Brain Tumor Classification using CNN

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Abstract - *The abnormal and uncontrolled multiplication of cells in the brain is identified as a brain tumor. Detection of such a tumor in its early stages is important in improving the quality of a patient's life. Current techniques which include segmentation, machine learning focus on classifying the tumor based on its presence and detects the size and the location of the tumor. In this research we have proposed supervised learning on CNN (Convolutional Neural Network) along with data augmentation and image pre-processing on 2-D MRI (Magnetic Resonance Imaging) to detect and classify tumors in the brain into four categories that are glioma, meningioma, pituitary, and no tumor. These classes were chosen as they contribute towards the majority of the type of tumor detected. A CNN model with the highest accuracy of 96.26% on the validation set is studied and implemented.*

***Key Words*: Brain Tumor, MRI, CNN, Classification, Glioma, Meningioma, Pituitary.**

1.INTRODUCTION

Brain tumor can be classified into two broad categories based on its severity and its location. Based on severity- benign and malignant. Based on location we have considered three types of tumors- glioma, meningioma, and pituitary which make up a large proportion of the total tumors present. Glioma brain tumor accounts for 37% of all cases, meningioma constituting 33% of all the cases, and pituitary tumor which constitutes about 12% of all the cases. The early diagnosis and classification of such brain tumors are of utmost importance in medicine. Based on the early diagnosis, the most suitable treatment can be decided [2]. Hence, the possibilities of survival of a tumor-infected patient can be increased considerably.

There are many ways to detect brain tumors, paper [4] shows the significantly better performance of CNN compared with Support Vector Machine (SVM) and Deep Neural Network (DNN). The proposed methodology which includes image acquisition, pre-processing, segmentation using binary threshold, feature extraction, image classification, and finally performance evaluation. The model focuses on detecting the presence of brain tumor. The overall accuracy that this system reached was 95.6% on the test dataset. Although, the dataset consisted of only 200 MRI scans, it helped in understanding the performance of CNN model with respect to other models. The paper [1] discusses a similar technique which determines whether a tumor is present or not but with a different methodology. The proposed system used NLTK biasing which resulted in a pre-trained CNN. Post-processing image enhancement and edge detection functions were performed on the image. Their dataset consisted of 159 images for tumor containing scans and 99 images where the tumor was not present. With this dataset, the CNN model was able to achieve a training accuracy of 98%. The remarkable accuracy does not compensate for the fact that the dataset is small and hence less diverse. Such a model may not be able to perform well with unique cases as they have been trained on a limited variety of images.

Knowing the size of tumor helps in determining the severity of the patient's condition. Paper [2] gives an insight on the works of detection and identification of brain tumor with Support Vector Machine (SVM) methodology on CT scanned images was done. The objective of the paper is to use the pre-processing input images, feature extraction, classification, and finally linear function SVM for finding the region, size, identity, and location of the tumor. The overall accuracy of 64% of the SVM model is highly unreliable. Such low accuracy maybe because of the use of CT scan as it contains a relatively low amount of information and thus the results are not accurate. The use of an MRI scan may help in getting a more precise result. Also, the use of CNN model gives more accurate result than SVM [4].

From [4] it is observed that CNN provides the most accurate results. Paper [3] puts that theory to test with segmentation and detection of brain tumor. The proposed methodology detects brain tumor for 2D MRI scans by Fuzzy C-Means clustering algorithm, followed by the implementation of 6 traditional classifiers which consists of K-Nearest Neighbour, logistic regression, multilayer perception, Naive Bayes, Random Forest and Support Vector Machine (SVM) for segmentation. Lastly, to detect the brain tumor CNN was implemented. This work gave an accuracy of 97.87%. But the dataset used contained merely 217 images, which may have been the cause of high accuracy as the images may not have been diverse. Furthermore, the proposed work has high complexity which may been reduced considering it only detects the brain tumor.

The paper [5] gave an insight on the direction to determine effective values for CNN filter size and number in magnetic resonance imaging classification. With the numerous numbers of filters and functions to choose from, this paper helped in understand which ones would be the best for our project. In this paper the accuracy of the system depends on network parameters such as convolutional filters, rectification functions, polling functions, and iteration numbers, and so on. This filter helped in choosing the appropriate filter size, hence improving the accuracy.

A review on various brain tumor segmentation and classification techniques along with other methodologies were discussed in this paper [6] so that an accurate method can be selected depending on the requirement of the researcher. Methods and techniques such as Gaussian filter, Median filter, contour and shape-based methods, K-means algorithm, fuzzy clustering, SVM, ANN were explained.

In paper [7], the authors have described their own model and compared it with the existing ones. Within the model, the authors have proposed a feature selection algorithm that will evaluate the importance of new feature sets by comparing them with the existing ones. Through this method, the most appropriate feature can be found. For this paper, the processing time and memory consumption of the presented model were high. In addition to that, the dataset that was used also limits the accuracy of the overall model.

2. PROPOSED ARCHITECTURE

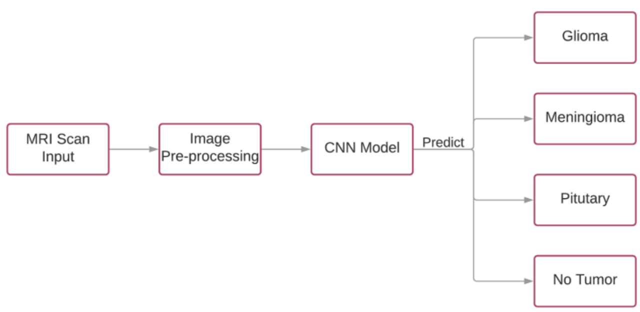

Fig -1: System Architecture of Brain Tumor Detection

2.1 Data Acquisition

The dataset contains several MRI scans from various patients which are categorized into training and testing. Adding on, these are further labeled into the four types of tumors which are glioma, meningioma, pituitary and no tumor; containing approximately 1000 images per class for training and approximately 100 images per class for testing. The diversity of this dataset helped in giving more accurate and reliable predictions.

2.2 Image Pre-processing

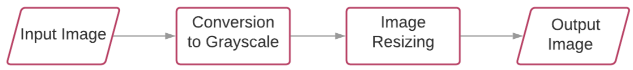

Fig -2: Image pre-processing

1) Conversion to grayscale: To make the operations less complicated and easier to process, the input image is converted to its gray scale.
2) Image Resizing: To make all the images of the same size i.e. 150×150 pixels we have used image resizing.

2.3 Data Augmentation

A small dataset does not contain enough examples to train the neural network. Therefore, data augmentation was done on the training set to add validation dataset which helped in avoiding the underfitting or overfitting of the CNN model.

2.4 CNN

There are two specific ways to build a Keras model i.e. sequential and functional. In this research a sequential model has been implemented. The sequential API allows the user to create models one layer after another. In this research we have used the following layers:

Table -1: Parameter table for CNN model

Layer (type)	Output Shape	Param #
Conv2D	(150, 150, 64)	1664
MaxPooling	(75, 75, 64)	0
Dropout	(75, 75, 64)	0
Conv2D	(75, 75, 128)	73856
MaxPooling	(37, 37, 128)	0
Dropout	(37, 37, 128)	0
Conv2D	(37, 37, 128)	147584
MaxPooling	(18, 18, 128)	0
Dropout	(18, 18, 128)	0
Conv2D	(18, 18, 128)	65664
MaxPooling	(9, 9, 128)	0

Dropout	(9, 9, 128)	0
Conv2D	(9, 9, 256)	131328
MaxPooling	(4, 4, 256)	0
Dropout	(4, 4, 256)	0
Flatten	(4096)	0
Dense	(1024)	4195328
Dropout	(1024)	0
Dense	(4)	4100

1) Convolutional Layer: The convolution layer is also called the feature extraction layer. As the name suggests, the convolution layer is used to extract features from a given image. This layer also accommodates the ReLU activation which makes all negative values zero. In this layer we have used 64, 128, 128, 128, and 256 filters respectively.
2) Max pool: Like the Convolutional Layer, the Pooling layer reduces the spatial size of the convoluted filter so that the computational power, which is required to process the data through dimensionality reduction, decreases. Moreover, it is also used for extracting dominant and significant features which are rotational and positional invariant, hence, maintaining the overall process of effectively training the CNN model.
3) Dropout: In this research, we have used a dropout of 0.25 which significantly helps in reducing the overfitting by ignoring a few selected neurons during the training.
4) Fully Connected Layer: Fully connected layer includes weights, biases, and neurons. It connects neurons of two adjacent layers and is used to classify images between different categories by training.
5) SoftMax: This is the last layer and is usually placed at the end for multi-classification. Decimal probabilities are assigned to each class in a multi-class problem by SoftMax.
6) ADAM: In this research, we have used an ADAM optimizer which is a stochastic gradient descent technique. It is based on adaptive approximation of 1st and 2nd moments.

Table -2: HyperParameter table for CNN model

Hyper-parameter	Value
Optimizer	Adam
Learning rate	0.001
beta_1	0.9
beta_2	0.999
Loss	categorical crossentropy
Metrics	accuracy
epochs	50
batch size	40
steps_per_epoch	57

3. PROCESS AND RESULT ANALYSIS

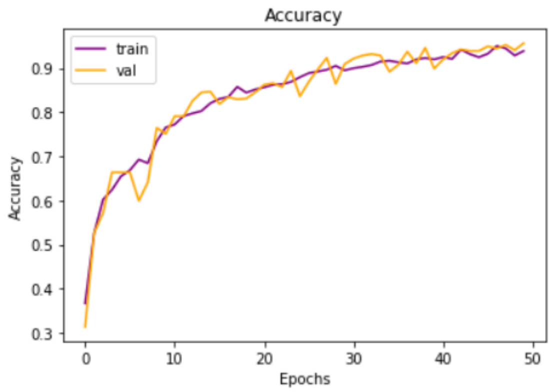

Fig -3: Accuracy versus Epochs Graph

Fig 3 shows the accuracy performance of training and validation. The accuracy was calculated using the compile function of Keras. The maximum accuracy of training and validation set was found at 49 epoch.

From fig 3 it can be observed that validation fluctuation is more than that of training. The reason for this variation is because during training the small changes in parameters are made to help optimize the accuracy of training set. Whereas the changes made in the parameters of validation are not made while keeping validation in mind.

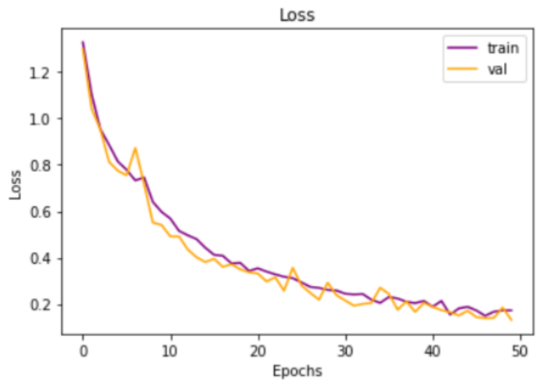

Fig -4: Loss versus Epochs Graph

The graph for Loss versus Epochs is shown in fig 4. The Loss decreases significantly for both, training, and validation. This significant decrease is because of the dropout of 0.25 and the Adam optimizer that is used. The Average Loss for Training is 16.45% and the Average Validation Loss is 25.24 %.

Table -3: Performance Table

Dataset	Max. Accuracy	Min. Loss	Avg. Accuracy	Avg. Loss
Training	97.75%	14.13%	96.954%	16.45%
Validation	96.26%	13.19%	94.505%	25.24%

The results achieved, shown in the table 3, were possible because of 5 convolutional layers with max pooling at every layer helped in extracting features from every pixel possible and the fully connected layers made sure that the images were classified into proper classes. For training and validation purposes the dataset was split into 8:2 i.e. 80% images were used for training purpose and 20% were used for validation purpose with the help of data augmentation. In addition to that, tuning parameters and hyper-parameters according to our dataset helped in improving the accuracy of the model.

4. CONCLUSIONS

In this research the proposed system used MRI scan image as an input to a multi-layered CNN model. We investigated the capabilities of CNN architectures by building them with small kernels, as opposed to standard deep CNN implementations that use shallow architectures with big filtering algorithms. We also discovered that shallow architectures performed worse even when employing a larger number of feature maps. The system apart from just classifying the brain tumor into yes or no categories, further classifies the tumor into four classes i.e. Glioma, Meningioma, Pituitary and No Tumor. The average accuracy reached by the proposed methodology was 96.26%.

Accuracy of 96.26% was accomplished with the help of wide and diverse range of dataset containing more than 4500 images. The multi-layered CNN architecture containing convolution, max pool, dropout, fully connected and SoftMax layer.

In this section few seed points have been added which can be used by researchers to work further on this topic. An automatic classification system can be built to classify types of tumors, reinforcement learning can be used instead of the supervised CNN model which will remove the need to update the model every time a new type of tumor is detected. Moreover, the model can be further developed for commercial purposes along with providing more features and privileges for the user.

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