

Central Nervous System Tumour Classification Using Residual Neural Network

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ABSTRACT

A brain tumor occurs when an abnormal growth of cells form within the brain. There are two main types of tumors: cancerous (malignant) tumors and benign tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These symptoms may include headaches, seizures, problems with vision, vomiting, and mental changes. Other symptoms may include difficulty walking, speaking, or sensations. As the disease progresses, unconsciousness may occur. One of the problems that brain tumor diagnosis faces is the similarities of its initial symptoms with that of commonly occurring diseases, making it prone to misdiagnosis. The brain and spinal column make up the central nervous system (CNS), where all vital functions, including thought, speech, and body movements are controlled. This means that when a tumor grows in the CNS, it can affect a person's thought process or the way they talk or move. The main purpose of this project is to build a CNN model that would classify if the subject has a tumor or not based on MRI scans. This would help ensure that proper diagnosis takes place and can help doctors recommend the most effective treatment.

Keywords: A brain tumor, central nervous system, diagnosis, CNN, classify

1. INTRODUCTION

The brain can be consensually agreed upon as the control center of the human body. It is responsible for handling all conscious and subconscious activities of the human body which include cognitive abilities and bodily functions, both voluntary and involuntary. Neurology, the study of the nervous system, is considered to be one of the most complex branches of medicine to date. Highly experienced doctors in the field are quite limited and hence are very valuable to the community. Of late, due to the introduction of chemicals and pollutants into the regular lifestyle of present-day individuals, there are multiple causes of abnormalities occurring in certain parts of the human body due to radicals from the external environment, namely in the form of abnormal

cell growth called tumors. The brain is no exception to this and due to the complex nature of the nervous system, it becomes quite difficult to diagnose and treat tumors in the nervous system. There are many ways through which we can map the image of an individual's brain structure. Magnetic Resonance Imaging (MRI) is by far the most preferred method for most neurologists due to the clarity and precision of MRI brain mapping [1, 2, 6]. In many cases, the tumor may be difficult to identify without the trained eye of an experienced neurologist. The problem we face is that, even with the rising number count of patients affected with tumors related to the CNS, there are not enough qualified medical experts to handle the multitude of cases.[4] This deficiency also causes an increase in the treatment costs and many will not be able to afford it, eventually contributing to the tumor death rate. Through our project, we aim to show the possibility of a reality where we can use Deep Learning implementations to create software that can accurately detect tumors to an extent. We use Deep Learning concepts to create a Residual Neural Network that is capable of differentiating between MRIs of healthy and tumor-affected brains.

Deep networks naturally integrate low/mid/high-level features and classifiers in an end-to-end multilayer fashion, and the "levels" of features can be enriched by the number of stacked layers (depth). This provides many deep-learning enthusiasts the general assumption that more layers equate to better results. An obstacle to answering this question was the notorious problem of vanishing/exploding gradients (no change/dramatic change in the value of the model weights), which hamper convergence towards the correct output from the beginning. This degradation can be resolved by introducing a deep residual network framework[3].

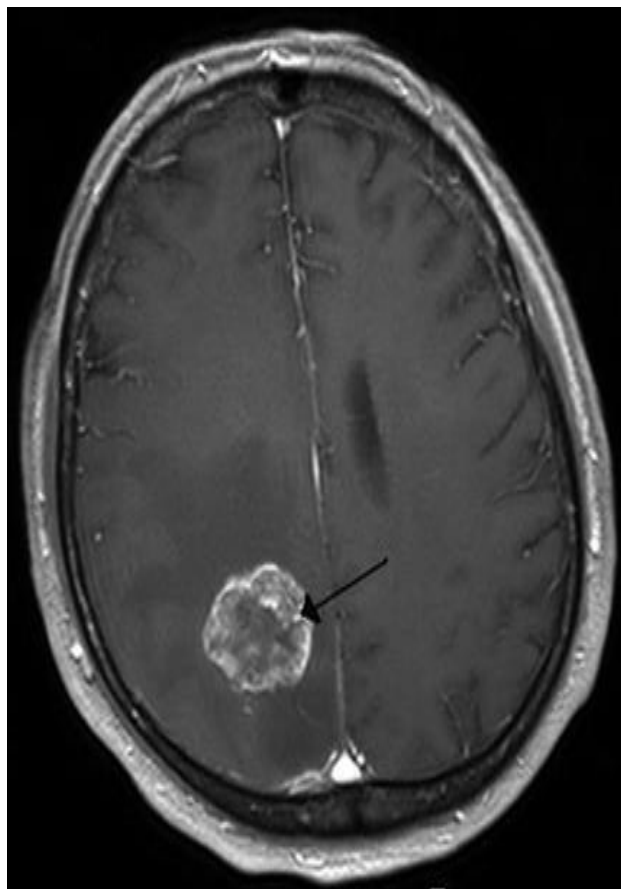


Figure 1: Representative Image of Brain with Identified Tumor

2. EXPERIMENTAL

The residual neural network we applied for this project consists of 83 layers in total, which includes both computational and activation layers. We can segregate the network into three sections for the simplicity of understanding. The input section contains the input layer and is responsible for setting the shape of the input vectors. In our network since we use images of 512x512 resolution, we send input vectors of [512, 512, 1] shape into the network. The vector passes through two sets of convolutional layers. Convolutional layers contain filters, which are 2-dimensional arrays of weights that perform dot product and summation operations to a set of the input data to give a single value as output. This process is called “convolution”. Our filter has a 3x3 dimension so hence it performs operations on 9 values at a time. This process continues till we cover the entire input vector and we get a two-dimensional array of values that form an entity called the feature map. The main function of filters is to find important features using the weights defined by the network. These weights are tweaked with every training cycle. The feature map stores the important features identified by these filters. Feature map data is then passed through an activation layer to introduce nonlinearity into the data. We usually use ReLU (Rectified Linear Unit) function in our network for this purpose. Nonlinearity in the data enables the network to comprehend more complex data. The MaxPooling layer performs Max Pooling operation, which down-samples the feature map i.e. it only takes out the highest value of a set of values in a feature map. It is akin to identifying features of higher priorities in a set of features. Overall data to be processed is reduced and is now passed into the residual blocks.

We use 10 residual blocks in our network which contain two sets of convolutional layers with BatchNormalization. BatchNormalization operation ensures that all feature values are brought into the same range of 0 - 1, so that huge differences in the values do not cause errors in the network training. At the end of the block, the initial input is added to the final output which is the essence of residual summation. This makes sure that features that are found at the initial layers of the network do not vanish or change drastically as the network grows bigger, commonly called as the vanishing/exploding gradient problem.

In the end, we pass the final output of the residual blocks through the output section of layers, which contain another convolutional layer with ReLU activation. We perform a GlobalAveragePooling before the activation which is similar to MaxPooling but takes the average of the set of features rather than the maximum value. This output is then sent into a Dense layer, which is alternatively called a fully connected layer, where every neuron in the layer is connected to all the neurons of the previous layer. The fully connected layers are responsible for flattening the data that comes from the pooling layers. Flattening refers to converting the two or more dimensional data into a one-dimensional vector. After flattening it is passed into another fully connected layer that performs the actual classification based on the features. We use the sigmoid function to ensure that the output remains in the binary range i.e. lies between 0 and 1. 0 indicates the absence of a tumor while 1 indicates the presence.

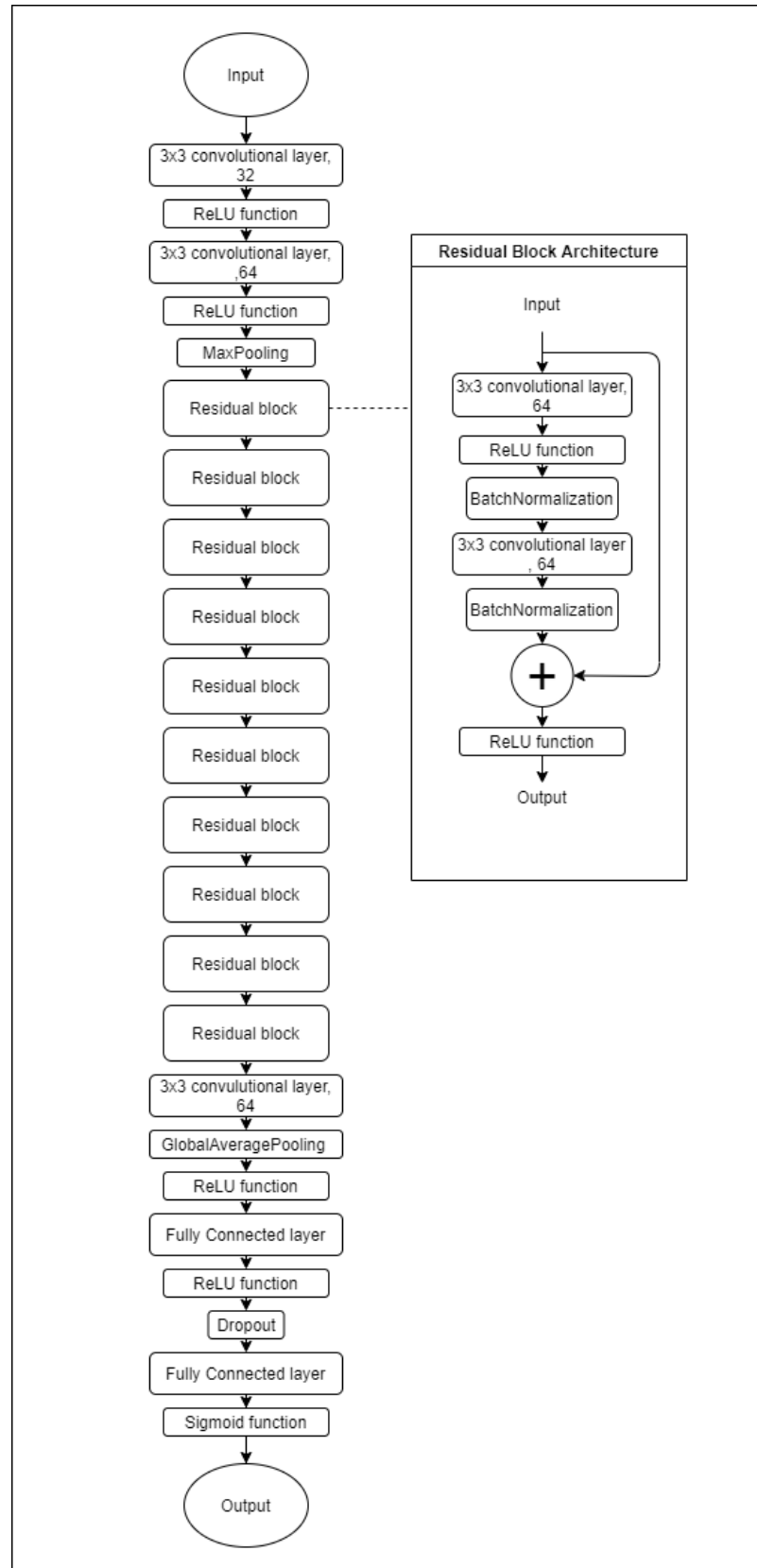
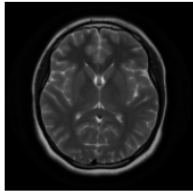
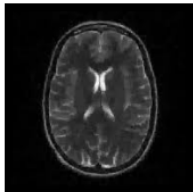
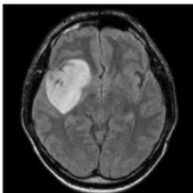


Figure 2: Architecture of Residual Neural Network

3. RESULTS AND DISCUSSION

Table 1: Test results from Trained Residual Network Model

Image	Expected Outcome	Actual Outcome (Prediction)
	0 (No)	0
	0 (No)	1
	1 (Yes)	1

Our model currently shows an accuracy of 75 percent. The dataset we used currently has 765 images consisting of MRI scans of both healthy and tumor-affected brains. It is noticed that the network has been able to identify tumors but somewhat identifies parts of the brain highlighted in white to be tumors as well. This will be corrected as part of future enhancements to the model.

Table 2: Performance Comparison of ResNet with Existing Models

Measures	Our model(ResNet)	FCM	VGG
Precision	0.79	0.61	0.71
Recall	0.71	0.59	0.75
F score	0.74	0.6	0.72
Accuracy	0.75	0.72	0.73

Four measures of performance that are commonly used with classification and prediction models are Precision score, Recall score, F-score (or) F1-measure, and Accuracy.

- **Precision score:** Precision score refers to the ratio of the correctly positively labeled by our program to all positively labeled. With respect to this project, it refers to the ratio of images correctly classified as tumor-affected by the model to all images that are labeled as tumor-affected by the model.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

- **Recall score:** Recall score refers to the ratio of the correctly positively labeled images by our program to all images who are positive in reality. In other words, it refers to the ratio of images classified as tumor-affected by the model to all images that are tumor-affected in reality.

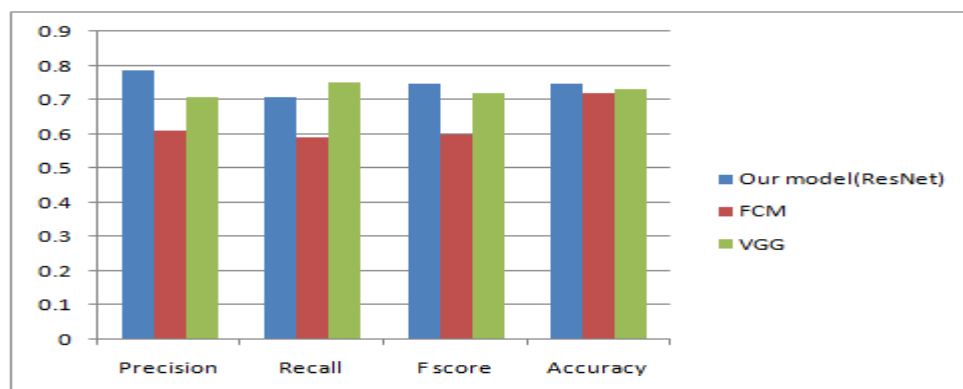
$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

In the above formulae,

- TP => True Positive = Number of positively classified MRI images i.e. classified as tumor-affected by the model, that are actually tumor-affected.
- FP => False Positive = Number of positively classified MRI images i.e. classified as tumor-affected by the model, that are actually healthy.
- FN => False Negative = Number of negatively classified MRI images i.e. classified as healthy by the model, that are actually tumor-affected.
- **F-score (F1-measure):** F-score is the harmonic mean of precision and recall. It is considered to be most apt for measuring performance as it considers both precision and recall values. A good F-score indicates a good balance between precision and recall of a model.

$$\text{F-Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

Figure 3: Graphical Representation of Performance Measures



The statistics provided earlier compares certain conventional models against our model (ResNet). In comparison to traditional machine learning-based classification models such as Fuzzy C-means, ResNet shows significant differences in its F-score. With more modern, neural-network-based models such as VGG, although the difference is somewhat marginal, ResNet does

show better performance. In totality, the ResNet model performs significantly better than other conventional classifiers available.

4. CONCLUSION

With cases of brain tumors rising dramatically all around the world and with the inadequacy of personnel to address these issues, we believe that the time has come to harness the power of modern-day technology to assist human beings, not just in business and lifestyle, but also to save lives at a higher level. With this project, we aim to build a classification model that:

- Classifies MRI Scanned Images with higher accuracy
- Stores record of the previously scanned images
- Aids medical personnel with the diagnosis

By comparing the results we obtained with some conventional models of classification, we were able to see significantly better performance by our ResNet model in results. Artificial Intelligence was never created to overtake us, it was always created to assist us when we needed it. We believe that with the correct application of AI, we can make great and powerful strides in improving the quality of life, both physically and mentally, of every human being.

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