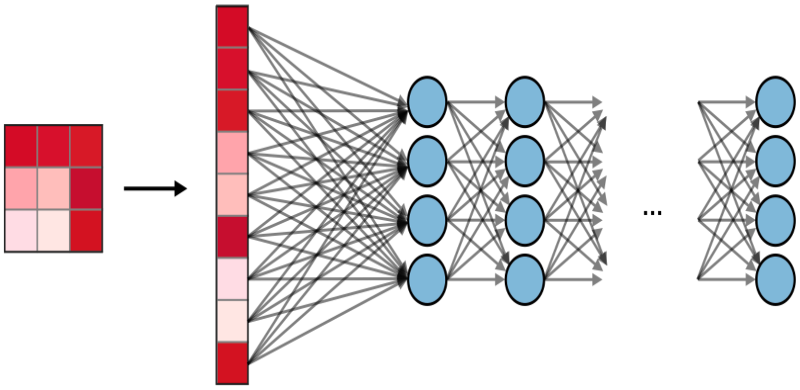

figure 3: fully connected layer cnn architecture

The output layer is the network's final layer and generates the required output, such as class probabilities. The activation function employed in the output layer is determined by the type of problem. A sigmoid activation function is typically used for binary classification, while softmax activation is used for multi-class classification.

table 2 : convolutional neural network (cnn) model

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 2629, 256)	3840
dense_5 (Dense)	(None, 2629, 515)	132355
dropout_2 (Dropout)	(None, 2629, 515)	0
dense_6 (Dense)	(None, 2629, 50)	25800
dropout_3 (Dropout)	(None, 2629, 50)	0
dense_7 (Dense)	(None, 2629, 1)	51
Total params: 162,046		
Trainable params: 162,046		
Non-trainable params: 0		

3.0 Methodology

3.1 Existing Framework

In this section, we discussed the existing framework for brain tumor detection using convolution neural networks (CNN). We also analyze the weaknesses or limitations of the current approaches and identify the need for an improved methodology.

3.2 Proposed Framework/Method

This section introduces the proposed framework or method for brain tumor detection using CNN. We outlined the key components and steps involved in the approach. The following phases comprise a system designed to detect brain tumors in their early stages. These phases are as follows: Image pre-processing and enhancement, feature extraction and tumor classification. Figure below depicts the system's block design of these phases.

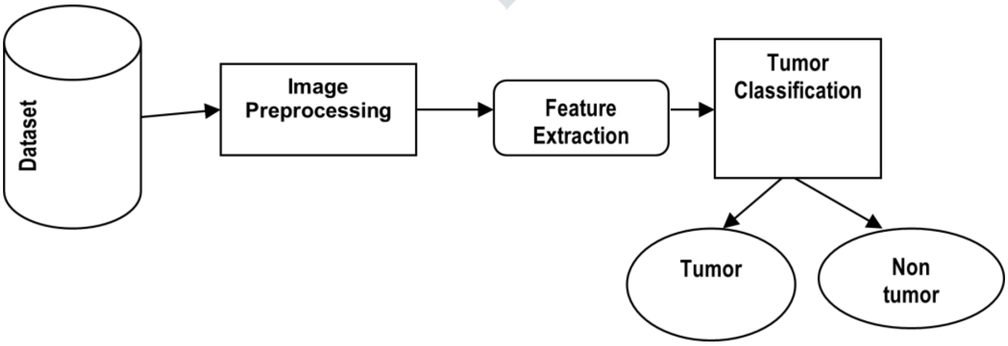

figure 4: proposed block diagram

3.2.1 Image Pre-processing

Image preprocessing is crucial for accurate and efficient classification in Convolutional Neural Networks (CNNs). It involves several techniques to enhance image quality and representation before being fed into CNN classifiers. Common techniques include resizing, normalization, data augmentation, gray-scale conversion, noise removal, edge detection, and histogram equalization. Resizing ensures uniform dimensions, normalization reduces lighting conditions, data augmentation increases dataset diversity, gray-scale conversion simplifies training, noise removal removes artifacts, edge detection extracts important features, and histogram equalization improves contrast.

After preprocessing, images are fed into CNN classifiers, which consist of multiple convolutional layers, pooling layers for downsampling, fully connected layers for high-level feature extraction, and a final softmax layer for classification. The specific preprocessing techniques used may vary depending on the dataset and classification task requirements, and experimentation and tuning are often necessary to achieve optimal results. Here are a few examples of CNN classifier architectures: LeNet-5, AlexNet, VGGNet, GoogLeNet, DenseNet, ResNet e.t.c.

3.2.2 Feature Extraction

Feature extraction is the process of identifying significant patterns or features from input data using convolutional layers in CNNs (Convolutional Neural Networks). In computer visualization applications including image classification, object recognition, and image segmentation, CNNs are frequently utilized. Multiple convolutional layers and non-linear activation functions are used in CNN's feature extraction procedure. A high-level description of the feature extraction procedure is given below:

The convolutional layer in neural networks involves convolving input data with learnable filters, producing feature maps. Activation functions like ReLU are applied element-wise to the feature maps, introducing non-linearity and allowing the network to learn more complex patterns. Pooling layers reduce feature maps while preserving salient information. Optional additional convolutional layers can be used to capture higher-level features, combining information from previous layers.

The ability of CNNs to automatically learn and extract features from raw data has been a significant advancement in computer vision, allowing them to achieve impressive performance on various visual recognition tasks.

3.2.3 Tumor Classification

The classification stage in CNN (Convolutional Neural Network) refers to the final step of using the learned features to predict the class or category of the input data. After the feature extraction process, typically involving convolutional layers and pooling layers, the extracted features are passed through fully connected layers for classification. It involves the following processes.

Flattening involves flattened feature maps into a 1D vector, which is then passed through fully connected layers to learn mapping between extracted features and class labels. Activation functions, such as ReLU, are applied to introduce non-linearity and allow the network to learn complex relationships between features and target classes. The output layer, consisting of neurons equal to the number of target classes, is connected to the final fully connected layer. A loss function measures the discrepancy between predicted class probabilities and true labels, and optimization algorithms like SGD or Adam are used to minimize the loss function and improve the model's predictive accuracy. After training and optimization, the classification stage is used for making predictions on new unseen data, with the output layer providing predicted class probabilities or labels.

3.3 Prediction Tools

Prediction tools or labels: The dataset will have ground truth labels or annotations indicating the presence or absence of brain tumors in each image. These labels will be utilized for training, validation, and evaluating the performance of the CNN model.

3.3.1 Software Requirement

Programming Language: The implementation of the proposed framework will require a programming language such as Python, MATLAB, or R.

Libraries/Frameworks: Specific libraries or frameworks for deep learning and neural networks, such as TensorFlow, PyTorch, or Keras, may be utilized.

3.3.2 Hardware Requirement

Processing Power: The computational requirements for training and testing the CNN model may demand a system with adequate processing power, such as a multi-core processor or GPU acceleration.

3.4 Performance Evaluation and Evaluation Metrics

In this section, we discussed the evaluation of the proposed method's performance and the evaluation metrics used to assess the accuracy and efficacy of the CNN model.

3.4.1 Evaluation Metrics: Common evaluation metrics such as accuracy, sensitivity, specificity, precision, and F1 score may be used to measure the performance of the brain tumor detection system.

Cross-Validation: Cross-validation techniques, such as k-fold cross-validation, may be employed to obtain more robust performance estimates and reduce overfitting.

Definition of terms:

Accuracy- is the fraction of total samples accurately predicted to the sum of the whole samples.

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ - - - - - equation 1

Sensitivity- also known as True positive rate **i**s the measure true positive Vs sum of predicted true positives and predicted false negatives.

$Sensitivity = \frac{TP}{TP+FN}$ - - - - - equation 2

Specificity- also called the true negative rate is the measure of the proportion of true negatives Vs sum of predicted false positives and predicted true negatives.

$Specificity = \frac{TP}{TP+FN}$ - - - - - equation 3

Precision- also known as positive predicted value is the measure of the proportion of true positives Vs sum of true positives and predicted false positives.

$Precision = \frac{TP}{TP+FP}$ - - - - - equation 4

F1 Score- it is termed as a harmonic mean of precision and recall and it can give us better metrics of incorrectly classified classes than the accuracy metric.

$F1\,Score = \frac{2TP}{2TP+FP+FN}$ - - - - - equation 5

4.0 Result and Discussion

This chapter presents the results obtained and general discussion. It explains further the processes involved from data collection and description to unravel proper understanding and preprocessing. The neural network model architecture, the training process and the evaluation metrics used in the study were also stated to ensure accurate and reliable detection performance.

4.2 Dataset

4.2.1 Data Description

The dataset is made up of over three thousand seven hundred entries (rows) and fifteen features (columns). Its features include; mean, variance, standard deviation, skewness, kurtosis, contrast, entropy, homogeneity, dissimilarity, correlation, coarseness and class which indicates/classify whether brain tumor exist or not. Dataset was collected from the largest community of data science in the globe, which is www.Kaggle.com.

4.2.2 Data Preprocessing

We check the null values in the dataset by applying the data.isnull().sum() expression to count the number of missing values (or NaN values) in each column of a DataFrame, data. This is done to ensure that all missing values found in the data are filled using appropriate method. The expression data.duplicated().sum() was used to count the number of duplicate rows in a DataFramedata. It was found that there is no duplicates rows in the data. This LabelEncoder class was imported from the sklearn.preprocessing module, which provides functionality for encoding categorical variables. The original categorical values in the 'Image' column are replaced with the encoded numerical labels, which are integers assigned to each unique value in the column. The transformation is performed in-place, meaning the 'Image' column in data is directly modified. Therefore, the 'Image' column in the dataset would contain the encoded numerical labels instead of the original categorical values. This step is important to improve models detection performance.

To further understand the data. We created a grid of subplots, each contained a distribution plot (histogram) for the selected columns in a DataFramedata. Fig object was used to contain a grid of subplots, each displayed a distribution plot for the selected columns of the DataFrame. The specific layout and appearance of the subplots as shown in the figure below depend largely on the number of columns and the size specified for the figure 5.

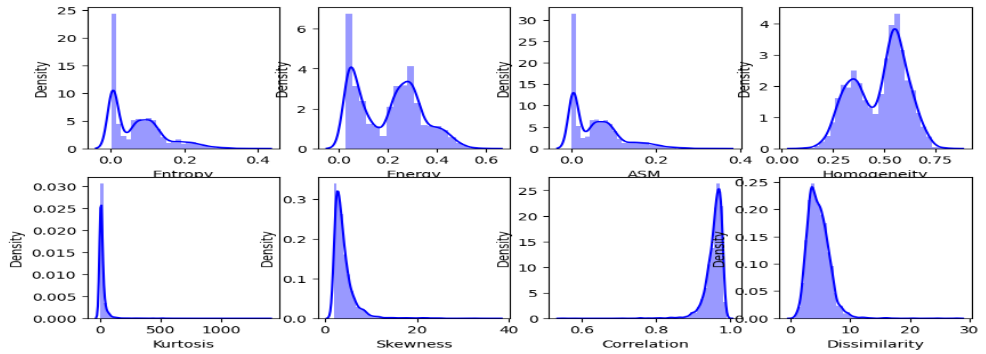

figure 5: grid of subplots

4.3 Neural Network Architecture

A computational model known as an artificial neural network (ANN) was modeled after the form and operation of biological neural networks were seen in the human brain. It was a particular kind of deep learning model made up of linked nodes, also known as artificial neurons or units, arranged in layers. The short form of the word "ANN" is inclusive of a wide range of topologies, including feedforward neural networks, recurrent neural networks, and self-organizing maps. The following are the main ideas and elements of artificial neural networks: neuron, layer, weights and biases, activation function, loss function, optimization algorithms and etc.

Many tasks involving especially image and video analysis used convolutional neural networks. They are designed to automatically recognize and extract features and hierarchical patterns from the given data. Convolutional layers, pooling layers, and fully linked layers make up CNNs. Pooling layers down sample the output, fully connected layers produce predictions based on the learnt features, and convolutional layers apply filters to the input data. In image classification, object recognition, and image segmentation tasks, CNNs have displayed impressive performance. Example of ANN includes, Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GAN), Convolutional Neural Networks (CNN), and so on. The pie chart in figure 6 below shows the percentage of individual in the dataset that have brain tumor and the percentage of individuals that have no brain tumor. Male and female are represented as 1 and 0 respectively.

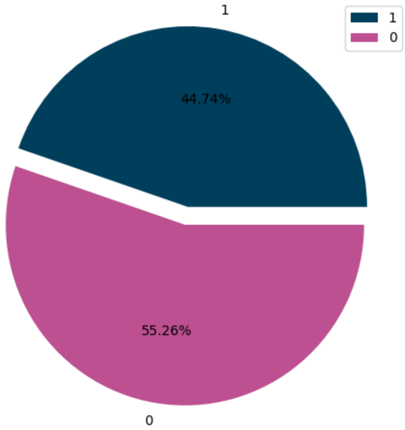

figure 6: percentage of brain with and without tumor

The CNN model was created with the help of the following parameters,cnn.compile(loss="binary_crossentropy", optimizer = "Adam",metrics=["accuracy"]). For this study we have chosen the loss function of binary_crossentropy base on the type of data we are using and the expected outcome. A loss function is vital when mounting a deep learning model to measure the difference between predicted and actual result to make neural networks adjust its weights to increase performance accuracy. Binary cross-entropy was used when image is to be classified in to two.Adam optimizer was applied to adjust the weights of the artificial neural networks and improve the learning speed of the model to reduce the losses. The data was then fit into the CNN modelthat was created.

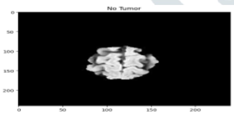

figure 7: brain Image without tumor

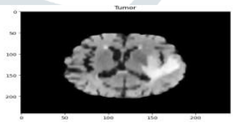

figure 8: brain image with tumor

4.4 Training Process

The training of the created model was started using the fit method of the model object. It was used to ensure that the training data was specified (X_train and y_train) and the validation data (X_test and y_test). The number of samples to be used in each iteration of the training was defined batch_size parameter. The epoch's parameter determines the number of times the entire dataset will be passed through the model during training. The callbacks parameter takes a list of callbacks, in this case including the early_stopping callback. The verbose parameter used to control the verbosity level of the training process.

4.5 Result of Convolutional Neural Network

In table 3 below, the results of training a Convolutional Neural Network (CNN) was presented for brain tumor detection. Each row corresponds to a specific training epoch, and the columns offer valuable insights into the CNN's performance. It indicate 50 epochs or training steps, training time and step loss that represent the loss value at the end of each training step. It also reflects the accuracy obtained at the end of each epoch. The validation loss donates the loss value on the validation dataset after each training step. As the epoch number increases, the model seems to improve in terms of accuracy and loss. Both training and validation accuracies are relatively high, suggesting that the model is learning well and generalizing to new data. The validation loss and validation accuracy show trends that can help determine when the model starts overfitting. If validation loss starts to rise while training loss continues to decrease, overfitting may be occurring.

table 3: results of convolutional neural network model

No.	Training Time	Step Loss	Binary Accuracy	Validation Loss	Validation Accuracy
1	2s 6ms/step	0.0413	0.9863	0.0605	0.9841
2	1s 6ms/step	0.0281	0.9905	0.0599	0.0599
3	1s 5ms/step	0.0265	0.9894	0.0806	0.9805
4	1s 5ms/step	0.0240	0.9905	0.0693	0.9858
5	1s 6ms/step	0.0259	0.9916	0.0620	0.9867
.	.	.	.	.	.
.	.	.	.	.	.
46	1s 6ms/step	0.0164	0.9924	0.1159	0.9796
47	1s 5ms/step	0.0117	0.9932	0.1166	0.9867
48	1s 5ms/step	0.0129	0.9954	0.1067	0.9858
49	1s 5ms/step	0.0087	0.9962	0.1226	0.9867
50	1s 5ms/step	0.0088	0.9977	0.1207	0.9867

4.6 Evaluation Metrics

A machine learning model's performance is evaluated using some known evaluation metrics. They offer quantitative measurements that show how accurately the model is making predictions. Here are some typical and common metrics for evaluating categorization tasks which are used in this research: accuracy, precision, recall (sensitivity or true positive rate) and f1-score. These evaluation measures offer several viewpoints on the model's performance and help in understanding of its advantages and disadvantages.

The proposed model achieved high detection performance, as shown or indicated by the evaluation metrics in figure 9 and the confusion matrix in figure 10 below. The accuracy, precision, recall, and F1-score were all above 0.98, demonstrating that the artificial neural network model's capability to make an accurate predictions.

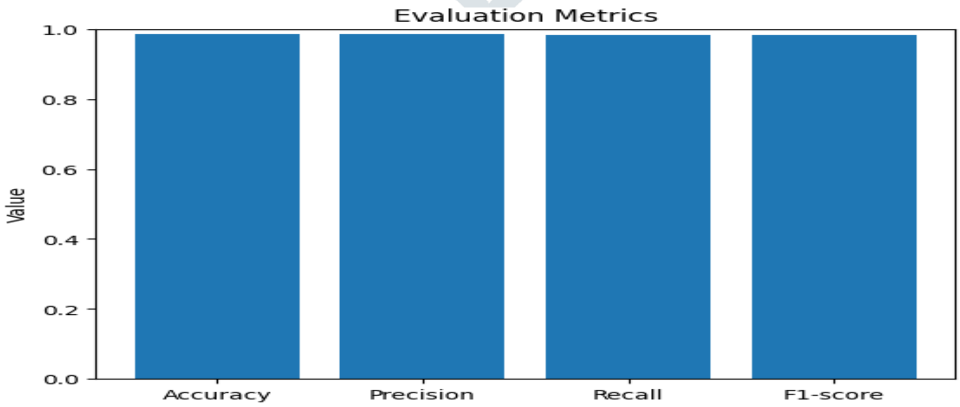

figure 9: performance evaluation matrix

4.6.1 Confusion Matrix

The confusion matrix was used in this study to provide detailed information about the model's predictions. Figure 10 shows that the number of true positives, true negatives, false positives, and false negatives. In this circumstance, the result obtained indicates that the confusion matrix have shown that the model correctly predicted 599 (53.06%) true negatives, 513 (45.44%) true positives, 8 (0.71%) false positives, and 9 (0.80%) false negatives.

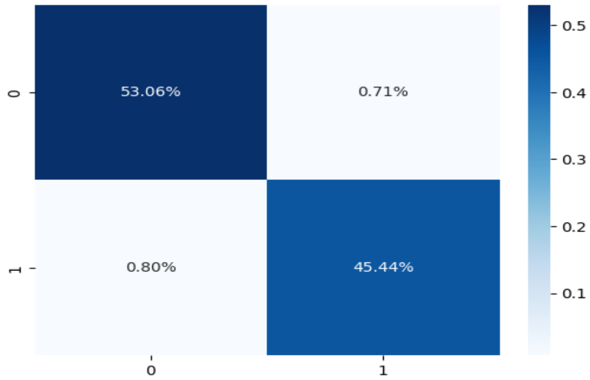

figure 10: confusion matrix

4.6.2 Precision Recall Curve

It is a graphical representation of the trade-off between precision and recall for various classification thresholds is a precision-recall curve. They are frequently employed when working with datasets that are unbalanced or when the positive class is the main emphasis. The precision-recall curve aids in determining an acceptable threshold based on the desired balance between precision and recall and in evaluating the model's performance at various operational points.

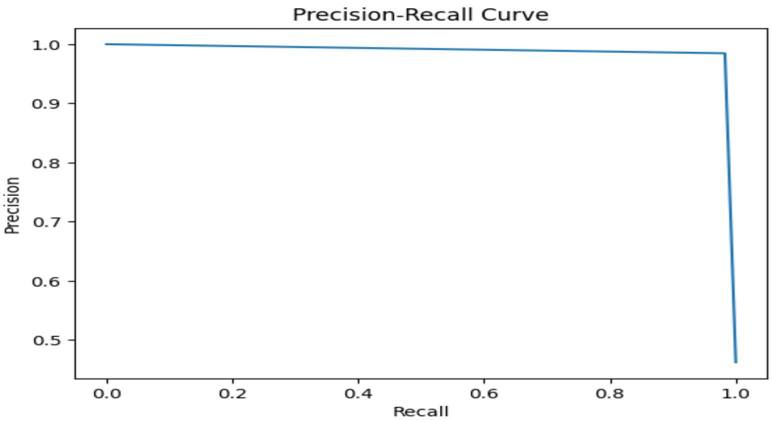

figure 11: precision-recall curve

A precision-recall curve precision indicates fewer false positives, while a higher recall indicates capturing more true positives. The shape and steepness of the curve provide insights into the model's performance and the chosen threshold.

Accuracy is the proportion of correct predictions compared to the total number of predictions. It is a general measure of how well the model performs in the overall. In this case study, our model achieved a higher performance accuracy of 0.9849 compared to [6], indicating that the model has achieved a high percentage of correct predictions. Precision measures the model's ability to correctly identify positive samples out of all the samples predicted as positive. It is calculated as the ratio of true positives to the sum of true positives and false positives. A precision of 0.9846 suggests that the model has a high proportion of true positive predictions compared to false positives. Recall (Sensitivity or True Positive Rate): Recall measures the model's ability to correctly identify positive samples out of all the actual positive samples. It was calculated as the ratio of true positives to the sum of true positives and false negatives. A recall of 0.9828 indicates that the model has a high proportion of correctly identifying positive samples.F1-score: The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of the model's performance by considering both precision and recall. The F1-score of 0.9837 suggests a good balance between precision and recall. The figure 12 and figure 13 below shows the training and testing loss function and the model performance accuracy.

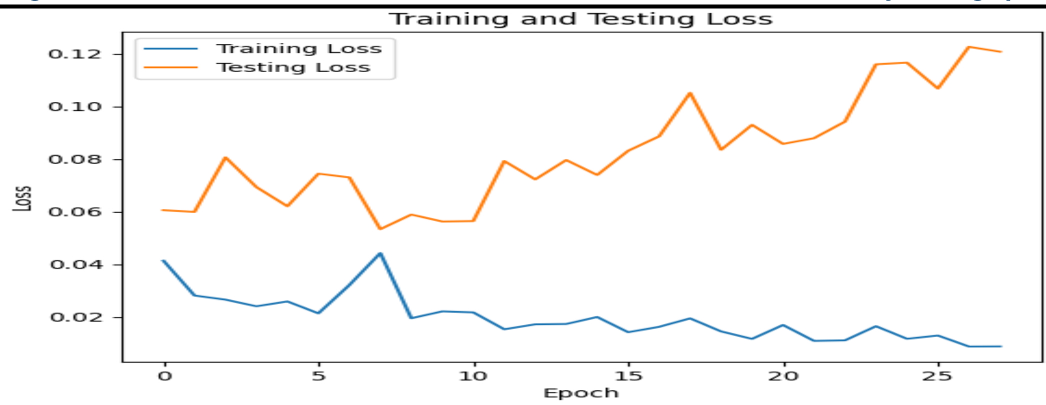

figure 12: training and testing loss

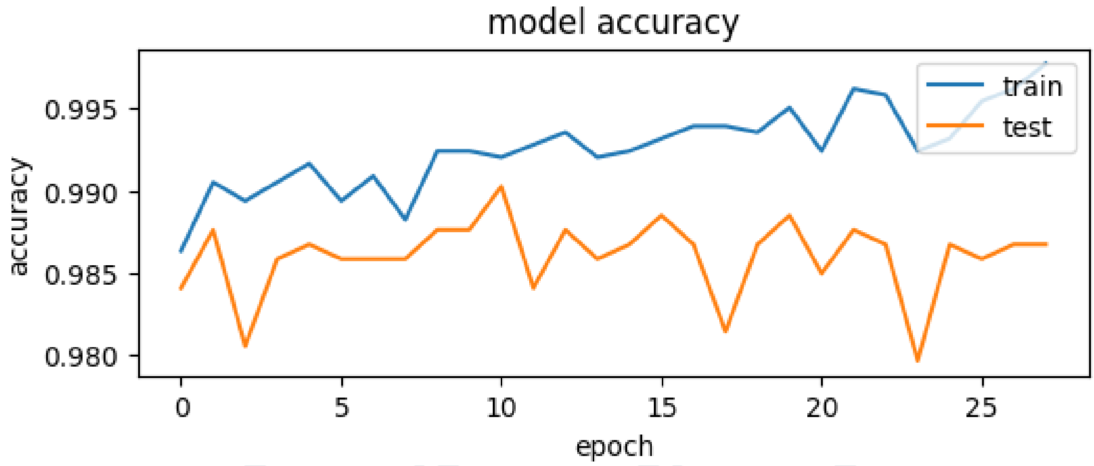

figure 13: performance accuracy measure

4.7 Comparative Result Analysis

The table below present the comparative analysis of the result obtained from our proposed model to the existing results in the literature reviewed in this work. This indicates that our proposed model achieved a higher performance accuracy of 0.9849 compared to [35] and [36], showing that the model has achieved a high percentage of correct predictions. Precision measures the model's ability to correctly identify positive samples out of all the samples predicted as positive. A precision of 0.9846 suggests that the model has a high proportion of true positive predictions compared to false positives. A recall of 0.9828 indicates that the model has a high proportion of correctly identifying positive samples. The F1-score of 0.9837 suggests a good balance between precision and recall. Therefore, the proposed model by this study has improved the accuracy, recall and f1-score of brain tumor detection using deep learning approach.

table 5: comparative result analysis

Methods	Model	Accuracy	Precision	Recall	F1-score
Proposed	CNN	0.9849	0.9846	0.9828	0.9837
Published					
Ghosh *et al* [34]	SVM	0.8500	0.8700	0.8500	0.8500
	KNN	0.7700	0.7700	0.8200	0.7800
	Random forest	0.8900	0.8900	0.8900	0.8900
	XGBoost	0.9000	0.9000	0.9000	0.9000
Siddique *et al* [35]	DCNN	0.9600	0.9300	1.0000	0.9700

5.1 Summary

In this work, a model for brain tumor detection using an artificial neural network was designed, conducted and experimented with the result obtained and evaluated using the popular metrics for machine learning model evaluation. The model achieved high performance, as indicated by the evaluation metrics and the confusion matrix in the figures above. The accuracy, precision, recall, and F1-score were all above 0.98, demonstrating the model's ability to make accurate predictions. The confusion matrix showed a low number of false positives and false negatives, further supporting the model's effectiveness.

5.2 Conclusion

The objective of the study was to design an artificial neural network model for the detection of brain tumor disease. Based on the results and the evaluation metrics, it can be concluded that the developed artificial neural network model specifically convolutional neural network was highly capable of accurately detecting brain tumors with high accuracy and precision. The proposed model further demonstrates an excellent overall performance, achieving a high accuracy and effectively identifying both positive and negative cases. In this study, our model detection accuracy was 0.9849, indicating that the model has achieved a high percentage of correct predictions. A precision of 0.9846 suggests that the model has a high proportion of true positive predictions when compared to false positives. A recall of 0.9828 obtained indicates that the model has a high proportion of correctly identifying positive samples. The F1-score of 0.9837 suggests a good balance between precision and recall. These results suggest that the model have the potential to be a valuable tool in assisting medical professionals that are responsible for brain tumor detection.

5.3 Recommendation

Considering the promising attribute of the detection performance of the developed model, it is recommended that further study should be conducted to explore its application in a real-world clinical setting. Therefore, collaboration with medical experts and practitioners is a key because that would be beneficial to validate the model's performance using an independent dataset and to assess its practical utility. Additionally, the model may continue to undergo model optimization and improvement efforts to enhance its performance even further and reliable system. Further validation and optimization efforts are recommended to enhance the model's performance and enable its deployment in real-world clinical settings.

Reference:

[1] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," 2020.

[2] P.G Patil, and K.J. Karende, "Brain tumor detection techniques: A survey. *International Research Journal of Engineering and Technology*," 2016.

[3] J. Priyanka and B. Singh, "A Review on Brain Tumor Detection Using Segmentation," *in International Journal of Computer Science and Mobile Computing, vol. 2,* pp. 48-54, 2013.

[4] P. Narendran, V. K. Narendira Kumar, and K. Somasundaram, "3D Brain Tumors and Internal Structures Segmentation in MR Images," *International Journal of Image, Graphics and Signal Processing, vol. 4,* no. 1, pp. 35, 2012.

[5] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey," *Complex Intelligence Systems, vol. 8,* pp. 3161-3183, 2021.

[6] D. N. George, H. B. Jehlol, and A. S. A. Olewei, "Brain Tumor Detection Using Shape Features and Machine Learning Algorithms," *International Journal of Scientific and Engineering Research*, vol. 6, 2015.

[7] E. M. Hussein and D. M. A. Mahmoud, "Brain Tumor Detection Using Artificial Neural Networks," *Journal of Science and Technology, vol. 13,* 2012.

[8] K. Sailunaz, D. Bestepe, S. Alhajj, T. Özyer, J. Rokne, et al., "Brain Tumor Detection and Segmentation": *Interactive Framework with a Visual Interface and Feedback Facility for Dynamically Improved Accuracy and Trust," PLOS ONE, vol. 18,* no. 4, pp. e0284418, 2023.

[9] B. S. Manjunath and W. Y. Ma, "Texture Features for Browsing and Retrieval of Image Data," *IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18,* no. 8, pp. 837-842, 1996.

[10] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach, 4th ed*., Pearson, 2021.

[11] T. Hastie, R. Tibshirani, and J. H. Friedman, The Elements of Statistical Learning, Data Mining, Inference, and Prediction, *2nd ed., Springer*, pp. 1-758, 2009.

[12] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, May 2015 [13] M. U. Akram and A. Usman, "Computer aided system for brain tumor detection and segmentation," *International Journal of Future Computer and Communication, vol. 1, no. 2, pp. 123-129, 2012.*

[14] R. A. Ratan, S. Sharma, and S. K. Sharma, "Brain Tumor Detection based on Multi-parameter MRI Image Analysis," *ICGST-GVIP Journal, vol. 9*, pp. 1-6, 2009.

[15] C. W. Chen, J. Luo, and K. J. Parker, "Image Segmentation via Adaptive K-mean Clustering and Knowledge-based Morphological Operations with Biomedical Applications," *IEEE Transactions on Image Processing, vol. 7, no. 12*, pp. 1673-1683, Dec. 1998.

[16] K. Sharma, A. Kaur, and S. Gujral, "Brain Tumor Detection based on Machine Learning Algorithms," *in 2nd International Conference on Computer and Intelligent Systems (ICCIS'2014) & 2nd International Conference of Electrical, Electronics, Instrumentation and Biomedical Engineering*, 2014

[17] M. Soltaninejad, G. Yang, T. Lambrou, N. Allison, T. L. Jones, T. R. Barrick, F. A. Howe, and X. Ye, "Automated brain tumor detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI," *IEEE International Journal of Computer Assisted Radiology, vol. 12*, no. 2, pp. 183-203, Feb. 2017.

[18] D. Konar, S. Bhattacharyya, B. K. Panigrahi, and E. C. Behrman, "Qutrit-Inspired Fully Self-Supervised Shallow Quantum Learning Network for Brain Tumor Segmentation," *IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 12*, pp. 6331-6345, Dec. 2022.

[19] Z. Tang, A. Sahar, Y. Pew-Thian, and S. Dinggang, "Multi-Atlas Segmentation of MR Tumor Brain Images Using Low-Rank Based Image Recovery," *IEEE Transactions on Medical Imaging, vol. 37, no. 10,* pp. 2224-2235, Oct. 2018.

[20] J. Amin, M. Sharif, M. Raza, T. Saba, and M. A. Anjum, "Brain tumor detection using statistical and machine learning method," *IEEE Computer Methods and Programs in Biomedicine, vol. 177,* pp. 69-79, 2019 [21] M. Pareek, C. K. Jha, and S. Mukherjee, "Brain Tumor Classification from MRI Images and Calculation of Tumor Area," *in Advances in Intelligent Systems and Computing, Springer, Singapore*, 2020, pp. 73-83.

[22] W. Ayadi, I. Charfi, W. Elhamzi, and M. Atri, "Brain tumor classification based on hybrid approach," *IEEE Transactions on Visualization and Computer Graphics, vol. 38,* no. 1, pp. 107-117, Jan. 2022.

[23] M. Arif, F. Ajesh, S. Shamsudheen, O. Geman, D. Izdrui, and D. Vicoveanu, "Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques," *IEEE Journal of Healthcare Engineering, vol. 2022,* article ID 2693621, 18 pages, 2022.

[24] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, "Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images," *IEEE Pattern Recognition Letters, vol. 129,* pp. 181-189, Dec. 2020.

[25] T. Hossain, F. S. Shishir, M. Ashraf, M. D. A. Al Nasim, and F. M. Shah, "Brain Tumor Detection Using Convolutional Neural Network," *in 1st International Conference on Advances in Science, Engineering and Robotics Technology,* 2019,

[26] N. Arunkumar, M. A. Mohammed, S. A. Mostafa, D. A. Ibrahim, J. J. Rodrigues, and V. H. C. de Albuquerque, "Fully automatic model-based segmentation and classification approach for MRI brain tumor using artificial neural networks," *IEEE Concurrency and Computation: Practice and Experience, vol. 32, no. 1, article e4962,* Jan. 2020.

[27] R. Nabalwar, U. Majhi, R. Patil, and S. Gonge, "Detection of Brain Tumor by using ANN," *IEEE International Journal of Research in Advent Technology, vol. 2*, 2014.

[28] S. Sajid, S. Hussain, and A. Sarwar, "Brain tumor detection and segmentation in MR images using deep learning," *IEEE Arabian Journal for Science and Engineering, vol. 44, no. 11*, pp. 9249-9261, Nov. 2019.

[29] P. Sapra, R. Sing, and S. Khurana, "Brain Tumor Detection Using Neural Network," *IEEE International Journal of Science and Modern Engineering (IJISME), vol. 1,* 2013.

[30] S. Iqbal, M. U. Ghani Khan, T. Saba, Z. Mehmood, N. Javaid, A. Rehman, and R. Abbasi, "Deep learning model integrating features and novel classifiers fusion for brain tumor segmentation," *IEEE Microscopy Research and Technique, vol. 82, no. 8,* pp. 1302-1315, Aug. 2019.

[31] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *IEEE Journal of Computational Science, vol. 30,* pp. 174-182, Oct. 2019.

[32] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, "Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images," *IEEE Pattern Recognition Letters, vol. 129,* pp. 181-189, Jan. 2020.

[33] H. Dong, G. Yang, F. Liu, Y. Mo, and Y. Guo, "Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks," *IEEE Transactions on Medical Imaging, vol. 2017,* pp. 1-12, 2017.

[34] A. Ghosh and A. L. O. K. Kole, "A comparative study of enhanced machine learning algorithms for brain tumor detection and classification," *in TechRxiv,* 2021. [Online]. Available: [Insert URL here].

[35] M. A. B. Siddique, S. Sakib, M. M. R. Khan, A. K. Tanzeem, M. Chowdhury, and N. Yasmin, "Deep convolutional neural networks model-based brain tumor detection in brain MRI images," *in 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC),* Oct. 2020, pp. 909-914.

[36] D. W. Coit, B. T. Jackson, and A. E. Smith, "Static neural network process models: considerations and case studies," *International Journal of Production Research, vol. 36, no. 11,* pp. 2953-2967, 1998.

[37] D. Hassabis, D. Kumaran, C. Summerfield, and M. Botvinick, "Neuroscience-inspired artificial intelligence," *Neuron, vol. 95, no. 2,* pp. 245-258, 2017.