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Investigation of Brain tumor detection using Convolution NeuralNetwork

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Abstract: Biomedical technology now plays a critical role in the detection and treatment of a wide range of diseases, from minor to life-threatening. One of the most hazardous diseases is brain tumor, which is defined as a mass growth of abnormal cells in the brain. By preventing the formation of aberrant cells, early discovery and treatment can save a person's life. It can be detected by analysing Magnetic Resonance Imaging (MRI) scans. To diagnose a brain tumor, accurate analysis of MRI scans is required, which may be accomplished using artificial neural network algorithms. Although humans can recognise the tumor manually, the risk of human mistake is higher, and the process is time consuming. This research proposes an algorithm model for predicting the likelihood of developing a brain tumor.

Keywords: Convolution Neural Network (CNN), TensorFlow, Keras, Brain tumor detection, Machine learning, Magnetic Resonance imaging (MRI)

I. INTRODUCTION

A brain tumour is a dangerous disease that affects human life and is caused by a collection of abnormal cells growing in the brain. It has an impact on one's mental health and stability. Brain tumor affect people in different ways, and some can be life-threatening. According to the study, the incidence of brain tumor has risen by more than 40% in adults in the last 20 years. The incidence of nervous system tumor varies widely among countries, with males experiencing 0.01 to 12.7 tumor per 100,000 people and females experiencing 0.01 to 10.7 tumor per 100,000 people, according to global statistics. Africa has the lowest prevalence.[1].The most active means of lowering death rates from brain cancer have been discovered to be early detection and therapy [2]. Rapid advancements in digital recognition and computational intelligence approaches have greatly enhanced medical picture understanding and aided in early detection. Image processing can be divided into several categories, suchas enhancing photographs, compressing them, segmenting them, analysing them, and so on [3].There are around 130 different types of tumor in the brain and nervous system. Brain tumor can be malignant (cancerous) or benign (noncancerous), but they can be damaging or life-threatening in any scenario. Tumors are classified according to their cell origin and activity[4]. Medical imaging is critical for detecting and diagnosing brain cancers, as well as preventing more serious disorders. Researchers use magnetic resonance imaging (MRI) to detect brain tumors[5]. Because it does not involve ionising radiation, MRI is one of the most extensively used medical imaging modalities for brain tumor [6]. The pre-processed brain MR images are turned into binary pictures during segmentation. The process of extracting higher level information from an image, such as shape, texture, and contrast, is known as feature extraction. The classifier is used to classify the normal trained image samples and the input image sample in the classification process[7].

CNN is made up of numerous layers, each of which captures features and uses partial differential functions to turn a complicated input into an activation form. The layers are stacked one on top of the other. A convolution layer, a pooling layer, and a fully connected layer are the three core layers of the CNN design. Whereas the convolution layer collects features progressively, the pooling layers sample along the spatial domain, and the fully connected layer classifies, the fully connected layer classifies. When small numbers appear while computing gradients, a vanishing gradient problem may arise. A Rectified Linear Unit (ReLU) layer is introduced after each convolution layer as an element-wise activation function to prevent vanishing gradient difficulties. The input layer, the dropout layer, the output layer, and the output layer are some of the other CNN layers.[8-9].

To distinguish between areas of the brain and those with tumor, Fuzzy C-Means was used. Following segmentation, feature extraction is performed using the Gray Level Run-Length Matrix (GLRLM). The goal of feature extraction is to locate important features in an image that can help in classification[10]

II. METHODOLOGY

Convolutional neural networks are widely employed in the field of medical image processing. Several experiments were conducted throughout the year in an attempt to establish a model that might better detect tumours. We tried to think of a decent example that might be utilised to accurately categorise objects. The tumour was created from 200 MRI images of the brain. The model, which has seven phases and incorporates the hidden layers see Figure, produces the most noticeable result. The workflow of the suggested CNN model.

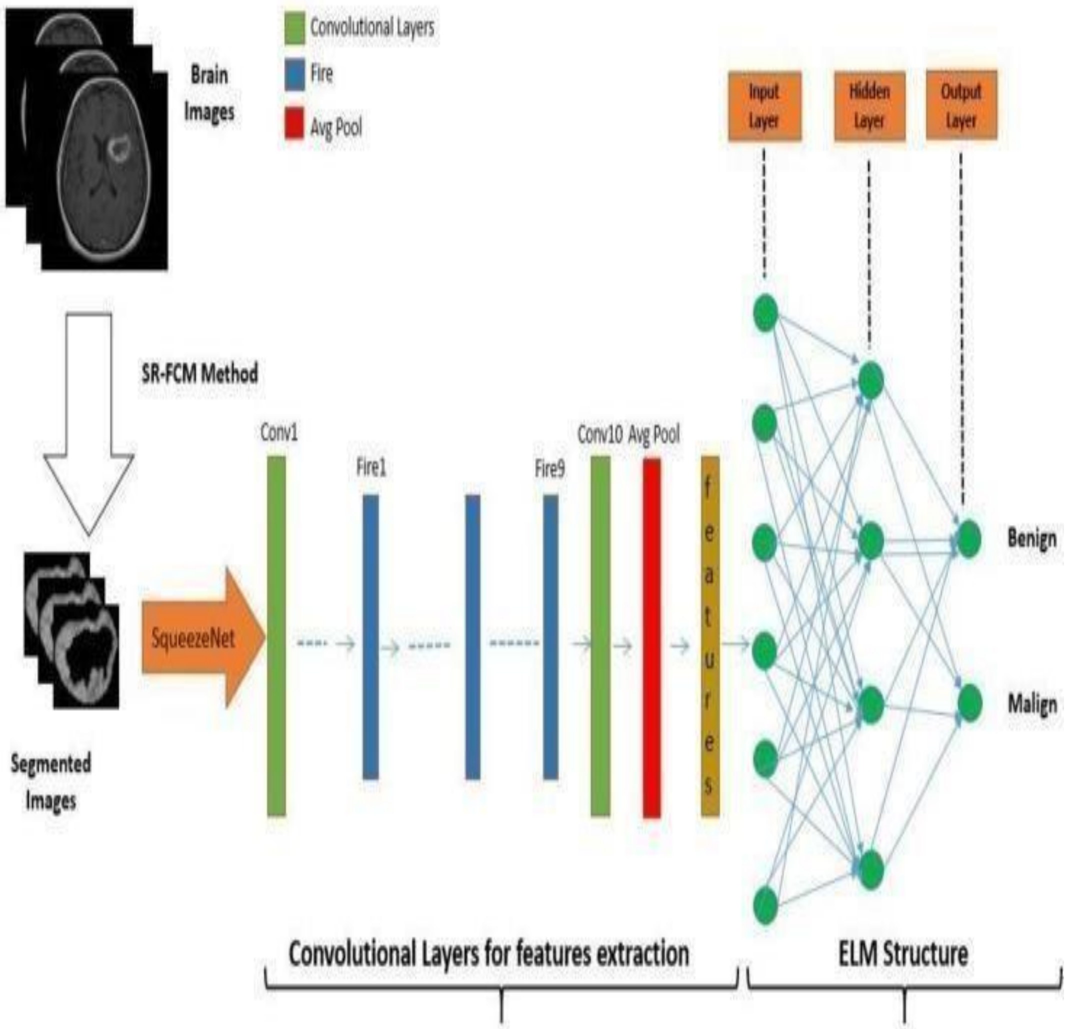

Fig 1.CNN Block diagram for tumor detection

Our proposed frameworks attempt to recognise and separate brain tumours in medical images using a deep learning technique that uses the convolutional neural network (CNN) algorithm. It also contains many stages that are dependent on the construction of this task, as shown in Figure 2, which depicts the main block diagram of the system for detecting brain tumours and their stages.

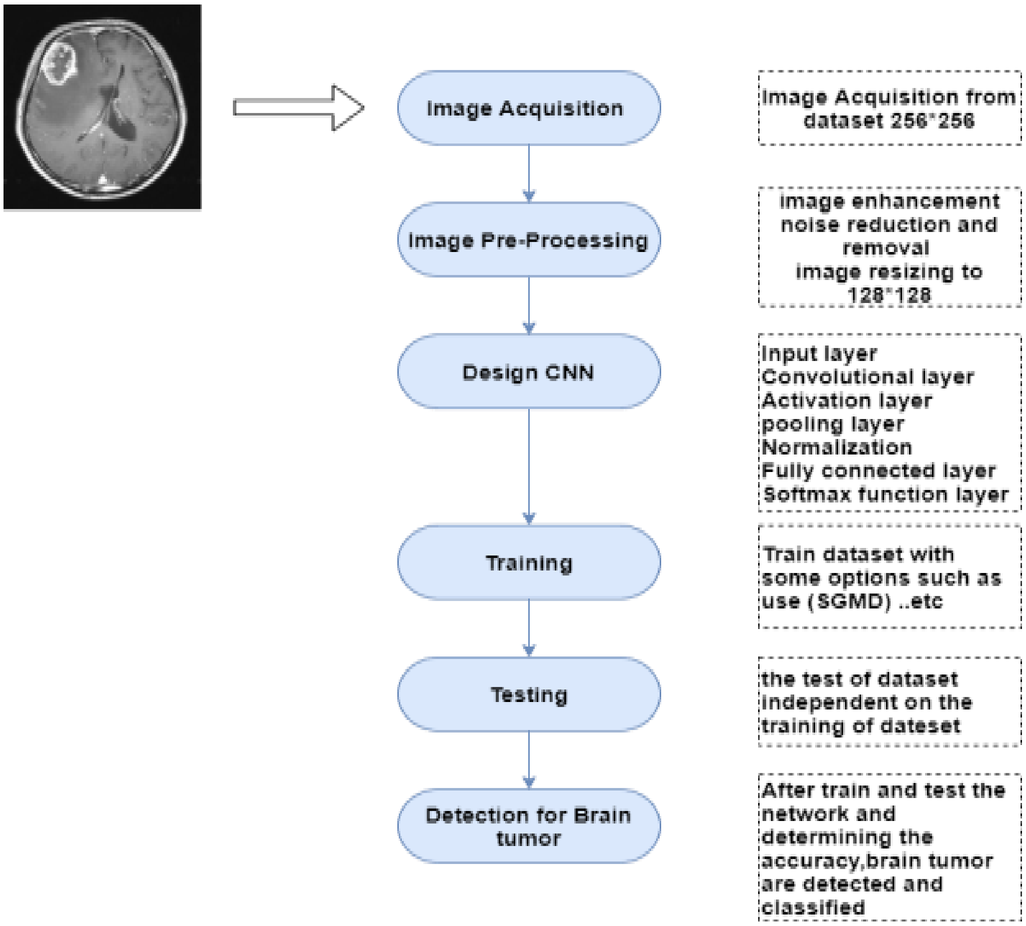

Fig 2. General Structure design for Brain Tumor Detection and classification

According to Fig 2 that shows, the major stages of a general diagram which will be applied for the used in this work, will be explained below:

A. Image Acquisition

The challenge in this study is to produce a dataset. The suggested approach tries to detect and categorise brain tumours, and the obtained data comprises of 3064 images related to several tumours, including meningioma(708 slices), glioma (1426 slices), and pituitary tumour (930 slices). [14] Only a small percentage of the photographs in this gallery are visible.

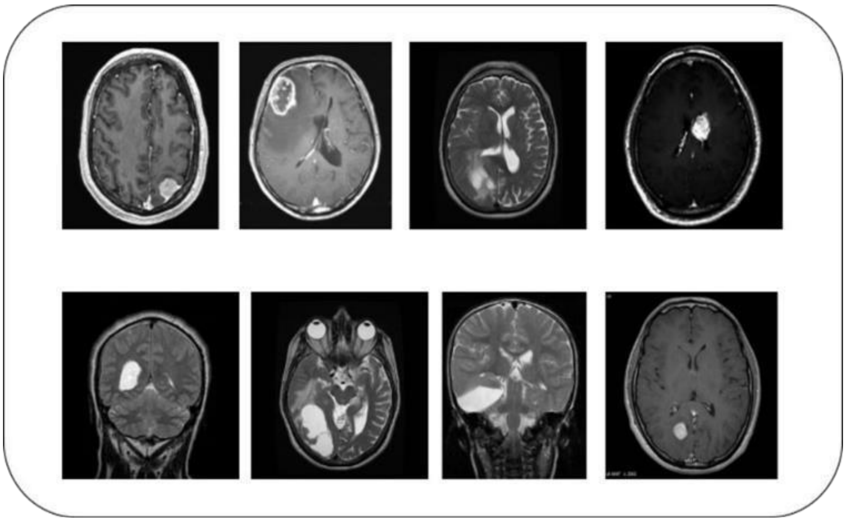

Fig 3. A Sample of MRI images for the different types of Brain images

B. Image Pre-Processing

This procedure is constantly changing or smoothing images in order to improve them and prepare them for the next stage of processing [15]. It is also used to do another specialised process that is required in the next stage. Before entering the CNN, the image is shrunk at this point. The goal of shrinking the photos is to speed up the training technique and calculate the model test more realistically. The MRI pictures are reduced in size from 256 * 256 pixels to 128 * 128 pixels

C. Design CNN

The CNN is one of the most well-known deep learning networks, and it has several properties that distinguish it from standard neural networks, such as the use of fewer parameters and a smaller number of neurons, which reduces training time. There are various well-known convolutional neural network architectures, such as Alex Net, Google Net, and LeNet, that can be used to create this network. As a result, the structure is being designed in Fig3.4. In order to suit the proposed strategy, and after adjusting many of the parameters and testing it, this network design was chosen for the best results [16].

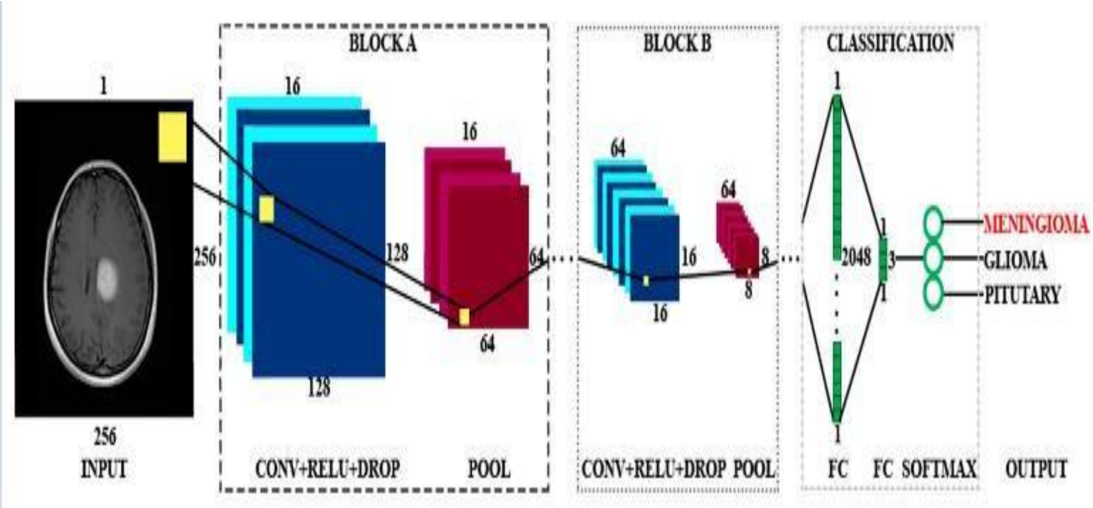

Fig 4. Structure of CNN

As shown in the above, the structure of the CNN algorithm consists of several layers for each layer a specific work and a different structure, the structure is designed as follows:

1) Input layer

The stage includes the inputted image as well as their pixel values. These images are the images of braintumors that entered in matrix form.

Convolution Layer

Convolution Neural Network (CNN) uses various kernels to turn the entire object into convolution layers,as well as optimised feature maps to construct several types of feature maps, as seen in "(1)" below. Four convolution layers are used in the suggested method. Ten filters with a dimension of 3*3 and "the same padding" were employed in the first convolution layer. The'same' padding was applied to the inputs across the edges, implying that the output will be the same size as the input. In the second convolution layer, 20 filters with a diameter of 3*3 and "identical" padding were utilised. 64 filters with 3*3 dimensions and padding'same' were employed in the third convolution layer, and in the fourth Authorized licenced use limited to: San Francisco State Univ. IEEE Xplore was used to get this document on July 2, 2021 at 00:48:53 UTC. There are several limitations. University of Zakho, Duhok Polytechnic University, Kurdistan Region, Iraq, Third International Conference on Advanced Science and Engineering (ICOASE2020) With 3*3 sizes and the same padding, 159 convolution layers and 30 filters were employed.

$(i,j) = \sum m \sum n\ I(m, n)F(i - m,j - n)$ (1)

2) Activation layer

The activation function also is applied in this work, the nonlinear translation function in the artificial neural network is sigmoid or hyperbolic tangent, this layer uses many types of activation functions the most popular is Rectified Linear Units (ReLU) that we used it in our work. In this function, negative values in the matrix resulting from the previous step are converted to zero and positive values remain the same. The following equation is used for rectified linear units[17].

$$y = Max\ (x, 0) \quad (2)$$

3) Normalization layer

The batch normalization layer it is a very important layer, it forms norms any channel by means of a mini-batch. The use of normalization layer can help to decrease the sensitivity of a mutation in the results.

4) Pooling layer

Another building block to the CNN is a pooling layer, It's usually follows the layer of convolutional and used to minimize parameters of the network and the dimensions of feature maps, so their measurements take into account adjacent pixels. Average pooling and max pooling are the most commonly used techniques . The pooling layer applied in this work is maxpooling function.

6) Fully connected layer

Often the last layers of a CNN are fully connected layers, so mainly the two neighboring layers inside the network will directly connect by a fully connected layer.

7) Softmax layer

The output of the neural network can be difficult to understand. It's typical to end convolution neural network (CNN) with the softmax layer for classification purposes, the result values are between the [0, 1] range which is good because that can prevent binary classification and fit as many classes or measurements in the CNN model that used, after extracting the values in a fully connected phase, softmax layer will be assigned in all process that will be done according to the extracted features that have been [16]. The following "(3)" expresses the Softmax:

$yi = e\ Zi / \sum e\ N\ Zi\ j{=}1$ (3)

D. Training

It's the process of obtaining the extracted kernels throughout the convolution layers as well as the extracted weights throughout the fully connected layers, which reduces the gap between defined ground truth tables in the training dataset and output predictions, in this work the dataset was divided so that the training data would be 70%, the network that builds will learn by extracting the feature from the MRI image of brain tumors in demand to learning from that feature that extracted from each image. Fig. 4. The Training, accuracy and Loss function progress.

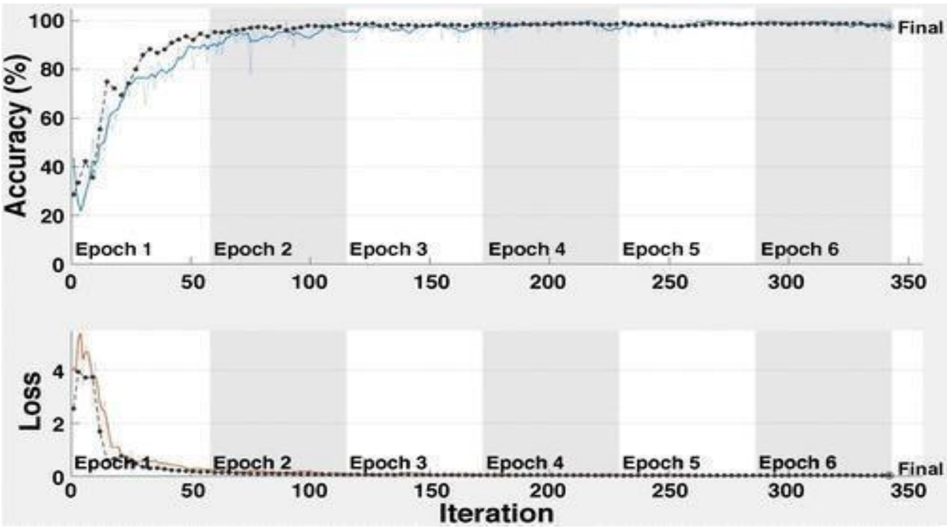

Fig 5 . Loss and Accuracy graph

E. Testing

Testing is the process to test the used dataset to supply an equitable final evaluation of the trained dataset, which have been trained at CNN, and the feature that is extracted by learning neural network, in this work we use 30% of dataset for testing.

F. Detection of brain tumor

Based on the previous steps and on the training and the testing of the neural network that designed, the results for the detection and classification of the brain tumor will be present in the following section in this paper.

ALGORITHM:

Working Flow Devised for Proposed Methodology

Step-1: Apply convolution filter in first layer

Step-2: The sensitivity of filter is reduced by smoothing the convolution filter (i.e)subsampling

Step-3: The signal transfers from one layer to another layer is controlled by activation layer

Step-4: Fasten the training period by using rectified linear unit (RELU)

Step-5: The neurons in proceeding layer is connected to every neuron in subsequent layer Step-6: During training Loss layer is added at the end to give a feedback to neural network

III. PERFORMANCE EVALUATION

In our work, CNN gained an accuracy of 97.87%, which is very compelling. The main aim of this project is to distinguish between normal and abnormal pixels, based on texture based and statistical based features.

On the BRATS and Kaggle datasets, the experiment was run in Google Collobratory. The photos in these datasets have been enhanced, and 200 photographs have been recreated. There are 100 photographs of positive brain tumor cases and 100 images of negative brain tumor cases among the total of 200 images. Illustrations of a case in 70:15:15 ratios, the full set of images is divided into training, validation, and testing. In training, validation, and testing, there are images for both scenarios. images. On training and validation photos, the model is trained. The two types of education the accuracy and loss of validation are calculated and presented on two graphs. in comparison to the total number of training epochs.

$Accurcy = number\ of\ correctly\ classified\ images$ X 100 (4)
$total\ number\ of\ images$

SNO	Percentage of training dataset andtesting dataset %	The overall accuracy rate for all classes in training %	The overall accuracy ratein testing %
1	50% training 50% testing	99.72%	91.81%
2	60% training 40% testing	99.71%	94.32%
3	**70% training 30% testing**	**97.87%**	**97.67%**
4	80% training 20% testing	99.91%	94.25%
5	90% training 10% testing	99.95%	95.51%

Table 2: Comparison of different ratios of size of data in training and testing for the overall accuracyrate

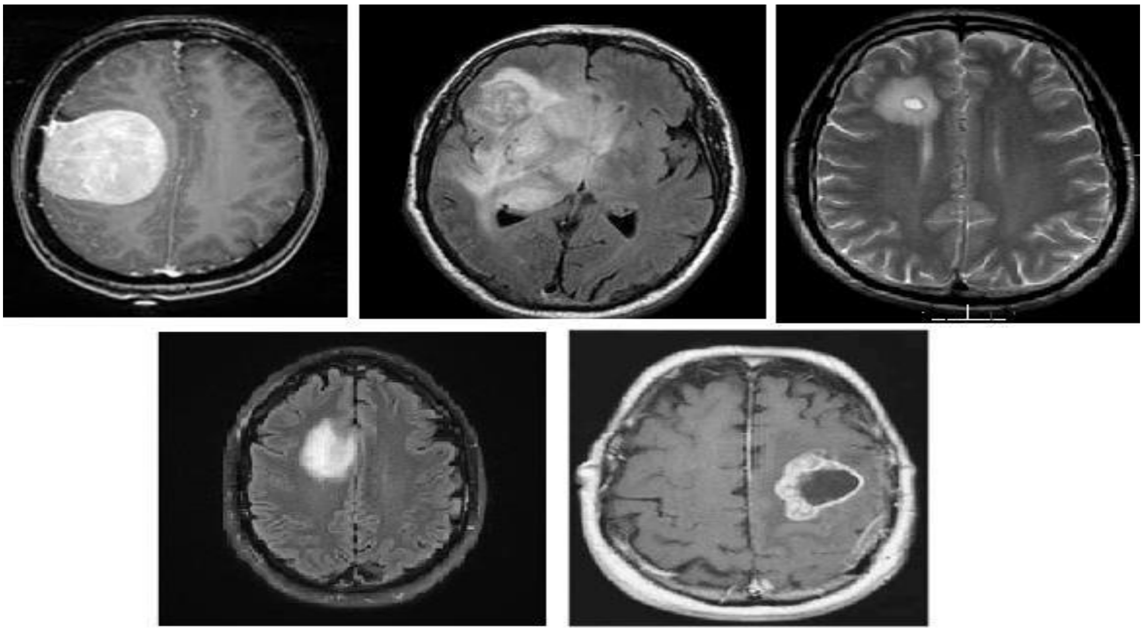

FIG 6. Images with tumor

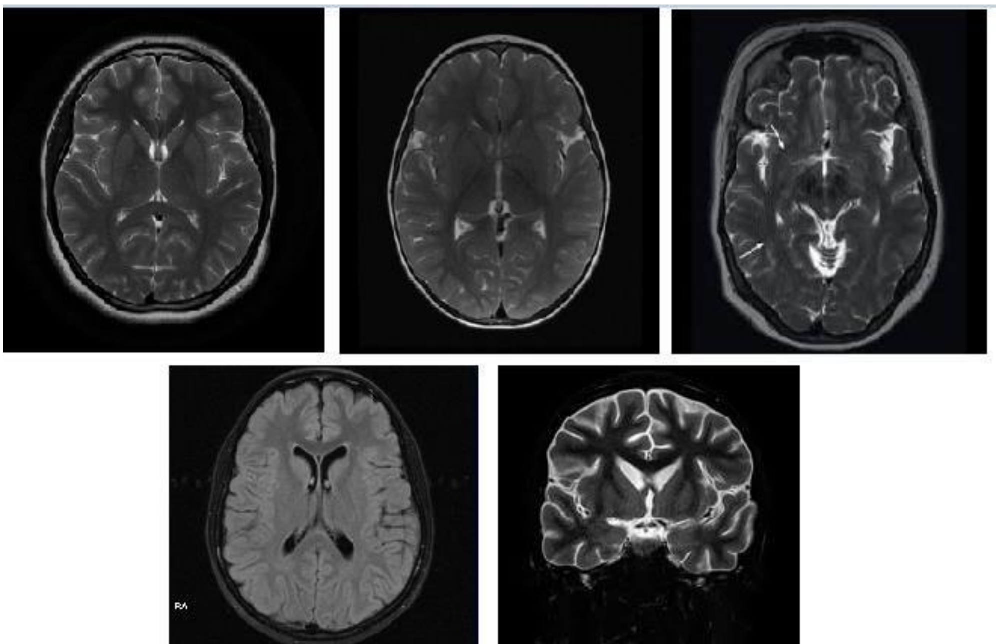

FIG 7. Images without tumor

***Performance Comparison**:*

Finally, we compared our proposed approaches, which include classification with classic machine learning classifiers and CNN. We also compared our findings to those of other studies that used the same dataset. Researchers from Seetha et al. achieved an accuracy of 83.0 percent using SVM-based classification and 97.5 percent using CNN. Both machine learning and CNN-based classification yielded better results using our proposed methodology. Mariam et al. received around 95% of the diceco-efficient, although our Dice score is 96 percent.

Table.3 . *Performance Comparison*

Methodology	***Accuracy (%)***
Seetha et al [17]	97.5
Proposed CNN Model	97.8

IV. CONCLUSION

We have presented a new CNN architecture for the detection and classification of brain cancers in this paper. The research was carried out utilising an MRI image collection that included Glioma, Meningioma, and other malignancies We used all photos as input for Pituitary. Preparing and to improve the accuracy of the results, the tumor were segmented. images. Our neural network design is easier to train and more efficient. Because the programme was built to run on multiple computers, it isfeasible to execute it on any of them. Less resources are required by the algorithm. The plan's implementation the neural network is made up of blocks. Each block has a variety of different typesof items. first the input layer, then the convolution layer, Rectified Linear Units was the activation function employed at the time. (ReLU), the normalisation layer, and the pooling layer are the three layers. The use of CNN algorithms and a combination of supervised with unsupervised and ML with the methods are promising to provide better results. Even, various fine tunings can sometimes offer promising improvements

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