Brain MRI Images Classification Method: Applying CNN

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Abstract

The purpose of this research is to explore classification method namely Convolutional Neural Network (CNN) and analyze its performance metrics to detect the presence of tumors in Magnetic Resonance Images (MRI). With MRI's being one of the most used non-invasive imaging methods in the healthcare industry, our research will be tremendously beneficial in speeding up the process of brain tumor detection. A successful outcome of our research would be to create a model that successfully identifies brain MRI images with a tumor present from those with a tumor that is not present. This is not only helpful for medical professionals in increasing the speed at which brain cancer is identified but may also be of great aid to other common manual classification methods that use images of other parts of the human body, such as a CT scan.

We will be dealing with a dataset that contains a total of 253 MRI images. 98 MRI images does not contain a tumor; 155 MRI images does contain a tumor. We will be following the general workflow of: 1.) One-Hot Encode the categorical column ([0]: no tumor | [1]: tumor) 2. Flatten the input image dimensions to 1D (Width pixels x Height pixels). 3.(Normalize the image pixel values 4.) Build a model architecture (Sequential) with Dense layers . 5.) Apply binary cross entropy + train the model . 6.) Make predictions + measure accuracy

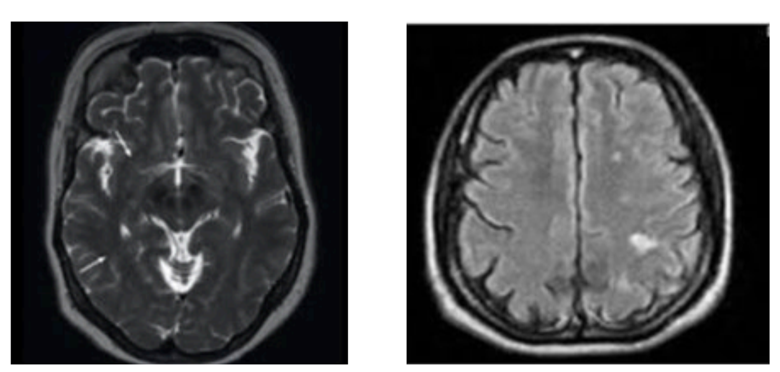

Figure. 1 images shown above does not contain a tumor

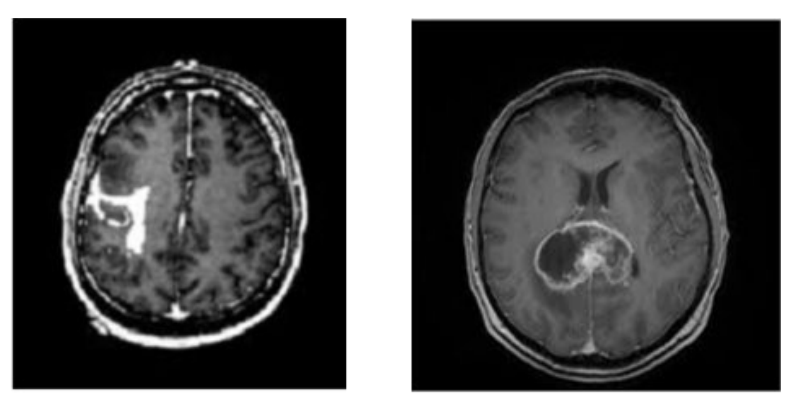

Figure. 2 images shown above does contain a tumor

Background

Brain tumors is an abnormal growth of mass cells in or around your brain. Brain tumors may be identified as either being benign (non-cancerous) or malignant (cancerous)

According to the most recent report by the Central Brain Tumor Registry of the United States, there were 81,246 deaths attributed to primary malignant brain and other central nervous system (CNS) tumors for the period of 2013-2017. On average, there are 16,249 deaths per year, and the survival rate after diagnosis of a primary malignant brain and other CNS was 36%, lowest in 40+ age groups (90.2%), while in age group 0-14 years, survival rates were 97.3% [1]. Over 700,000 Americans are living with a brain tumor today.

By emphasizing AI-powered approaches towards medical diagnoses, we will be able to speed up the process in interpreting MRI images and discourage regular error-prone approaches carried by manual classification and issue treatment plans in a timely manner .

IDE Applied:

- Google Colab (Web IDE for python)
  - Commonly used for Deep Learning + Machine Learning Projects given cloud capabilities

Model Type

- Using CNN: A Deep Learning Algorithm
  - The convolutional layer reduces the high dimensionality of images without losing information.
  - We hoped to use CNN to determine the efficiency of our model in classifying Brain MRI images to detect tumors

Imported Libraries

- ML Model: Keras , Tensorflow

Methods

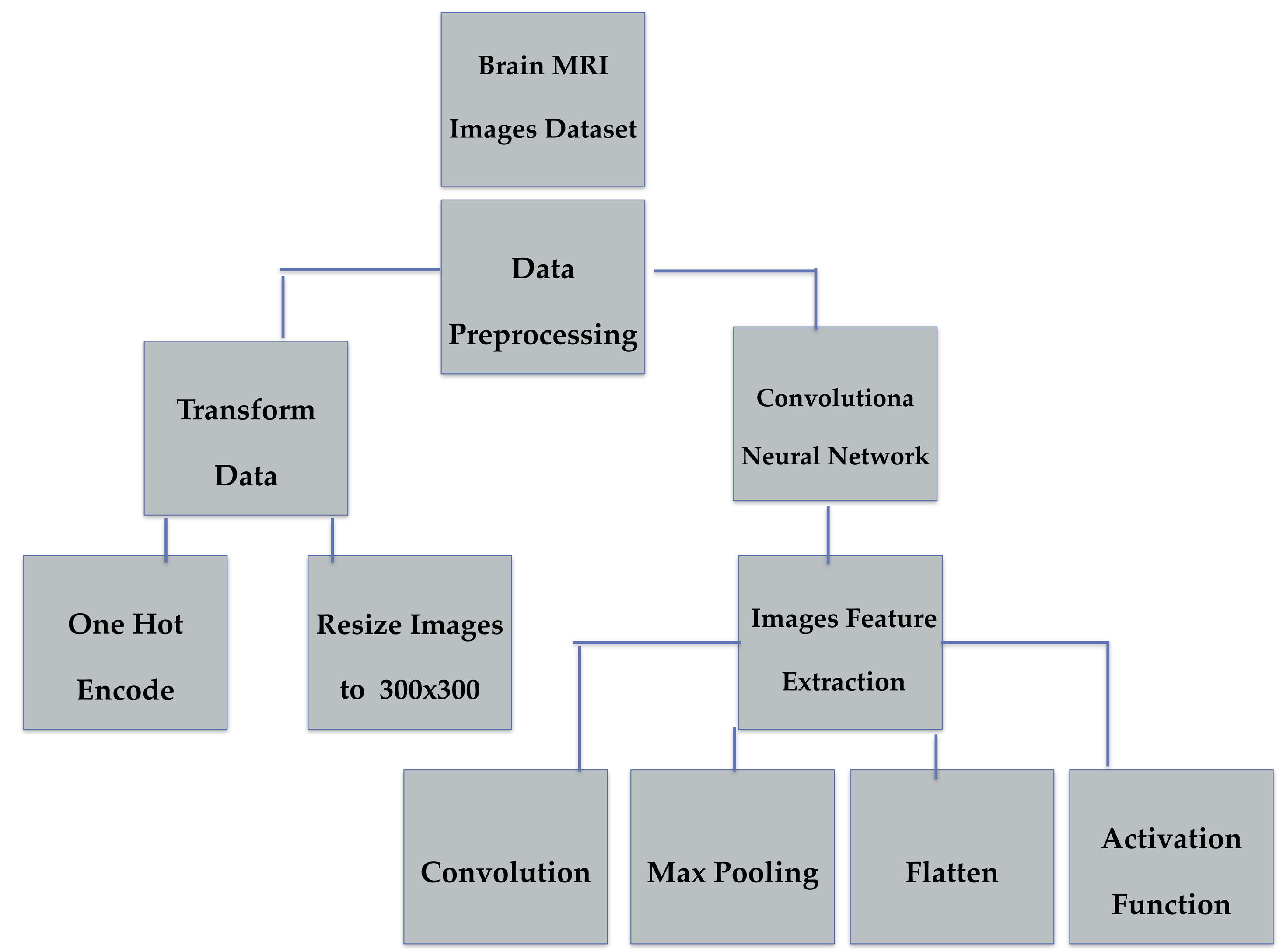

Figure 3. Tree Structure decscribing our CNN Model Performance

CNN is a subset of machine learning or network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.

We implemented the model architecture (Sequential) with Dense layers with an input size of (300,300, 3). During our preprocessing stage, we manipulated all of the images size and ensure that it is equal to 300,300,3 . Had we avoided this then this wouldve created issues when inputting the image into an artificial neural network. We then created a convolution kernel that is wind with layers input which helps produce a tensor of outputs and retain the important information or maximum feature.

We also applied a kernel size of 3x3 and the reason being for the small kernels is to allow a deeper architecture and help prevent overfitting. This will ultimately help us maintain accuracy

We imported keras then arrange the three dimensional volume of numbers into a 1 dimensional vector which will help create or output one dimensional final prediction and pass the data into every single neuron of the model effectively.

The dense layer is responsible for classifying image based on the output of the convolutional layers and create fully connected layers. The output is entirely dependent on every input.

There are various regularization techniques but we used the dropout function which results in about 50% neurons being dropped.

Finally, we applied the activation or RELU which is understood to be a linear function that will output the input directly if it is positive otherwise it will output zero. Recall that our model will be responsible for generating an output of 0 or 1 depending on whether there is a tumor present.

An optimizer known as the Adam optimizer was applied and oversees the operation of adjusting the weights throughout the neural network. We also applied a form of binary classification with an artificial network by Binary_crossentropy and Accuracy metrics metrics=['accuracy'] and most commonly used application for classification models. Accuracy metrics generally describes how the model performs across all classes and incredibly useful when all classes are of equal importance. Binary cross entropy is a loss function used when there is a classification problem between 2 categories only or in this case, images that contains a tumor and images that does not contain a tumor

The model was trained for 21 epochs and these are the loss & accuracy plots. The best validation achieved on the 7th iterations which is to be said that the model performed at its best at the 7th.

Results

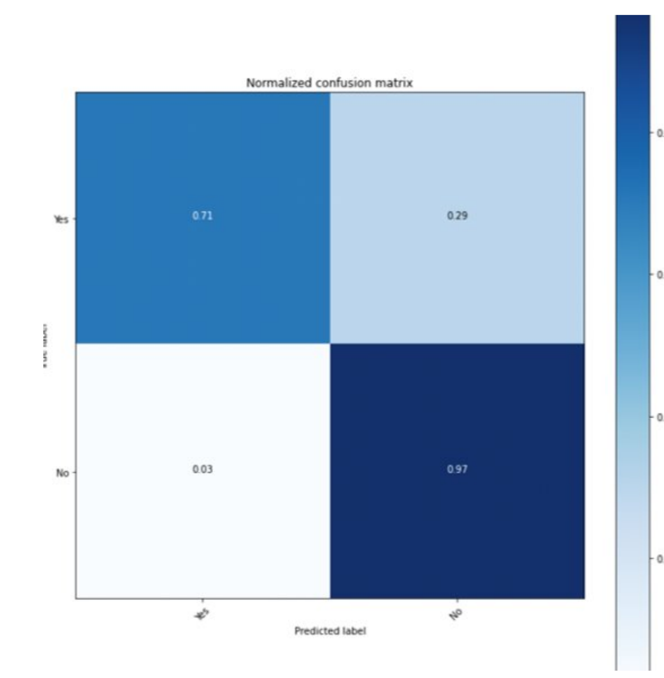

Figure 4. Heatmap — Accuracy Metrics

We perform a series convolution + pooling operations, followed by a number of fully connected layers. Total of 33 images that detected a tumor, 12 images that did not detect a tumor, and a overall total of 6 images that was not accurately accounted for either.

Accuracy rate of 71% for the "Yes" classification

Accuracy rate of 97% for the "No" classification

Overall, our results has shown that we succeeded in implementing in creating a model that returns a high accuracy rate , however, we would like to expand our dataset to prevent potential erroneous errors.

	precision	recall	f1-score	support
0	0.92	0.71	0.80	17
1	0.87	0.97	0.92	34
accuracy			0.88	51
macro avg	0.90	0.84	0.86	51
weighted avg	0.89	0.88	0.88	51

Figure 5. Classification Report

Conclusions

CNN is a wonderful resource that may be worth applying in future health diagnoses as well as other similar AI-Powered technology. We assume that Machine Learning techniques or tools will continue to progress tremendously and become more successful in image-related tasks, such as image recognition or classification, and pattern recognition. Our conclusion is that our model accuracy results are good. However, our results are slightest skewed towards "No" classification. Our model could improve with an increased number of train MRI images or through model hyper parameters tuning. Our model yield an Accuracy rate of 71% for the "Yes" classification and an Accuracy rate of 97% for the "No" classification.

Future Direction

For future references, we hope to pursue data augmentation and consider VGG16 for our model in order to consider alternative accuracy rates. Data augmentation will help improve or enrich the training data by generating new examples via random transformation of existing ones. In other words, this will result in boosting the size of the training set, reducing the odds of overfitting. Data augmentation can also be considered as regularization technique. By emphasizing AI-powered approaches towards medical diagnoses, we will be able to speed up the process in interpreting MRI images and discourage regular error-prone approaches carried by manual classification and issue treatment plans in a timely manner .

Acknowledgement

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https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection
https://towardsdatascience.com/parameters-and-hyperparameters-aa609601a9ac
https://www.techopedia.com/definition/34625/hyperparameter-ml-hyperparameter