

BRAIN TUMOR CLASSIFICATION USING CNN

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ABSTRACT

A brain tumor is a growth of abnormal cells in the brain or central spinal cord. When a tumor is benign, it does not spread to other areas of the body, but when a tumor is malignant, it can infect neighboring tissues and do so. Brain tumors can afflict people of any age, although the likelihood of getting one increases with age. Certain malignancies can be found and located with great accuracy using Magnetic resonance Imaging (MRI). The most accurate technique to detect brain and spinal cord cancers is via a contrast-enhanced MRI. Sometimes, doctors can determine if a tumor is cancerous or not using MRI. However certain concept of machine learning and deep learning such as transfer learning, convolutional neural network (CNN) can be used to train an AI model which can assist doctor to perform diagnosis more accurately. In this proposed project CNN is used to classify between a abnormal brain MRI and normal Brain MRI. The proposed model has training accuracy of 98.51% and validation accuracy of 95.3%.

Keywords: Analysis, CNN, Machine Learning, Brian Tumor, MRI, neural network, binary classification

I. INTRODUCTION

With more than 700,000 new cases of brain tumor being discovered globally each year, this condition is a serious health problem. Improving patient outcomes and raising survival rates depend on early and accurate diagnosis. Yet, locating and categorizing brain tumor may be difficult and calls both highly skilled medical personnel and cutting-edge imaging equipment.[1] The most dreaded illnesses include brain tumors, It was the most frequent reason for cancer-related death among children (ages 0–14) in the US in 2016. Moreover, 86,970 new cases of brain, other Central Nervous System (CNS), and other malignant tumors are anticipated in the United States through 2019. Many patients die due to miss diagnosis or lack of experience of doctor, Early diagnosis of brain tumor can significantly improve treatment options and increase the likelihood of a high chance of survival. Yet, since many MRI scans are carried out in a hospital context, separating wounds or ulcers is a time-consuming as well as complex task. According to WHO 2.6 million people die every year due to wrong diagnosis of diseases.

This horrific number can be reduced with the help of Various approaches of ML and DL Convolutional neural networks (CNNs) is among one of them. Convolutional neural networks (CNNs) have become a potential method for identifying and categorizing brain cancers in recent years. CNNs are an artificial neural network design specifically made for visual data analysis and interpretation, which makes them a good choice for evaluating medical imaging. It Is well suited for image and video analysis tasks. This is because they are designed to automatically identify and extract relevant features from images, which can then be used to make predictions or classifications. By using CNNs to analyze medical images, healthcare professionals can potentially improve the accuracy and speed of diagnosis, which in turn can lead to better patient outcomes. Additionally, this technology can help reduce the workload of medical professionals, allowing them to focus on other aspects of patient care.

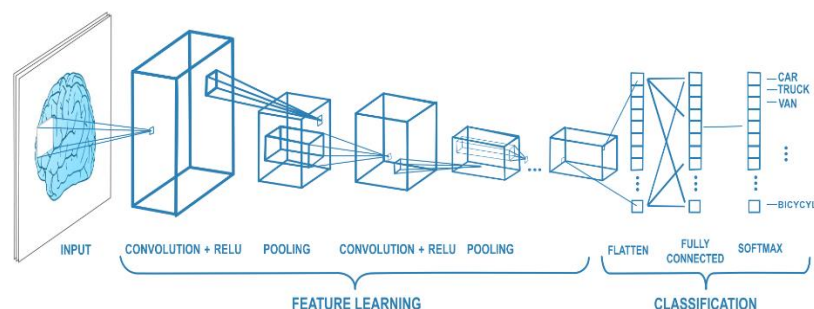


Fig 1: Architecture of CNN For multiclass classification

However, collecting and preprocessing large amount of data for training the model is time consuming to overcome this we can use Transfer Learning. It is a machine learning technique where a model is trained on a large dataset, typically for a specific task, and then the learned knowledge or representations are transferred to another model for a different task. Rather than starting from scratch, the pre-trained model provides a head start in learning the new task, thereby reducing the amount of training required and improving the accuracy of the new model. The pre-trained model can be modified by adding new layers or retraining certain layers, depending on the specific requirements of the new task. [3] M. J. Horry in his research use VGG19 model to conclude that it could be used to create appropriate deep learning-based COVID-19 detection systems. The model can distinguish between COVID-19 vs. Pneumonia and Pneumonia vs. Normal conditions for a variety of imaging modalities, including X-ray, ultrasound, and CT scan. We can also use such pre-trained models like inception-resnetV2, Dense Net can be used for brain tumor classification

II. RELATED WORKS

various studies and approaches are proposed in same direction such as , [2] Anaraki et al proposed a model which is combination of both CNN and Genetic Algorithms (GA-CNN), In first test case of classifying three grades of glioma the model attained accuracy of 90.9% whereas in second case of classification of meningioma, glioma and pituitary tumor model achieve 94.2% accuracy.[4]Achieve accuracy 99.04% using pre-trained model AlexNet. Without any previous region-based pre-processing stages,[5] Abiwinada et al. trained a straightforward CNN architecture to categorize the three most common forms of brain tumors, namely meningioma, glioma, and pituitary. They discovered a CNN model with two convolutional layers, activation function (ReLU), max-pooling, and one fully connected layer that was the most effective. Their classification model achieved 84.18 percent validation accuracy and 98.51% training accuracy. Khairandish et al proposed A hybrid CNN-SVM Threshold segmentation approach with there approach of hybrid CNN-SVM they obtain accuracy of 98.49%. In [7] Ginni et al approach the classification is done by hybrid ensemble classifier KNN-RF-DT (K-Nearest Neighbor, Random Forest, Decision Tree). Instead of using Deep learning they use traditional classifiers and gain 97.305% accuracy. [8] In Seetha J, et al approach The Gradient decent based loss function is applied to achieve high accuracy. The training accuracy, validation accuracy and validation loss are calculated. The training accuracy is 97.5%. Similarly, the validation accuracy is high and validation loss is very low.[9] There work describes the detection of brain tumor area by predicting type of tumor with bounding box.MRI brain tumor images are trained from the scratch using Faster R-CNN. Faster R-CNN combines AlexNet model and RPN. The proposed method achieved hopeful result when compared to segmentation of brain tumor detection system

III. PROPOSED METHODOLOGY

The proposed model is a binary classification model for classification of normal and abnormal brain MRI. Below Figure 2 summarizes the approach proposed for binary classification model which is further explored in subsections that follows.

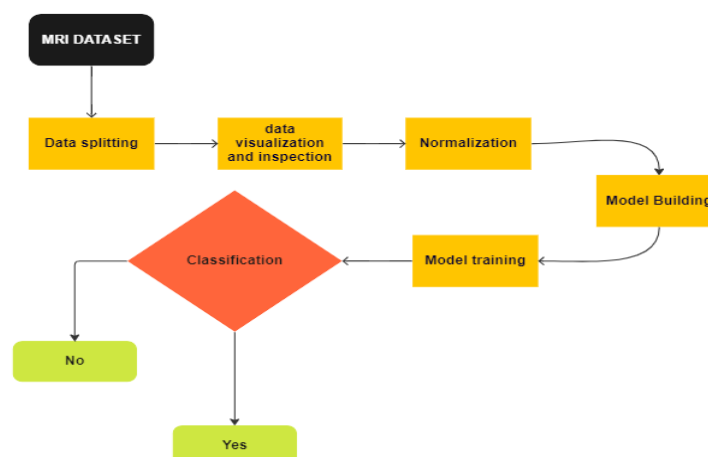


Figure 2: Binary classification model implementation

1. **MRI Dataset and preparations** -First steps are to collect the MRI data from various sources the more the data the better the accuracy we have around 3030 images if Brain MRI we will further divide this images into training and testing in Data splitting section. 2 classes make up these 3030 images. Yes and No 1510 images of tumorous brain MRI are in the Yes folder, whereas 1520 photos of non-tumor brain MRI are in the No folder. This steps also include loading this data into working environment and setting up the environment by importing required libraries such as NumPy, Pandas, OS, TensorFlow, matplotlib, keras, etc.
2. **Data Splitting**-In these sections we will divide our data into training and validation data.

```

Data_set
|--val
|   |--no
|   |--yes
|--train
|   |--no
|   |--yes

```

Figure 3: Data splitting representation

Figure 3 above shows that the folder Data set has two subfolders, Val and train, each of which has two subfolders, no and yes. 606 MRI pictures are stored in two files in the Val directory. It has 302 images of aberrant brain MRIs, thus yes whereas no, it has 304 images of a typical MRI of the brain. Within train directory we have 2424 MRI images 1216 for yes and 1208 for No. Below figure 4 shows the distribution of data into graphical form.

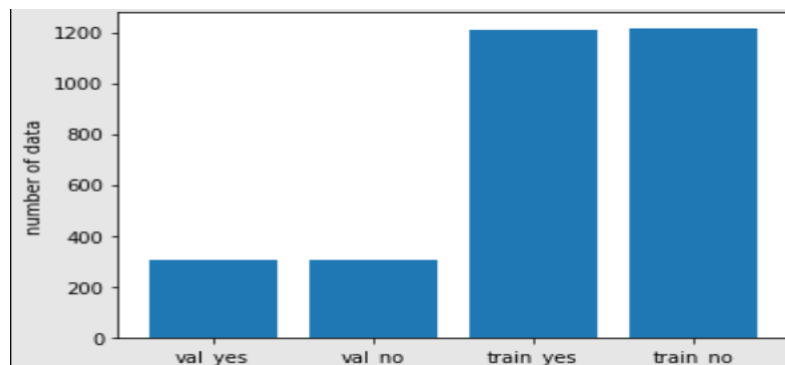


Figure 4: Data splitting for validation and Training

3. **Data visualization and inspection**- To ensure that the data we use to train our model is reliable, we must visualize it first.

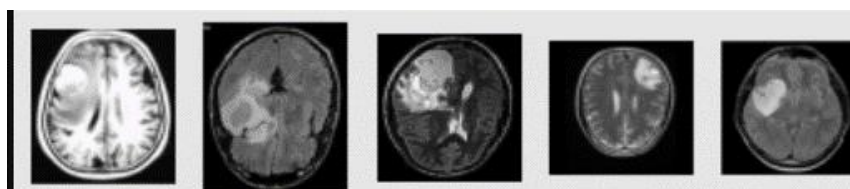


Figure 5: Tumorous Brain MRI Images

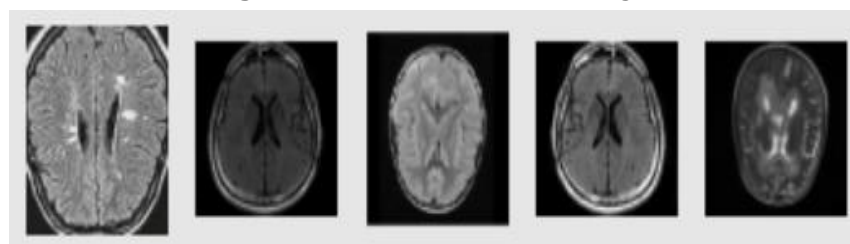


Figure 6: Normal Brain MRI images

Above figure 5 and 6 displays images samples chosen randomly from their respective directories

4. **Normalization**-It ensures that each input (in this case, each pixel value) is drawn from a standard distribution. The range of pixel values in one input image is equivalent to the range in another image, in other words. Our model can be trained and get to a minimum error faster thanks to standardization! We will also divide our training images into batches with a target size in order to pass it to model.

5. **Model building and training** -Below is the figure 7 representing convolutional neural network used into training of the proposed model

This neural network receives images with the shape (224, 224, 3) for model training and evaluation.

Images will be transmitted sequentially from each of the layers listed below.

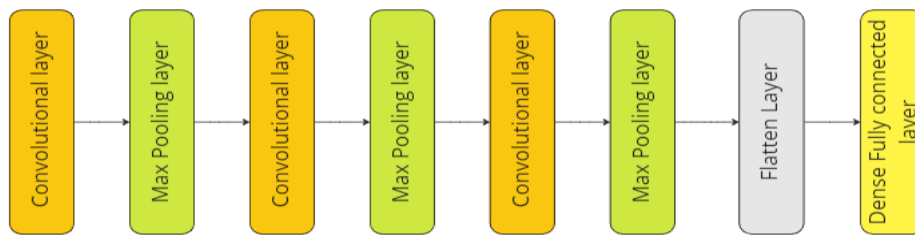


Figure 7: convolutional neural network

➤ **Convolutional layer**-Convolutional Neural Networks (CNNs), a kind of deep neural networks that have shown to be particularly effective in image recognition, natural language processing, and other tasks that entail processing structured input, use convolutional layers as a key building component.

A convolutional layer applies a set of filters (also known as kernels or weights) to the input image, computing the dot product between each filter and a local region of the input image. The final product is a feature map that draws attention to particular patterns or features in the input.

A non-linear activation function, such as ReLU (Rectified Linear Unit), is also included in the convolutional layer. ReLU introduces non-linearity into the model and aids in the capture of more intricate patterns in the input. Convolutional layers are typically followed by pooling layers, which reduce the spatial dimensionality of the output feature map, and by fully connected layers, which perform the final classification or regression task based on the extracted features.

➤ **Max Pooling layer**-Convolutional neural networks (CNNs) frequently use the max pooling kind of pooling layer to minimize the spatial dimensionality of the output feature maps.

The maximum value within the rectangular window that slides across the feature map in max pooling is chosen as the output value for that region. During training, it is possible to fine-tune the window's size and stride (the distance it travels between choices).

The most important features can be preserved while the spatial dimensionality of the feature maps is reduced with the help of max pooling. The network can recognize an object independent of its location inside the input image thanks to improved translation invariance, reduced computational complexity, and control over overfitting.

➤ **Flatten layer**-In deep neural networks, particularly convolutional neural networks (CNNs), a flatten layer is a type of layer that is frequently used to reduce a multi-dimensional tensor to a one-dimensional vector.

In CNNs, the convolutional and pooling layers' output typically takes the form of a 3D tensor of the form (batch size, height, width, channels), where batch size denotes the quantity of input samples, height and width denote the feature map's spatial dimensions, and channels denotes the quantity of filters applied in the convolutional layer.

This 3D tensor is fed into a flatten layer, which converts it into a form vector with the dimensions batch size, height, width, and channels. A fully connected layer

➤ **Dense Fully connected**

For classification and regression applications, dense layers are frequently utilized as the last layers in neural networks. The output of the dense layer is frequently input into a softmax activation function for classification tasks to generate a probability distribution over the various classes. The output is frequently utilized as the projected output in regression projects. For binary classification sigmoid is used.

In a dense layer, the number of neurons is a hyperparameter that can be adjusted during training. The ability of the model to recognize intricate patterns in the data can be improved with more neurons, but this can also result in overfitting. The effectiveness of the model can also be impacted by the activation function selection. ReLU, sigmoid, and tanh activation functions are frequently utilized in dense layers.

IV. RESULTS AND DISCUSSION

In Conclusion Convolutional Neural Networks (CNNs) have demonstrated encouraging results in reliably detecting the existence of tumors when used for binary categorization of tumor MRI. CNNs can efficiently capture the complex patterns and structures in the MRI data because they have the ability to automatically train and extract essential features from the input pictures, leading to high accuracy and resilience.

The CNN model can learn to identify between normal and pathological brain tissue with a high degree of accuracy by training on a huge dataset of labelled MRI images, making it an invaluable tool for physicians in the diagnosis of brain cancers.

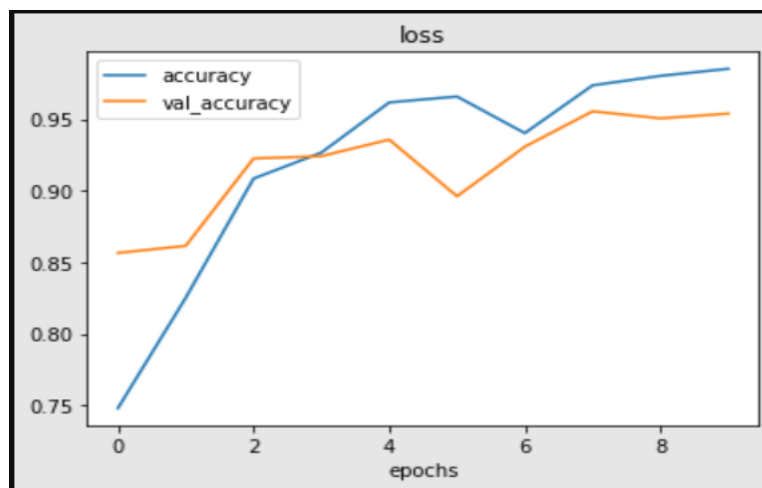


Figure 8: Training accuracy and Validation Accuracy

$$\text{Accuracy} = \text{TP} / ((\text{TP} + \text{FN}))$$

Training accuracy refers to the accuracy of the model on the training data during the training process. As the model is trained on the training data, the training accuracy increases, indicating that the model is getting better at fitting the training data

Validation accuracy, on the other hand, refers to the accuracy of the model on a validation set of data that is not used for training. The validation accuracy gives an estimate of how well the model will generalize to new, unseen data.

Figure 8 shows the validation and training Accuracy of proposed model. Accuracy on validation data is 95.3 and Training accuracy is 98.51. This accuracy is achieved within 10 epochs

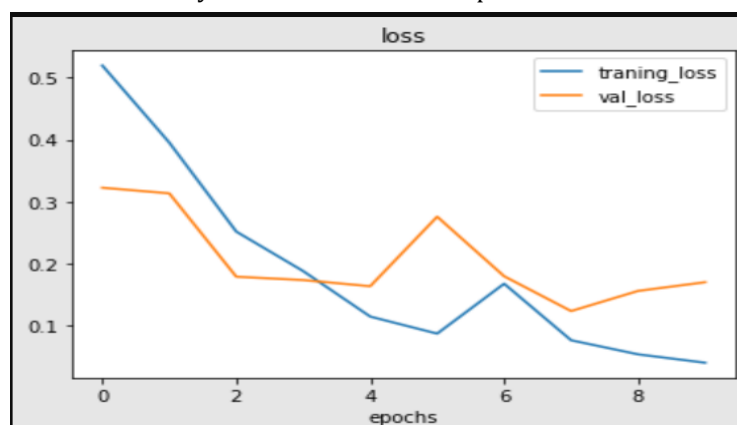


Figure 9: Loss curves

Training loss refers to the loss of the model on the training data during the training process. As the model is trained on the training data, the training loss decreases, indicating that the model is getting better at fitting the training data. Validation loss, on the other hand, refers to the loss of the model on a validation set of data that is not used for training. The validation loss gives an estimate of how well the model will generalize to new, unseen data. If the validation loss is significantly higher than the training loss, it is an indication of overfitting. Figure 9 shows the training loss of 0.0392 and validation loss of 0.1694 of proposed model

V. CONCLUSION

In conclusion, binary classification of tumor MRI using Convolutional Neural Networks (CNNs) has shown to be a promising approach for accurately detecting the presence of tumors. By training on a large dataset of labeled MRI images, the CNN model can learn to distinguish between normal and abnormal brain tissue with high accuracy and robustness, making it a valuable tool for clinicians in the diagnosis of brain tumors. Using proposed model 98.51% accuracy is achieved on training data and 95.35 accuracy on unseen data. Overall, the application of CNNs in binary classification of tumor MRI represents a significant advancement in medical image analysis and has the potential to improve the accuracy and efficiency of brain tumor diagnosis and treatment. The incorporation of data preprocessing and augmentation techniques, as well as advancements in CNN architecture, can further improve model performance and bring us closer to more effective brain tumor diagnosis and treatment.

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