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Brain Tumor Detection using Convolutional Neural Network

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Abstract: Identification of brain tumor is a highly difficult task in early life stages. The presence of brain tumor among humans has increased in large amounts in recent years. Gliomas are one of the most common types of primary brain tumors that account for 30% of all human brain tumors and 80% of all malignant tumors. The World Health Organization (WHO) specified rating system is used as a basic method for medical diagnosis, prognosis and life. The main ideology is to propose and develop reliable, typical methods for detecting the brain tumor, extracting its characteristic and classifying the glioma using Magnetic Resonance Imaging (MRI). The model developed automatically assists in brain tumor detection and is implemented using image processing and artificial neural network. Detecting the tumors at starting point is very critical for a patient's healthy life. There are several literatures on identifying these kinds of brain tumors and enhancing the precision of detection. This method use Convolutional Neural Network algorithm to estimate the severity of the brain tumor which gives us accurate results.
Keywords: Brain tumor, Convolutional neural Network, MRI images, hemorrhage, non-hemorrhage

I. INTRODUCTION

A brain tumor is a mass of the tissue produced by anomalous cells. Tumors do not die the same way as normal cells. Brain tumors can be both malignant and noncancerous. Cancerous brain tumors grow faster than non-cancerous tumors, and they invade the tissue surrounding them. Noncancerous tumors are easier to kill than malignant tumors and are not considered life- threatening in general. Cancerous brain tumors exert pressure on the skull beneath, around, and inside, causing inflammation in the brain. Symptoms of the brain tumor differ, but a typical symptom is headaches. Many signs of brain tumor include headaches, problems with balance, changes in personality, vision and speech disorders, and attention difficulties.

Medical imaging technology plays an important role in medical diagnosis and medical research. Brain tumor has become key research topic in the medical diagnosis because of its complexity and frequent occurrence. The diagnosis of brain tumor is usually based on imaging data analysis of brain tumor images. Accurate analysis of brain tumor image is a key step in determining patient's condition. Accumulation of doctor's personal medical knowledge, differences in the experience level and visual fatigue can affect the accurate analysis of brain tumor. Separation of the brain tumors using MRI has been an intense field of research. Tumors of the brain have various dimensions and sizes, which occur at different places. The varying amount of tumors in brain magnetic resonance imaging (MRI) activates the automatic tumor division tremendously.

Magnetic Resonance imaging(MRI) can provide information on shape, size and position of human tissues and organs. MRI greatly improves the diagnostic efficiency and provides good guide for surgical treatment. Compared with 2D images, 3D MRI can provide the coordinate position of lesion area to assist the doctor to accurately locate the lesion area. Brain MRI imaging can be divided into four modes based on the imaging auxiliary conditions: T1 weighted mode, T1ce mode, T2 weighted mode and Flair mode.

The existing methods of neoplasm detection and methods supported convolutional neural networks generally have the subsequent problems: 1) The tactic is single and therefore the accuracy is low, which cannot provide valuable information for clinicians 2) Strong dependence on manual intervention and data pre-processing 3) Most of them are processed supported one modality, and MRI data of various modalities don't seem to be utilized efficiently.

II. METHODOLOGY

The input training dataset comprises of the dataset given by the user. This training dataset is given as input to the convolutional neural network. The convolutional network consists of many layers. The input passes through all the layers. Once the training process is done testing dataset is given to the network to perform testing. Finally the result is predicted whether the tumor is present or not.

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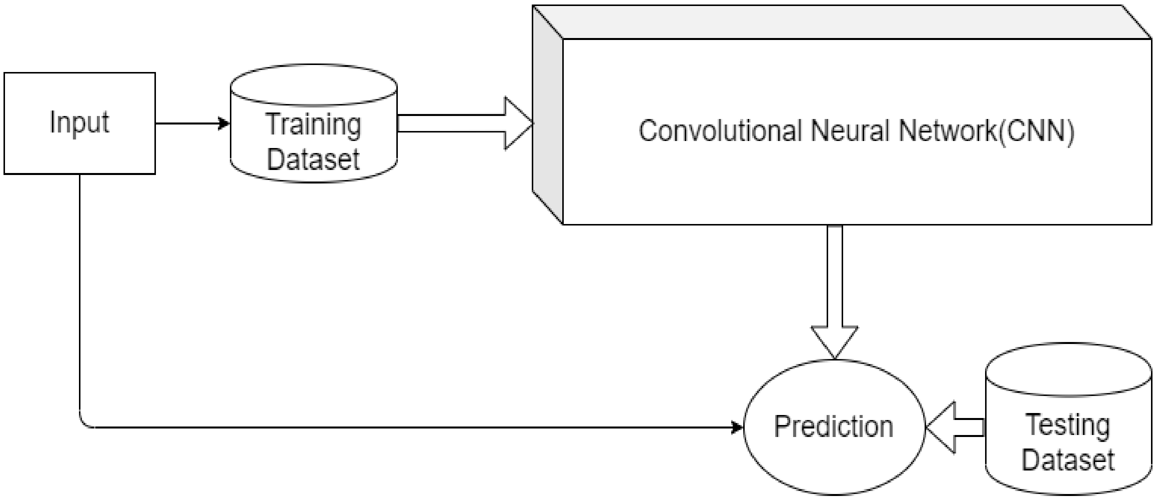

Fig 1: System architecture

A. Pre processing

MRI picture pre-preparing is huge to improve the enhanced visualization of the picture for additional handling. Typically the gathered pictures in the dataset are so poor in quality which requires sifting commotion and honing the picture. In pre- preparing step, the procured picture in the dataset is changed over into a two dimensional grid and the picture is changed over into RGB picture to dim scale pictureFor the most part, improvement of a picture implies improving the complexity of the picture. After that various highlights are at first removed verifiably.

B. CNN Model Creation

The calculation runs on Tensor flow stage and depends on the exchange learning philosophy. The classifier has been pre prepared to perform fundamental arrangement dependent on directed preparing technique. This calculation held for the outskirt risk dataset to group different degrees of dangers. In view of how huge the dataset is and how well it is prepared, the calculation arrange the new pictures. In this stage, we initially introduce the convolutional neural system by characterizing a consecutive constructor. This consecutive constructor contains a direct pile of layers. Here we have used VGG Neural Networks.

1) *Input:* VGG Neural Network takes MRI brain images as an input
2) *Convolutional Layers:* The convolutional layers in VGG utilize an exceptionally little open field (3x3, the littlest conceivable size that despite everything catches left/right and up/down). There are likewise 1x1 convolution channels which go about as a straight change of the information, which is trailed by a ReLU unit. The convolution stride is fixed to 1 pixel with the goal that the spatial goals is saved after convolution.
3) *Fully-Connected Layers:* VGG has three completely associated layers: the initial two have 4096 channels each and the third has 1000 channels, 1 for each class.
4) *Hidden Layers:* The entirety of VGG's shrouded layers use ReLU. VGG doesn't for the most part utilize Local Response Normalization, as LRN builds memory utilization and preparing time with no specific increment in precision.

C. Compiling and Training the Model:

First, we load the pre-installed VGG-16 Convolutional neural network model package. This model is primarily used for image classification using deep learning. We can download the VGG-16 pre-trained package online. Once the model is downloaded, it has to be imported into the algorithm by specifying the path. Next, after importing the VGG-16 model, it has to be trained through multiple iterations (called Epochs in ML). Epochs are nothing but the rounds of optimization applied during the model training. Thus, through more rounds of optimizations i.e. epochs, the error in the training data will be highly reduced. However, there comes a point where the model might start to lose performance due to over-fitting of the train dataset. If the validation error starts increasing, this might be a sign of overfitting. It is recommended to set as many epochs as possible and terminate the training by looking at the error rates.

An epoch usually consists of one full processing through the entire training dataset. It is basically a full iteration over the provided samples. This happens in the form of multiple steps. This can be best illustrated through an example. Let us suppose we have 1000 images in the train dataset and a batch size of 10 is used. Then every single epoch consists of 1000 images i.e. 10 images (batch size) in each step, accounting for (1000/10) steps in total or 100 steps. For this model, we standardized the number of epochs to 30 because we have observed that the learning rate degrades if the model is fed with too many iterations.

Furthermore, the model loses its effectiveness because of the over-fitting of the data. Due to this, the learning rate of the model decreases which results in poor accuracy. Therefore, it is always important to keep an eye on the accuracy of the results produced and the model loss after each epoch. We obtain the metrics like the training loss, the training accuracy, 18 the validation loss and the validation accuracy once the model has completed each epoch. In the end, we plot the results for all these metrics and draw a conclusion based on the performance graphs.

D. Evaluation and Model Testing

1) *Model Performance:* Two significant measurements characterize the presentation of a model for example Model Accuracy and Model Loss. Accuracy = (Number of Correct Predictions)/(Total Number of Predictions) This is the essential measurement used to assess character ization models.
2) *Model Loss:* Exactness shows signs of improvement while Loss deteriorates and the other way around. An AI calculation can be advanced by utilizing a Loss work. Truth be told, the machine learns through this misfortune work. In the event that the expectations go astray a lot from the real outcomes, the misfortune capacity will create an exceptionally high number.
3) *Evaluation:* During the procedure of model preparing for example going through 30 ages, an approve dataset is used to prepare the model to tune the hyper parameters. After the model is fabricated, the equivalent approve dataset is given as a test dataset to test the model's presentation.

E. Prediction of Tumor

In the final stage we expect our CNN model to predict the result of the images provided by the user. We need to pre- process the image that we need to upload. Once the image is uploaded we can find out the type of the image. Once we get the output, we need to find out the resulting prediction corresponding to which of the input images. We can also use conditions to check whether our prediction is correct or incorrect.

F. Work flow

The below table represents the work flow of the proposed system.

Sl No	Work	Duration(Weeks)
1	Dataset Collection	1
2	Information collection on Neural networks	2
3	Labelling the data	2
4	Extraction of features	4
5	Front-end	3
6	Detecting the presence of cancer	4
7	Testing	2

Table 1: Work flow

III. EXPERIMENTAL RESULTS

The datasets used for brain tumor detection are MRI images of brain. The dataset is divided into two sets, namely, training set and testing set, each having two classes i,e., tumor and no tumor. The result obtained for two types of classification, namely, brain images with tumor and brain images without tumor are shown below.

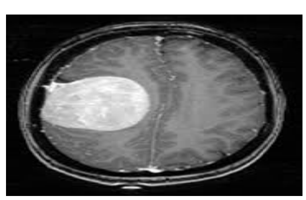

Fig 2: Brain MRI image with tumor

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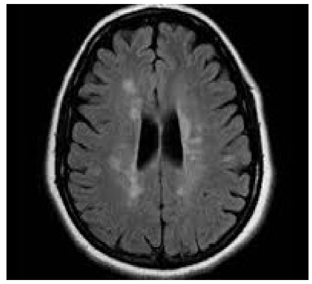

Fig 3: Brain MRI image without tumor

Figure 4 and Figure 5 shows the snapshots of how do we select the brain MRI image to which we need to test for the presence or absence of brain tumor.

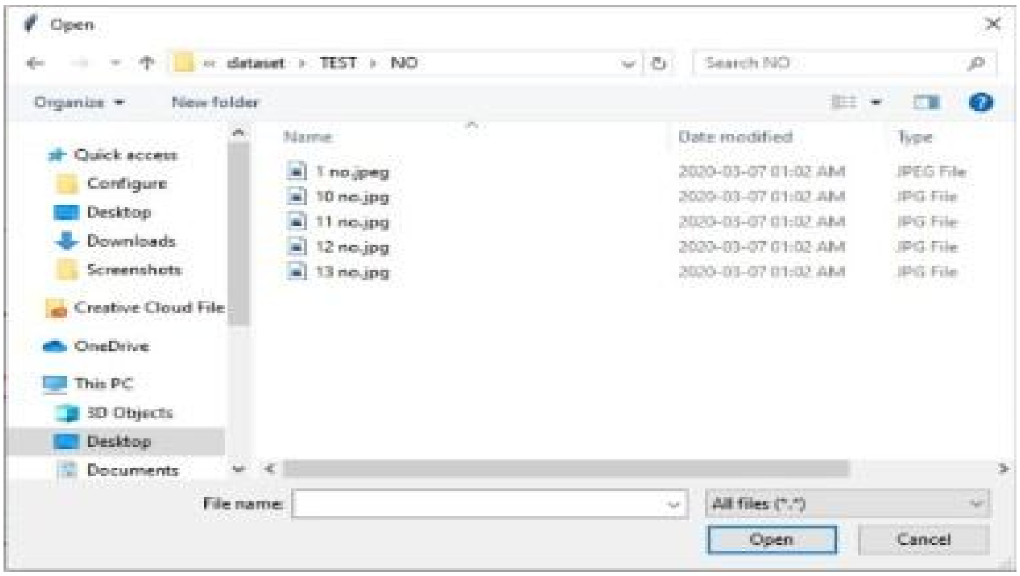

Fig 4: Selection of Brain MRI image with no tumor

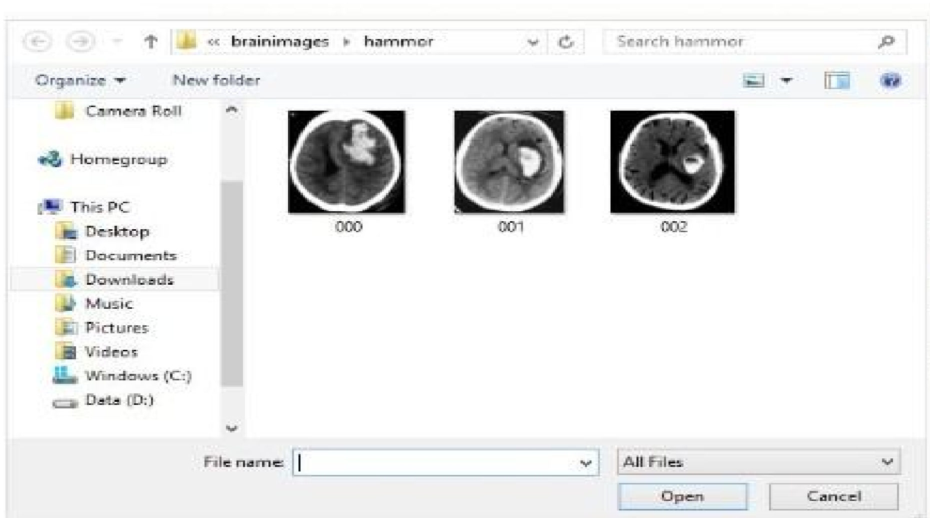

Fig 5: Selection of Brain MRI image with tumor

Figure 6 shows the window which displays the result of detection is non hemorrhage. Figure 7 shows the window which displays detection result is hemorrhage. It also displays the detection accuracy along with the chosen image for the detection of tumor.

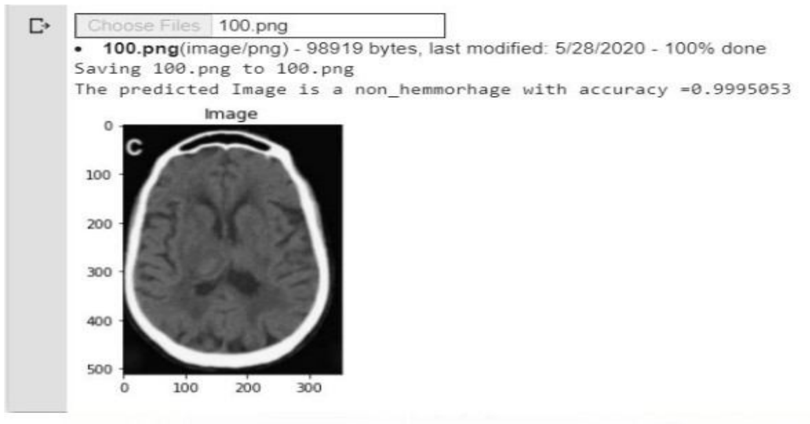

Fig 6: Result indicating non tumor

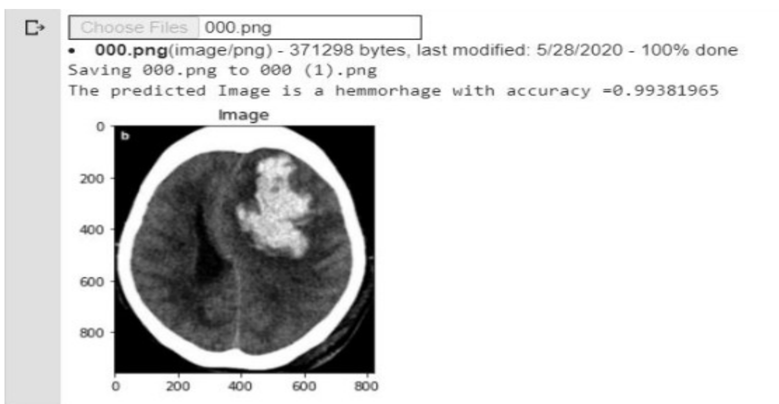

Fig 7: Result indicating tumor

Accuracy of the detection can be calculated using the below formula,

Accuracy = (TT+TNT) / (TT+TNT+FT+FNT)

Where TT represents the true tumor prediction, TNT represents the non-tumor prediction, FT represents the false tumor prediction and FNT represents the false non-tumor prediction.

IV. CONCLUSIONS

Brain cancer is the one of the leading cause of the deaths over many years. Manual detection of brain tumor is prone to errors thus increases the risk associated with diagnosis. This proposed system helps to detect the brain tumor at the earlier stage thus increases the survival rate of the brain tumor patients. In the proposed model we initially develop an convolutional neural network and fit the CNN into images. The obtained result is passed through various layers of the network where which will train the network. The trained system is capable of making better prediction about the presence of tumor. The developed application reduces the manual errors.

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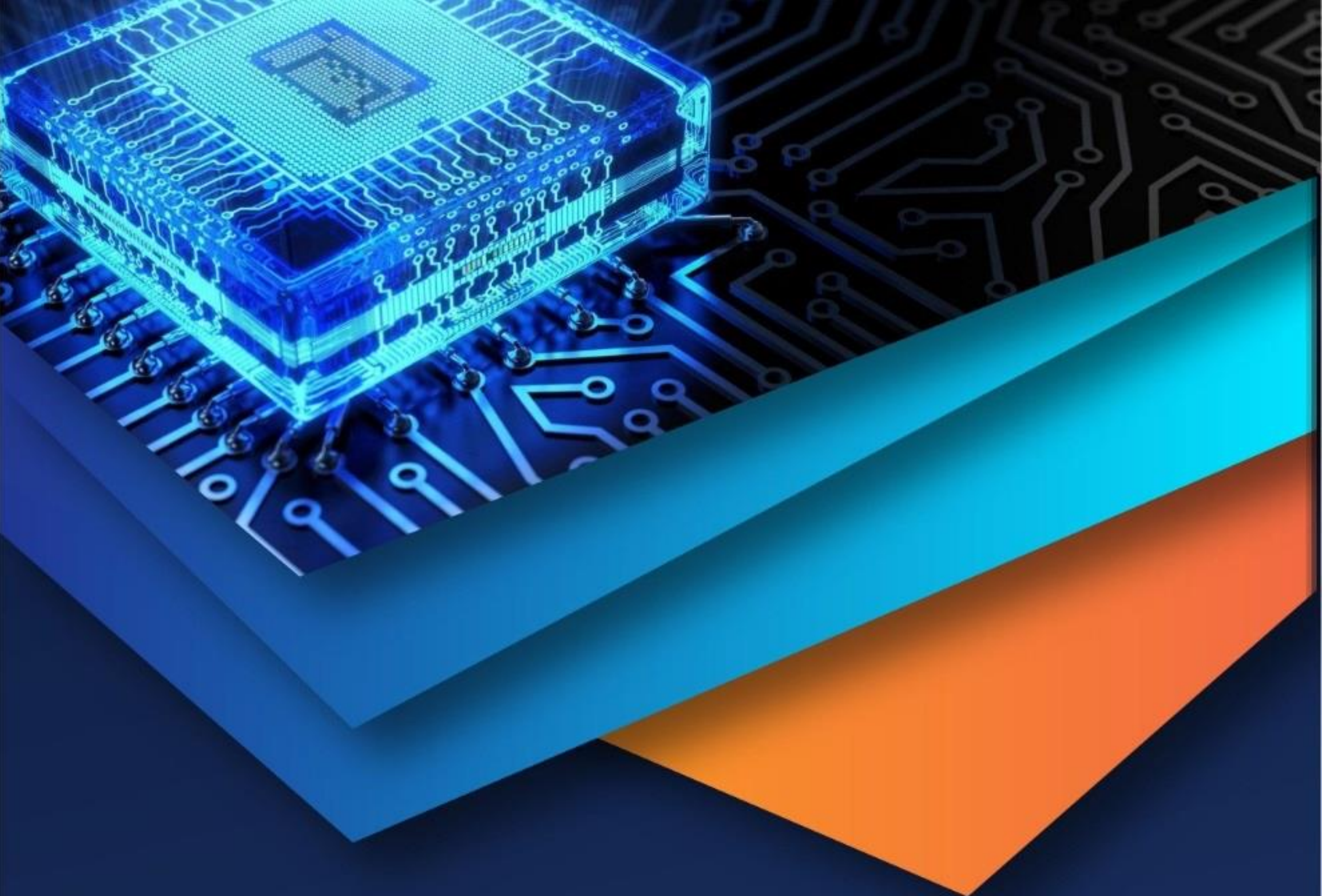

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