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Brain Tumor Detetction Using AI: A Deep Learning Approach using a CNN model

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Abstract: Brain tumors pose a significant threat to human health, making early detection crucial for effective treatment. This study explores the application of deep learning techniques, particularly the VGG-16 model, for brain tumor classification. The proposed model processes MRI images to distinguish between tumor and non-tumor cases with high accuracy. The system is implemented using Python, TensorFlow, and OpenCV, with a web-based deployment for real-time predictions.
Keywords: Brain tumor detection; Deep learning; MRI classification; VGG-16; CNN; Medical Imaging

I. INTRODUCTION

Brain tumors are abnormal growths in brain tissue that can be malignant or benign. They arise due to uncontrolled cell division in the brain, and their severity depends on the type, location, and growth rate. Brain tumors can lead to severe neurological complications, including memory loss, vision impairment, and cognitive dysfunction. Magnetic Resonance Imaging (MRI) is the most common imaging technique used to diagnose brain tumors. However, manual interpretation of MRI scans is time-consuming and subject to human error, which may lead to delays in treatment. Computer-aided diagnosis (CAD) systems powered by deep learning can significantly enhance diagnostic accuracy and speed by automating tumor detection and classification. In recent years, Convolutional Neural Networks (CNNs) have emerged as a powerful tool for medical image analysis. These deep learning models can extract complex patterns from MRI images, enabling precise classification of brain tumors. This study investigates the application of the VGG-16 CNN architecture for brain tumor detection, leveraging transfer learning to achieve high accuracy with minimal training data. The proposed system automates tumor identification, reducing dependency on expert radiologists and improving early detection rates.

II. LITERATURE REVIEW

Brain tumor detection has seen significant advancements with the integration of deep learning techniques. Several studies have explored the potential of convolutional neural networks (CNNs) and hybrid learning approaches to improve classification accuracy and computational efficiency.

Qureshi et al. (2022) proposed an ultra-light deep learning model for multi-class brain tumor detection, focusing on improving efficiency and accuracy while reducing computational complexity. Their approach enhances diagnostic precision using deep learning in medical imaging.

Zahoor et al. (2022) introduced a hybrid boosted and ensemble learning-based model for brain tumor detection using MRI scans. Their study integrates multiple deep learning techniques to improve classification accuracy and robustness.

Arabahmadi et al. (2022) conducted a survey on deep learning applications in smart healthcare, emphasizing brain tumor detection. They analyzed various deep learning methodologies used for medical imaging and highlighted their potential to revolutionize tumor diagnosis.

Tandel et al. (2019) reviewed deep learning approaches in brain cancer classification, discussing various CNN architectures and their performance. Their study emphasized the significance of deep learning in improving diagnostic accuracy and assisting radiologists in early tumor detection.

These studies collectively indicate that deep learning, especially CNN-based architectures, plays a crucial role in automating and improving brain tumor detection. However, challenges such as dataset diversity, model generalization, and computational requirements remain areas for further research and enhancement.

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III. METHODOLOGY

To build an efficient AI-driven brain tumor detection system, we adopted a deep learning-based approach using Convolutional Neural Networks (CNNs). The methodology consists of multiple stages, including data collection, preprocessing, model development, training, evaluation, and deployment.

A. Dataset

The dataset consists of MRI scans categorized into two classes: "No Tumor" and "Pituitary Tumor." Images undergo preprocessing, including resizing (224x224 pixels), normalization, and augmentation (flipping, rotation) to enhance model generalization. Data augmentation techniques help in increasing the diversity of the training data, reducing overfitting and improving the model's ability to generalize to unseen images.

B. Model Architecture

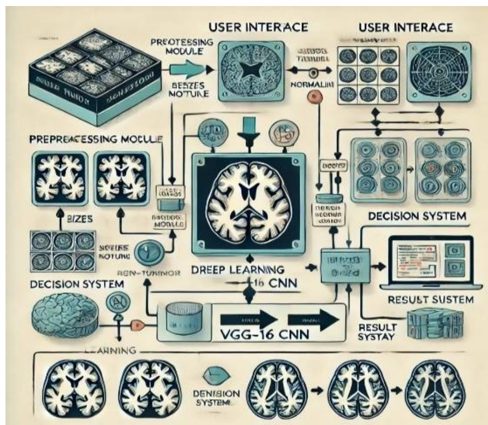

Figure 1 System Architecture

VGG-16, a pre-trained convolutional neural network (CNN), is used for feature extraction. The architecture includes:

- Convolutional Layers: Used for feature extraction, capturing spatial and texture details in MRI scans. ReLU activation functions are applied to introduce non-linearity.
- Max-Pooling Layers: Reduce the spatial dimensions of feature maps, helping retain the most important information while reducing computational complexity.
- Fully Connected Layers: Convert extracted features into a format suitable for classification.
- Softmax Activation: Provides probability-based output, determining whether an MRI scan has a tumor or not.

C. Implementation

The implementation follows these key steps:

1) Data Preprocessing: The MRI images are resized to 224x224 pixels, normalized, and augmented.
2) Model Training: The dataset is divided into 80% training and 20% validation sets. The VGG-16 model is fine-tuned using transfer learning.
3) Optimization: The Adam optimizer is used to minimize categorical cross-entropy loss, ensuring fast convergence and stable training.
4) Evaluation: The trained model is evaluated using accuracy, precision, recall, and F1-score to measure its effectiveness.

D. Deployment

After training, the model is deployed as a web application for real-time MRI scan classification. The deployment process involves:

1) Backend: Flask is used to serve the trained model as an API.
2) Frontend: A ReactJS-based web interface allows users to upload MRI images for classification.
3) Integration: The frontend communicates with the backend to process uploaded images and return classification results in real time.

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A. *Implementation Details*

The flowchart represents the step-by-step process of detecting brain tumors using deep learning, specifically leveraging the VGG-16 model. Below is an explanation of each stage:

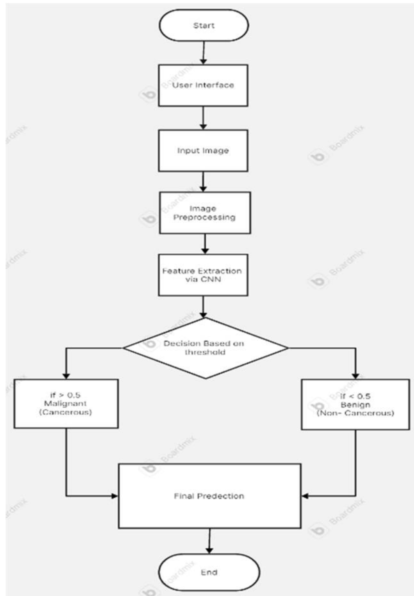

Figure 2.Step-by-step implementation of cnn model

B. *Step-by-Step Process*

1) User Interaction – The user interacts with the system via a web-based interface to upload an MRI scan for analysis.
2) Input Image – The MRI image is received by the system for further processing.
3) Image Preprocessing – The uploaded image undergoes preprocessing, including resizing, normalization, and noise removal, to enhance model performance.
4) Feature Extraction via CNN – The Convolutional Neural Network (CNN), specifically the VGG-16 model, extracts essential features from the image, identifying patterns crucial for classification.
5) Flattening & Fully Connected Layer – The extracted features are flattened and passed through fully connected layers to interpret and classify the image.
6) Decision Based on Threshold – A classification threshold determines the tumor category:

- If > 0.5 → The system classifies the tumor as Malignant (Cancerous).
- If < 0.5 → The system classifies the tumor as Benign (Non-Cancerous).

7) Final Prediction – The final classification result is displayed to the user.
8) End – The process concludes.

This structured approach enables automated brain tumor detection, reducing diagnostic time and improving accuracy through deep learning techniques.

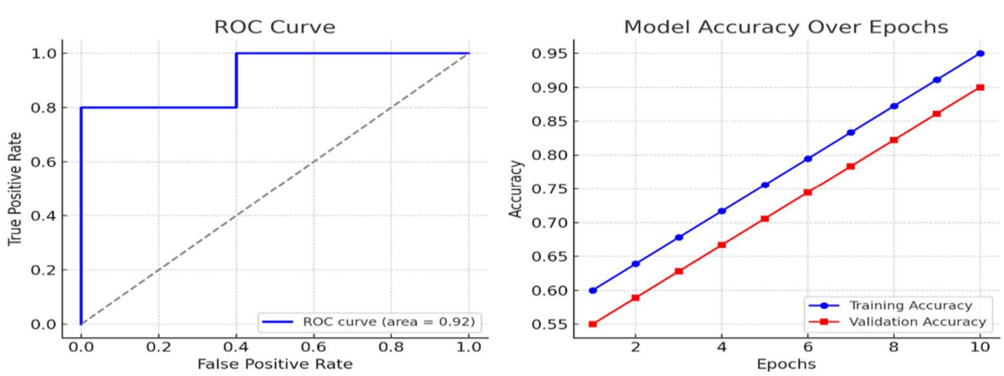

Figure 4 ROC CURVE & Model Accuracy graphs

IV. CONCLUSION

Early detection of brain tumors can play a significant role in preventing higher mortality rates globally. Due to the tumor's form, changing size, and structure, the correct detection of brain tumors is still highly challenging. Clinical diagnosis and therapy decisionmaking for brain tumor patients are greatly influenced by the classification of MR images. Early brain tumor identification using MR images and the tumor segmentation method appear promising. Nevertheless, there is still a long way to go before the tumor location can be precisely recognized and categorized. For the purposes of early brain tumor detection in our study, we used a variety of MRI brain tumor images. Deep learning models also have a significant impact on classification and detection. We proposed a CNN model for the early detection of brain tumors, where we obtained promising result using a large amount of MR images. We employed a variety of indicators to ensure the efficiency of the ML models during the evaluation process. In addition to the proposed model, we also took into account a few other ML models to assess our outcomes. Regarding the limitations of our research, as the CNN had several layers and the computer did not have a good GPU, the training process took a long time. If the dataset is large, such as having a thousand images, it would take more time to train. After improving our GPU system, we minimized the training time. Future work can be performed to better correctly identify brain cancers by using individual patient information gathered from any source.

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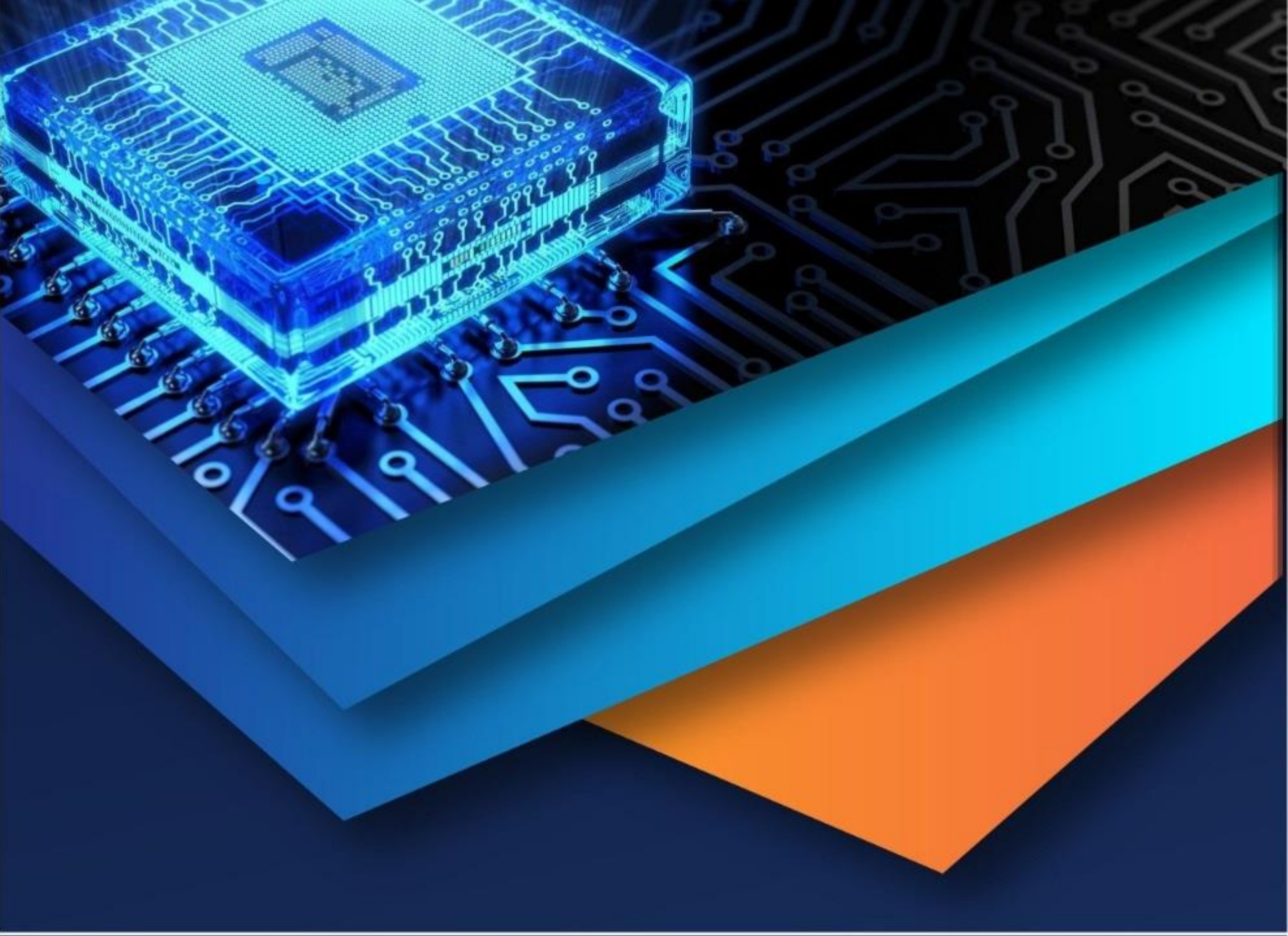

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