

Brain Tumor Detection from MRI using CNN

Sri Naga Harshitha Jampani
School of Engineering and
Applied Sciences
University at Buffalo
Buffalo, NY, USA
srinagah@buffalo.edu

Mohith Raja Chava
School of Engineering and
Applied Sciences
University at Buffalo
Buffalo, NY, USA
mohithra@buffalo.edu

Giri Sai Sriram Mullangi
School of Engineering and
Applied Sciences
University at Buffalo
Buffalo, NY, USA
girisais@buffalo.edu

Sai Lavaneesh Reddy Pothula
School of Engineering and
Applied Sciences
University at Buffalo
Buffalo, NY, USA
sailavan@buffalo.edu

Sahana Kandukuri
School of Engineering and
Applied Sciences
University at Buffalo
Buffalo, NY, USA
skanduku@buffalo.edu

Abstract— Brain tumor classification is one of the most rigorous and time consuming tasks in the field of image processing and there are huge drawbacks in manual diagnosis in terms of human error and diagnosis time hence in this paper, we are building a model which is developed in order to improve the time of diagnosis done to locate the tumor in MRI with high precision, which can also classify input MRI images into tumor and non-tumor images using multi layered convolutional neural networks. The KERAS and TENSORFLOW packages are used for identifying the tumor and improve the accuracy and performance of our model. Our proposed model analyzes images without huge pre-processing of input image data set with high accuracy. Our data set is extracted from Kaggle which has nearly 3000 images of MRI scans where 1500 images contain the tumor and the other 1500 are tumor free. 70% of data is being used to train the model in order to reduce the risk of overfitting and underfitting while increasing the stability and reliability of our model making it usable on real-time images.

Keywords:

MRI, Image Classification, CNN, Brain tumor, tensorflow

I. INTRODUCTION

An important organ of the human body which helps in the functioning of the entire body is the “Brain”. It is responsible for the emotions, actions, vision, motor skills, respiration and finally memory. All these regulatory functions are equally important for a human body to be able to function normally. The regulation may be affected if there’s some tumor grows within the brain, which finally results in non-working of the motor senses leading to immobility, memory loss, dementia, Alzheimer’s. There’s also another type of tumor known as metastasis brain tumor, in which the tumor growth occurs in some other body parts growing up to the brain tissues leading to malfunction of the brain.

These tumors are detected using the MRI’s (Magnetic resonance imaging) of the brain. These images are further

loaded to detect the progress of the tumor inside the brain. The detailed information is used to proceed for the future treatment of the brain to regain its normal state or prevent from deteriorating.

The manual verification of these images may produce error because of the rapid increase in the tumor among the humans hence an automated process to detect the tumors is very helpful and accurate compared to manual verification.

In this paper, the MRIs are taken as input and the convolutional neural networks technique is used to process these images and detect the tumor.

The CNN process is a sequence in which there are multiple layers in each segment. Here, each layer extracts features from the image and then transforms the complex (image) data into the simple processed image with less size. All these layers are built one upon the other.

A. Related Work:

CNN has wider impact in different areas to solve various problems. In the medical field, for many applications, [3] CNN is the root for providing highest performance and accuracy in image detection and classification. For the detection of brain tumor, a hybrid technique is used in which the features are extracted by using CNN method and further the SVM (Support Vector Machine) and KNN (K-Nearest Neighbors) are used [4]. From the past years the use of ML methods has been rapidly increasing [5] in the research field of image detection. In the medical area image detection and its analysis finds most of the help from the automated image detection systems which in turn assists the doctors to give out better treatment plan and help cure the tumor if it is detected in the early stages.

B. Research gaps:

Convolution Neural networks is great at handling the data in a supervised learning environment which requires large amounts of training data. Training the model becomes difficult when the complexity of the task at hand increases because for CNN then to work needs large datasets to train the CNN model to get acceptable results which leads to larger training times and leads to expensive computation.

Translation Invariance is one of the issues with using convolution neural networks. The model faces problems in classification of the image when the targeted image in the picture orientation changes or the position. Data augmentation that we have used may solve this issue to some extent, but it does not solve the problem entirely.

CNN performs well in a supervised learning environment depending on the task, but we have no idea how it performs when implemented in an Unsupervised learning environment when the model has to learn on its own. CNN highly follows the labelled data which is an issue when the input image properties even change slightly.

II. MOTIVATION

The main-intention/motivation for us behind taking this topic as a project is the alarming number of deaths and people suffering due to this disease. Generally these tumors are detected using MRI's (Magnetic Resonance Imaging's). But as we have a lot of images, manual diagnosis by doctors is less accurate and consumes a lot of time. The two constraints time and accuracy are costing people their life expectancy and even in a lot of cases the life of the people suffering from this disease. So to improve the life expectancy of a person suffering from this disease, we need to detect the disease and this process must be accurate and also must consume less time as it plays a major role. Because once the disease is detected we can then treat it and improve the life expectancy of people and even save them. This model aims at detecting whether a person has brain tumor or not by taking the MRI scans of the person as input. Compared to manual diagnosis of these MRI's this model is more accurate and is less time consuming.

Hence by using this model we can improve the accuracy and the time consumed to detect the disease and save the people suffering from the disease.

III. METHODOLOGY

The current research focuses on classifying brain tumor MRI images using a CNN model. The CNN model extracts features from a prelabelled dataset and learns to classify the images as whether or not they have a tumor in them. The images

are preprocessed before feeding them to the model for a better performance. The major steps in the research are extracting data, labelling it, preprocessing the images, gradual training of the model, testing the model on an unseen dataset of brain MRIs, exploring evaluation metrics and presenting the results.

A. Dataset:

MRI - Magnetic Resonance Image is an imaging technology which produces detailed 3D images which is used in various aspects of medical field such as detection of diseases, diagnosis, and to monitor progress of ongoing treatments. In specific to brain tumor, MRIs are very effective way of diagnosing the tumor as well as understanding the progress of the tumor throughout the treatment. MRI's can help us locate where exactly the tumor is present along with its shape and size which makes the treatment and diagnosis much easier.

The current research uses a dataset extracted from Kaggle. The dataset contains 3087 images of which 1501 images have tumor in them and the rest 1586 don't have tumor in them.

The images are labelled accordingly.



Fig 1. MRI with brain tumor

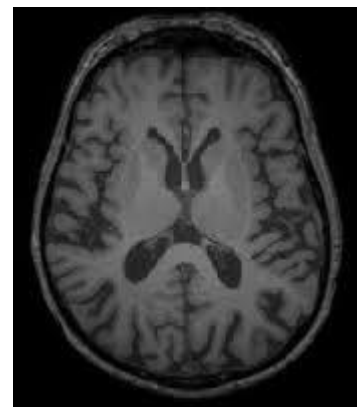


Fig 2. MRI without brain tumor

B. Preprocessing the image data:

All the images in the dataset (both training and testing) are preprocessed before feeding them to the CNN model. The preprocessing has two main steps, namely, geometric data augmentation and color data augmentation.

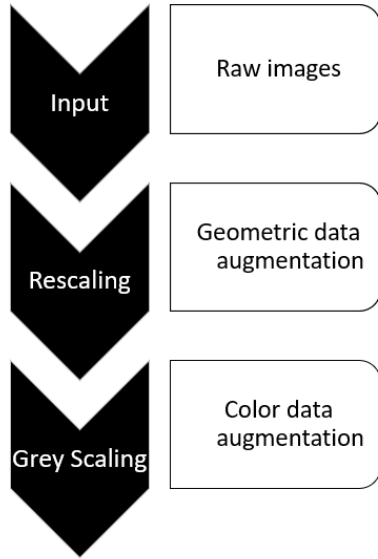


Fig 3. Flowchart describing the Pre-processing steps

Geometric data augmentation: It includes scaling of the images. As all the images in the research are of different sizes, they are all rescaled to a size of 32 X 32.

Color data augmentation: The images are converted to single-channel images, i.e, greyscale images.

The following figure shows a sample of MRI before and after the above preprocessing steps.

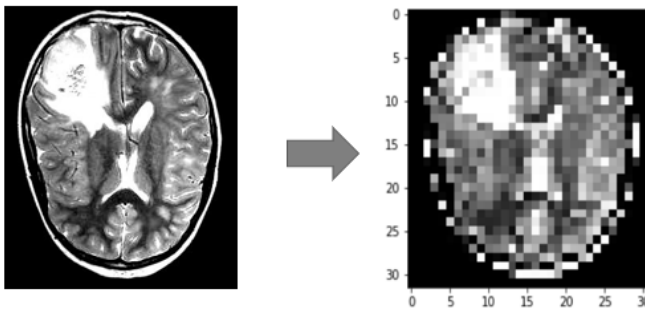


Fig 4. A sample MRI before and after Pre-processing

After the above steps, the data is now normalized to make the pixel values between 0 and 1 for faster computation.

Now, in the preprocessed data, the images with no tumor are mapped to 0 and the images with tumor are mapped to 1 so as to create the supervised learning model of CNN.

C. CNN Architecture:

The following image describes the layers in the proposed CNN model.

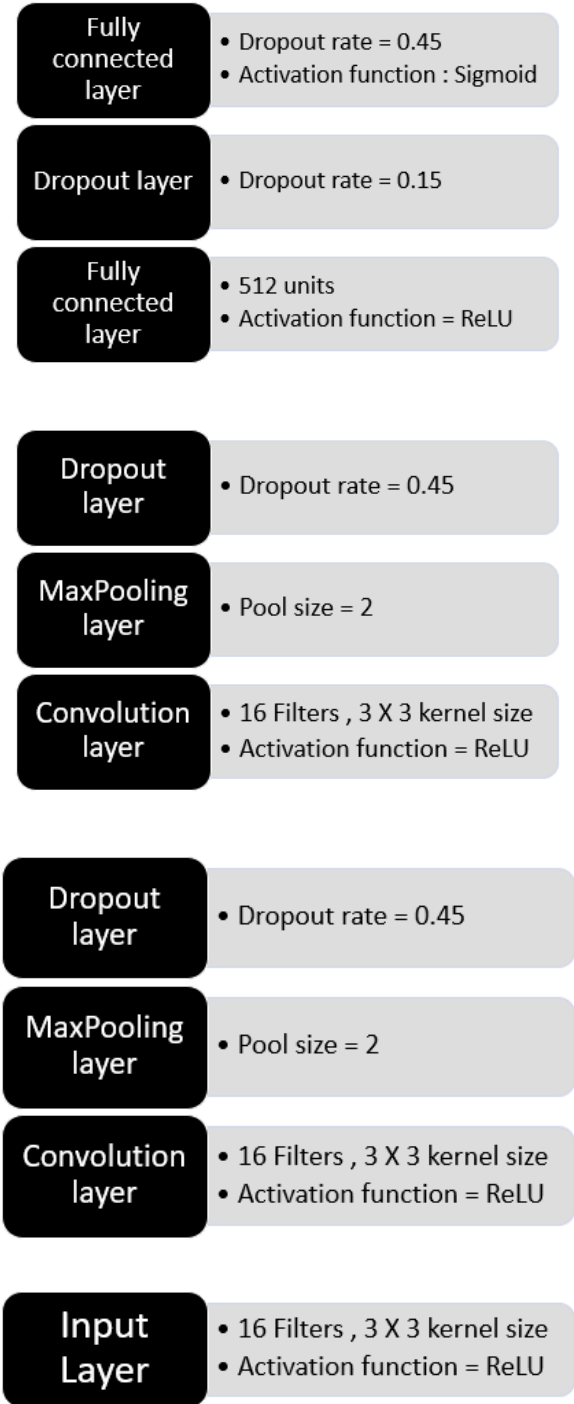


Fig 5. CNN Architecture in the model with the proposed layers

The CNN architecture is defined sequentially, i.e., the CNN layers are built layer by layer. The first layer is the input layer. It takes in the size of the input images. It has 16 filters and a 3X3 kernel size. The Rectified Linear unit function is used because it computes cheaply and converges quickly.

A 2D convolution layer is added over this with 16 filters and a 3X3 kernel size. After this a MaxPooling layer is added to reduce and summarize the feature mapping. A dropout layer is added over this with the dropout rate taken as 0.45.

The same 2D convolution architecture is repeated over this with all the parameters set as before.

A flattening technique is used after this. A fully connected dense layer with ReLU activation function and unit 512 is added over. A dropout layer is added here to reduce overfitting of the model. The dropout rate here is set to 0.15

A final fully connected dense layer is added for the output with a sigmoid activation function and unit 1.

Dropout layer applied over the convolution layer adds noise to the feature map. The dropout layers applied over a fully connected layers drops the neurons helps in avoiding overfitting.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 16)	448
max_pooling2d (MaxPooling2D)	(None, 16, 16, 16)	0
dropout (Dropout)	(None, 16, 16, 16)	0
conv2d_1 (Conv2D)	(None, 16, 16, 16)	2320
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 16)	0
dropout_1 (Dropout)	(None, 8, 8, 16)	0
conv2d_2 (Conv2D)	(None, 8, 8, 36)	5220
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 36)	0
dropout_2 (Dropout)	(None, 4, 4, 36)	0
flatten (Flatten)	(None, 576)	0
dense (Dense)	(None, 512)	295424
dropout_3 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Fig 6. Summary of the CNN model

D. Training

After preprocessing the images and building the CNN model, the data is now split into train and test sets. 70% of the data is used for training and the model is later tested on the remaining 30% of the data.

The model is first configured using the binary classification cross entropy for the loss function, which is given in the following equation.

$$CE = - \sum_{i=1}^{c'=m} l_i \log(s_i) - (1 - l_i) \log(1 - s_i)$$

Here the l_i and s_i are the CNN scores for positive and negative classes respectively. The value of m is 2 for a binary classifier.

Adam optimizer algorithm is used for training the images in the data. The learning rate used for training the model is 0.01(default training rate for *model.fit* in Python).

Instead of training the model in a single go, it is trained gradually by increasing the number of epochs at each step. Initially, the no of epochs taken was 15, which yielded an accuracy of **86.57%** in the training set. It was then increased step by step to up to 90 epochs which gave an accuracy of **97.41%**.

The following graphs demonstrate the training accuracy and training loss with different epochs.

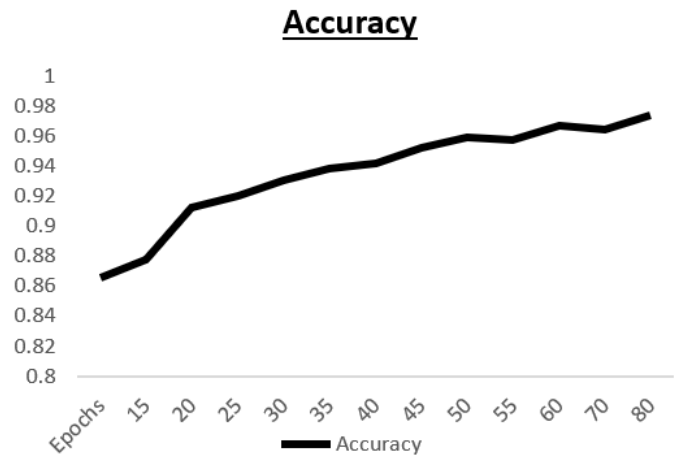


Fig 7. Accuracy vs Epochs

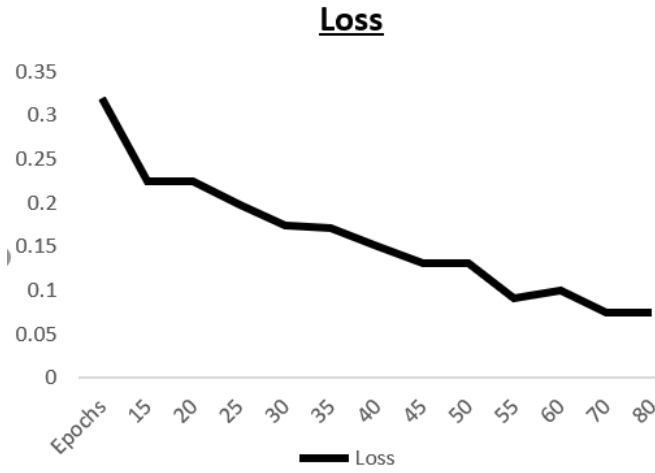


Fig 8. Loss vs Epochs

E. Testing

The test dataset contains 927 images, which is again a mix of tumor and non-tumor images.

The testing dataset images are now inputted to the model to predict whether they have tumors. The *model.predict* function used in Python gives the probability values of a tumor being present or not. To convert this to a categorical variable, the images which have a probability of less than or equal to 0.5 are mapped to 0(non-tumor) and those with probability greater than 0.5 are mapped to 1(tumor).

IV. RESULTS

The following image shows a random sample of nine images from the test set and their respective actual and prediction values. It can be seen that only one of them is misclassified.

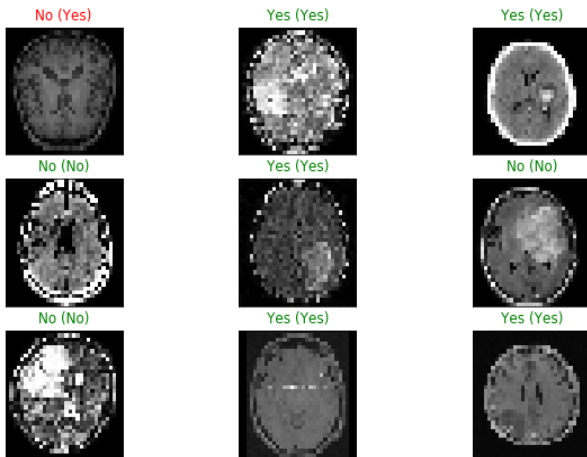


Fig 9. Sample results – Prediction (Actual)

A. Confusion matrix:

After testing the model on the test set and predicting the results, it was observed that the model yielded an accuracy of 96% on the test set images.

The following table depicts the Confusion Matrix of the model.

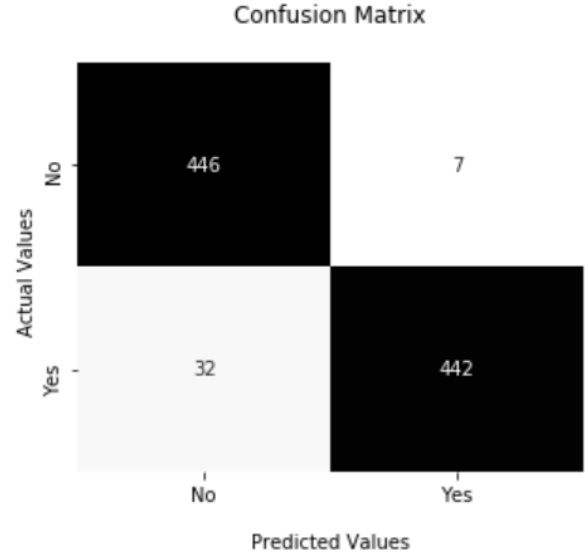


Fig 10. Confusion matrix depicting the results on the test dataset

B. Evaluation metrics

The current CNN model's performance is evaluated based on precision, recall, F1 score and sensitivity, which are calculated as follows.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall(or)Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Sensitivity} = \frac{TN}{TN + FP}$$

The above values were evaluated and are presented in the following table.

TABLE I. VALUES OF THE EVALUATION METRICS

Metric	Value
Precision	98.44%
Recall	93.24%
F1 Score	95.77%
Sensitivity	98.45%

The ROC curve is also plotted to understand the True positive rate vs. the False positive rate of the model.

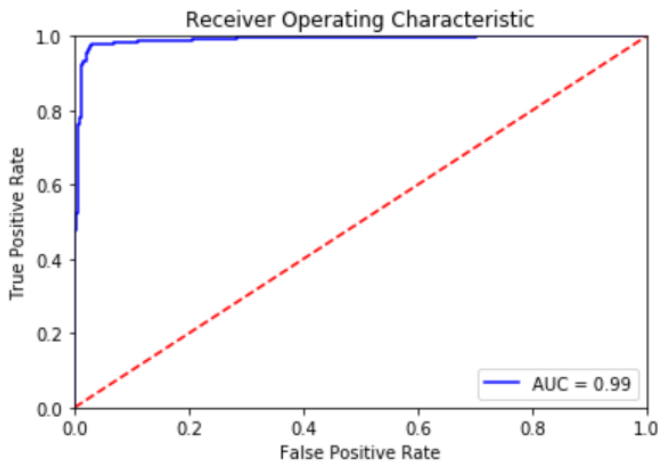


Fig 11. ROC Curve: True positive rate vs False positive rate

V. CONCLUSION

The current model can be considered a good one because out of the 474 images that have tumor in them, the model incorrectly classified only 32 images. This is further supported by the non-tumor images' prediction, where the model's incorrect predictions were 7 out of 453 images. Also, the overall accuracy of the model on the test set is 96%, which is an acceptable value.

The entire model is built in python. The code takes 102 seconds to run, which includes loading the images, pre-processing the data (3087 images), building and training the model, testing the model on the test set, evaluating the model's performance.

Considering the above details, we can say that the model is a reliable one and can be used to detect brain tumors on any unseen set of images.

VI. BROADER IMPACT OF THE RESEARCH

- The segmented images can be further processed and be used to predict the clinical disorder, survival and response to any therapy given.
- This method has a role in the segmentation of glioblastoma and lower grade astrocytomas - types of brain tumors.
- The future performance of CNN-based brain tumor detection can be enhanced using deep networks and other categories in CNN.

- Other techniques such as feature maps and augmentation techniques can also be used and worked properly to get more accuracy for the trained model.

VII. SUMMARY AND FUTURE WORK

In the current research, brain tumor detection from MRI's using convoluted neural network (CNN) is proposed which can yield high accuracy with very little pre-processing of data. In this model 70% is used for training and 30% is used for testing which is the unseen data with an accuracy of 96%. In future, the performance of this CNN-based brain tumor detection model can be further improved by further research on deep learning and different neural network techniques and different augmentation techniques. This model can further be developed in order to detect exact location of the tumor and its shape and size along with the type of tumor by taking different input images which are tumor type specified.

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