Brain Tumor Detection using Machine Learning

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INTRODUCTION:

In this modern world it is prevalent that growth in medical techniques is influential in the saving of human lives. Due to this, researchers all over the world are scaled up to work in various aspects of the medical field for the greater benefit of mankind, in this technology and its advancement plays a major role. Among many disorders and abnormalities caused nowadays, tumor is believed to have an adverse effect. A Brain tumor is considered as one of the aggressive diseases, among children and adults.

The best technique to detect brain tumors is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. Application of automated classification techniques using Machine Learning (ML) and Artificial Intelligence (AI) has consistently shown higher accuracy than manual classification.

We aim to detect brain tumors from a given brain MRI image using appropriate image processing techniques and machine learning algorithms. We train the model with positive and negative test MRI images of the brain, evaluate the model in order to ready itself to rightly classify a new MRI image.

PROBLEM STATEMENT:

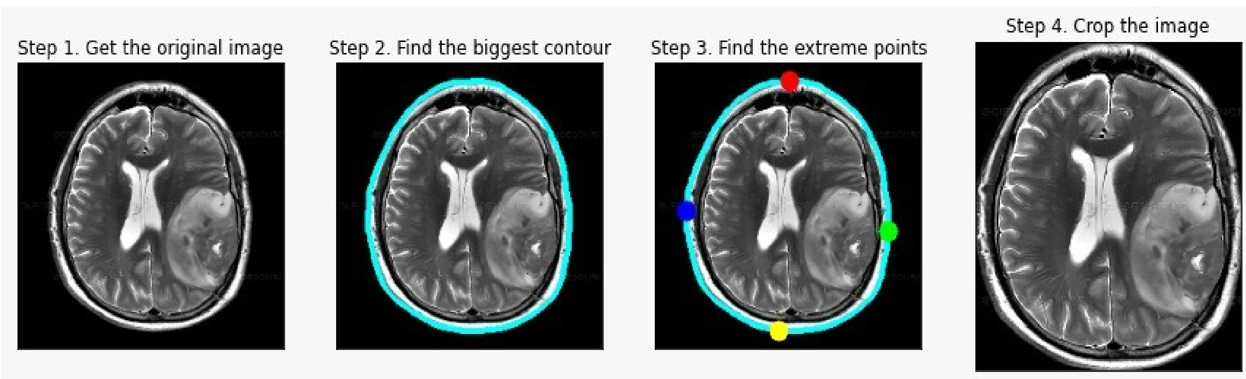
While it is possible for an experienced doctor to correctly identify brain tumor tissues from MRI images, a system that classifies brain MRI images to 'tumor detected' and 'tumor not detected' labels would significantly enhance the operations of most hospitals. After training a machine learning model with labelled datasets, we can deploy this model to perform a binary classification of new images to the predefined classes confirming the presence and absence of brain tumor.

DATASET DESCRIPTION:

The dataset we have chosen here comprises of magnetic resonance imaging (MRI) images of the brain; the images are rightly labelled into tumor affected and not tumor affected. The dataset consists of 98 images of data labeled as 'NO' and 155 images of data labelled as 'YES'. The images used are in .JPG/.JPEG format. 80 percent of the images are taken as training set, while the 20 percent forms the testing set.

IMAGE CLEANING AND PREPROCESSING

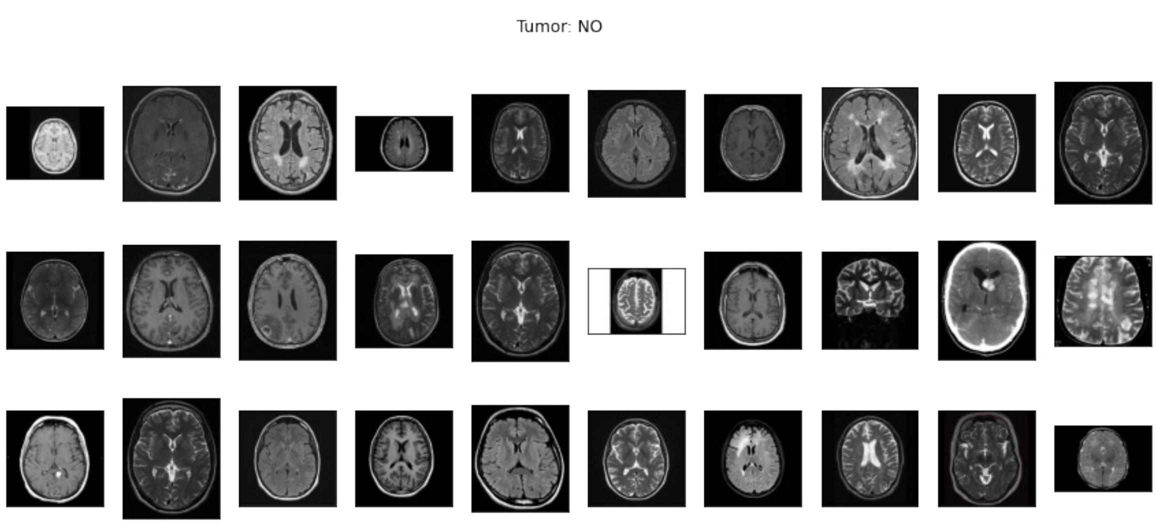
The steps taken to format images before they are used by the model training and inference together forms Image Preprocessing. This includes, but is not limited to, resizing, orienting, and color corrections. Additionally, model preprocessing may shorten model training time and quicken model inference.



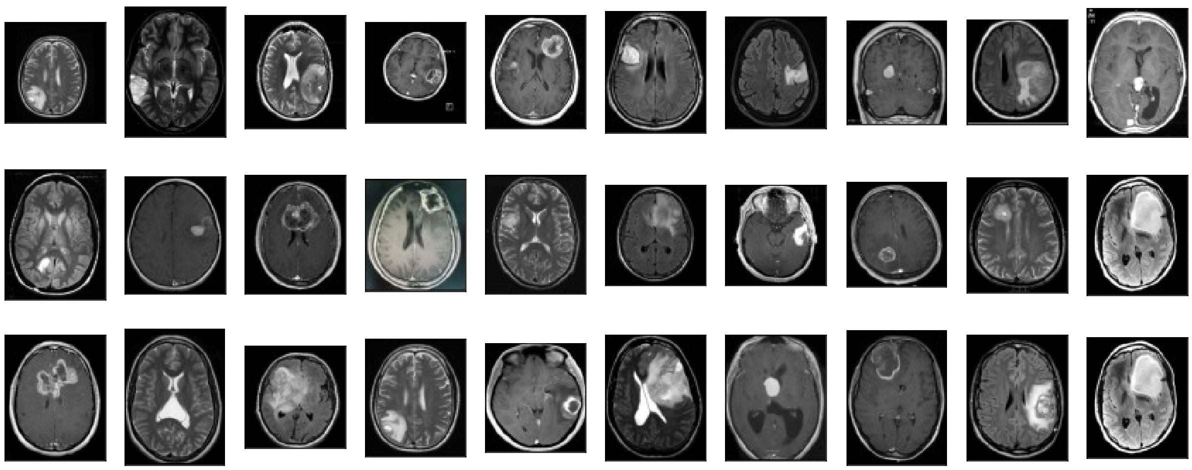
During this preprocessing we used the technique of image contouring. The line connecting all the points along an image's edge that have the same intensity is referred to as the contour. Contours are useful for object detection, determining the size of an object of interest, and shape analysis.

Here, the original is taken in which the outermost boundary is found and outlined to form the biggest contour. After the biggest contour is found, then the extreme points along the four axes are marked. This marking is used for the appropriate cropping of the image.

The preprocessing steps are applied to all the images.



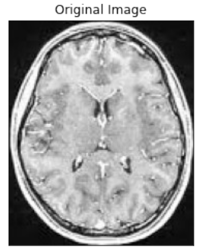
Tumor: YES



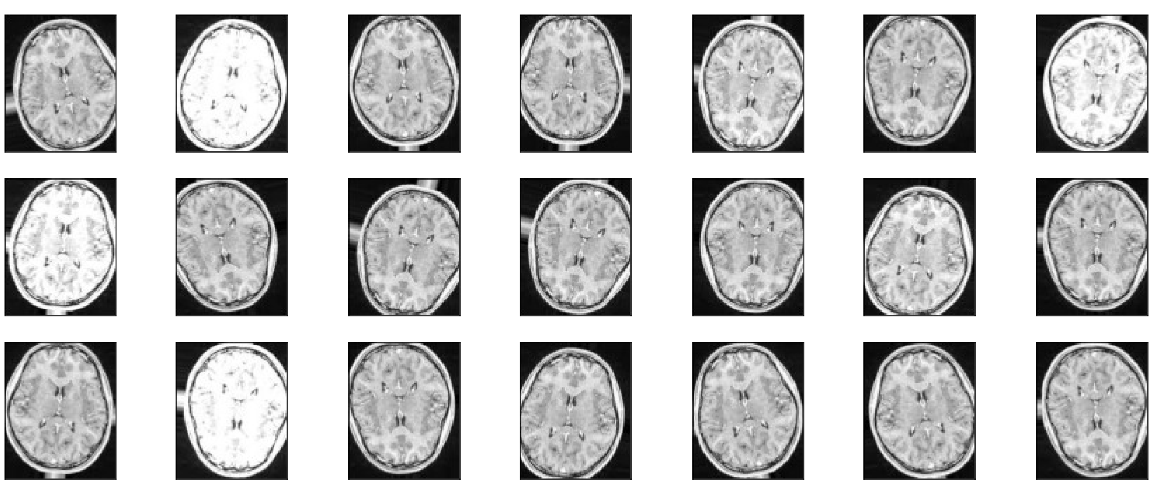
DATA AUGMENTATION

Data augmentation comprises of techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model. For example, for images we can use: Geometric transformations – you can randomly flip, crop, rotate or translate images, and that is just the tip of the iceberg. Color space transformations – change RGB color channels, intensify any color.

Original Image



Augemented Images



CONVOLUTIONAL NEURAL NETWORK MODELS:

The CNN models we have used in this project are VGG-16 and ResNet50V2.

A convolutional neural network, also known as a CNN, is a kind of artificial neural network. An input layer, an output layer, and many hidden layers make up a convolutional neural network. One of the top computer vision models to date is the CNN variant known as VGG16. This model's developers analyzed the networks and enhanced the depth using an architecture with incredibly tiny convolution filters, which demonstrated a notable advancement over the state-of-the-art setups. VGG-16 is very appealing because of its very uniform Architecture.

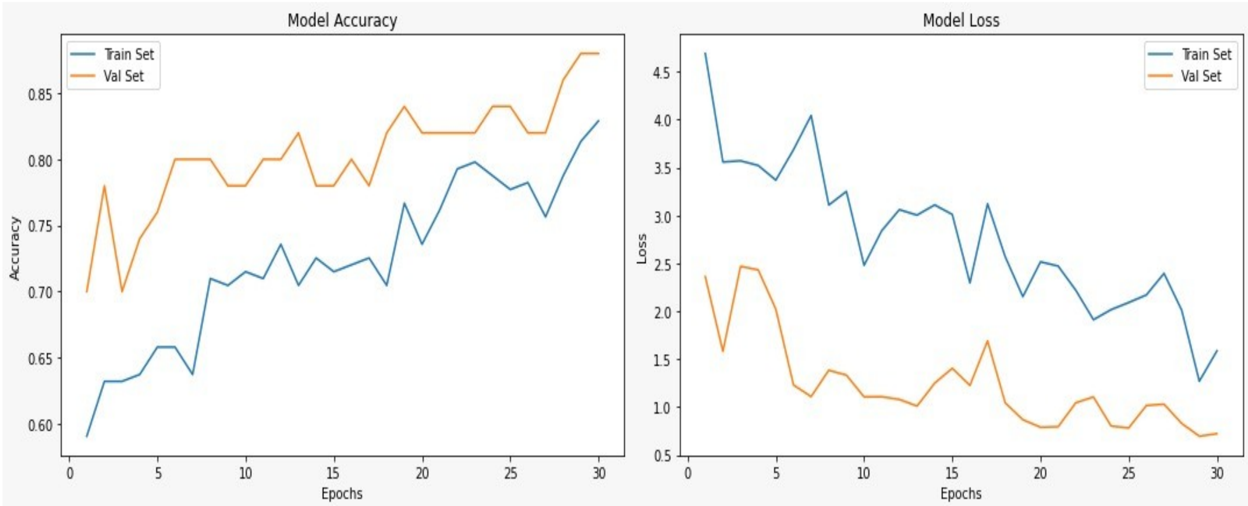
```
[ ]  # load base model
     vgg16_weight_path = '/content/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
     base_model = VGG16(
         weights=vgg16_weight_path,
         include_top=False,
         input_shape=IMG_SIZE + (3,)
     )
```

The other CNN model is ResNet50V2 which is 50 layers deep which comprises of 48 convolution layers along with 1 Max Pool and 1 Average Pool layer. A residual neural network is an artificial neural network of a kind that stacks residual blocks on top of each other to form a network. We can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. The network has an image input size of 224-by-224.

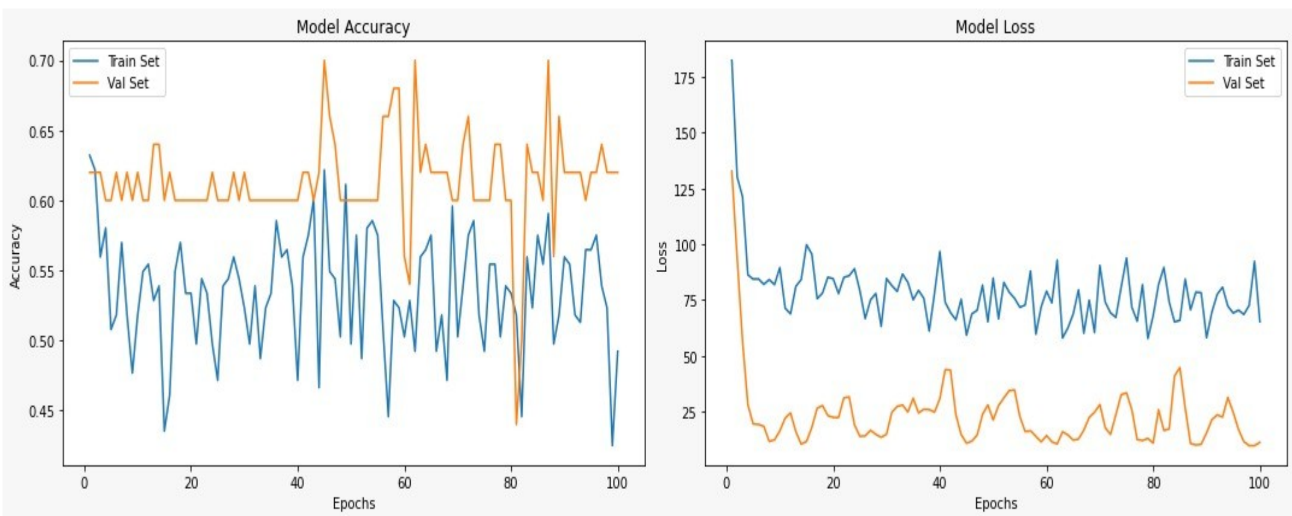
```
#RESNET
from tensorflow import keras
base_model = keras.applications.ResNet50V2(
    weights="imagenet",  # Load weights pre-trained on ImageNet.
    input_shape=(224, 224, 3),
    include_top=False,
)  # Do not include the ImageNet classifier at the top.
```

MODEL PERFORMANCE AND EVALUATION

In the case of VGG16 model, we can see that the accuracy increases as the number of epoch increases, and finally attains a validation accuracy of 90% and test accuracy of 100%



Whereas when it comes to ResNet50, the performance fluctuates in order to reach a validation accuracy of 64% and test accuracy of 90%



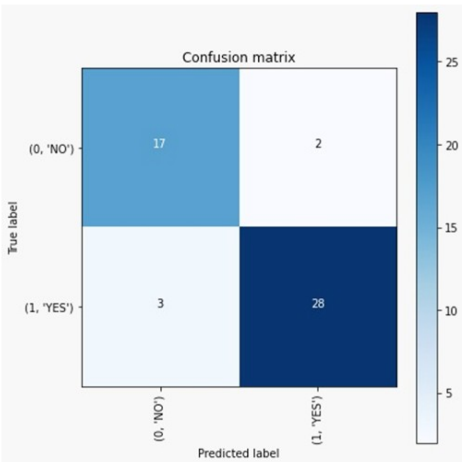
When both the analyzed both the models by comparing them for the better efficiency and accuracy, it was evident that the working of ResNet50V2 had best accuracy than the VGG-16 model. This is very much clear when we take the Epoch values of both and apply some intuition.

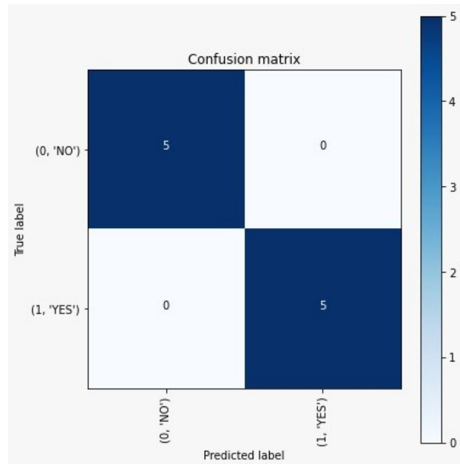
Even though ResNet50V2 is much deeper than VGG16, the model size is actually substantially smaller due to the usage of global average pooling rather than fully-connected layers, this reduces the model size down to 102MB for ResNet50.

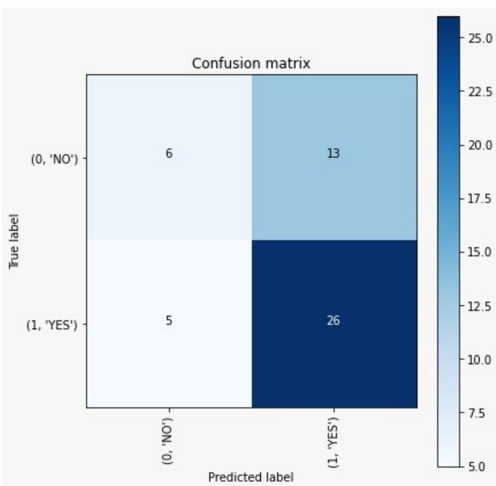
CONFUSION MATRIX:
A confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one.

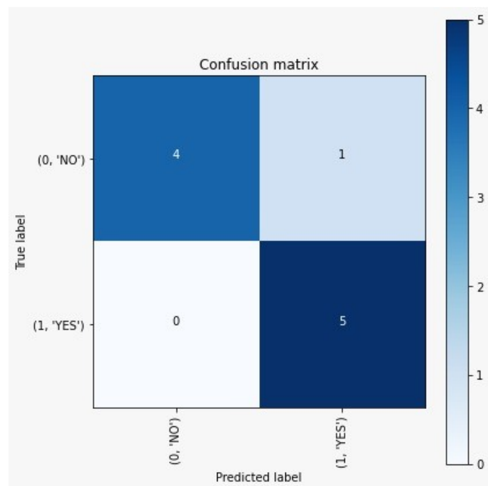
Both variations of the matrix, where each row represents examples in an actual class and each column represents instances in a predicted class, are documented in the literature. The name refers to the fact that it is simple to determine whether the system is misclassifying one class as another or if two classes are being treated as one.

VGG-16 Confusion Matrix









ResNet50 Confusion Matrix

CONCLUSION:

We used Convolutional Neural Network to predict whether the subject has Brain Tumor or not from MRI Images. Using large no. of images i.e., a larger dataset, Hyperparameter Tuning and Using a different Convolutional Neural Network Model may result in higher accuracy.

REFERENCES:

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CONTRIBUTIONS:

We worked in a team fashion where every single team member contributed to every milestone

Megha Manoj(mm2773) – Dataset cleaning, preprocessing, model training, evaluation, report work

Vishnupriya Santhosh(vs263) - Dataset cleaning, preprocessing, model training, evaluation, report work

Anand Senkuttuvan(as4326) - Dataset cleaning, preprocessing, model training, evaluation, report work

SOURCE CODE:

https://github.com/Megha23manoj/BrainTumorDetection.git