CNN based Brain Tumor Diagnosis using MRI images

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ABSTRACT: In the recent times, there has been a sudden increase in the number of cancer patients due to genetics or mutations. Although the cases of brain tumor are less in number, they are hazardous. And the detection of brain tumor is time taking process, more human errors might occur and sometimes it might be late for the cure. The objective of this project is to create a real time application to predict the brain tumor via taking the MRI scan reports and find the position of the tumor. Using CNN, VGG-16 models and other deep learning concepts we predict the tumor in given MRI scan and help the doctors in finding it early and reduce time complexity.

Index Terms: Brain tumor, CNN, VGG-16, DL, MRI Scan.

I. INTRODUCTION

In recent years Image processing has been widely used, and it has also played a role in the medical profession. Mind tumors are caused by an abnormal enlargement of cells in the brain. Intracranial neoplasm was another term for a brain tumor. Malignant and benign tumors were the two types of tumors. Standard MRI ordering were formerly utilized to distinguish between various types of brain tumors based on visual grade and soft tissue touch and feel. The World Health Organization's report on the level malignancy divided more than 120 types of brain tumors into four categories [2]. The overripe region of the brain causes various symptoms in all types of brain tumors. Headaches, seizures, vision problems, vomiting, mental speculation, memory lapses, and a loss of balance are among of the most common symptoms [3]. Brain tumors were caused by division, ionizing radiation from cell phones, and a very low prevalence rate. Magnetic fields, chemicals, head trauma and damage, and resistive variables such as illness, allergies, poisoning, and so on [5] are all introduced. As a result of the ideas, tumors will form, which will begin to expand and compete with the brain. Vinyl chloride, neurofibromatosis, ionizing radiations, and other factors posed a threat to brain tumors. Machine-based data analysis techniques will teach a private computer how to act like a human and how to do so in their own unique way. A non-public computer model will be utilized in deep learning to distinguish certain tasks from images, voice, text, or video. Shows whose human degrees have been surpassed by deep learning algorithms. An artificial neural network, which had created a set of acts as neurons, was the most recent method of the most famous neural networks. Each neuron operates as a fork, and each fork is linked to another by connections. [6]. The purpose of this paper is to create a model that uses a complicated neural network to aid in cancer detection from MRI scans. To determine the correctness of the complexity method, the proposed method is evaluated and compared to current distinct methodologies.

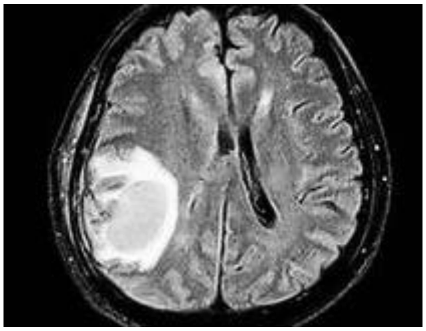

Figure1: Scanned MRI pic

II. RELATED WORKS

Image separation & differentiation will be one of the most important tasks in machine learning, and it has also been widely used in medical purposes. CWT, DWT, and SVM are all suggested by MG, ML, DL et al [7]. The technique of finding and distinguishing cancers using deep learning models is described by SS, and DR et al [8]. 3-D based CNN, ANN and SVM were employed for deeper separation. DS, and RD et al [9] address the separation of pathological matter(Tumor), normal matter, and fluid (Cerebrospinal Fluid (CSF)) by removing the same side from each separated matter and disparate tumor pictures with NN.

According to G. Hemanth, M. Janardhan, and L. Sujihelen et al. [10], initial tumor diagnosis was made sensible using the same data mining curving technique. It is a repurposed CNN-based electronic analysis approach. Reema The examination of MRI tumor position could be connected, according to M A. and Dr. B A P. et al. [11]. Radiological examinations could be used to determine the size and location of tumors. For the time being, the evaluation has been finished and delivered. An isotropic spreading filter was used for pre-processing. Support vector machines were used to perform this parathion and difference. This suggested method for brain tumor separation included super pixel separation, feature extraction, and segmentation model development.

III. METHOD PROPOSED

The compiled system's system design was clearly visible. Image collection, pre-processing, separation, feature collection, and separation became the elements.

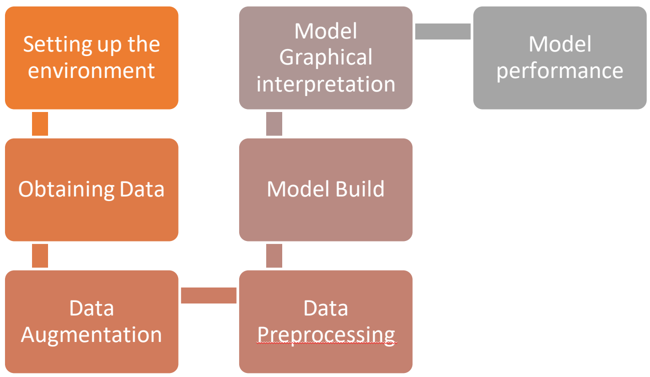

Figure 2: Methodology

Image Collection

For the investigation of brain tumor detection, many bio-scientific picture facts were used. CT and MRI have shown to be most effective approaches. High-priced MRIs, on the other hand, have been operating under the assumption that each magnetic barrier and radio wave may build a pictorial graph of the inside of the human body by identifying the water molecules there.

Very small MRI equipment was used to avoid the complexity of traditional scanning techniques. MRI has a good object and can store a lot of data. NC's MRI dataset from Google was employed in this study [13]. Ours will include 1500 images of normal brains and 1500 photographs of abnormal brains. 'Yes' means tumor photos, while 'No' denotes healthy images in that collection. We split the dataset into three parts 70% for training, 15% for testing, and rest 15% for validation.

Preprocessing

"The use of the preprocessing stage was to get the brain pictures ready for future processing [12]". Suppose the raw data was in 3D, grayscale or 2D conversions were required. To overcome the noise, median filtering became good and the same for biomedical images. Pictures in one-of-a-kind artefacts are included in the data set. As part of the growth process, each image was rotated and resized to a common format. Image quality is improved via histogram razing. The photos would undoubtedly benefit from the contrast limited supply histogram razing technique"[20]. We used the dataset which was in grayscale and used data generator to prepare the data, using 0.2 zoom-range, 0.2 shear-range, and rescale of 1/255.

Image segmentation

A certain area of the image being separated from the backdrop this step was for very quality extraction. The easy stages to separate upset were thresholding and morphological force. However, in the case of brain tumor imaging, the separation technique at that level would not reveal the tumor area's features. Following the tumor size, the total number of photographs taken was also identical. As a result, the separation method might be utilized to separate the brain from the rest of the body.

In healthy photos, this approach may not produce satisfactory results. This aspect of the photograph might be utilized to see the object in the tumor region, which would aid in calculating the area.

The process of computing and assessing authentic features to define a diagnosis observation or symptom is known as feature extraction. The most significant influence on the scale is the feature selection. Asymmetry, diameter, and border asymmetry were all common traits [15].

Classification

Classification In disorder identity from mental images, many systems mastering detains have been carried out. If the article were drawn out in order, artificial neural networks could be used to distinguish [17]. An ANN classifier considers a single feature that is unrelated to any other article.

To classify tumor photos without dividing, deep learning algorithms would be accurate. To generate a DNN, CNN can be used.

Figure 3 depicts convolutional neural networks. In device learning, the presentation is impulsively given out from the entire picture. This procedure is carried out using convolution in the CNN design. The number of article maps grows in sync with the CONV layer. To stimulate training, a reduction in dimension became necessary. The pooling layer down samples the article capacity. Each label's score is manipulated by fully attaching layers. The model is ready with article and class core thanks to soft axe layers.

For training the brain tumor photos, the CNN architecture was slightly altered in dimension. Table 1 shows the changing model design.

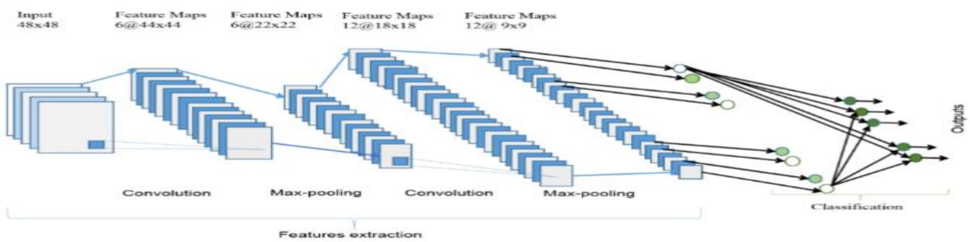

Figure 3: Architecture of CNN [24]

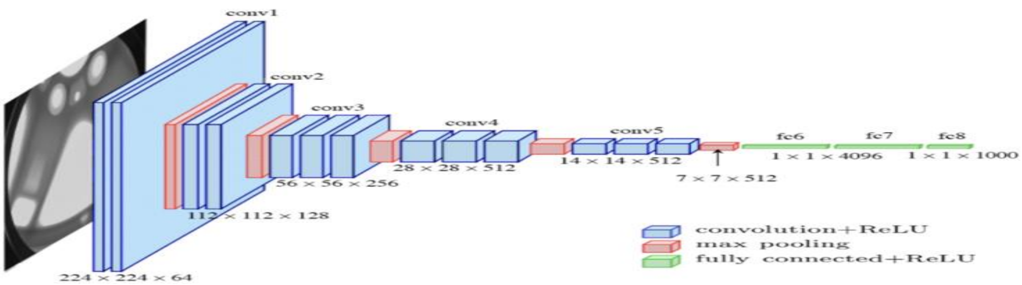

Figure 4: VGG-16 Architecture [23]

VGG-16 model is simple architecture with 3x3 convs, stride=1, padding=”same”,2x2 max pooling. It is with 16 layers which results in having the highest efficient model the difference between VGG-19 and VGG-16 is that there are 3 more additional layers included in VGG-19 model as the name suggests. The main disadvantage of this model is that it takes a lot of time to run as there will be a large number of parameters and specifically a GPU is needed to run this model.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 16)	448
conv2d_1 (Conv2D)	(None, 220, 220, 36)	5220
max_pooling2d (MaxPooling2D)	(None, 110, 110, 36)	0
conv2d_2 (Conv2D)	(None, 108, 108, 64)	20800
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_3 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
dropout (Dropout)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 64)	5537856
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 5,638,245
Trainable params: 5,638,245
Non-trainable params: 0

Table 1: Model Summary

The model is compiled with “adam” optimizer in ‘keras’ and loss in ‘binary_crossentropy’. We added 4 layers with increase in filters for each next layer i.e. 16 filters for 1st layer and 36 for 2nd , 64 for 3rd and 128 for last layer and the activation used was ‘relu’ the model is sequential.

The dropout rate is 0.25% then the dense layer units are 64 with ‘relu’ activation and then the final dense layer units were 1 unit with sigmoid activation.

We create an early stopping and model check point to save the best accuracy from “kreas.callbacks”. Then we plot the graph accuracy vs loss.

IV. RESULTS AND DISCUSSIONS

The results of this model are very accurate and the loss percentage is also less. This model ran in 30 epochs which resulted in accuracy although the time complexity was a little more than expected the better results were achieved.

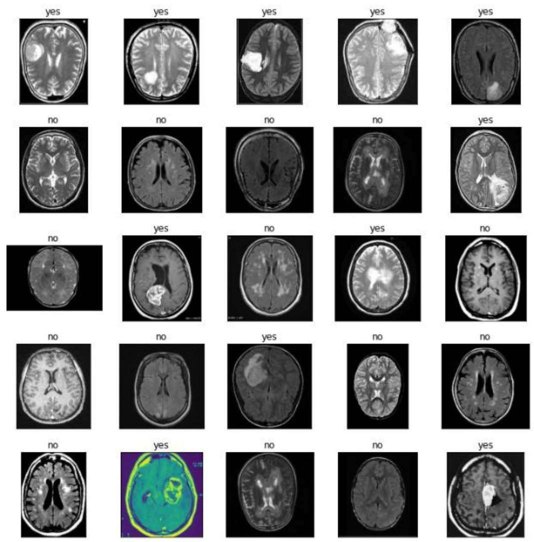

Figure 5: Results from the trained model

This model is built using CNN with first being feature extraction and then classifier model with 5638245 training parameters. This model gives 97.8% accuracy. This method is simple yet efficient, we were successful in predicting the tumor and positioning it.

T. E and K. S [19] has got an accuracy of 97.67% using FCSE-GAN method where as our model we used VGG16 model.

Algorithm	Overall Accuracy
Nandpuru [16]	96.77%
T.E and K.S [20]	97.67%
Ibrahim [18]	96.33%
Rajini [19]	90%
Proposed Method	97.8%

Table 2: Performance Analysis

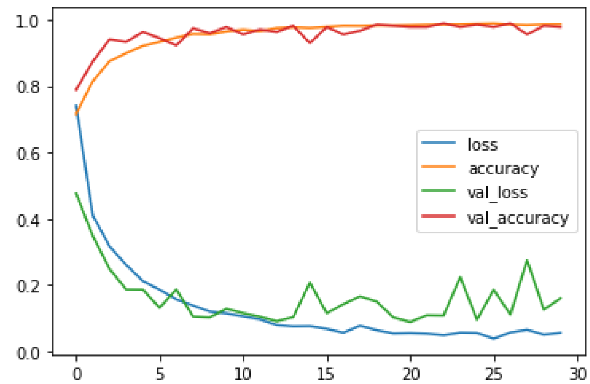

Figure 6: Prediction score in divided data

This is a graph plotted between loss, accuracy, val-loss, and val-accuracy. The X-axis is Epoch and Y-axis is loss value.

As we can see the loss is gradually decreasing as the number of epochs run. The same goes with the validation loss whereas, the accuracy and validation accuracy increases and they are equal at a point of epoch.

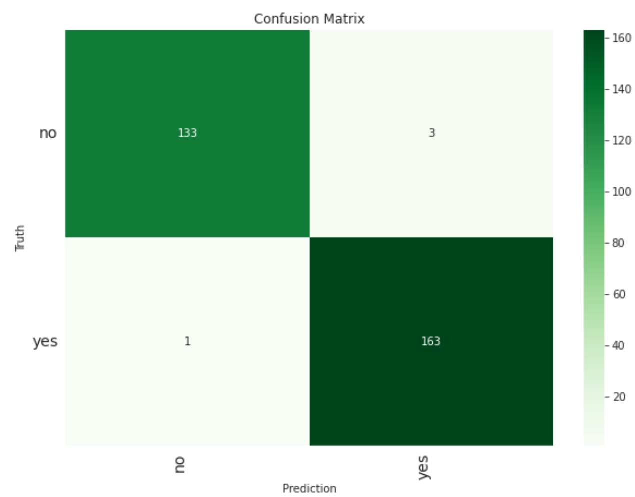

Figure 7: Confusion Matrix

The split data which were used for training, validation, and testing are the data which we use. Number of true negatives are 133 and number of true positives are 163. Here, true negative is "No" dataset i.e., healthy brain and true positive is "Yes" dataset i.e., tumor brain. As we can see the prediction made has the most efficient outcomes so, this model has the highest chances of classifying the MRI scans.

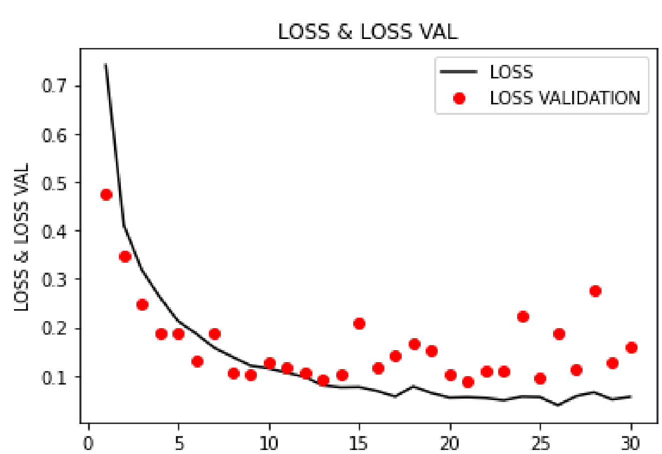

Figure 8: Loss and Loss Val plot

As we can see the loss percentage has been decreasing gradually with the increase in the epoch.

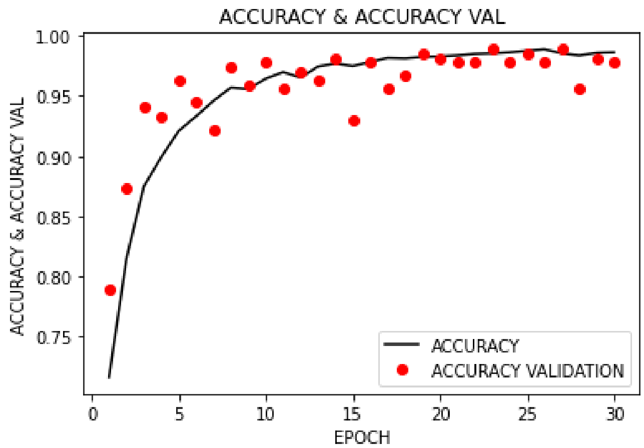

Figure 9: Accuracy and Accuracy Val plot

The accuracy has been increasing with the increase in epoch this resulted in highly efficient model.

V. CONCLUSION AND FUTURE SCOPE

Although the brain tumor is a time taking process to analyze via MRI scans our model helps the doctor to verify whether the tumor is present in the MRI scan and position it faster. And reduce the human efforts and errors while classifying the MRI images.

Our project (model) helps the doctors in finding the tumor. Our main aim was to help the doctors who has no proper infrastructure in the hospitals sometimes even the knowledge about the tumors is unknown to some doctors but when help is needed or to gain knowledge about the tumor users can easily access the data from our project and they can check the MRI scan reports to re-check/confirm about the tumor so that the treatment can be given in time.

Our future scope of this project is to also suggest the doctors an alternative treatment for the user i.e., less cost-effective treatment and highest success rate surgery.

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