Analysis of the Convolutional Neural Network Model in Detecting Brain Tumor

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Abstract— **Detecting brain tumors is an active area of research in brain image processing. This paper proposes a methodology to segment and classify brain tumors using magnetic resonance images (MRI). Convolutional Neural Networks (CNN) are one of the effective detection methods and have been employed for tumor segmentation. We optimized the total number of layers and epochs in the model. First, we run the CNN with 1000 epochs to see its best-optimized number. Then we consider six models, increasing the number of layers from one to six. It allows seeing the overfitting according to the number of layers.**

Keywords-component; Convolutional Neural Network, Brain Tumor, Data Augmentation

I. INTRODUCTION

Brain tumors have dangerous implications where the location and size of the mass helps to determine the level of impact. Magnetic Resonance Imaging (MRI) produces many tissue contrasts in each imaging modality and has been widely used to diagnose brain tumors [1]. MRIs provide cross-sectional images of the brain, and each image is analyzed separately to determine the location of the tumor and the size of the tumor mass [2], [3]. When examining potential cases of Alzheimer's disease, the current standard of diagnosis depends on highly skilled neurologists to conduct an examination of a structural MRI [4].

Harper specified an imaging-based disease diagnosis [5] but it used only the scanned brain images from the MRI, which limits the ability. To overcome this, the application of deep learning, such as convolutional neural networks (CNNs), for MRI and multimodal data-based classification of cognitive status has been suggested [6], [7]. Images are represented as a n rows by m columns 1- or 2- dimensional matrix, depending on the color system of the image. We are able to input the matrix representation of the image, after preprocessing the data, into the feature learning step of the CNN [8]. The transformation of the matrix representation of the image into a 1-dimensional array using stacking gives the required data shape to process the CNN. The data then enters the first layer of the assigned number of hidden layers. In that layer, some predefined model process occurs, i.e. MaxPooling, convolution, and/or activation functions, which gives an output which is utilized as the input of the succeeding hidden layer. This process reoccurs through all hidden layers until reaching the final node which will give the prediction of the image class and it's accuracy tested against the validation set.

Even though Convolutional Neural Network (CNN) models have a lot of benefits to the improvement of diagnosis technologies, it has a weakness as overfitting occurs when a trained network performs very accurately on the given data but cannot generalize well to new data [9], [10]. This means that the fitting process has focused too heavily on the unimportant and unrepresentative “noise” in the given data. So, it should be careful about designing CNN model such as considering on the number of convolution layers and epochs for training and test. However, it has not provided the descriptions of why the number of the layers and epochs in the model should be optimized in terms of the accuracy and loss of the predictions

In this paper, we investigate the models according to the number of convolutional layers and number of epochs. We used the code created by Irsheidat and Duwairi (See [11]) along with the data set from Kaggle Data Warehouse to duplicate the results. Then we update and modify the code based on the number of the layers and fix the number of epochs 25. Finally, we have seen an accuracy and loss based on the several graphs and figures, leading to predicting the best number of layers. This paper is organized as follows: The methodology is introduced providing the architecture of the CNN model with augmented data, Description of the main results based on the graphs of the training and validation accuracies and losses, finally concluding with the number of the layers and epochs which gives best results through optimization.

II. Methods

A. Data

We begin by taking the initial 253 MRI images of the brain, opening them in the Kaggle Data Warehouse data set duplicating the results [11]. The MRI image is an array of pixels that have height and width. In each layer of the CNN, several mathematical operations and filters are applied to the images. For example, opening the images in Grayscale (2-D array) reduces complexity because the color system only includes colors that are shades of gray. Other color systems such as RGB (3-D array), whose color system includes many combinations offered, green, and blue, would require more information for each pixel.

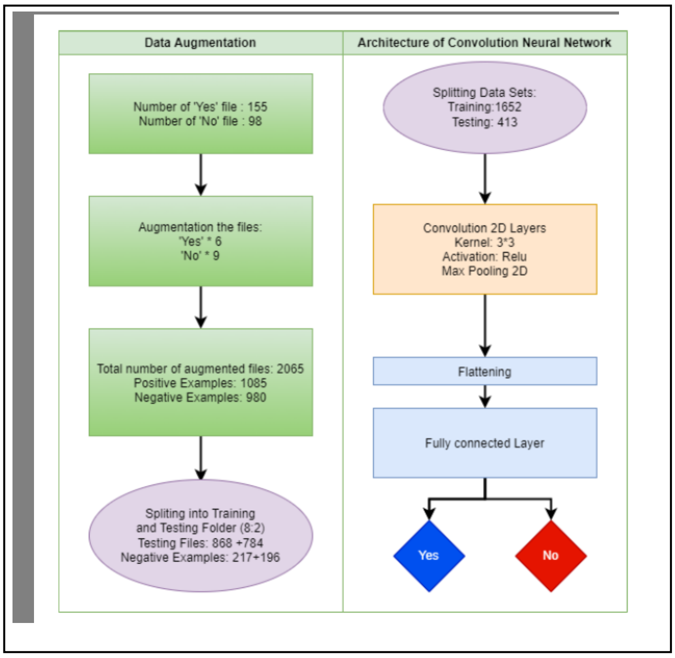

Figure 1. Architecture for the CNN modelAugmentation of Data: It saparated two steps 1. Data augmentation, 2 Machine Learning using the method of CNN detecting Brain tumor.

We augment the data by resizing, rotating, scaling, and flipping the images. This process has been done to each image six times for the brain image of the tumor(s) (see figure 2) and nine times for a non-tumor image (See figure 3). This increased the data set to 2065 MRI images of the brains (1085 images with tumor(s) and 980 images of non-tumor). This made the number of each data set (tumors and non-tumor) balanced. The images were then resized and flattened to pass in the CNN in a unified shape (See the right diagram in figure 1). After training the images in the CNN, the results were received and analyzed. We learned that the original data had been augmented during the preprocessing stage because a deep learning model requires an enormous amount of data to learn from. Using the new imaging data set, we could replicate the results to determine the accuracy of the model and its reliability.

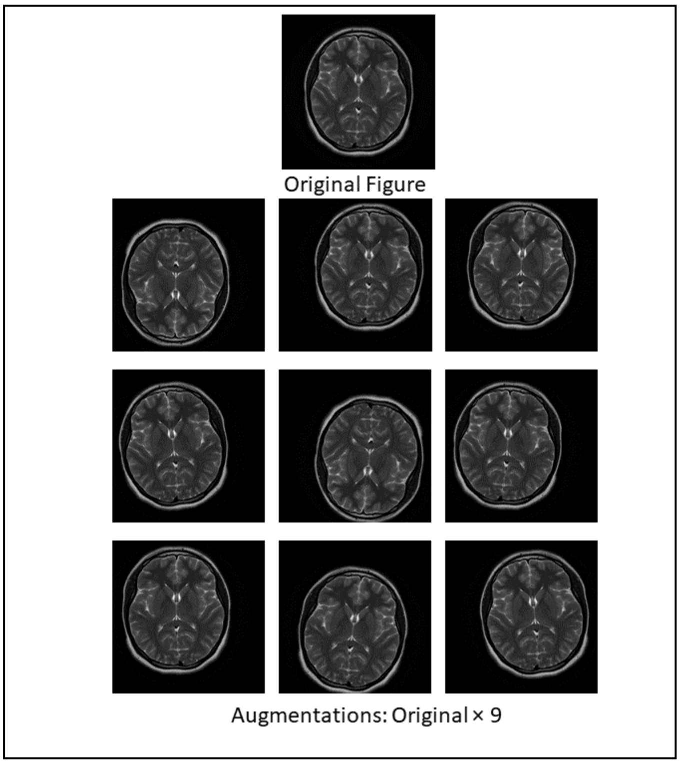

Figure 2. Augmentation of the date for non-tumor: Because of unbalanced number of data, we have 9 copy of original data using the augmentation method, resizing, rotating, scaling and flipping.

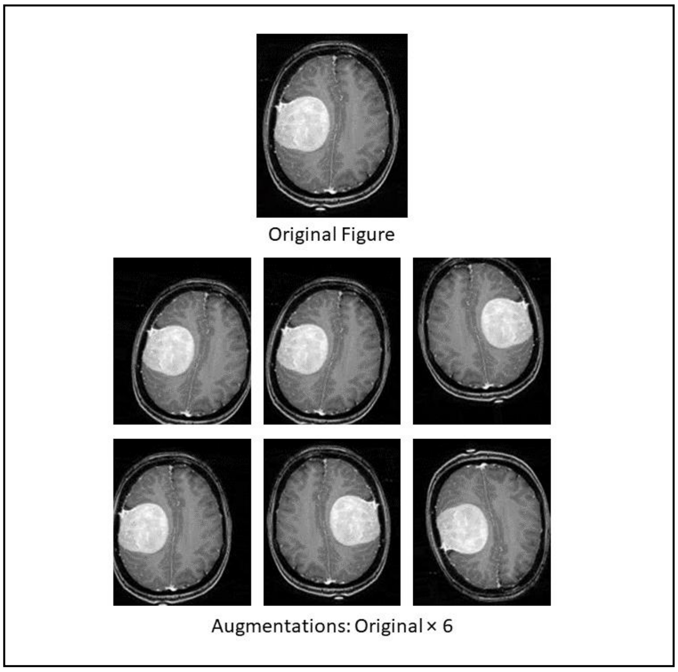

Figure 3. Augmentation of the data for tumor: We can see the white portion of the figures, showing the brain tumor. Since the number of images having brain tumor is less than others. We copied the 6 images from original data using the augmentation method, resizing, rotating, scaling and flipping.

B. CNN Model

Researchers use the package, TensorFlow and its subpackage called the Keras Sequential model to create the CNN, which consists of five convolutional blocks. The design included several Convolutional 2D blocks with MaxPooling and Rectified Linear Unit (RELU) functions. The MaxPooling process is used to reduce the dimensions across each layer. RELU is the activation function used to activate the next layer in the CNN model. The activation function's primary role is that the nonlinearity of the function in the layer makes the training parameters updated more effectively from the Back-propagation step. Two Fully Connected layers help assemble the data from previous layers connecting every input and output of each hidden layer to the last dataset which helps to form the output layer. The Dropout technique is used to prevent overfitting. Finally, the SoftMax function is used in the final output neuron as the activation function which outputs the final prediction. It is a regression layer that only returns one of two outcomes. Specifically, if the output returned "0," then there was no tumor detected in the brain, and if it yielded "1", there was a tumor detected.

C. Modifications of CNN Model

We modified the CNN model by increasing the number of epochs (number of times the entire data set passes through the model) from twenty to one thousand epochs. We compared the results from the model after one hundred, three hundred, and five hundred epochs. After comparing them, we see which number of epochs would be the most reliable. To find the best number of convolutional layers, we run the code with one to six layers to show the best number of layers around twenty-five epochs and we did the training and test with 25 epoch numbers. This optimization process is essential because it helps minimize cost and loss, thus improving the model's accuracy.

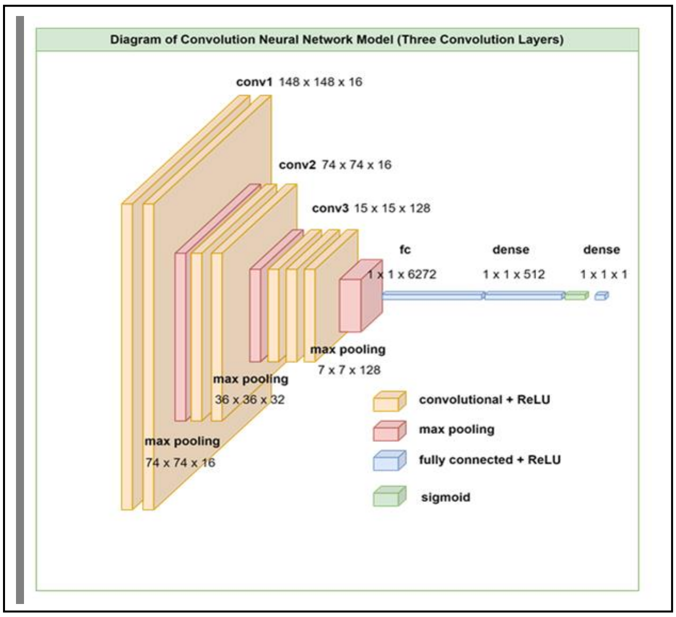

Figure 4. Diagram of Convolution Layers: it has three convolution layer including convolution, maxpooling, fully connected, and dense layers.

D. Training and Testing

The 2065 data was divided into two sets for this study, training, and testing to evaluate the model's performance. The process helped evaluate the cost function corresponding to the validation or test data. The cost function returns the error between predicted outcomes and the actual outcomes. Fifteen percent of the data was used for testing, and the remaining eighty-five percent of the data was used to train the model. The model has been working and fitting the parameters as they change and update with each layer in the CNN. When working with large data, accurately fitting the training data is essential because overfitting will affect the model's performance.

III. RESULTS

A. Optimized Epoch Number

We have considered two cases, where we alternated the number of epochs from 25 to 1000 allowing us to determine the best epoch of the two.. The main reason for considering a large epoch number is to see the trajectories of the graphs for training and test, which allows to investigate what number would be the best optimized. In figure [5], we have seen the trajectories of the graphs do not change too much after the epoch number 30 and are just oscillating constantly. It demonstrates that the number 25 is the best number of epochs for advancing the accuracy and reducing the computational cost.

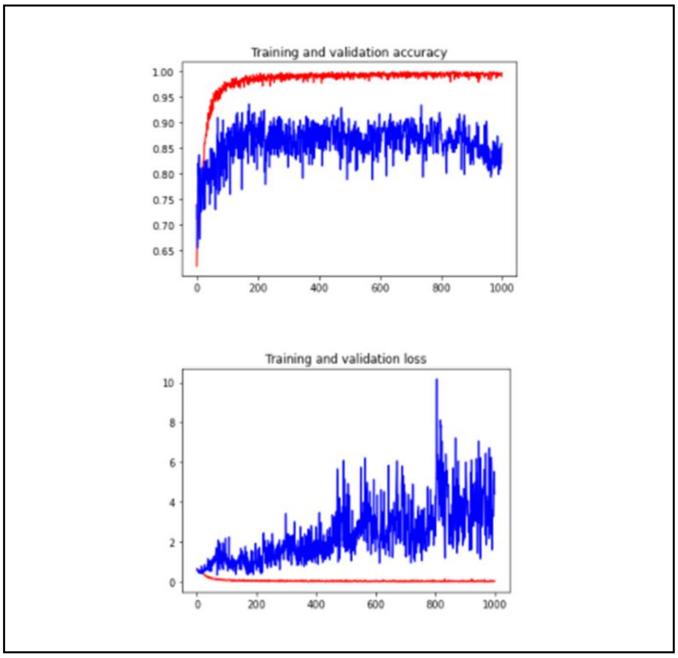

Figure 5. 1000 Epoch number excuted: It shows after 25-30 epochs, it maintain the same accuracy and loss.

B. Optimized Number of Convolution Layers

The best number of convolution layers is Five convolutions to be optimum for this model. However, we wanted to compare models up to six convolutions to gauge how the model behaves with the added layers. When adding this many convolutions, a value error can occur. This error occurs because after each layer in the convolution, the dimensions are reduced, and this can lead to a negative dimension size. To address this error, padding can be added to each layer. "Padding works by extending the area of which a convolutional neural network processes an image." This was done for model six and model seven. These models did not perform well on the validation data used to test the model. In figures six and seven, the validation accuracy and loss are oscillating, while the training accuracy and loss are showing a steady increase and decrease. In figures 6 and 7, the training and validation loss show accuracy during the first ten epochs. Then we see a significant increase in the validation loss while the training loss is steadily decreasing. We can now speculate that this may be due to overfitting. As aforementioned, overfitting occurs when the model focuses on insignificant noise in the data. Since several of the models have shown improvement on the training data without improving on the validation data, we should use another technique to try to address overfitting and improve the accuracy of the model. We know that the Dropout technique has been used to help overfitting. To achieve more optimum results on the data, we adjusted the add more convolutions and the parameters in each convolutional layer.

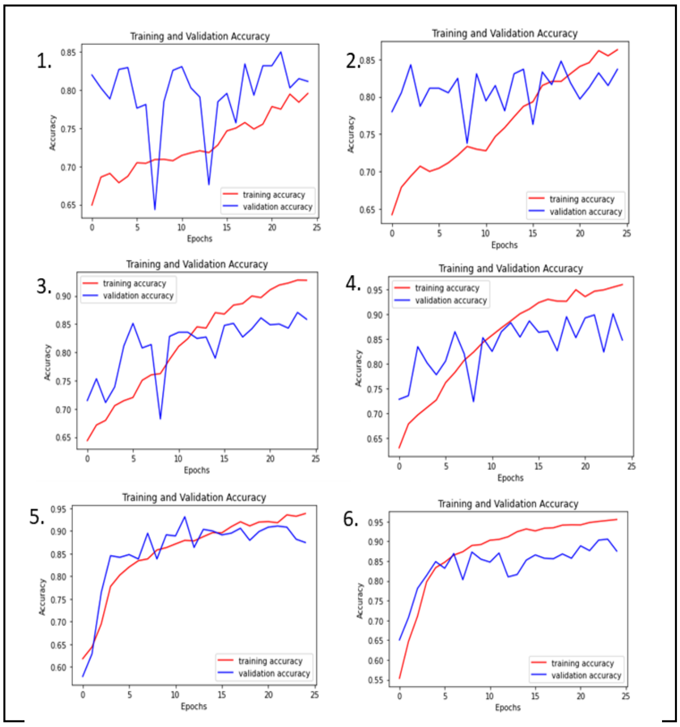

Figure 6. Graphs for accuracy rate according to the epoch number: the number 1-6 means the number of convolution layers. For example, left top is the accuracy result when the model has only one convolution layer.

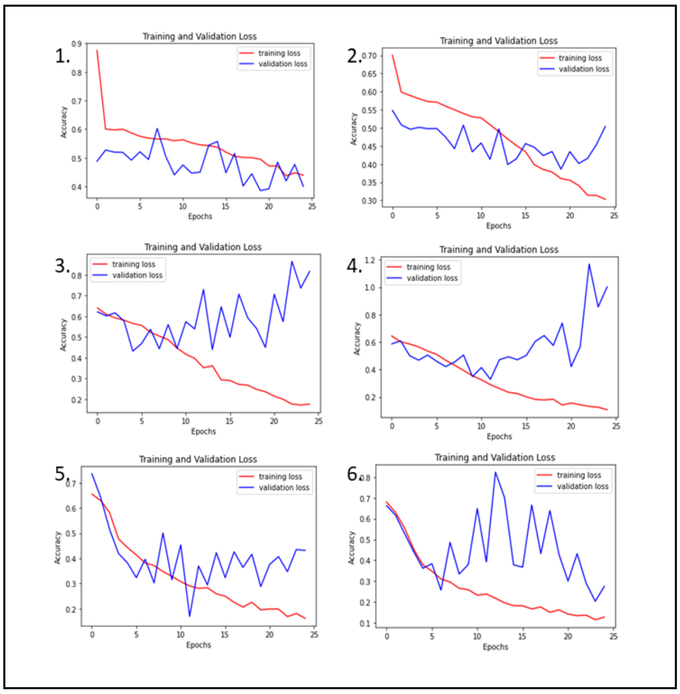

Figure 7. Graphs for loss rate according to the epoch number: the number 1-6 means the number of convolution layers.

IV. DISCUSSION

It becomes increasingly important to use the machine learning model to determine diseases such as brain tumors and Alzheimer's disease. In particular, we are using the convolutional neural network algorithm, deciding the epoch number and number of CNN layers to advance accuracy and reduce computation cost. In this paper, as one of the effective methods with Two-dimensional MRI, the deep learning model, Convolutional Neural Network, is proposed. Firstly, we found the best epoch number of the model to reduce the computational cost. Running the model with 1000 epoch numbers provided us with the clue that a high number is unnecessary to get accurate outcomes. Secondly, to estimate the best number of convolutional layers, we have tried six times with the different number of convolutional layers from one to six. In the process, we have seen that when running the model with five layers, accuracy and loss graphs in terms of training and test follow each other. It means that it does not have overfitting only when having the number five. It would be challenging to find the reasons for mathematical analysis why the number is the best.

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