Capstone Proposal

Kanchi Tank

AWS Machine Learning Engineer Nanodegree

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Brain Tumor Detection Using CNN

Domain Background

Advancement in technology has resulted in the generation of a prodigious amount of data from everywhere. Due to the increasing amounts of electronic data in the healthcare, life sciences, and bioscience industry, medical doctors and physicians are facing problems in analyzing the data using traditional diagnosing systems. Nevertheless, machine learning and deep learning techniques have aided doctors and experts in detecting deadly diseases in their early stages.

The aim of this project is to build a Brain Tumor detection model using a Convolutional Neural Network using the Brain MRI Images Dataset.

Problem Statement

A brain tumor is the growth of abnormal cells in the brain tissues [4]. It can be cancerous and non-cancerous. The brain tumor is the most dangerous disease and can be diagnosed efficiently and reliably with the help of technology. We can use automated techniques on MRI Images for accurate detection of brain tumors. The brain is one of the most complicated organs inside the human body. It works with a plethora of cells. Myriads of approaches for the efficient diagnosis of brain tumors have been proposed by numerous practitioners and researchers for adequate tumor detection [8].

The goal of this project is to build a Convolutional Neural Network model to accurately predict brain tumors from brain images.

Datasets and inputs

The dataset that will be used in this project is Brain MRI Images for Brain Tumor Detection. This dataset will be obtained from Kaggle. The dataset encompasses two folders named "yes" and "no." These folders collectively contain 253 brain MRI images. The images are grayscale and come in different sizes, i.e., they have distinct widths, heights, and the number of channels. The folder "yes" consists of 155 tumorous brain MRI images, and the folder "no" consists of 98 non-tumorous brain MRI images.

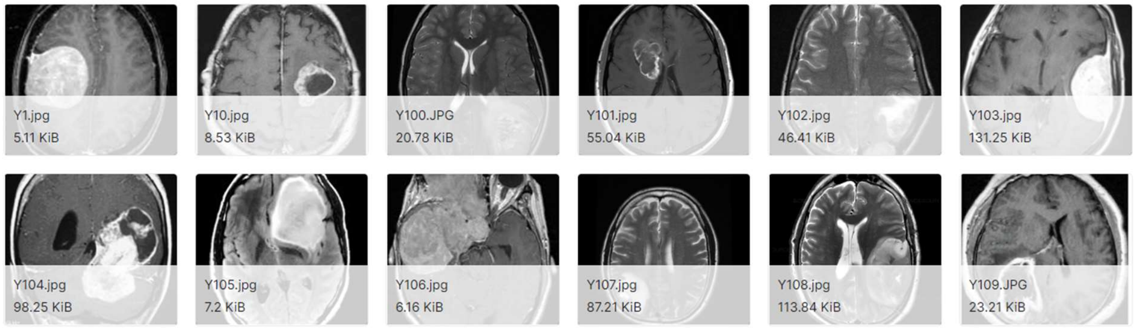

Fig. 1. Tumorous Brain MRI Images

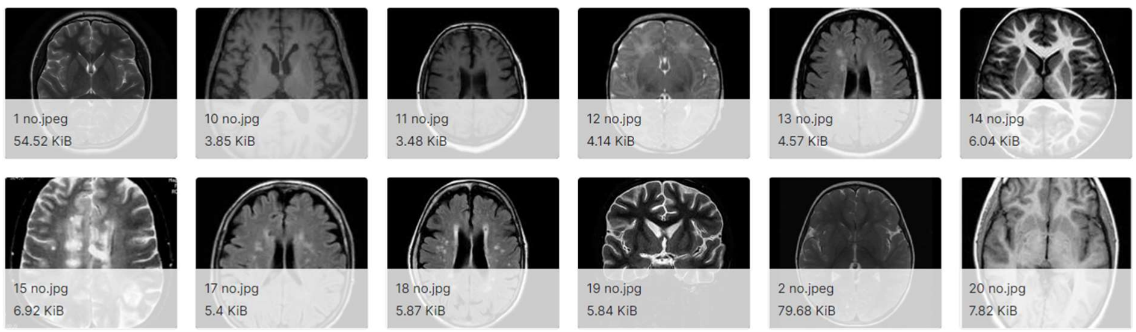

Fig. 2. Non-tumorous Brain MRI Images

Solution Statement

Data Augmentation

Since the number of images in the dataset is less, we will perform data augmentation. It is a set of techniques to artificially expand the amount of data by spawning new data points from existing data. It includes making minor modifications to data or using deep learning methods to render new data points.

Moreover, data augmentation can also solve the data imbalance issue. In our case, 61% (155 images) belong to the tumorous class, and 39% (98 images) belong to the non-tumorous class, creating a data imbalance. So, to solve the data imbalance issue, we will generate nine new images for every image belonging to the "no" class, and six images for every image belonging to the "yes" class.

Data Preprocessing

The preprocessing of data consists of the following steps:

1. To compute the extreme points along the contour of the brain in the image, apply a cropping strategy using OpenCV. Crop the part of the image that represents only the brain.
2. Resize the images as they come in distinct sizes from the dataset. Resize all our images to (240, 240, 3) to feed them as input to the Convolutional Neural Network.
3. Apply normalization techniques as we want to scale the pixel values in the range 0-1.

4. Append the label to y and the image to X.
5. Shuffle X and y as the data is ordered, meaning the first part of the array belongs to one class and the second part belongs to the other, and we don't desire that.
6. Split X and y into training, validation, and test set by 70%, 15%, and 15%.

Benchmark Model

A Convolutional Neural Network (CNN) model will be used in this problem. CNN is a robust algorithm for image and video processing. It is currently one of the best algorithms for the automated processing of images. Applications involving object detection, image recognition, image segmentation, etc., are some of the tasks that CNN specializes in.

Convolutional Neural Network aspires to process data with a grid structure [6, 7]. CNN consists of three-layer types: the Convolutional Layer, Pooling Layer, and Fully Connected Layer. The convolutional layer is the most essential and the primary layer in the CNN architecture [7]. Next, to reduce the dimensionality of the feature map, the pooling layer comes into play. Lastly, the outputs from the final pooling layer or the convolutional layer are fed as the input to the fully connected layer after flattening.

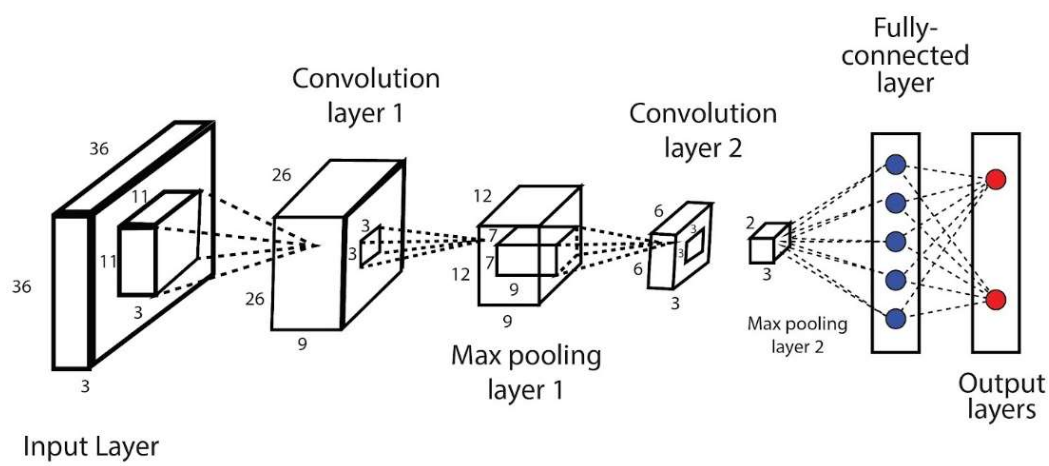

Fig. 3. CNN Architecture [3]

Evaluation Metrics

1. Accuracy
   It is a metric that illustrates how the model functions across all classes. It is a usual metric for binary classifiers and is useful when all classes are of equal significance. It is calculated as the ratio between the number of correctly classified data instances to the total number of data instances [1].

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

2. F1 Score

This metric is elucidated as the harmonic mean of precision and recall. It becomes 1 only when precision and recall are both 1. Similarly, it becomes high when both precision and recall are high [5].

$$\text{F1 Score} = \frac{True\ Positive}{True\ Positive + \frac{1}{2}(False\ Positive + False\ Negative)}$$

3. AUC-ROC Curve

The Receiver Operator Characteristic (ROC) curve metric is mainly for binary classification problems. It is a probability curve that plots True Positive Rate against False Positive Rate at various threshold values.

The Area Under the Curve (AUC) measures the 2-dimensional area present underneath the entire ROC curve [2].

Project Design

A Convolution Neural Network (CNN) model will be developed from scratch as it will be the best Deep Learning model for this project. We will also try implementing transfer learning using VGG-19 and use the model with the best results. These models will be evaluated using the evaluation metrics: Accuracy, F1 Score, and AUC-ROC Curve.

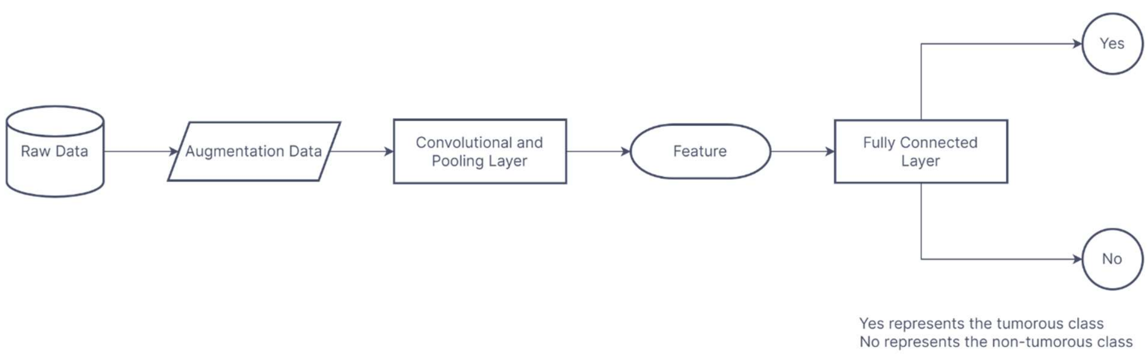

Fig. 4. Proposed method

References

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