Develop a Hybrid Model for Brain Tumor Detection with VGG-16 and CNN Transfer Learning

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Topic Area: Deep Learning.

Abstract:- A brain tumor is a fatal condition that needs to be surgically removed with precision. Brain cancers were identified utilizing magnetic resonance imaging (MRI). The goal of image segmentation for MRI brain tumors is to create a distinct tumor boundary and to identify the tumor area (also known as the region of interest, or ROI) from the healthy brain. A brain tumor is a malformed mass of tissue in which cells multiply quickly and endlessly, unable to stop the tumor's growth. Severe forms of cancer have a limited life expectancy, often just a few months, in their most advanced stages. MRI, CT, and ultrasound scans are a few types of image modalities.

A brain tumor is a dangerous disorder brought on by aberrant growth of brain cells. It is brought on by the tissues encircling the skull or brain. Brain tumor patients have aberrant mental states, vomiting, headaches, seizures, trouble speaking and walking, and eyesight impairments. The proliferation of malignant cells Tissue is detected in magnetic resonance imaging (MRI) images. We introduced a deep learning method for identifying brain tumors in MRI data that is based on the (Visual Geometry Group). VGG-16 Architecture.

The massive volumes of data produced by these image scanning methods, however, make manual analysis challenging and time-consuming. In this study, deep learning techniques such as Convolutional Neural Networks (CNNs) and Visual Geometry Group (VGG-16) outperformed conventional methods in the classification of brain cancers. The best deep features from a variety of well-known CNNs and abstraction levels were used in this fully automated computerized approach to classify brain tumors. Transfer learning was also applied to the images for the Visual Geometry Group (VGG-16) change in relation to the number filters in its feature training. In order to avoid over fitting, I was analyzing the results after incorporating dropout layers into this design.

Keywords:- *MRI, CNN, VGG-16 and Brain Tumor.*

I. INTRODUCTION

In today's environment, the application of machine learning and information technology in medicine has become increasingly significant. The creation of a machine that can self-learn, foresee issues, and act when necessary is the aim of artificial intelligence research. A brain tumor is an abnormal and uncontrollably growing tumor that can be lethal. Developments in deep learning for medical imaging were assisting in the diagnosis of some illnesses. (Mohsen, 2018; Classification for the brain using deep learning neural networks).

The CNN architecture is the most popular and extensively used machine learning technique. It is used for both visual learning and picture identification. In this study, we used a convolutional neural network (CNN) technique in conjunction with Visual Geometry Group VGG-16 in data augmentation and image processing to analyze MRI scans and determine which images contain and which do not have brain tumors. The VGG, often known as VGGNet, is the standard convolutional neural network architecture. In this study, VGG will deepen these CNNs in order to enhance their performance.

II. METHODOLOGY

A. Data analysis

Finding answers via research and interpretation is the process of data analysis. the analysis is required to convey the information and comprehend the outcomes of administrative sources and surveys. Data analysis is anticipated to improve readers' comprehension of the topic and spark their interest in this section of the research, as well as provide some insight into the study's topic and respondents' perspectives. Using scientific data analysis tools, Google Collab was utilized to analyze the data and show the results (Burns, 2017).

B. Deep Learning Models

➢ *Convolutional Neural Networks model (CNN)*

Medical image processing uses a well-organized method called Convolutional Neural Networks (CNNs). Convolutional neural networks (CNNs) are a particular kind of artificial neural network that are used in picture recognition and processing. They are specifically made for understanding method components. CNN, or deep learning, is a potent image processing and computing technology that can perform both generative and descriptive tasks, including recommender systems, language communication processes, and picture and video recognition. (LeCun et al., 1998) (NLP)

A CNN uses a system that is similar to a multilayer view-point but designed with fewer requirements for processing. A system that is substantially more efficient and simpler to train data for image processing and language communication is the consequence of the removal of constraints and the increase in image processing power. We improved upon the basic CNN model by making several adjustments. Our nine-layer CNN model, which includes hidden layers as well, has fourteen phases that provide us with the best tumor identification results. The graphic below depicts the procedure:

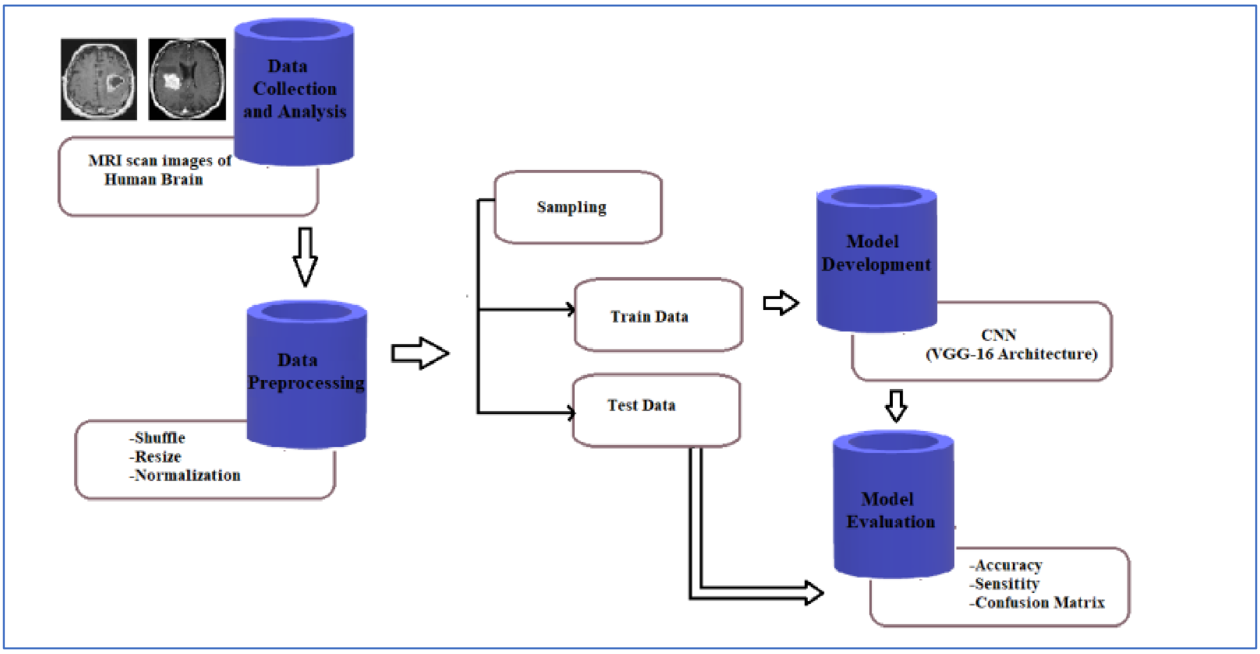

Fig. 1: Methodology for tumor detection using 16 – VGG-16

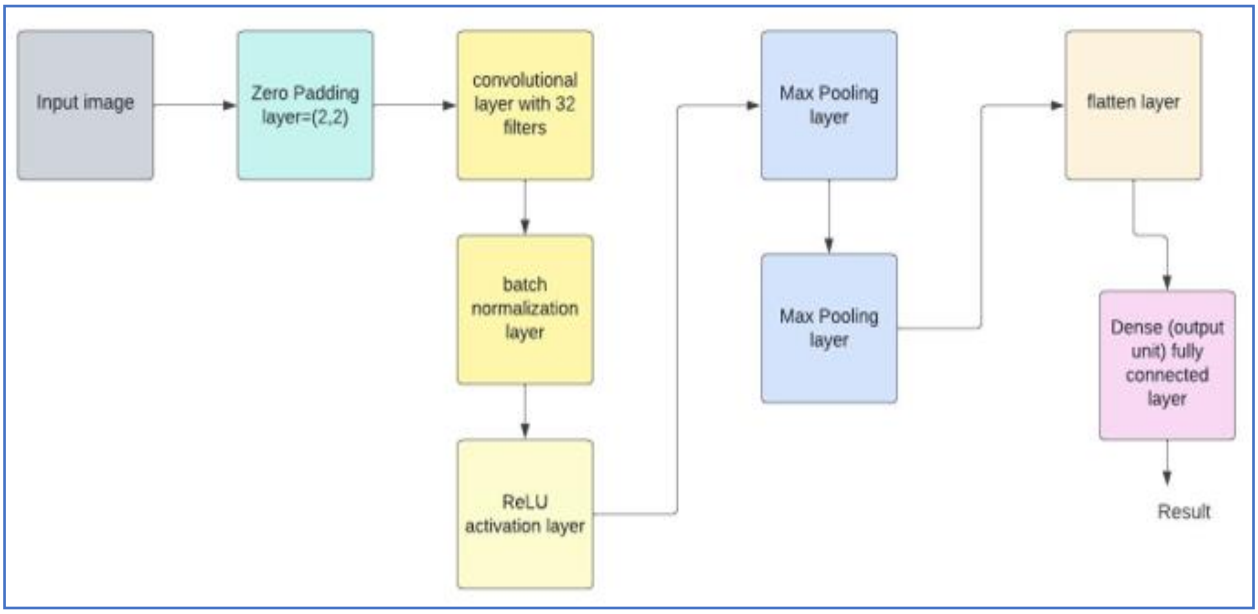

Fig. 2: Methodology for tumor detection using Layer Convolutional Neural Network

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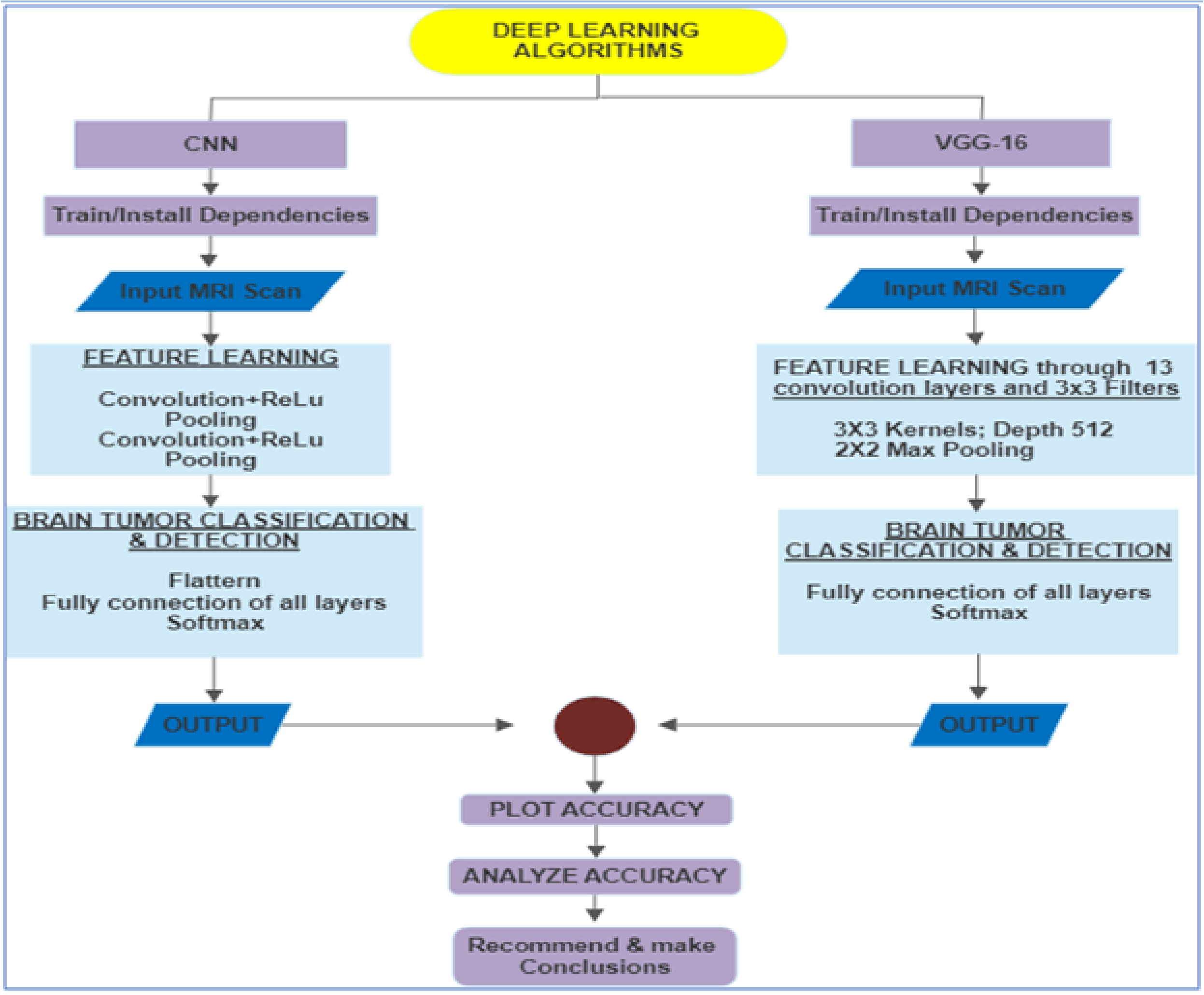

Fig. 3: Brain tumor detector analysis using CNN and VGG-16 Approach Model

➤ *Layers to a Build CNN Model*

A basic CNN consists of several layers, where each layer converts one activation volume to another using a differentiable function. Three primary sorts of layers are utilized in CNN architecture construction:

- **Convolutional Layer***:* Convolutional Neural Network-based. It has a few unique characteristics. It does much of the hard lifting in terms of computing. A group of learnable filters comprise the CONV layer's parameters. Each filter spans the entire depth of the input volume despite being small (both in width and height).

Convolutional layer also contains a few fundamental characteristics, like:

✓ Zero Padding: This technique, commonly referred to as zero-padding, involves padding the input image with zeros in the input layer. By employing zero padding, we were able to regulate the input layer's size. It's possible to lose some of the edge attribute if zero-padding is not used.

✓ Local Connectivity: Unlike neural networks, which have fully connected neurons, local networks have neurons that are only connected to a portion of the input image. These characteristics lead to a more effective computation and a decrease in the total number of parameters in the system. Three hyper-parameters govern the size of the output volume of the convolutional layer.

✓ Parameter Sharing: Parameter sharing is the sharing of weights among all neurons in a given feature map.

- **Pooling Layer**: Another part of CNN is the pooling layer. The pooling layer usually appears after the convolutional layer. Its goal is to gradually reduce the spatial dimension of the representation so that more control over fitting is possible by lowering the number of parameters and computation in the network. The Pooling Layer resizes the input spatially while operating independently on each depth slice. The input volume's depth dimension is unaffected by pooling.

In order to perform pooling, the input's sub-regions are summarized using techniques like averaging, maximizing, or minimizing the sub-regions' individual values. We refer to these as pooling functions.

✓ Different Kinds of Pooling Functions**:** The pooling layer consists of some symmetric aggregation functions such as:

✓ Max Pooling: It returns the maximum value from its rectangular neighborhood.

✓ Average Pooling: It returns the maximum value from its rectangular neighborhood.

- ✓ Weighted Average Pooling: It calculates its neighborhood weight based on distance from its center pixel.
- ✓ Norm Pooling: It returns the square root sum of its rectangular neighborhood. In most of the ConvNet architectures, Max Pooling isused to reduce the computational cost.
- ✓ Pooling Layer Arithmetic: The pooling layer operates through sliding the window or filter across the input. Let, Spatial Extent = f Stride = s window size = w The equation [shows that the output size from the pooling layer will be, O=w−fs+1 (4.9)

- **Fully-Connected Layer:** Similar to a neural network, each neuron in the fully connected layer is connected to every other neuron in the layer above it. Similar to a neural network, it too is activated by matrix multiplication with weight and bias. A fully connected layer is often a vector in columns. The connection between two layers is depicted in the image below, with the fully connected layer on the right.

III. DATA IMPORT AND PREPROCESSING

Due to the movement's heterogeneous nature and potential interruptions inhomogeneity deformations during the acquisition of MRI machine boundaries, MR images may exhibit discrepancies. These objects produce false positive imaging results by producing erroneous intensity rates. After the MRI image was examined, a preprocessing technique was first applied.

The uneven black margins of MR pictures make it difficult for CNN to adapt to the unique characteristics of each classifier. Amplitude normalization was used to reduce the intensity distribution within a typical range, producing a normal range with a mean intensity value of 0 and a standard deviation of 1. Initially, the images were thresholded at a 45-degree angle to exclude any background noise.

IV. DISTRIBUTION OF CLASSES AMONG SETS

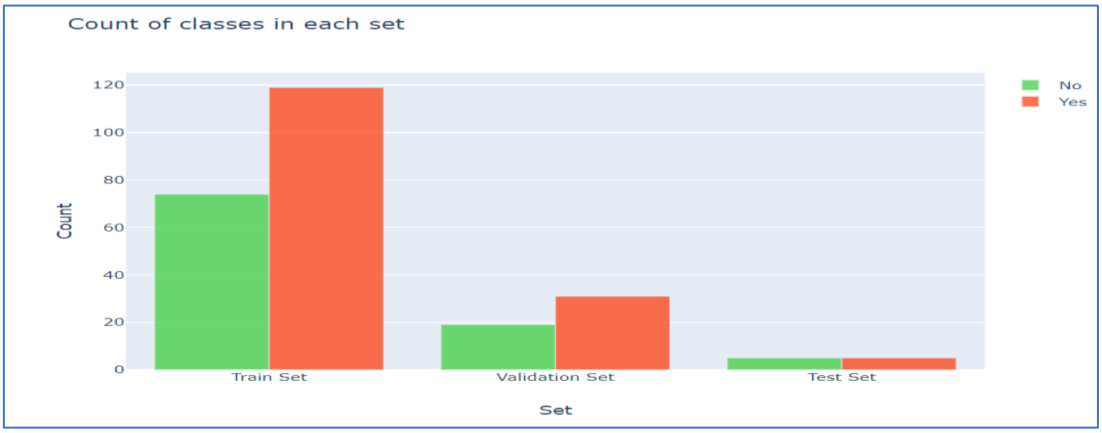

Fig. 4: Distribution of Classes among Sets

V. CHANGING PIXEL VALUES

As may be seen, images have different width and height and defend size of "black corners".Since the image size for VGG-16 input layer is (224,224) some wide images may look weird after resizing. Histogram of ratio distributions (ratio =width/height

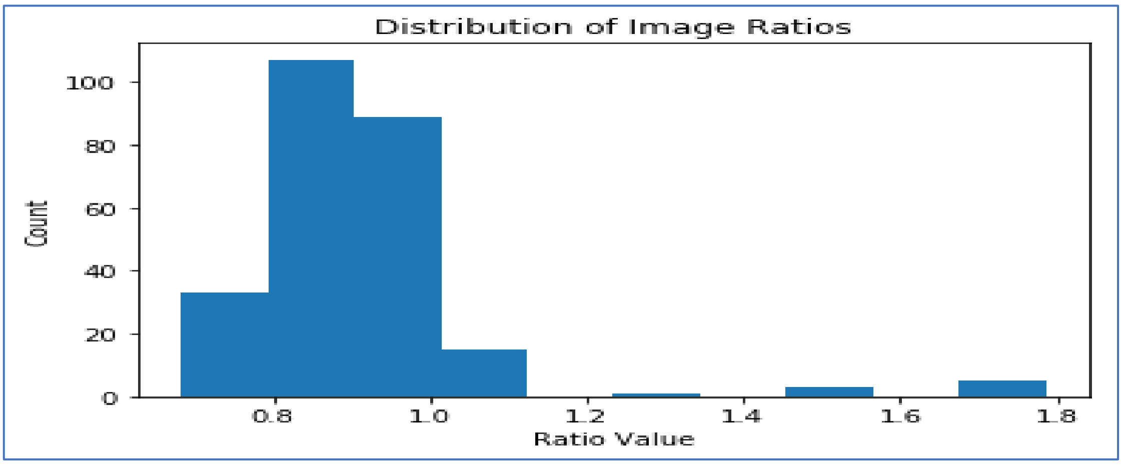

Fig. 5: Distribution of images

A. Normalization

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The elimination of the pictures' (Images') brain is the first step in the "normalization" process. The images would then need to be resized to (224,224) and the required preprocessing for VGG-16 model input would be applied.

B. CNN Model

CNN's chief Because the geometry of the photographs can be used to reveal hidden possibilities, photo altering software is available. In graph analysis, CNN outperforms several other methods. Among the architectural features that are combined are batch normalizing, receptive fields, and spatial or temporal normalization subsampling. The structure of the suggested CNN model.

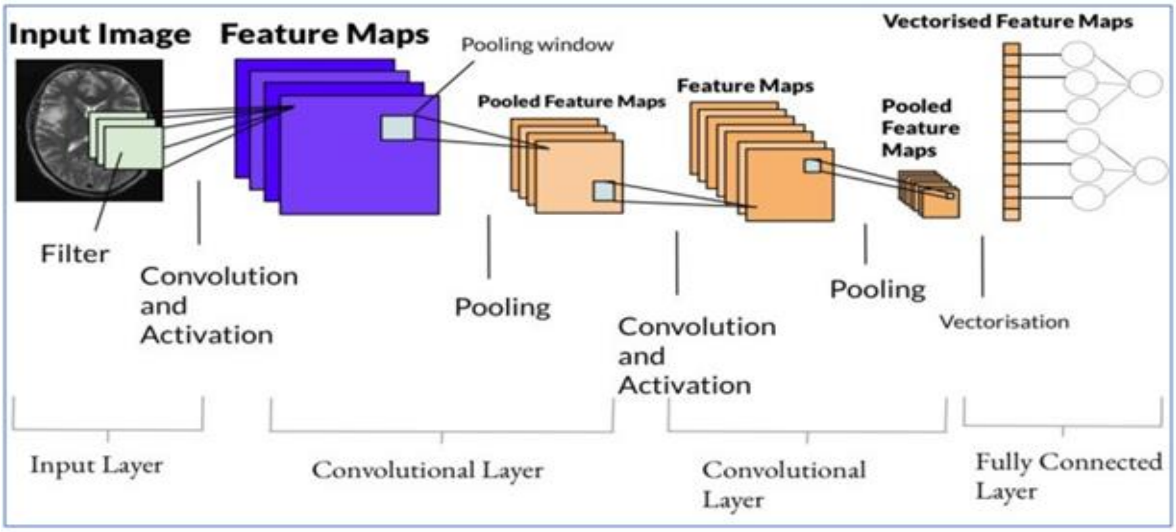

Fig. 6: CNN Models

VI. VISUALIZING THE IMAGES

Convolutional neural networks (CNNs) like VGG16 have been pre-trained using the ImageNet dataset. This indicates that it is already capable of recognizing the characteristics of objects in pictures. By extracting the characteristics that the model was able to find, we may utilize VGG16 to visualize photos.

Here are the steps on how to visualize images on VGG16:

- Import the VGG16 model from the Keras library.
- Load the image that you want to visualize.
- Pre-process the image so that it is compatible with the VGG16 model.
- Distribute the image to the VGG16 model.
- Extract the features from the model.
- Visualize the features.The VGG16 model will be loaded, the picture will be loaded, pre-processed, uploaded to the model, features will be extracted, and features will be visualized thanks to this code. A set of pictures displaying the features that the VGG16 model has learned will be the code's output.

VGG16 is a potent tool for visualizing images. It can be used to recognize items in photos and to comprehend the characteristics of images. It is a useful tool for engineers and researchers studying computer vision.

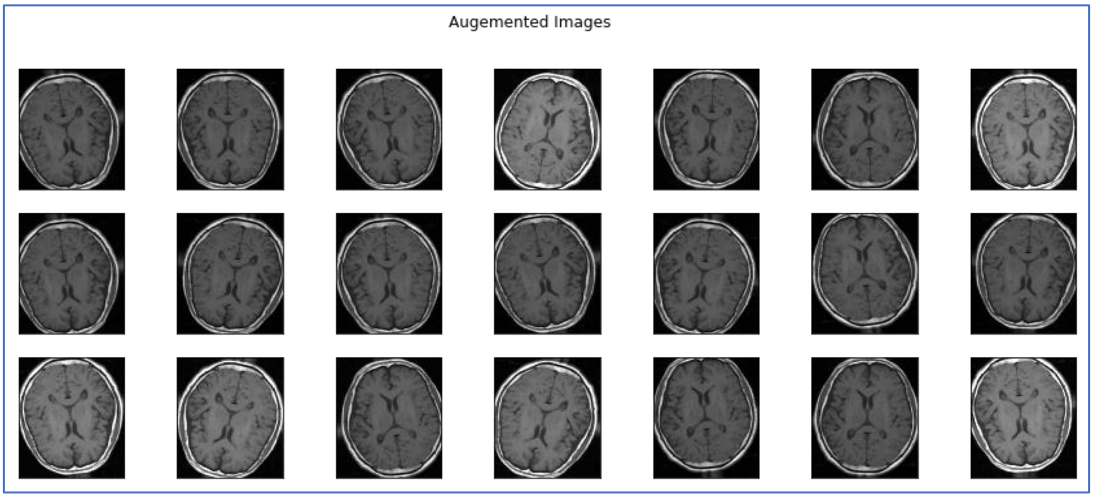

Fig. 7: Brain images augmented

A. Model Building

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 240, 240, 3)]     0

 zero_padding2d (ZeroPadding  (None, 244, 244, 3)      0
 2D)

 conv2d (Conv2D)             (None, 238, 238, 32)      4736

 bn0 (BatchNormalization)    (None, 238, 238, 32)      128

 activation (Activation)     (None, 238, 238, 32)      0

 max_pooling2d (MaxPooling2D  (None, 59, 59, 32)       0
 )

 max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 flatten (Flatten)           (None, 6272)              0

 dense (Dense)               (None, 1)                 6273

=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
_________________________________________________________________
```

Fig. 8: Image of CCN model build

B. Model Performance

- ➢ *CNNs and VGG16 are both convolutional neural networks, but they have different architectures and performance.*
- **CNNs** are a general neural network type that can be applied to a variety of tasks, including image classification, object categorization detection, and natural language processing. They are typically composed of a series of convolution layers, pooling layers, and fully connected layers.
- **VGG16** is a specific type of CNN that was designed for image classification. It is composed of 16 layers, with each layer consisting of a convolution layer after which comes a pooling layer. VGG16 was trained on the ImageNet dataset, which contains over 14 million images across 1000 object classes.

With a top-5 error rate of 7.3%, VGG16 has attained cutting-edge performance on the ImageNet dataset. This indicates that 92.7% of the photos in the ImageNet dataset can be accurately classified by VGG16. On the other hand, depending on the scenario architecture and the dataset they are trained on, CNNs can perform throughout a greater range. Nevertheless, in most cases, they can outperform VGG16 in picture classification tasks.

Training VGG16 is comparatively slow since it needs a large number of variables. On the other hand, CNNs require less parameters, thus they may be trained more quickly.

All things considered, VGG16 is a potent CNN that has produced cutting-edge outcomes on picture classification tasks. But it has a lot of settings and requires a long time to train. CNNs, on the other hand, are faster to train and have greater versatility. Additionally, they are usually smaller than VGG16, which increases their deployment efficiency.

Table 1: Difference between VGG-16 and CNN

Feature	**CNN**	**VGG16**
Architecture	General Purpose	Image Classification
Dataset	Varied	ImageNet
Performance	State of the art on some tasks	State of the art on image classification
Speed	Faster	Slow
Size	Smaller	Larger

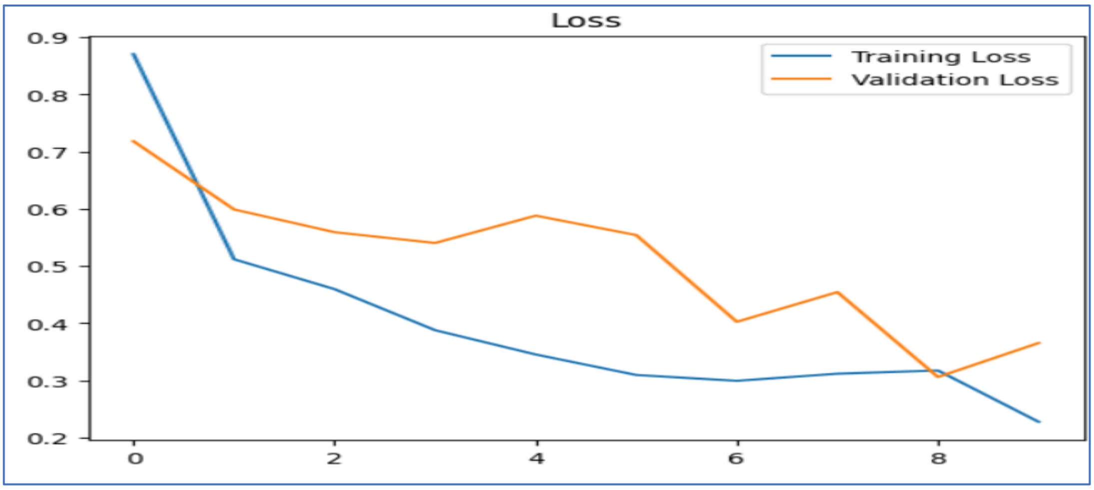

Fig. 9: Model Performance

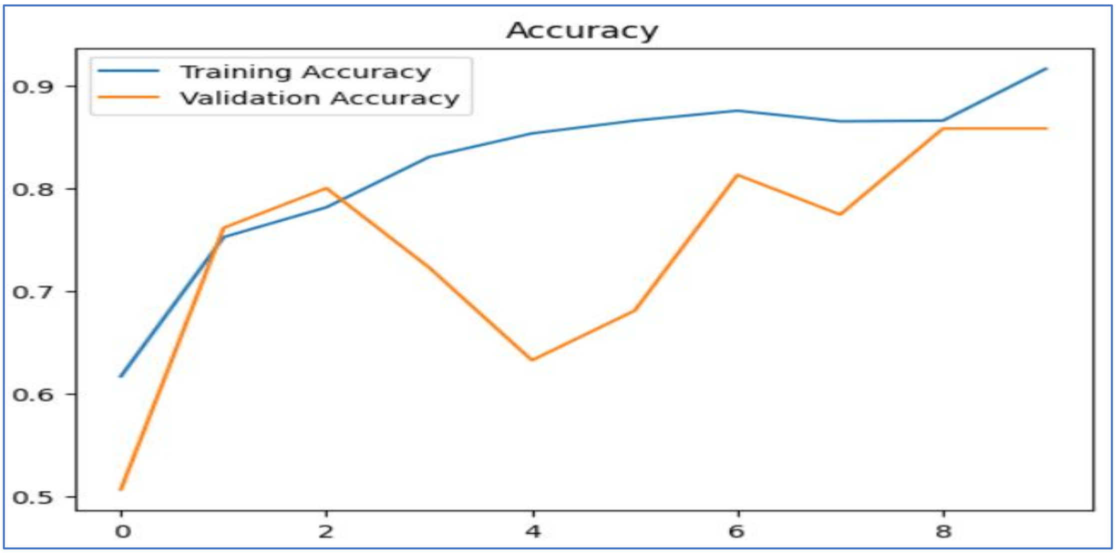

Fig. 10: CNN plotting Loss during training

➢ *VGG-16 Performance Model Accuracy & Loss Curves*

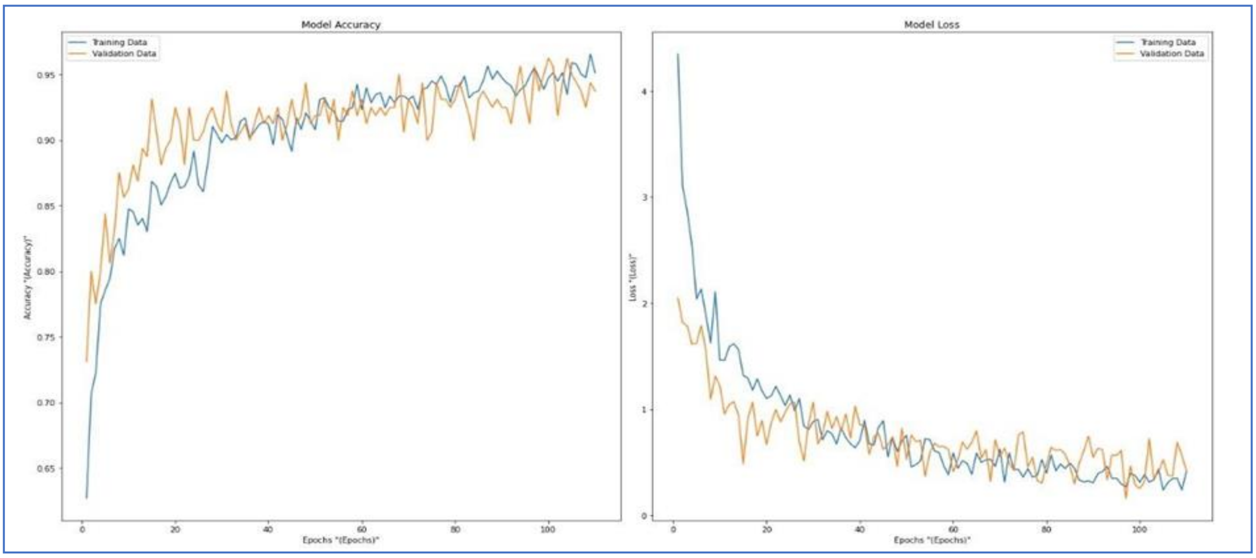

Fig. 11: VGG-16 Performance Model Accuracy & Loss Curves

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➢ *CNN VS VGG16 Hybrid Model For Brain Tumor Detection*

This code uses two pre-trained models, CNN and VGG16, to construct a hybrid neural network model for brain tumor identification. MRI brain pictures are fed into the model, which preprocesses and categorizes the data into two groups: "yes" for a tumor and "no" for no tumor.

The method imports the data first, then preprocesses it by saving the images as numpy arrays and resizing them to a predetermined size. The train test split function from scikit-learn is then used to divide the data into training and validation sets. The labels are categorical from keras and one-hot encoded.

The pre-trained VGG16 and InceptionV3 models are then loaded by the code, which then concatenates the two models' outputs to produce a hybrid model. Every model has its final layer removed and two additional dense layers with dropout added at the end. Predictions for every class are then derived from the output of each dense layer. Ultimately, the model is assembled with the Adam optimizer, together with the accuracy metric and categorical cross entropy loss.

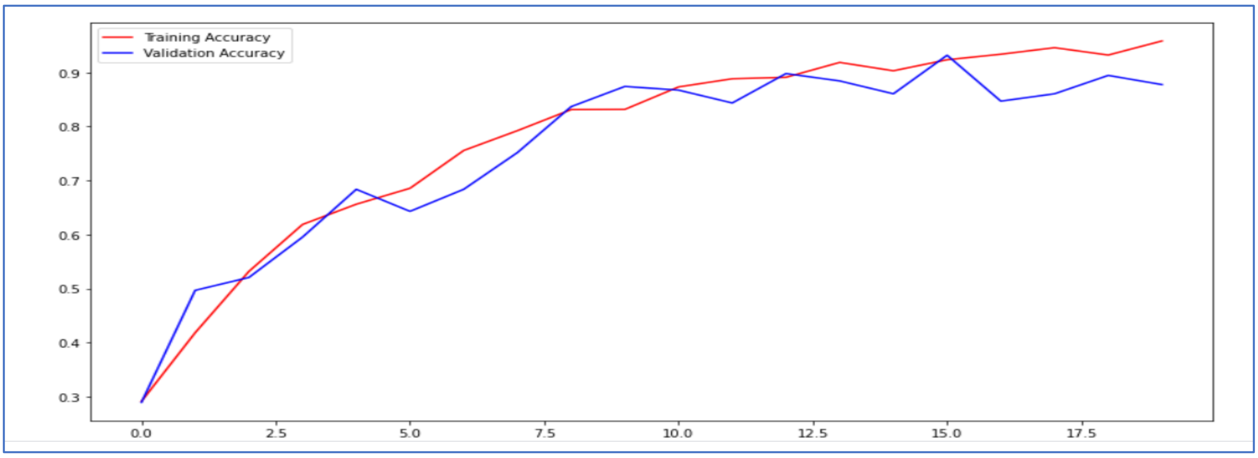

Fig. 12: CNN VS VGG16 Hybrid Model For Brain Tumor Detection

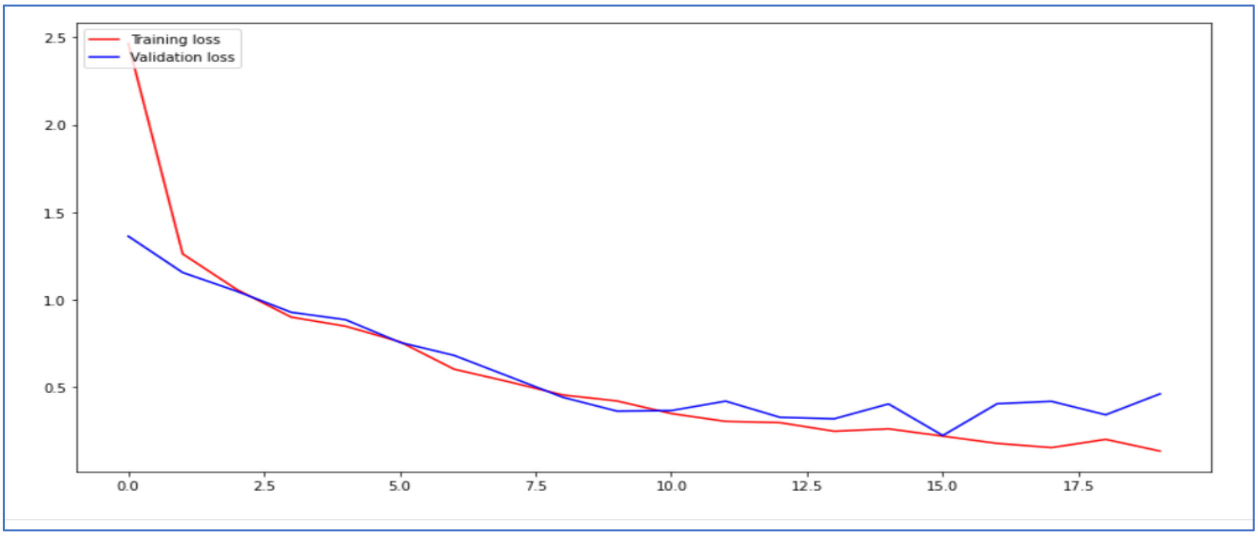

Fig. 13: CNN Performance Model Accuracy & Loss Curve

VII. CONCLUSIONS OF THE STUDY

Brain magnetic resonance imaging was used to assess brain cancers using automated categorization algorithms, and deep learning was incorporated in the recommended tumor diagnosis technique. This work used a CNN model to enhance classification and image quality. The study was effective in yielding superior outcomes with reduced computational time. We applied our method to MR images to identify brain tumors.

The algorithm significantly outperformed previous research. With regard to brain cancer diagnosis in testing data, CNN 96%, VGG 16 98.5%, and Ensemble Model 98.14% achieved excellent accuracy (Precision = 96%, 98.15%, 98.41%).

There was learning and validation, which was dependable. discovered to be increasing, as did the results. They might be employed to ascertain whether a brain tumor exists.

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