Deep Learning based Analysis of MRI Images for Brain Tumor Diagnosis

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***Abstract*—This Identification and examination of brain tumour are critical components of any indication system, as evidenced by extensive research and methodological advancement over the years. As part of this approach, an efficient automated system must be put in place to enhance the rate of tumor identification. Today, manually examining thousands of MRI images to locate a brain tumor is arduous and imprecise. It may impair patient care. Since it incorporates several picture datasets, it might be time-consuming. Tumor cells present in the brain look a lot like healthy tissue, making it hard to distinguish between the two while doing segmentation. In this study, we present an approach for classification and prediction of MRI images of the brain using a convolutional neural network, conventional classifiers, and deep learning. Here we have proposed a new method for the automatic and exact categorization of brain tumour utilizing a two-stage feature composition of deep convolutional neural networks (CNNs). We used a deep learning approach to categorize MRI scans into several pathologies, including gliomas, meningiomas, benign lesions, and pituitary tumour, after first extracting characteristics from the scans. Additionally, the most accurate classifier is selected from a pool of five possible classifiers. The principal components analysis (PCA) is used to identify the most important characteristics from the retrieved features, which are then used to train the classifier. We develop our proposed model in Python, utilizing TensorFlow and Keras since it is an effective language for programming and performing work quickly. In our work, CNN got a 98.6% accuracy rate, which is better than what has been done so far.**

Keywords*—Convolutional neural networks (CNN); magnetic resonance imaging (MRI); principal components analysis (PCA)

I. INTRODUCTION

In the field of medicine, images need to be segmented to be broken down into their constituent pieces. To better analyze a picture, it is helpful to "spit out" the representation of the image. This is because the picture is segmented into several individual parts. Recently, deep learning models have begun to make their presence known in the world of biomedical applications. The network that is used for deep learning has many layers that are hidden from view.

Brain tumour is one of the most debilitating diseases. Brain tumours are frequently found in several locations in the brain. The diagnosis of brain tumour at an earlier stage is essential for more effective treatment. After a clinical suspicion of a brain tumour, imaging studies are necessary to pinpoint the exact location of the tumour, measure its size, and assess its potential for spreading to other parts of the brain and skull. Based on these findings, doctors select the most effective course of treatment from among surgery, radiation, and chemotherapy. The survival rate of a patient afflicted with a tumour can obviously be raised with precise early detection. Therefore, the radiology department has placed a greater emphasis on the research of brain malignancies through imaging modalities.

Brain tumours are malignant growths that start in the brain or the protective membranes that surround the brain and skull. Finding malignant tumours anywhere on the body and treating them early is challenging. According to a current study, the incidence of brain tumours has grown significantly. Problems with hearing or speech, persistent headaches, memory decline, vision loss, and behavioral shifts are all indicators of a more serious brain disorder. The performance of image processing steps depends heavily on the results of image segmentation [1]. In this situation, we have been particularly concerned with extracting the tumour from the MRI scans of the brain. Medical professionals can pinpoint the exact site of the brain tumour with greater precision. Radiologists, engineers, and physicians all use medical image processing to gain a deeper understanding of patients. Considering the difficulties in segmenting brain tumours and the importance of this task in clinical practice, a wide range of segmentation, automation, and semi-automation mechanisms have been developed. Deep learning techniques rule medical image processing techniques and research [2]. The CNN is a classification method that uses deep learning to determine different types of brain tumors.

The different analyses were performed using deep learning techniques to segment and detect brain tumors. For brain tumour segmentation, Yanming Sun et al. [3] proposed a robust and efficient CNN technique. John Schmeelk [4] worked with two-dimensional images by employing a two-dimensional wavelet transform. To complete the procedure of segmenting MRI brain images, Parra et al. [5] utilised an artificial neural network (ANN) method. In this study, a learning vector quantization (LVQ) network was constructed using an ANN method. Papageorgiou et al. [6] used fuzzy cognitive maps (FCMs) to describe design specialists. Incorporating a computationally clever training strategy known as the activation Hebbian algorithm enhanced the FCM ranking model's classification accuracy. El-Sayed et al. recently introduced decision support systems in medicine that use normal and abnormal categories. MRI scans were classified using a hybrid framework [7]. There are three main phases to the hybrid architecture that is proposed. In the first step, MRI scans are extracted using discrete wavelet transformations (DWT). In the second step to minimize the number of MR image features, we used principal component analysis (PCA). In the end, two different classifiers were utilized to differentiate normal MR images from those that were aberrant. Othman et al. used a probabilistic neural network (PNN) and image processing to classify brain tumours automatically [8]. The suggested PNN classifier went through the decision-making process in two stages. The first stage involved the extraction of features via the use of principle component analysis (PCA), and the second stage involved classification through PNN. Pei et al. suggested a method that improves texture-based tumour segmentation in longitudinal MRI by utilizing tumour growth patterns as novel characteristics. This method makes use of tumour growth patterns [9]. A new convolutional neural network (CNN) model for brain tumour classification was proposed by Muhammad Sajjad et al [10].

The MR images were segmented to determine where the tumour was located. The next step was to enrich the existing data set. Next, they used the proposed CNN to carry out the categorization procedure. They have a 94.58% success rate when classifying data. The MR dataset was split into two categories, normal and aberrant, by Kanmani et al. [11]. To improve classification efficiency, they applied the threshold-based region optimization (TBRO) technique. They used this technique to carry out segmentation. The proposed method was experimentally validated with a success percentage of 96.57 percent. Seetha J. et al. [13] proposed an approach to speed up computations while maintaining high precision. The ImageNet database is utilised for categorization purposes. To obtain high accuracy, a loss function that is based on gradient descent is implemented. Fuzzy C-Means clustering was used for tumour segmentation by Tonmoy Hossain et al. [14], and it accurately predicted tumour cells. After performing segmentation, they applied traditional classifiers and a convolutional neural network to choose features for classification. In the traditional classifier section, they applied and compared the outcomes of various traditional classifiers such as K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Nave Bayes, Random Forest, and Support Vector Machine. A comprehensive overview of existing techniques for segmenting and identifying MRI brain images was provided by Srinivasarao Gajula et al. [15]. You may learn in this article how many people are diagnosed with brain tumours annually. General advice about how to stay healthy while dealing with the sickness is included [16]. The modality-paired learning approach, which employs a 3D U-Net as its backbone network, was proposed by Yixin Wang et al. [17]. This method employs paralleled branches to independently extract features from multiple modalities before combining them via efficient layer connections. Gajula, S., et al. [18] proposed that the machine-learning technique of logistic regression may be used to do automatic brain abnormality identification. Disorders including Alzheimer's, transient ischemic attacks (TIAs), and brain tumours are all identifiable by this TSLR model. The most frequently accessed data sources were reported by Wenyin Zhang et al. [19]. The authors then provide a brief overview of the three types of multi-modal brain tumour MRI image segmentation techniques: traditional segmentation techniques, segmentation techniques based on classical machine learning techniques, and segmentation techniques based on deep learning techniques. Typical algorithmic structures, principles, and benefits and drawbacks are outlined for each approach. At last, they discuss the difficulties and offer a possible perspective for future patterns of development. Gupta, Gaurav, and colleagues [20] proposed data mining techniques for MRI image classification. This research proposes a novel hybrid approach to brain tumour classification using support vector machines (SVM) and fuzzy c-means. Image-enhancing methods including contrast enhancement and mid-range stretching are implemented in this algorithm. Skull striping uses a combination of double-thresholding and morphological processes. To find the suspicious area in a brain MRI, fuzzy c-means (FCM) clustering is applied to the segmented image. Brain MRI images are classified using support vector machines (SVMs) after features are extracted using a grey-level run-length matrix (GLRLM). A modified KNN-based clustering and segmentation method is proposed by Xie et al. [21] that uses Minkowski distance as the primary parameter. Using transfer learning, Srinivasarao Gajula et al. [22] presented the super pixel method for detecting and segmenting brain tumours. Data sets were pre-processed initially before being fed into a VGG-19 transfer learning network, which was then used to detect brain tumours. The next step is for a UNet model to locate malignant growths. In this study, we offer an effective and skilled technique based on both conventional classifiers and convolutional neural networks for automatically segmenting and detecting brain tumours.

The focus of this research is on the use of magnetic resonance imaging (MRI) of the brain to detect tumors. Finding brain tumours early is important because it helps medical professionals make a correct clinical diagnosis. The purpose of this work is to develop an algorithm for detecting tumours in MR brain images that is both accurate and reliable. Neurosurgeons and other medical professionals can use the system. The technology, which makes use of image processing, pattern analysis, and computer vision, is designed to boost the sensitivity, specificity, and efficiency of screening for brain tumours.

This paper is organized as follows: Section II of this study presents the proposed methodology that will be discussed in detail. Section III presents the results and discussion, and Section IV presents the conclusion and future work.

II. Proposed Methodology

Using a convolutional neural network, which we show here, we provide a method for the categorization and prediction of MRI images of the brain. Our initial prospective model classified and identified brain tumours using machine learning methods. The suggested approach aims to improve human health and longevity by classifying brain cancers. The suggested effort attempts to simplify the classification of brain tumours while simultaneously increasing their accuracy compared to existing methods. This technique was selected because, in comparison to conventional CNN, it possesses greater capabilities in terms of both accuracy and speed when it comes to classification.

A. Data Acquisition

The dataset that was gathered is separated into two categories: training brain images and testing brain images. Among these training datasets contains 2870 images of 4 different classes like pituitary, meningioma, glioma, and no tumor, and the testing dataset contains 394 images of 4 different classes. These images are analyzed, and then the algorithms get processed once they've been pre-processed.

B. Pre-Processing

During the pre-processing step, the primary objective is to precisely eliminate the redundancy that was present in the image that was collected while maintaining the details that are an important part of the entire method. This is done to improve not just the quality of an image but also its entire appearance. Removing unwanted noise from an image is a key part of any pre-processing method used to fix a degraded image [12]. Adaptive filtering is one kind of denoising in which the process is carried out in accordance with the noise data already present in an image on a regional level. Possible image de-noising methods are as follows:

$$I(x,y) = \frac{\sigma_y^2}{\sigma_{local}^2}\left(I(x,y) - \mu_{local}\right) \quad (1)$$

Where $I(x,y)$ is the reduced image,

σ_y^2 =variance

μ_{local} = mean around window pixel

σ_{local}^2 = local variance of window.

C. Segmentation

The process of segmentation is used with several medical imaging modalities to identify contaminated tumour tissue. Image analysis must begin with the stage of segmentation because it is essential to the process. Segmentation is the process of dividing an image into distinct sections or blocks that have similar and identical characteristics. The procedure of segmenting a brain tumour involves separating the normal brain tissues and solid tumours from the tumour tissues, such as hydrocephalus and dead cells, which are found within the tumour. Image segmentation has several methods. The choice of segmentation techniques, on the other hand, is determined by the kinds of features that are going to be processed and extracted.

D. Global Threshold Segmentation:

A threshold image can be given as $g(x,y)$

$$\text{Here } g(x,y) = \begin{cases} 1, & if \quad f(x,y) > T \\ 0, & if \quad f(x,y) < T \end{cases} \quad (2)$$

here 1 is object and 0 is background and $f(x,y)$ is input image. In case of global thresholding T is constant applicable over whole image. Algorithm for automatic estimation of threshold T is as follows.

Step 1: Select an initial estimate for T.

Step 2: Segment image using T as two groups with group1 (G1) values as greater than T and group 2 (G2) values as less than or equal to T

Step 3: Compute average intensity values for G1 as m1 and for G2 as m2

Step 4: Compute a new threshold value T_{new} =1/2 (m1+m2)

Step 5: Repeat (2) through (4) until the difference in T_{new} in successive iterations is smaller than ΔT.

In the past, the most prevalent segmentation methods were pre-processing and thresholding, or a mixture of the two. The thresholding method is the simplest, and it incurs the least amount of calculation cost. The histogram of the image is an essential factor in determining the global threshold. Utilizing the values of the local attributes allows for not only the enhancement of the histogram but also the computation of the global threshold to be performed. At the beginning of this procedure, we will select the MRI image of the brain. In the following stage, we will be calculating the value of the threshold. After that, we will have two distinct groupings of pixel values. We are computing the arithmetic mean by utilizing these two groups. The new threshold is determined by arithmetically averaging the two means. This technique is repeated until the desired number of iterations has been reached.

E. Feature Extraction

The term "feature extraction" is used to describe the procedure of reducing unstructured data to a set of quantifiable characteristics that may then be processed without losing any of the original data's context. To better characterize a large dataset with fewer resources, feature extraction is employed. To classify the data, two different kinds of features were extracted: texture-based features and statistically based features. During the process of feature extraction, we will obtain several characteristics of the images, such as their mean, skewness, entropy, standard deviation, centroid, energy, dissimilarity, homogeneity, and correlation features.

F. Proposed Methodology using CNN

To detect tumours, a five-layer convolutional neural network has been developed and is currently being used. In our 5-layer CNN model, there are seventeen stages, as well as the hidden layers, which provide us with the best possible outcome in terms of tumour detection. In the domain of medical image processing, convolutional neural networks have found widespread application. Throughout the years, several researchers have attempted to construct a model that can detect the tumour in a more effective manner. We attempted to develop a model that is capable of accurately classifying the tumour based on images taken from a 2D MRI of the brain. Although a fully connected neural network is capable of tumour detection, we elected to employ a convolutional neural network (CNN) for our model due to parameter sharing and sparsity of connection.

The process by which the suggested work will be carried out on the chosen data sets is depicted for us in Fig. 1. Fig. 2 displays a variety of MRI images, some of which contain tumours while others do not.

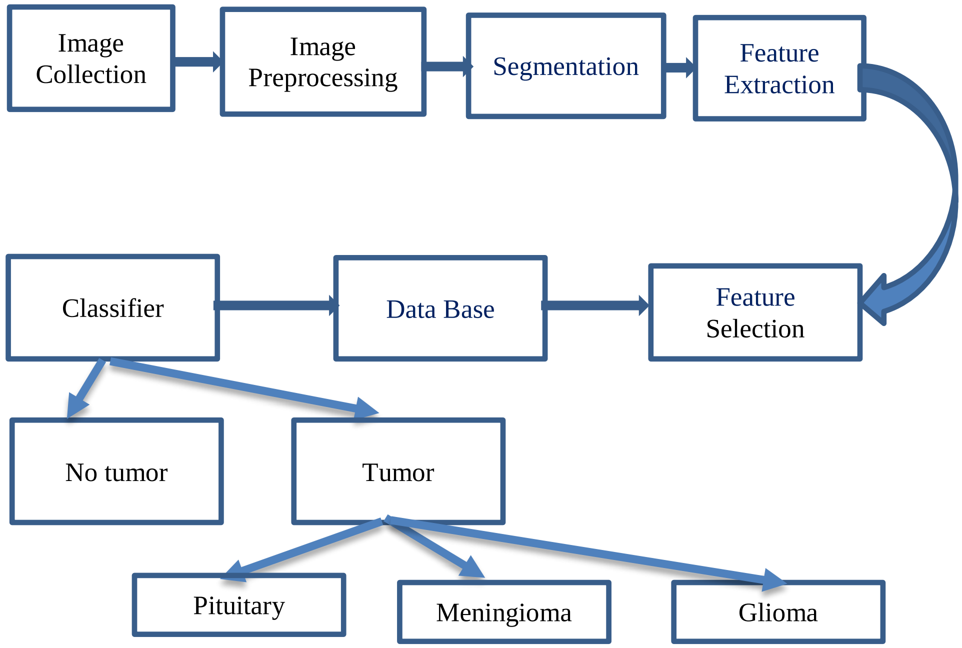

Fig. 1. Basic block diagram of proposed work

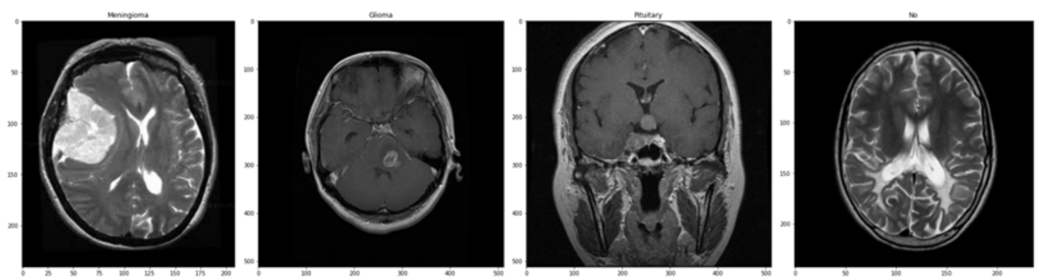

Fig. 2. (a) Meningioma (b) Glioma (c) Pituitary (d) No tumor

Our suggested method takes an exhaustive set of images as input and scales them all to the same dimensions as 256*256*3. The input layer is typically administered by sixty-four convolutional filters of size 2*2, and we use this to design a convolutional kernel that is both complex and efficient. Here we are using the ReLU activation function. If the input is positive, ReLU may be a piecewise linear operation that returns that value directly; otherwise, it returns zero. The pooling process involves summing the features that fall inside a 2D filter's coverage zone, as if the filter were dragged over each channel of the feature map. In a typical CNN model design, numerous convolutional and pooling layers are stacked on top of one another. Pooling layers is used to reduce dimensionality when working with large feature maps. As a result, the number of parameters that need to be learned to determine the level of computation carried out in the network is reduced. The pooling layer is responsible for summing up the features that are available in a certain portion of the feature map that was produced by a convolutional layer. Because of this, subsequent operations are carried out on summarized data rather than correctly positioned features that were generated by the convolutional layer. Because of this, the model is more capable of distinguishing between distinct positions held by features in the input image.

Pooled feature maps are created after pooling. After merging many images into one, we need to flatten the resulting matrix into a column vector for further processing. After that, the data is sent to a neural network for evaluation. The use of two stacked, interconnected layers, the dense layer, was exemplified by Dense-1 and Dense-2. Keras processes the neural network using the dense function, and the resultant vector feeds the network's layer.

The RMS optimizer was utilised in the construction of the model, and binary cross-entropy was chosen to serve as the loss function. Because of this, we were able to evaluate the accuracy of the tumour detection. A suggested method for locating tumours is depicted in Fig. 3, and it makes use of a convolutional neural network (CNN).

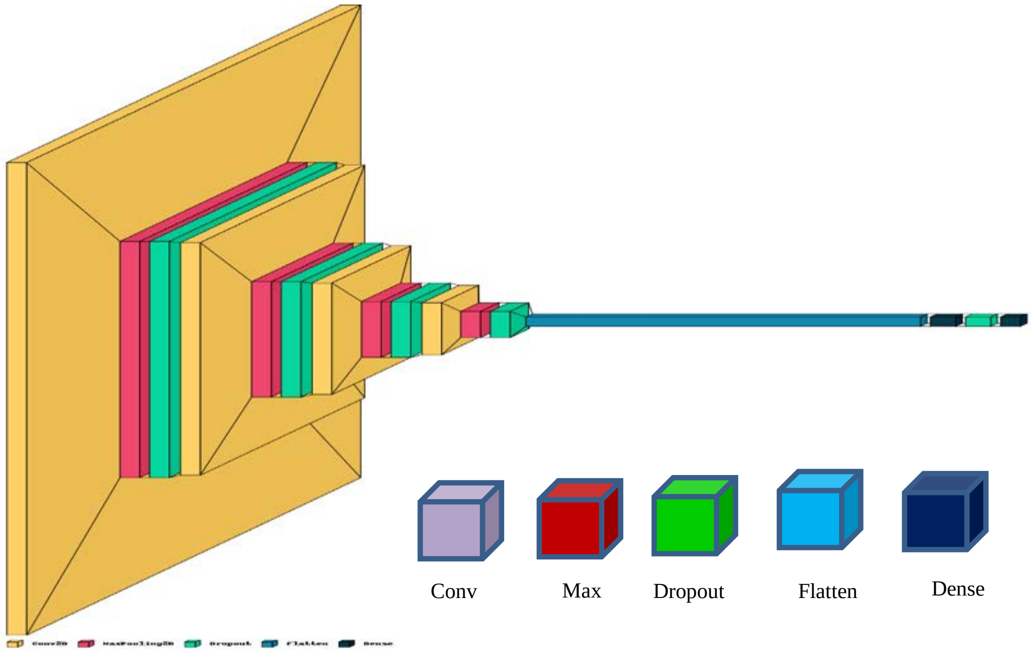

Fig. 3. Proposed methodology for tumor detection convolutional neural network

III. Results and Discussion

The effectiveness of the proposed network will be assessed based on the following quality metrics.

$$Sensitivity = \frac{TP}{TP+FN} * 100\% \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} * 100\% \quad (4)$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} * 100\% \quad (5)$$

$$Precision = \frac{TP}{TP+FP} * 100\% \quad (6)$$

TABLE I. Performance of Existing and Proposed Algorithms

CNN Architecture	Sensitivity	Specificity	Precision	Accuracy
AlexNet	84.3	92.3	93.1	87.9
GoogleNet	84.8	95	95.5	88.6
VGG-16	81.2	87.3	88.1	83.4
Seetha et al. [13]	85	85.3	88.5	97.5
Tonmoy Hossain et al. [14]	86.2	91.5	93.5	97.87
Proposed Method	90	92	94.1	98.6

The comparison of several quality metrics with both existing and suggested methods is presented in Table I.

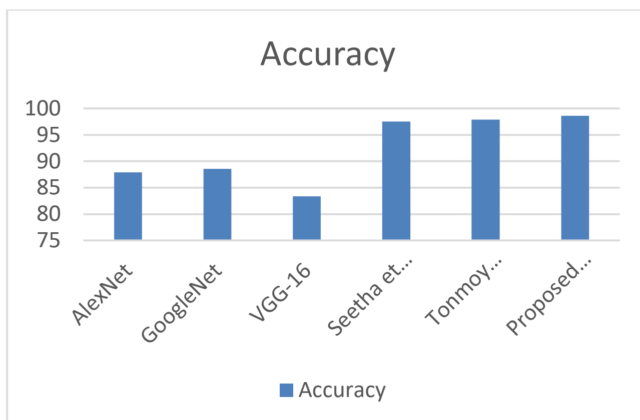

Fig. 4. Accuracy comparison

Fig. 4 shows the results of a comparison of different quality metrics using both existing and recommended methods. Fig. 5 depicts the model structure and various layers of the proposed model. Fig. 6 shows different MRI images- Prediction of brain tumours by the proposed model. Fig. 7 shows the accuracy and loss curves of the proposed model.

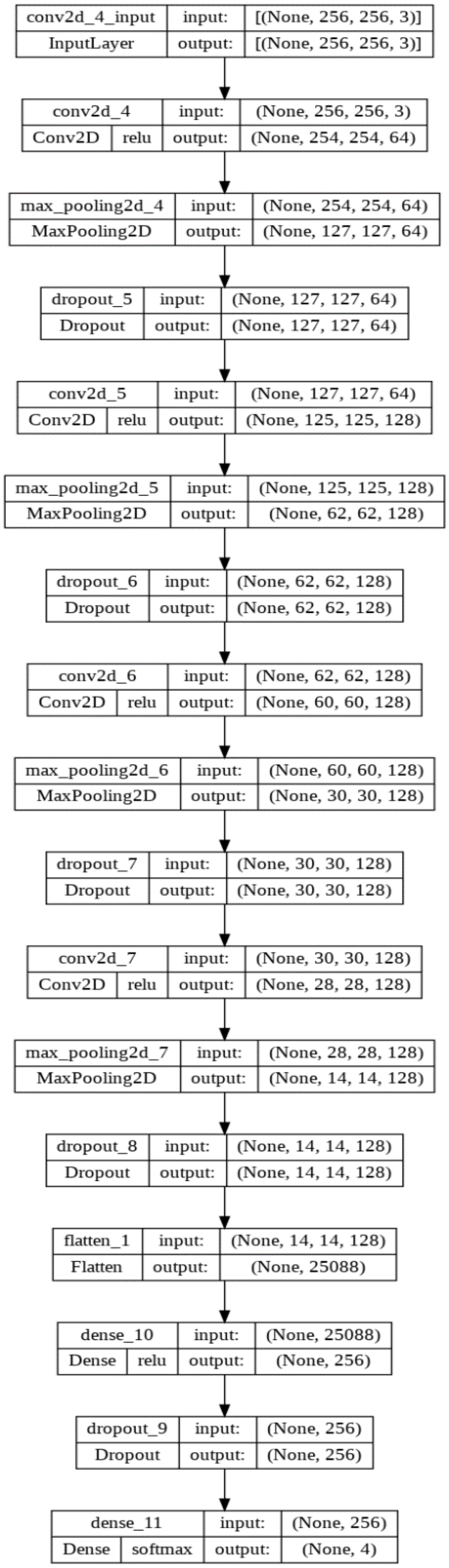

Fig. 5. Model structure and different layers of proposed model

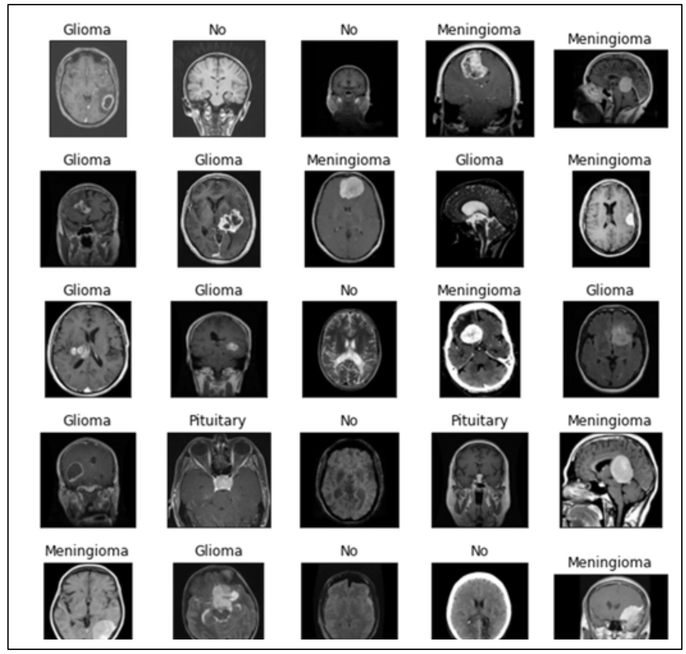

Fig. 6. Prediction of brain tumor by proposed model

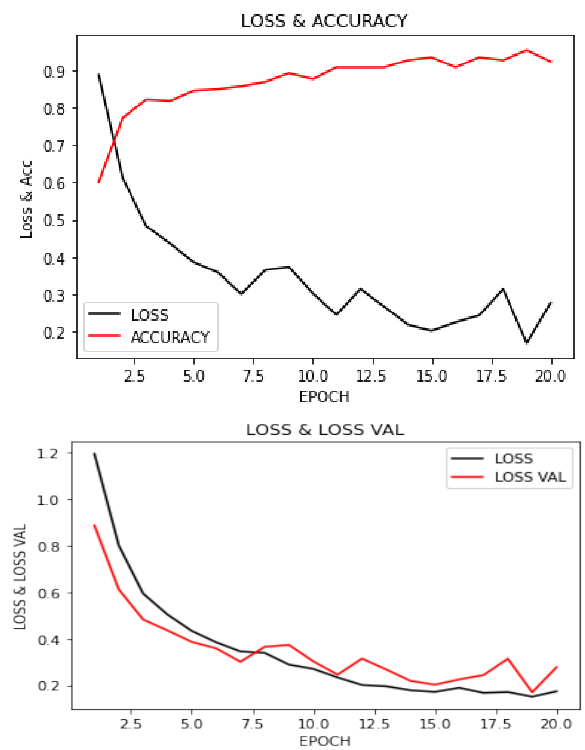

Fig. 7. The accuracy and loss curves of the proposed model

IV. Conclusion

Image segmentation is an essential part of medical image processing because of the extensive variety of medical images. The primary objective of this study is to develop a low-complexity, high-accuracy, automatic brain tumour categorization system. Images obtained from MRI and CT scans were analyzed and employed in the segmentation of the brain tumour. The proposed research was divided into four stages: data collection and pre-processing, data segmentation, MR image feature extraction, and data classification. In our research, we applied a method called global threshold segmentation for tumour segmentation, which accurately predicted the presence of tumour cells. The procedure of segmentation was then followed by classification using both conventional classifiers and a convolutional neural network. Following that, we put a variety of conventional classifiers to use and analyzed the results of each. The proposed method successfully distinguished between healthy and diseased tissues in MR images with an accuracy of 98.6%. The same method can also be utilised to detect and study a variety of disorders that are present in other areas of the body. Future research can improve accuracy by combining more effective segmentation and extraction methods with real-time images and clinical settings, as well as a large data set covering a wide range of conditions and classifiers with optimization methodology.

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According to the author's declaration, there was no informed consent given.

Declaration of competing interest

The authors have no conflicts of interest.

Ethical Approval

This article does not contain any data or other information derived from experiments or research in which human or animal participants participated.

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