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A Comparative Study for Brain Tumor Detection Analysis using CNN and VGG-16 and its Application

(Area of Focus: Deep Learning)

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Abstract:- The incidence of brain tumors, a highly malignant form of cancer, is widespread around the world, affecting millions of individuals. Early detection plays a crucial role in saving lives, but the process of identifying and classifying tumor types accurately requires reviewing numerous MRI images. Deep learning models have the capability to handle such large datasets and provide precise results. However, it is important to note that the outcomes produced by deep learning models can vary depending on the dataset used.

This comparative study focused on evaluating the effectiveness of deep learning models on two distinct Magnetic Resonance Imaging (MRI) brain tumor datasets. The goal of this research was to identify the best deep learning model that can achieve the highest accuracy in detecting brain tumors compared to others in the dataset. The models were individually applied to pre-processed datasets to extract features from the MRI images. Segmentation of tumor regions can be challenging due to the visual similarity between normal tissue and brain tumor cells. Therefore, an automatic tumor detection approach with high accuracy is necessary.

To train our algorithm effectively, a diverse range of MRI images with different tumor sizes, locations, shapes, and intensities was utilized. We employed "TensorFlow" and "Keras" frameworks within the programming language "Python" to develop our optimal solution, as this language provides efficient functionality for rapid implementation. As part of the research process, a comprehensive literature review was conducted, and secondary data was collected. Performance metrics were employed for data analysis, leading to conclusions and recommendations for the most suitable deep learning approach model.

I. INTRODUCTION

Brain tumor detection using deep learning models such as CNN and VGG-16 has gained attention in recent years due to their high accuracy and potential for early detection and diagnosis of brain tumors. These models utilize medical imaging data, such as MRI, to categorize images as either indicative of a tumor presence or not.

CNN models have been used to analyze brain tumor images by detecting features such as edges and patterns in the images. VGG-16, on the other hand, has shown promising results in brain tumor detection due to its deeper architecture allowing for more complex feature extraction from the images. Both models have demonstrated immense potential in enhancing the precision and efficiency of brain tumor detection, consequently enabling more prompt interventions and enhancing patient outcomes. However, additional research is necessary to enhance the accuracy and adaptability of these models when applied to various brain tumor image types and pathologies. Additionally, ethical considerations around the use of these models in healthcare and patient privacy must be considered.

II. METHODOLOGY

- *Data Collection Methods and Instruments/ Tools*

The practice of gathering information using specified procedures in order to react to the study's predetermined research subject is known as data collecting. In this study, the researcher used mixed method (both qualitative and quantitative) and examined secondary data.

- *Data Analysis*

The process of discovering solutions through study and interpretation is referred to as data analysis. This analysis is crucial in gaining insights into the research problem and the perspectives of the participants involved. For the purpose of analyzing the data and presenting the results using scientific data analysis techniques, Jupyter notebook and Kaggle platforms were utilized (Burns, 2022).

To evaluate the effectiveness of the CNN and VGG-16 models, performance metrics such as accuracy, sensitivity, specificity, precision (positive predictive value), and F1 score were computed. These metrics are widely employed to assess the overall accuracy and effectiveness of deep learning models in detecting brain tumors. They serve as data analysis techniques for evaluating the models' performance.

- *Research Design*

This is a strategy or blueprint which shows how data required for the solution of the problem that the researcher focused on as follow:

- *Collecting of Data:*
  Appropriate datasets of MRIs medical images was obtained from RMH and preprocessed for analysis.

- *Model Training:*
  CNN and/or VGG-16 models were trained on the dataset of brain tumor images using suitable training algorithms.

- *Hyper-Parameter Optimization:*
  The hyperparameters of the trained model are fine-tuned to achieve optimal accuracy and efficiency in identifying and analyzing brain tumors.

- *Model Evaluation:*
  The trained models were evaluated on a test set to assess performances in accurately detecting brain tumors.

- *Interpreting the Results:*
  The relevant features and patterns in brain tumor images analyzed by these models were interpreted and understood by clinicians and radiologists for further diagnosis and treatment.

- *Implementation:*
  User-friendly interfaces were developed for clinicians and radiologists to use CNN and VGG-16 models for tumor detection in brain during clinical practice.

- *Ethical Considerations:*
  Policies were developed to ensure patient privacy and informed consent.

➢ *CNN (Convolutional Neural Networks)*

CNN are a specific type of neural network designed for processing data that possesses a grid-like structure. Examples of such data include time series data, which is regarded as a 1D grid with regularly spaced samples over time, and image data, which is treated as a 2D grid composed of pixels. CNNs have demonstrated remarkable effectiveness in practical applications. The term "convolutional neural network" refers to the network's utilization of the mathematical operation called convolution. Convolution belongs to the broader category of linear operations. Convolutional networks can be viewed as neural networks that incorporate at least one layer where convolution operations are employed instead of general matrix multiplication (LeCun, 1989).

➢ *VGG16 (Visual Geometry Group 16)*

The VGG-16 model is a convolutional neural network (CNN) consisting of 16 layers. It is widely recognized as one of the top-performing and efficient models available today. In contrast to architectures with different params, VGG16 model relies on Convolutional Network layers using a 3x3 size of the kernel. This model is particularly valuable because it can be found and downloaded online for various systems and applications. Its simplicity stands out compared to other comprehensive models that have been developed.

For the VGG-16 model, the minimum input image size required is 224x224 pixels with three channels. In neural networks, optimization techniques are employed to assess the involvement of a neuron by calculating the weighted sum of its inputs. A kernel function is utilized to introduce non-linearity in the output neuron. Neurons in a neural network interact with weights, biases, and training techniques. The connection weights between neurons are adjusted based on the desired output. Input images and activation functions play a significant role in introducing nonlinearity into artificial neural networks.

➢ *CNN and VGG-16 Hybrid Approach Model for Brain Tumor Detection Analysis*

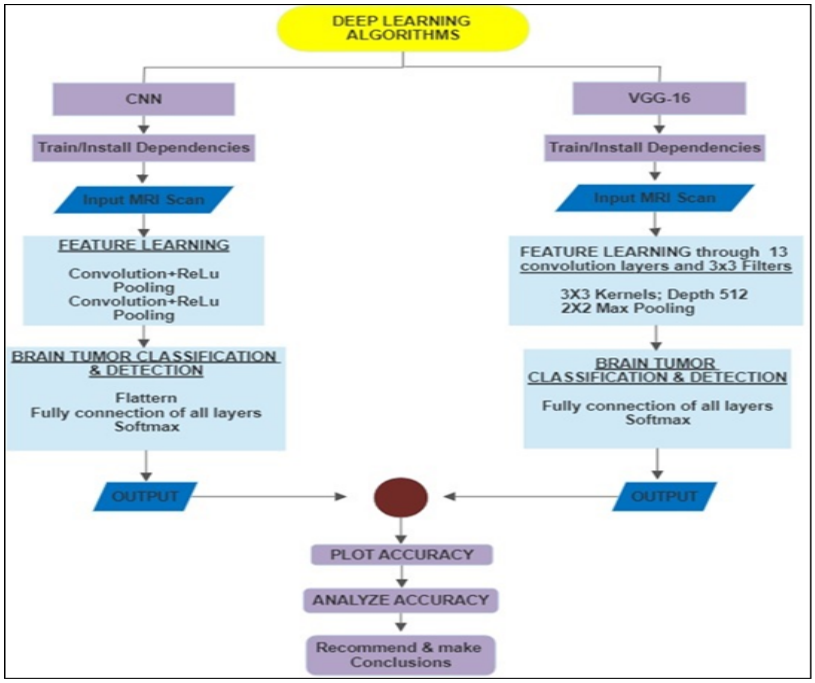

Fig 1 CNN and VGG-16 Hybrid Model

III. DATA PRESENTATION

- *Creating a Single Folder where all Dataset Images are found and that include Train, Validation and Test Folders*

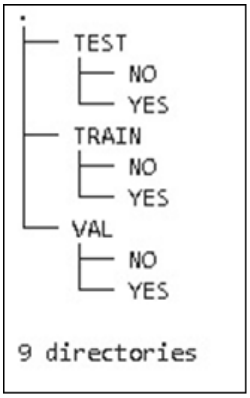

Fig 2 Dataset Split

- *Sample Plotting (Train X Crop,train Y, _Labels, 30) after Cropping*

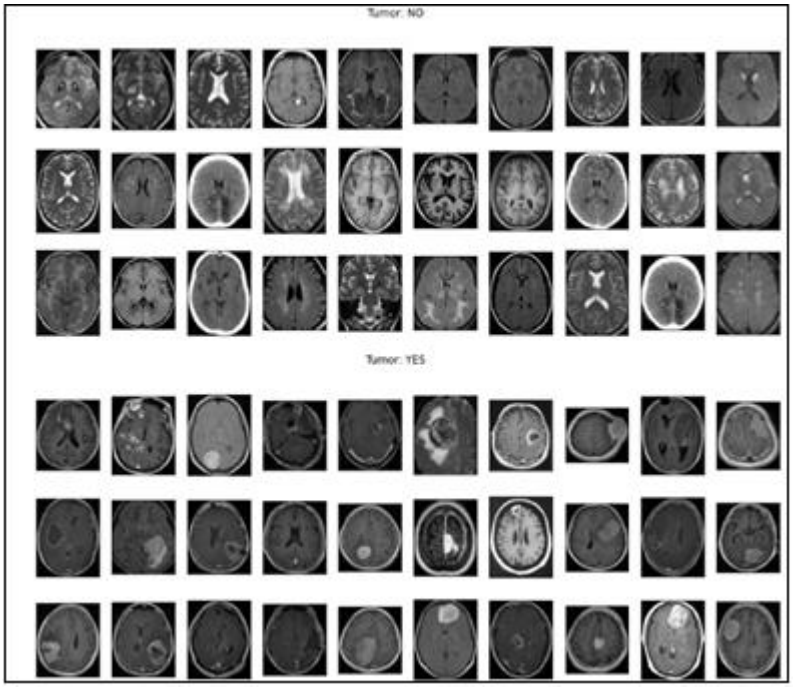

Fig 3 Samples (Tumor Yes/No)

- *Data Augmentation to the Data set since the Dataset is Small here is the Sample*

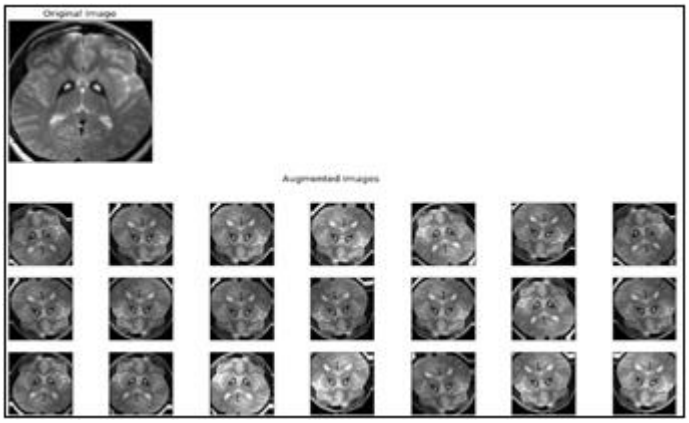

Fig 4 Data Augmentation

- *VGG-16 Model Parameters*

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dropout (Dropout)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 1)                 25089
=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
```

Fig 5 Parameters Set

- *CNN Model Parameters*

```
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 6 Parameters Set

IV. DATA ANALYSIS AND PRESENTATION OF FINDINGS

- *VGG-16 Training vs Validation Curves*

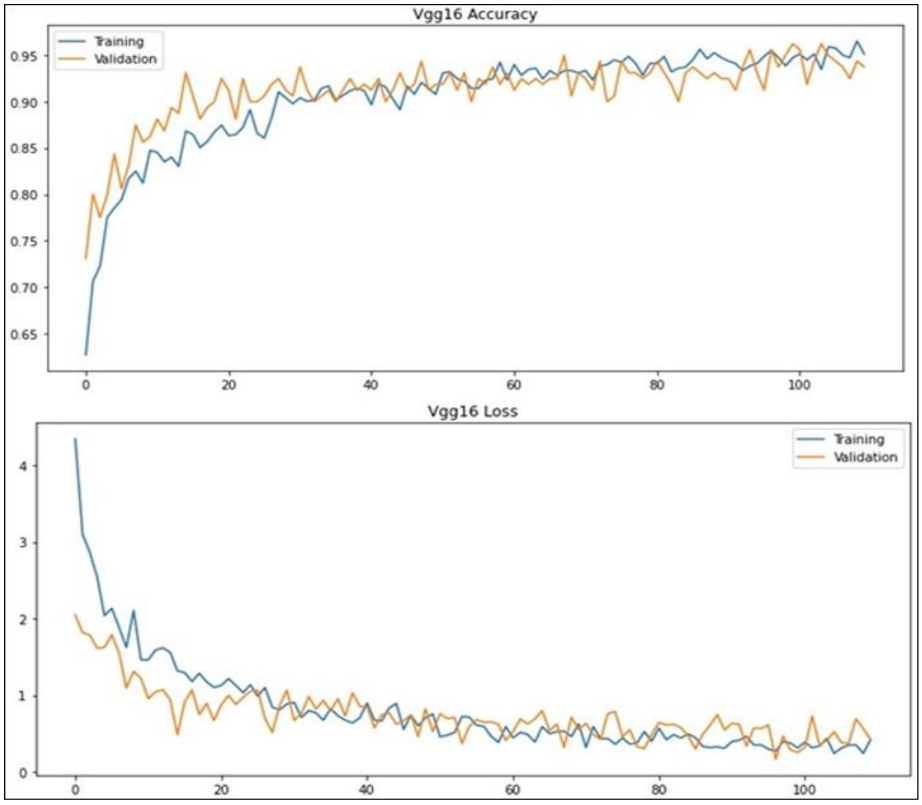

Fig 7 Curves Loss and Accuracy on VGG-16

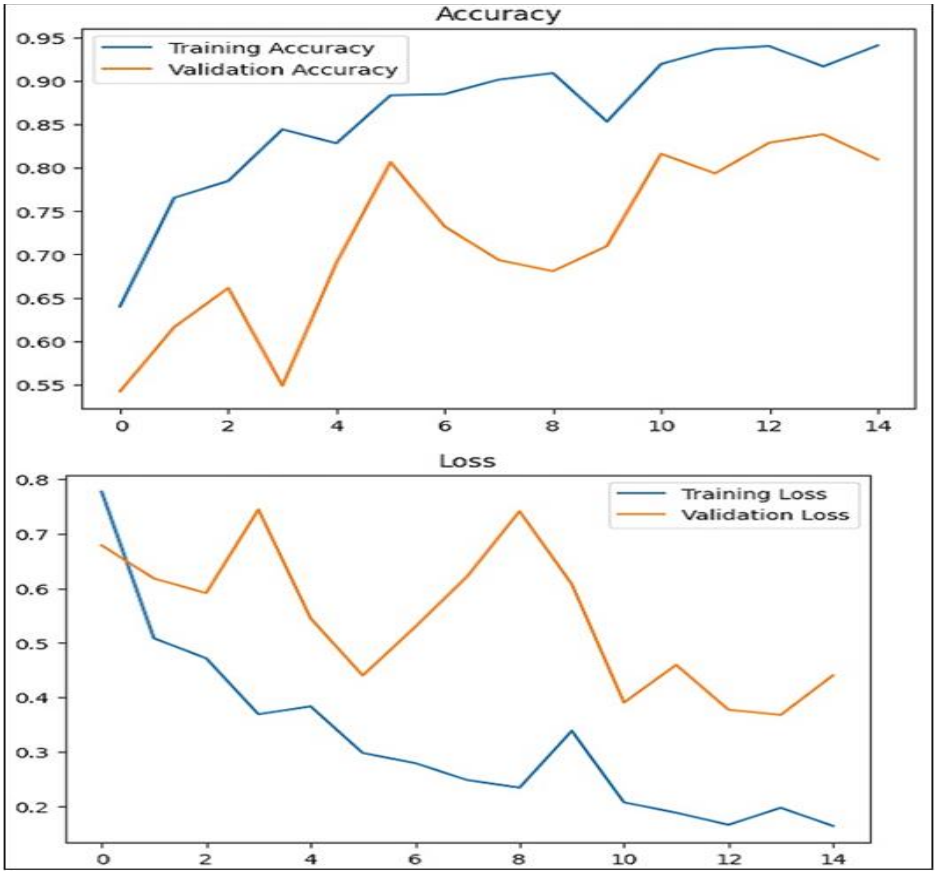

Fig 8 CNN Loss and Accuracy Curves

➢ *Performance Curves*

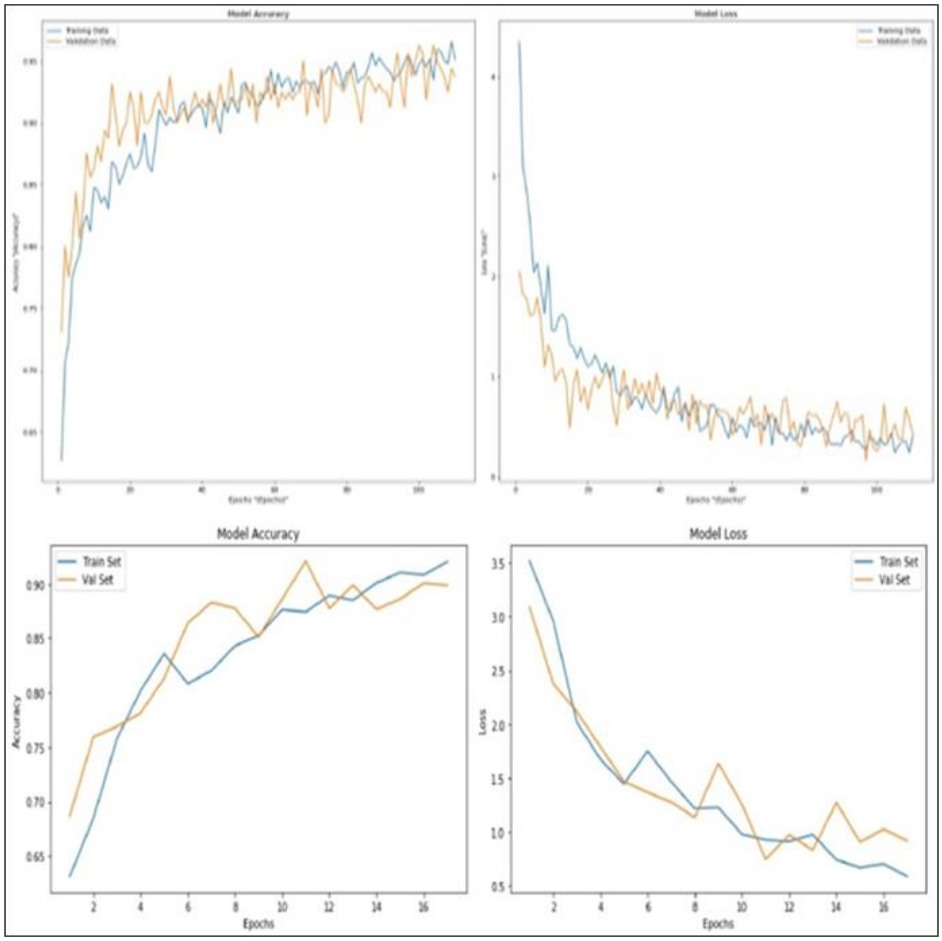

Fig 9 Both VGG-16 vs CNN Performance Curves

V. COMPARATIVE INTERPRETATION OF FINDINGS BETWEEN VGG-16 AND CNN APPROACH MODEL

VGG-16 Deep learning Model	**CNN Deep learning Model**
Accuracy: 95%	**Accuracy**: 91%
Precision: 98%	**Precision**: 88%
Recall Score: 92%	**Recall Score**: 89%
F1 Score: 0.95	**F1 Score**: 0.91
Training Data: 94%, Test Data: 95%	Training Data: 40%, Test Data: 84%
Validate Data Accuracy = 94%	Validate Data Accuracy = 92%
Test Data Accuracy = 95%	Test Data Accuracy = 80%
Here **VGG-16 model**, detects brain tumor with: 95% accuracy on the test set. 98% precision on the test set 0.95 F1 score on the test set.	Here CNN model, detects brain tumor with: 91% accuracy on the test set. 88% precision on the test set 0.91 F1 score on the test set.
These results are the **best one ever** considering that the data is balanced.	These results are **very good** considering that the data is also balanced.

Fig 10 Comparative Interpretation of Findings between Vgg-16 and CNN Approach Model

VI. CONCLUSIONS AND DISCUSSIONS ON THE FINDINGS

Based on our objectives, we applied deep learning models, namely CNN and VGG-16, to detect brain tumors from MRI images. The results showed that on the test set, VGG-16 achieved the highest accuracy of 95% with a precision of 98%. Similarly, CNN demonstrated a respectable accuracy of 91% with a precision of 88% for brain tumor detection, which falls within an acceptable range.

It is important to note that the VGG-16 model performed better than the CNN model in terms of accuracy and F1 score. This implies that VGG-16 model delivered more precise results and achieved a better balance between precision and recall in the specific context of brain tumor detection.

In conclusion, after meticulously analyzing performance metrics, plotted graphs, and confusion matrices, I strongly recommend that Rwanda Military Hospital to deploy the VGG-16 Approach model for brain tumor detection. The VGG-16 model demonstrated exceptional accuracy and precision on the test set. By deploying this model, the hospital can ensure reliable and accurate brain tumor detection outcomes.

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