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# MRI-based Brain Tumor Image Classification Using CNN

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***Authors' contributions***

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## ABSTRACT

Though all brain tumors are not cancerous but they caused a critical disease produced by irrepressible and unusual dividing of cells. For the case of Medical diagnostics of many diseases, the health industry needs help, the current development in the arena of deep learning has assisted to detect diseases. In recent years medical image classification has gained remarkable attention. The most well-known neural network model for image classification problems is the Convolutional Neural Network (CNN). CNN is the frequently employed machine-learning algorithm that is used in Visual learning and Image Recognition research. It is considered to derive features adaptively through convolution, activation, pooling, and fully connected layers. In our paper, we present the convolutional neural network method to determine cancerous and non-cancerous brain tumors. We also used Data Augmentation and Image Processing to classify brain (Magnetic Resonance Imaging (MRI). We used two significant steps in our proposed system. First, different image processing techniques are used to preprocess the images and secondly we classify the preprocessed image using CNN. Brain tumor classification is a process of identifying and separating the cancerous and non-cancerous brain tissues and labeling them automatically. We use the famous machine learning algorithms Convolutional Neural Network which is broadly

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employed for image classifications. This experiment is conducted on a dataset of 2065 images. In our dataset number of training, examples are 1445, the number of validation examples is 310, and the number of testing example is 310. We also used data augmentation to raise the number of the dataset. We achieved a high testing accuracy of 94.39%. The proposed system displayed sufficient accuracy on the dataset and beat many of the noticeable present methods.

*Keywords: Brain MRI images; CNN; augmentation; tumor; deep learning; machine learning.*

## 1. INTRODUCTION

Medical imaging is the pictorial representation of the role of organs or tissues of the human body. It is a practice and method of imaging the inner body for clinical investigation and medical inquiry [1-4]. The medical images of the human body are mainly used for conducting medical treatment and investigation. As such, it produces a substantial part in the improvement of medical prescriptions and the health of humans.

Magnetic Resonance Imaging (MRI) gives the detailed images of the human organs and tissues of that are captured by applying a magnetic field and computer-simulated high frequency signals [5]. MRI is used to diagnose pathologies or conduct medical investigations or research purposes.

Tumor: The term "Tumor" is a synonym for the word "neo-plasm" which means the abnormal growth of cells.

Basically, tumors are of three varieties: 1) Benign; 2) Pre-Malignant; 3) Malignant [6-8] where malignant can only cause cancer.

- Benign: A benign tumor is a noncancerous group of cells. It might not occupy nearby tissue or reveal different constituents of the body the way cancer normally exhibit. A benign tumor is not malignant. Benign tumor develops more slowly, its borders is even, and doesn't spread to other parts of your body. It is harmless and sometimes doesn't require treatment.
- Pre-Malignant tumor: In this case, the human cells are not like the cancer cells, but it may progress towards cancer-affected cells. After that, the cells may develop further and may attack different parts of the body. Treatment can cure the tumor, sometimes needs surgery.
- Malignant tumor: The word malignancy is coined from the two words, "mal" and "ignis" that mean "bad" and "fire", respectively. Most of the areas of the malignant tumor are severely cancerous. They progress as soon as cells grow and unfold violently. Within a few days the tumor will become threating. The method in which malignant tumors will develop rapidly and attack to other segments of the human body is called metastasis.

The latest study on the brain or spinal cord tumor [9] in the year 2022 states that 25,050 adults, in which 14,170 are men and 10,880 are women in the United States of America (USA). The patient of the brain and spinal cord cancerous tumors are increasingly in tremendously. Every human being has the chance to developing this type of tumor less than 1% person in their lifetime. Among all primary central nervous system (CNS) tumors, brain tumors can attack for 85% to 90%. In 2020 an about 308,102 people received treatment worldwide with a major brain or spinal cord tumor. Children are also suffering from cancer, a survey of the United States shows that under the age 15 about 4,170 children may be identified with a brain or CNS tumor in the year 2022. The tenth prominent factor of demise for men and women is brain and CNS cancer. The survey projected that around 18,280 adults in the United States among them about 10,710 men and 7,570 are women may die from brain cancer and CNS tumors in the year 2022. In 2020, 251,329 people died worldwide mainly due to the brain cancer and CNS tumors.

In 1980, CNN was used for the first time [10-12]. We can associate CNN with a Multilayer Perceptron (MLP) network. The computing supremacy of the CNN model is comparable with the human brain. Based on their visual appearance of object humans can identify and detect objects. When we want to teach our children to detect and recognize an object we show them lot of images of the same item. CNN works in a similar process, the training dataset helps to train the network to recognize the objects. And then the testing dataset is used to identify or classify the objects. A CNN is the mixture of feature mining and sorting methods.

Hence, for the progress of medical image research, it is significant to escalate the precision of the previously suggested methods of image processing. In this work, we developed a CNN-based model to help medical representatives for the betterment of their treatment. Through our proposed algorithm, we can acquire a testing accuracy of 90.39% in detecting tumors in MRI images of brain tumors. Nowadays they don't need to analyze the MRI images manually for enhanced treatment speed.

## 2. RELATED WORKS

Machine learning and deep learning are largely used to detect brain tumors. So this techniques are widely used to classify the MRI images in image processing.. A great amount of research investigation are being continued on the organization of brain MRI images. We reviewed some of the national and international journals that segregated and categorized brain tumors employing deep learning techniques. Hassan Ali Khan et al categorized MRI images of brain under two basic classes, such as cancerous and non-cancerous tumor. As such, they used the CNN method in parallel with data augmentation and image processing techniques [13]. They applied the transfer learning approach to match the outcomes of their scratched CNN model with pertained VGG-16, ResNet-50, and Inception-v3 models. They applied the CNN model for the binary classification of brain tumors, where the computational time is higher than our proposed system. Their computational time is 205 sec per epoch, in our research we get approximately 140 sec per epoch. Their datasets are too small only 253 images so their computational time is less and shows a higher accuracy. They achieved 96% for VGG-16, 89% for ResNet-50, and 75% accuracy for Inception-V3. We use the larger dataset of 2065 images; we also use image augmentation for increasing the number of images.

Three fully automatic CNN models are designed by Emrah Irmak et al for different classification tasks of brain tumors employing openly accessible datasets [14]. The CNN model is proposed to identify brain tumors. The five types of brain tumors that are normal, glioma, meningioma, pituitary, and metastatic are specified with the second CNN model. The additional CNN models are also developed to categorize brain tumors into three ranks, such as Grade II, Grade III, and Grade IV. The grid-search optimization algorithm is engaged to detect every vital hyperactive parameter of the CNN models automatically. They proposed three different CNN models for three different classifications, we proposed binary classification for the CNN model to detect whether there is a tumor or not.

Wadhah Ayadi et al proposed an exploit new model of CNN for the classification of a brain tumor in their paper [15]. The CNN comprises diverse layers, for example, the convolution layer, Rectified Linear Unit (ReLu), and the pooling layer. In their approach, they did not use any segmentation in the pre-processing stage, in our work we have done pre-processing of MRI images by cutting edge of the images from the brain part. A benchmark dataset is used to experimentally evaluate the suggested model.

Ahmad Saleh et al targeted in their work [16] to raise efficiency of MRI images to classify brain tumors and identify their category. In their paper, they used five models that were trained beforehand, as for example, InceptionV3, ResNet50, Xception, VGG16, and MobileNet to classify brain tumors. They identified four rankings of tumors in their models, such as glioma, meningioma, none, and pituitary tumors. They have adopted three pre-trained CNN architectures which is Keras a model that is available as an open-source neural network library written in python. But we develop our own CNN model for the binary classification of brain tumors.

Pallavi Tiwari et al in their study [17] suggested an automatic process for identifying multiclass sorting of brain tumors utilizing MRI. In this paper, they applied CNN for the classification brain tumor. Their offered model was effectively able to categorize the brain pictures into four diverse categories, as for example, glioma, meningioma, and pituitary tumor, and no tumor, which indicate the particular MRI of the brain does not contain any tumor. They did not mention the computational speed of the work. The main reason for our work is to find a network that obtains a higher categorizing outcome while attaining a more speedy operation than that of the conventional deep learning models.

J. Seetha et al proposed in their work [18] an automatic brain tumor detection by using Convolutional Neural Networks (CNN) classification. They classify brain tumors or no tumors in brain MRI images. For classification, they used the image net database which is one of the pre-trained models. They claimed that their model is less complex and computational speed is fast. They did not mention the data size of their work. For our cases, we mentioned the data size and it was enhanced by using data augmentation. Our complexity is also low and our computational speed is fast at approximately 140 sec per epoch.

Sunanda Das et al in their paper [19] mainly focused on brain tumor classification using the CNN model for T1-weighted contrast-enhanced MRI images. Two significant steps are done to perform the process, first, they pre-process the images and then classify the images by using CNN classifier. They preprocessed the images by using a Gaussian filter and then applied a histogram equalization technique to the filtered images. In their paper, they did not mention anything about complexity and computational speed.

## 3. METHODOLOGY

### 3.1 Data Set

In our current research work, we employed image processing and data intensification methods on a 2065 MRI image datasets of human brain. At first, we trained the dataset by utilizing a CNN model's simple convolutional layer. We split our dataset into three separate segments or phases; they are training, validation, and testing. For model learning we used training data to evaluate the model and to tune its parameters for validating the dataset [18-20]. Finally, the test data is used to evaluation of our model. In our dataset number of training, examples are 1445, the number of validation examples is 310, and the number of testing example is 310. As we used data augmentation our dataset become much larger.

### 3.2 Methodology

The various stages of our working methodology according to our proposition is depicted in the flow chart of Fig. 1.

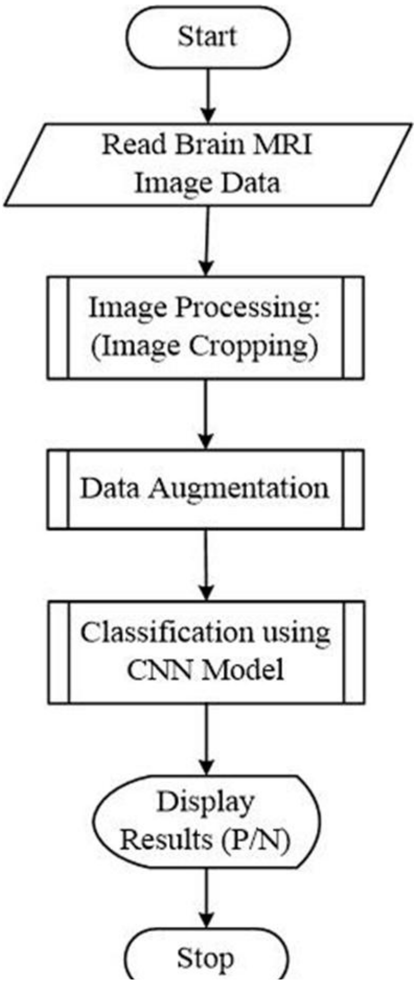


**Fig. 1. Flow chart of the working method's stages**

Brain image classification is a challenging task. In machine learning, this can be characterized by, pre-processing, feature extraction, and classification steps. Due to noise and organ movements are other issues in brain tumor detection some inconsistencies occur in the MRI images [21]. At first, we get brain MRI images to form a data source and then do the preprocessing of the image by cutting the dark edge of the images from the brain part. After that, we did the data augmentation to raise the amount of data for classification purposes. Then we classify our brain MRI images into tumorous and non-tumorous phases. At last, we display our MRI images to show whether our images are positive or tumorous or negative or non-tumorous.

### 3.3 Image Processing Steps

We have MRI images of the brain, at first, we need to remove the skull from the brain portion, for this purpose we used OpenCV, which is a library of Python bindings designed to solve computer vision problems to cropped the dark edge of the image from the brain portion. This is shown in Fig. 2.

### 3.4 Data Augmentation

Preprocessed data is needed when we work with neural networks and deep learning and models. Plentiful high-quality data is needed to get good results from the deep learning method. If we want to increase the number and artificially enhanced complexity of existing data, then data augmentation is used. Seven different states of the MRI images of brain after applying the data augmentation technique are shown in Fig. 3.

To train a deep neural network and to tune its parameters finely, we require a huge amount of data. As such, we applied the data augmentation technique to our training dataset to increase our small dataset. We modified our images by creating slight changes, e.g., flipping the images, rotate image sides, and increase and decrease brightness. By using these techniques, we can proliferate our data size so that each small change is recognized as an individual image. Fig. 3 shows the images of MRI brain tumor data after the augmentation.

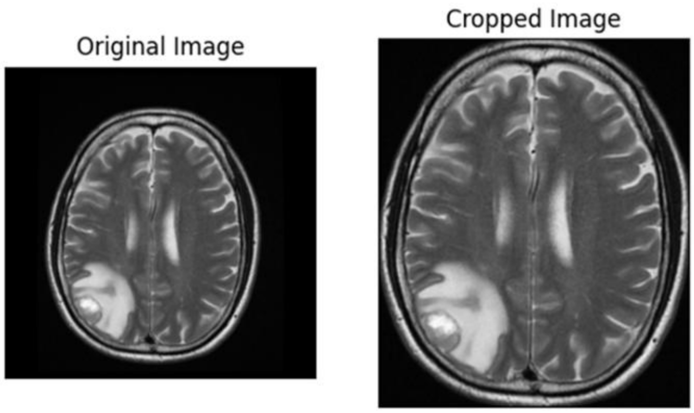


**Fig. 2. Finding the brain part by cropping edges**

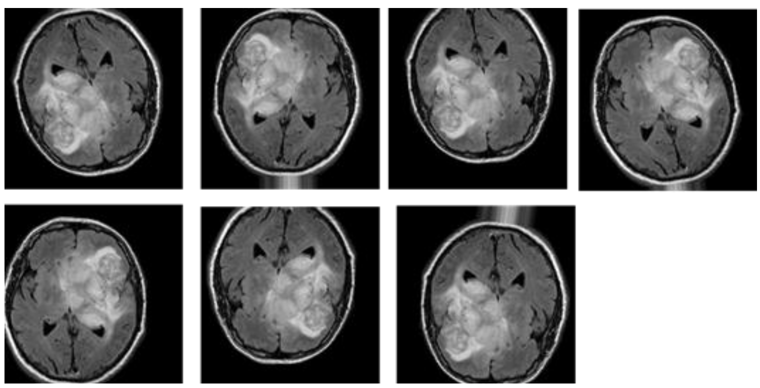

**Fig. 3. Brain MRI images after applying data augmentation**

## 4. PROPOSED CNN MODEL

Under this current research investigation, we proposed a modest CNN model that would extract the MRI images of 224×224 sizes at the input with a grayscale. The filter has a total of 32 convolutional layers through this CNN model. We used a filter size of 7×7 and a max-pooling layer having a pool size of 4×4. This layer was added to it to get the maximum value of that image so that we can reduce the spatial dimensions of the output. We used strides size 1×1. The batch size is 32 and the epoch is 30. Fig. 4 shows the basic structure of a CNN. Fig. 5 shows the proposed method of our experimental convolutional neural network.

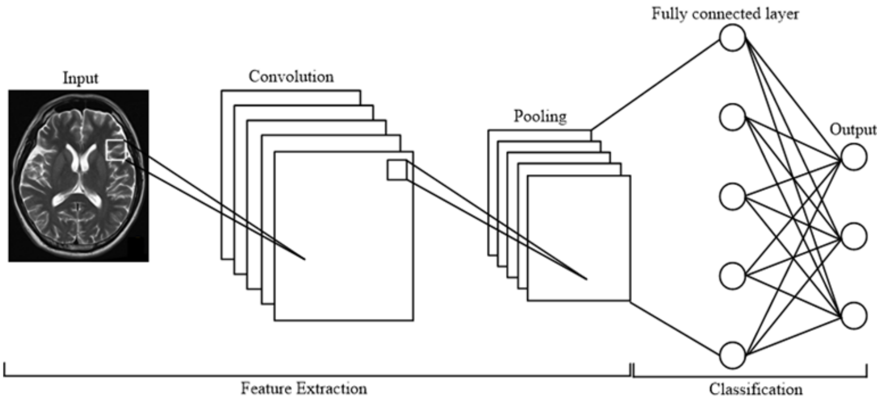


**Fig. 4. Basic structure of a convolutional neural network**

```
Number of examples is: 2062
X shape is: (2062, 240, 240, 3)
y shape is: (2062, 1)
number of training examples = 1443
number of validation examples = 310
number of test examples = 309
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 240, 240, 3)]     0

 zero_padding2d (ZeroPadding  (None, 244, 244, 3)      0
 2D)

 conv2d (Conv2D)             (None, 238, 238, 32)      4736

 bn0 (BatchNormalization)    (None, 238, 238, 32)      128

 activation (Activation)     (None, 238, 238, 32)      0

 max_pooling2d (MaxPooling2D  (None, 59, 59, 32)       0
 )

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 1)                 6273

=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
_________________________________________________________________
```

**Fig. 5. Proposed method of our experimental convolutional neural network**

In this paper, the Rectified Linear Unit (ReLU) is applied for every individual convolutional layer as an activation function. Vinod and Hinton [22] characterized that the activation function renovates the node's output by adding the whole input weight. In hidden layers of the convolutional neural network rectifiers, the linear unit function is repeatedly used. Mathematically, ReLU is represented by

$$f(z') = \max(0, z') \tag{1}$$

Where z' refers to the input where the value of z' is negative or equal to zero, the output will be zero otherwise the output will be 1. So, the derivative of ReLUs will be

$$f(z) = \begin{cases} 1, for\ z' \geq 0 \\ 0, for\ z' < 1 \end{cases} \tag{2}$$

Here the zero input denotes a dead neuron in the ReLU function and it won't be activated.

## 5. RESULTS AND DISCUSSION

Image classification is the task of identifying what an image is represented. To recognize various classes of images we trained an image classification model. In our research, we train a model to recognize MRI images to represent whether there is tumor tissue or not. In Fig. 6 we show the MRI images with no tumor, and in Fig. 7, MRI images with a tumor are detected.

Furthermore, the performance evaluation of the CNN classifiers is graphically represented in Fig. 8 in terms of accuracy within the training and validation phase. At epoch number 25 the training, as well as validation accuracy, are 99.90% and 90% respectively.

We also evaluate the performance of the CNN classifier in terms of loss factor. This is shown in Fig. 9. At epoch number 25 the training, as well as validation loss, is 1.03% and 5.05% respectively [23,24].

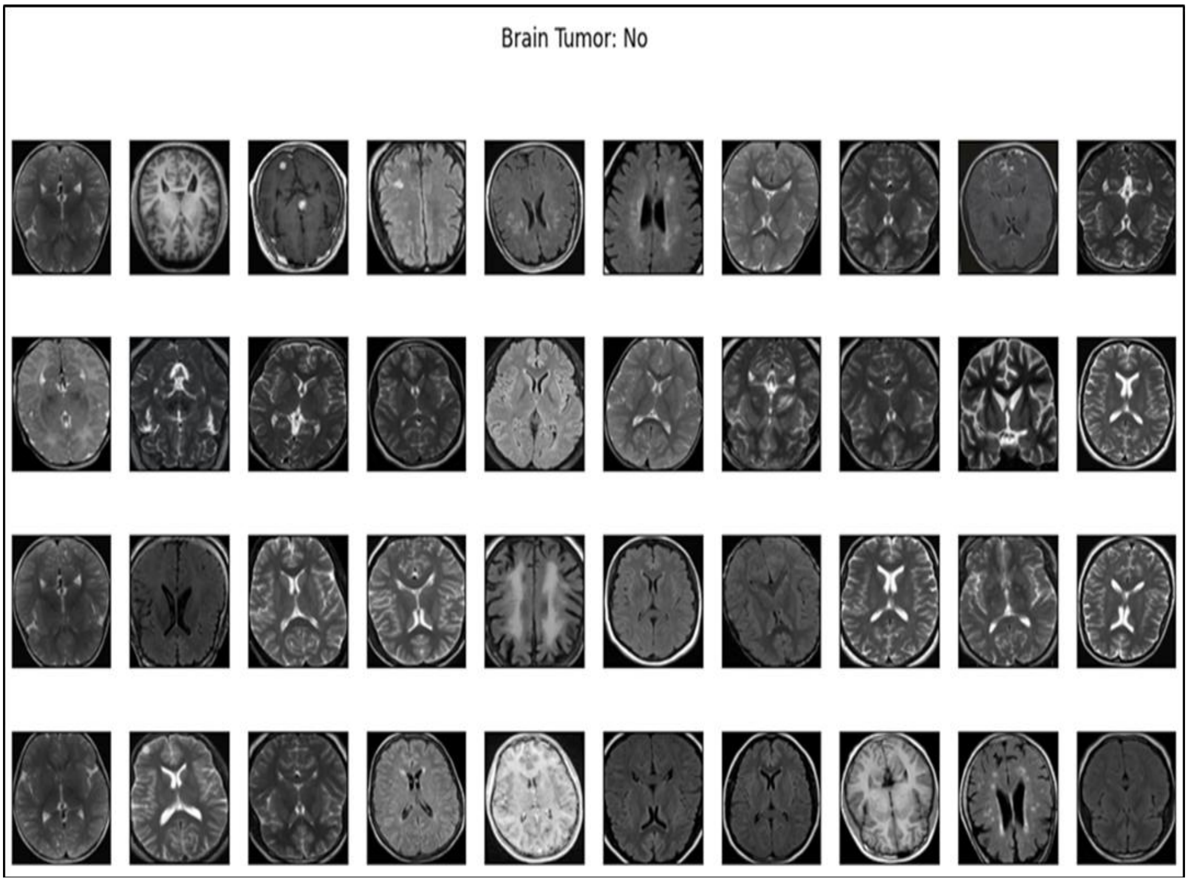


**Fig. 6. Detected MRI images with no tumor**

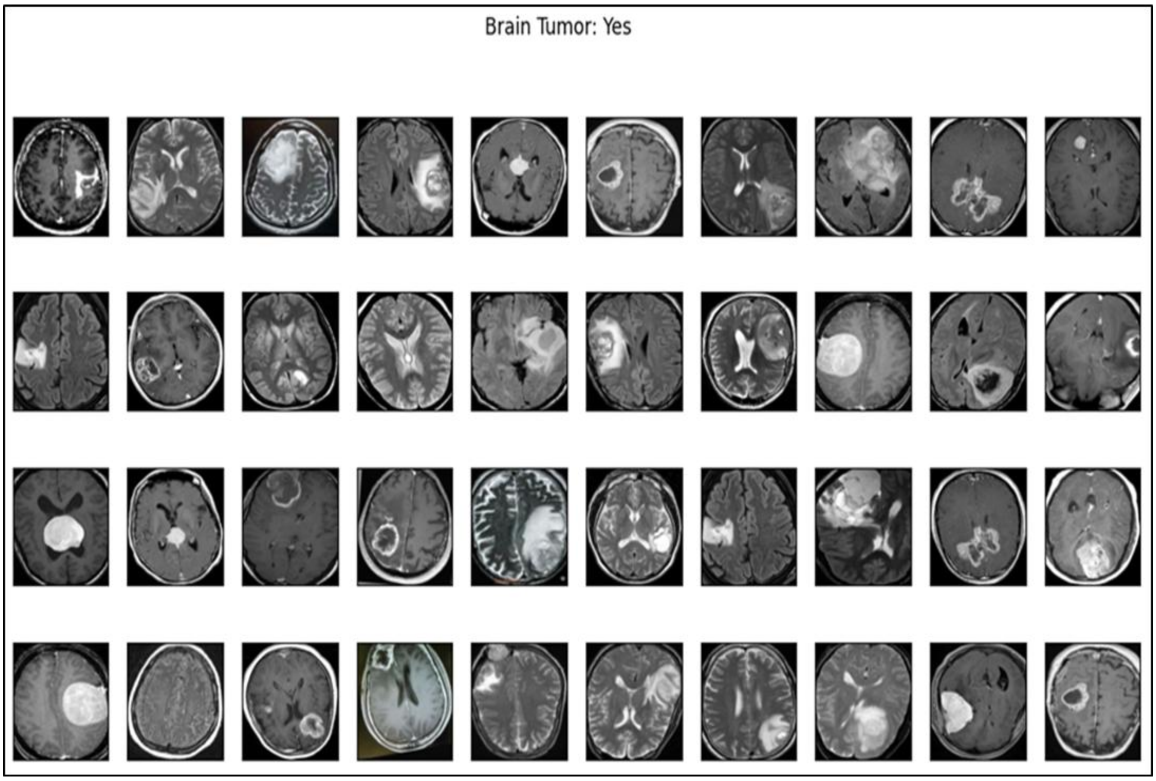


**Fig. 7. Detected MRI images with tumor**

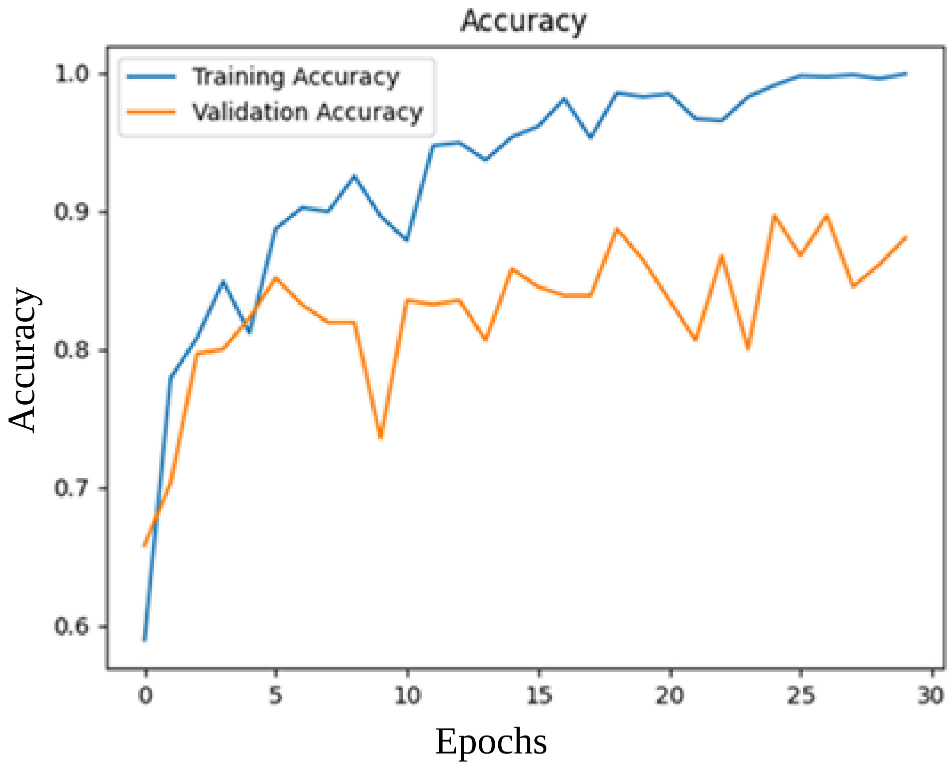


**Fig. 8. Graph of accuracy of the proposed method**

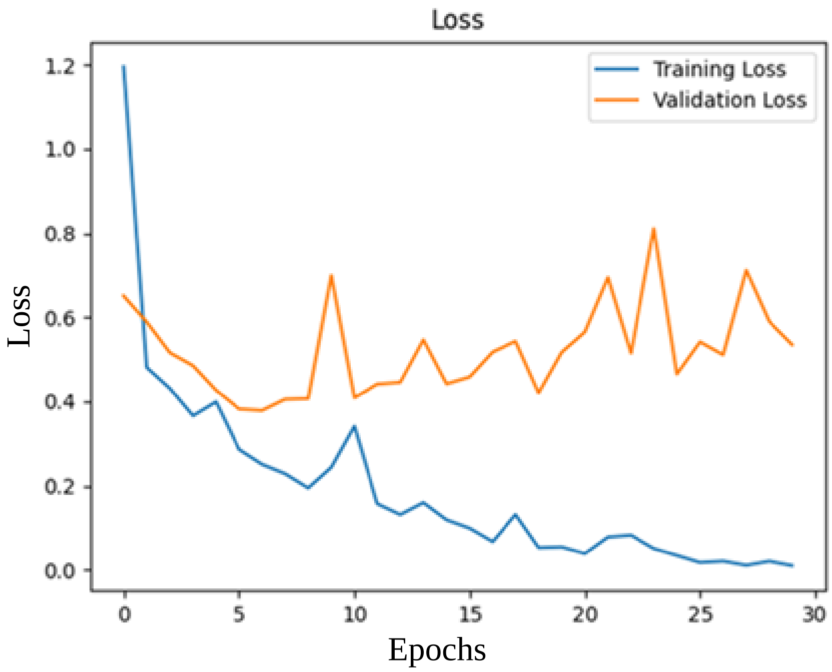


**Fig. 9. Graph of loss of the proposed method**

## 6. CONCLUSIONS

In this research, a new method was represented to categorize brain tumors. In deep learning method, the CNN is the most efficient method for classifying the MRI images. In our research we propose a simple CNN network to classify the cancerous and non-cancerous image, First, we extract the brain part of the MRI images by cropped the black edge of the images, secondly, to increasing the size of our training data set, data augmentation technique is used. Thirdly, we propose a simple CNN network for brain tumor classification. We achieved a testing accuracy of 90.39%. In this way we have helped medical imaging technique to identify diseases a quickly and accurately

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

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