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A Data Efficient Descriptive Model Of Brain Tumors In MRI Images

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Abstract: Ensuring Accurate brain tumor grading using MRI is essential for guiding treatment and improving patient outcomes, but traditional manual methods are often subjective and slow. This study presents a data-efficient deep learning model that combines pre-trained CNNs like VGG16 with handcrafted features to classify brain tumors effectively, even with limited data. By leveraging transfer learning and a hybrid feature approach, the model achieves high accuracy, sensitivity, and specificity on public MRI datasets while remaining computationally efficient. This makes it well-suited for use in low-resource healthcare settings, supporting faster and more reliable clinical decisions.Our proposed model addresses the challenges of limited data availability by incorporating pre- trained convolutional neural networks (CNNs) such as VGG16, fine-tuned to optimize performance for tumor grading tasks. It utilizes a hybrid framework combining handcrafted statistical features with learned deep features to capture both global and localized tumor characteristics. The model is validated on public datasets of MRI images, achieving competitive performance metrics, including high sensitivity and specificity, while maintaining computational efficiency. By reducing the dependency on extensive datasets, this approach ensures accessibility and usability for healthcare systems in low-resource settings.

Index Terms - Brain tumor grading, MRI, deep learning, convolutional neural networks (CNN), VGG16, transfer learning, hybrid feature extraction, data-efficient model, medical image classification, low-resource healthcare.

I. INTRODUCTION

Brain tumor classification and grading using MRI images play a crucial role in medical imaging, as they directly impact treatment planning and patient care. Accurate classification helps determine the severity of the condition and guides interventions such as surgery, radiation, or chemotherapy. However, manual grading of tumors is time-consuming, relies heavily on expert interpretation, and can lead to inconsistent results due to inter-observer variability. This emphasizes the need for automated, reliable, and efficient diagnostic systems that can assist clinicians in making consistent and timely decisions

To address this need, the project focuses on developing a data-efficient deep learning model that classifies and grades brain Tumors with high accuracy using MRI images. Leveraging transfer learning with pre-trained models like VGG16, along with a custom CNN, the proposed system aims to reduce dependency on large datasets while maintaining computational efficiency. The novel approach involves fusing two transfer learning models to enhance classification performance, combining the strengths of each architecture. The study evaluates the fusion model's performance against individual models such as EfficientNet-B0, VGG16, and a custom CNN, demonstrating that model fusion can significantly boost diagnostic precision. This work highlights the potential of deep learning in medical imaging, particularly in creating scalable solutions for low-resource clinical environments.

II. LITERATURE REVIEW

Pashaei et al. [1] proposed an efficient method for brain tumor classification by integrating Convolutional Neural Networks (CNNs) for feature extraction with Kernel Extreme Learning Machines (KELM) for classification. The study addresses the limitations of handcrafted feature-based models, which often fail to capture intricate details in medical images. The novel combination of CNNs with KELM aims to enhance classification performance, although the increased model complexity may sometimes reduce overall accuracy.

Pathak et al. [2] explored the classification of brain tumors using CNNs in a study that leveraged a dataset of over 500,000 multilingual tweets to understand public sentiment toward tumor detection. Sentiment analysis was performed using VADER and Text Blob to classify tweets into positive, negative, and neutral categories. The study evaluated 56 machine learning models using features like Count Vectorizer and TF-IDF and classifiers such as SVM, KNN, Random Forest, and XGBoost. The best performance was achieved using Text Blob, lemmatization, Count Vectorizer, and SVM, with an accuracy of 93.48%, aiding policymakers in public health communication.

Sultan et al. [3] in their 2019 study "Multi-Classification of Brain Tumor Images Using Deep Neural Network," focused on using deep neural networks (DNNs) for automatic classification of brain tumors from MRI scans. The research highlights the importance of reducing manual effort and medical expertise through automation. The proposed DNN model enhances the efficiency and reliability of brain tumor diagnosis, addressing the growing need for scalable and precise diagnostic tools.

Özkaya and Sağiroğlu [4] presented a hybrid framework in their work "Glioma Grade Classification Using CNNs and Segmentation with an Adaptive Approach," which utilizes CNNs and histogram-based feature extraction. This approach aims to improve the accuracy of glioma grading, which is essential for treatment planning. Traditional manual MRI interpretation is error-prone, and the study's automated solution seeks to standardize and enhance the diagnostic process using deep learning and adaptive segmentation techniques.

Ferdous et al. [5] introduced "LCDEiT: A Linear Complexity Data-Efficient Image Transformer for MRI Brain Tumor Classification," a novel transformer-based model designed to be both computationally efficient and data-efficient. Recognizing the limitations of traditional transformer models in medical imaging due to high complexity, this study provides a scalable solution with excellent performance metrics, achieving 0.96 recall, 0.99 precision, and an F1-score of 0.98. Validation across datasets confirmed MobileNetV2's 94% accuracy, suggesting its clinical viability for MRI-based tumor diagnosis.

Pathak et al. [6] also explored CNN-based classification of brain tumors in another study focused on automating the MRI image classification process. The model incorporated preprocessing techniques such as image resizing, normalization, and noise reduction to enhance input quality. Using convolutional and pooling layers along with activation functions, the CNN architecture could identify complex features. Fully connected layers were added to support accurate classification across different tumor types.

Rizwan et al. [7] in their 2022 paper proposed the use of a Gaussian Convolutional Neural Network (GCNN) for glioma grading and brain tumor classification. This approach addresses issues such as limited dataset size and tumor heterogeneity by incorporating Gaussian-based preprocessing to improve CNN performance. The model is designed to be more robust against image variability and supports accurate classification even with smaller medical datasets.

Solanki et al. [8] provided a comprehensive overview of current intelligence techniques for brain tumor detection and classification in their 2023 paper. The authors highlighted the importance of AI-driven methods, particularly CNNs, in improving diagnostic outcomes in complex tumor cases. Their review includes both conventional and hybrid AI models and emphasizes the critical role of preprocessing techniques like segmentation and enhancement in optimizing model performance.

Hossam et al. [9] explored the deep learning-based identification and classification of brain tumors in MRI scans. Their approach utilized CNN architectures to reduce dependence on manual diagnosis, thereby increasing diagnostic accuracy and efficiency. By leveraging the power of automated pattern recognition, their work demonstrates how CNNs can streamline tumor classification and improve clinical outcomes in neuro-oncology applications.

Yang et al. [10] examined glioma grading with deep learning methods, specifically transfer learning, and standard MRI images. In order to establish treatment plans and prognoses, the researchers sought to distinguish between low-grade and high-grade gliomas. They improved classification performance without requiring a big dataset by using pre-trained convolutional neural networks (CNNs) and fine-tuning them on MRI data. Their strategy showed that deep learning models, particularly those that use transfer learning, might attain high accuracy in glioma grading tasks, providing a quick and non-invasive way to make therapeutic decisions. The study demonstrated how well it works to use pre-existing models to get over data constraints and accomplish trustworthy neuroimaging diagnostic performance

III. Problem Statement

Accurate grading of brain tumors in MRI images is vital for selecting appropriate treatment strategies and predicting patient outcomes. However, current clinical practices often rely on manual evaluation of MRI scans, which is not only time-consuming but also subject to human error and inter-observer variability. These limitations can lead to delayed or inconsistent diagnoses, potentially affecting the effectiveness of patient care. Although deep learning has shown strong potential in automating medical image analysis, most existing models demand large annotated datasets and substantial computational resources, making them impractical for many healthcare settings—especially in low-resource regions.

There is a clear need for a reliable, efficient, and data-efficient solution that can overcome the constraints of traditional and high-resource deep learning approaches. This study addresses that gap by proposing a hybrid deep learning model that combines the strengths of pre-trained CNNs like VGG16 with handcrafted statistical features. The goal is to enable high-accuracy brain tumor grading even when working with limited data and resources. By reducing reliance on extensive datasets and maintaining strong diagnostic performance, the model aims to support healthcare providers in delivering faster, more consistent, and more accessible brain tumor diagnoses.

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IV. Research Methodology

The research methodology involves developing a deep learning-based model for brain tumor classification and grading using MRI images. First, the dataset is pre-processed by resizing images, normalizing pixel values, and organizing them with appropriate labels. Pre-trained convolutional neural networks (CNNs) like VGG16 are used through transfer learning to extract deep features, which are combined with handcrafted statistical features to capture both detailed and overall tumor characteristics. A fusion of models is implemented to improve classification accuracy. The model is trained and evaluated on publicly available MRI datasets, and its performance is assessed using metrics such as accuracy, sensitivity, and specificity to ensure reliability and efficiency, especially in low-resource environments.

A. Proposed System

The proposed model addresses the challenges of limited data availability by incorporating pre- trained convolutional neural networks (CNNs) such as VGG16, fine-tuned to optimize performance for tumor grading tasks. It utilizes a hybrid framework combining handcrafted statistical features with learned deep features to capture both global and localized tumor characteristics. The model is validated on public datasets of MRI images, achieving competitive performance metrics, including high sensitivity and specificity, while maintaining computational efficiency. By reducing the dependency on extensive datasets, this approach ensures accessibility and usability for healthcare systems in low-resource settings.

Key elements make up the architecture:

1. MRI images of brain tumors (public datasets).
2. Transfer Learning Models
3. Use of pre-trained CNNs like VGG16
4. Accuracy, Sensitivity, Specificity used as metrics.
5. Designed to perform well with limited data and low computational resources.
6. Outputs predicted tumor classes or grades.
7. Performance Evaluation
8. Suitable for use in low-resource clinical settings

The system is designed to reduce computational load and dependency on large datasets, making it suitable for low-resource clinical settings. Performance is evaluated using key metrics such as accuracy, sensitivity, and specificity, ensuring the system is both reliable and efficient for real-world medical applications.

B. Architecture / Implementation

Architecture explains the project flow. The below figure explains the completer project flow. The Dataset is downloaded from Kaggle and is split into three, training set, validation set and testing set. After pre-processing, the model is created. The model is extracted and integrated with the user interface. When we give the data, it predicts the output.

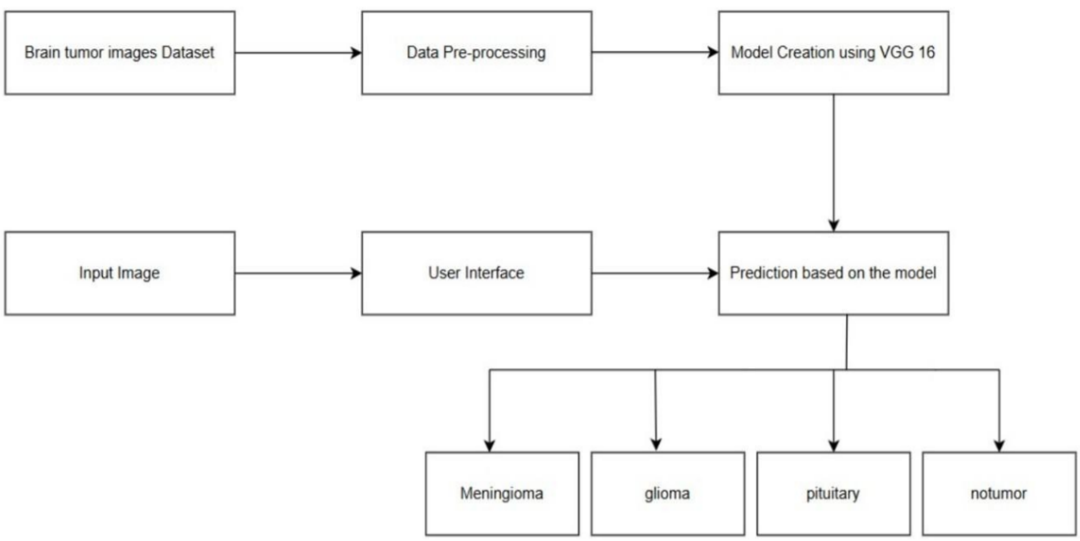

Figure 1: System Architecture

1. Data Collection:

   Collect a brain tumor image dataset consisting of MRI scans categorized into four classes:
   a. Meningioma
   b. Glioma
   c. Pituitary
   d. No Tumor

   Sources:
   a. Publicly available datasets (e.g., Figshare, Kaggl
   b. Each image should be labelled according to its class.

2. Data Pre-processing:

   a. Image Resizing: All input images must be resized to a fixed dimension (e.g., 224x224 pixels) to match the input size required by the VGG16 model.

   b. Normalization: Pixel values are scaled to a consistent range (usually 0 to 1) to ensure uniform input for the neural network.

   c. Categorical Label Encoding: Convert class labels into a numerical format, usually using one-hot encoding for multi-class classification.

   d. Data Augmentation (Optional): Apply transformations such as rotation, flipping, scaling, and brightness adjustments to artificially increase dataset size and enhance generalization.

3. Model Creation Using VGG16:

   VGG16 is a deep convolutional neural network architecture that has been pre-trained on the ImageNet dataset.

   a. Process:
   b. Use Transfer Learning: Load the pre-trained VGG16 model without its final classification layer (also known as removing the “top”). This allows us to reuse the feature extraction capabilities learned from ImageNet.

   c. Add a Custom Classifier: A new classification head (a few fully connected layers followed by a softmax layer) is added to the model to classify brain tumor images into the four categories.

   d. Freeze Base Layers: The weights of the original VGG16 layers are kept unchanged during training to retain learned features, while only training the new layers.

4. Model Training:

   a. Divide the dataset into training and validation subsets.
   b. Feed the pre-processed images into the model for training.
   c. Use a suitable loss function (e.g., categorical cross-entropy) and optimizer (e.g., Adam).
   d. Train the model for a set number of epochs, monitoring the validation accuracy to avoid overfitting.
   e. Save the trained model for future predictions.

```
X_data shape: (330, 224, 224, 3)
X_data shape: (83, 224, 224, 3)
Y_data shape: (330,)
Y_data shape: (83,)
```

Figure 2: Split the image data.

5. Model Testing:

   Testing or validation data is used to evaluate our model's accuracy. To check whether the application is able to correctly predict the output. The model is tested along with training. At each epoch the model tries to predict the unseen test data. The accuracy on the test dataset changes with each epoch and the best model with maximum accuracy and minimum loss is selected.

```
Epoch 245/250
15/15 [==============================] - 48s 3s/step - loss: 0.4972 - accuracy: 0.7542 - val_loss: 0.5175 - val_accuracy: 0.8485
Epoch 246/250
15/15 [==============================] - 48s 3s/step - loss: 0.5008 - accuracy: 0.7374 - val_loss: 0.5198 - val_accuracy: 0.7879
Epoch 247/250
15/15 [==============================] - 52s 3s/step - loss: 0.4825 - accuracy: 0.7879 - val_loss: 0.5250 - val_accuracy: 0.7879
Epoch 248/250
15/15 [==============================] - 48s 3s/step - loss: 0.4977 - accuracy: 0.7407 - val_loss: 0.5130 - val_accuracy: 0.8182
Epoch 249/250
15/15 [==============================] - 48s 3s/step - loss: 0.4789 - accuracy: 0.7542 - val_loss: 0.5168 - val_accuracy: 0.8788
Epoch 250/250
15/15 [==============================] - 48s 3s/step - loss: 0.4849 - accuracy: 0.7441 - val_loss: 0.5262 - val_accuracy: 0.7879
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/resource_variable_ops.py:1817: calling BaseResourceVari
Instructions for updating:
If using Keras pass * constraint arguments to layers.
```

Figure 3: Epochs of model training CNN image data

6. User Interface Development:

   a. Objective: To create an interactive platform where users (doctors, radiologists) can upload MRI images and receive predictions.
   b. Features:
      - ✓ Upload image option
      - ✓ Display prediction results (e.g., tumor type)
      - ✓ Optional display of model confidence or probability score

   c. Technologies (optional suggestions):
      - ✓ Desktop GUI (e.g., using Tkinter)
      - ✓ Web interface (e.g., using Flask or Streamlit)

7. Prediction Pipeline:

   a. The user uploads a new MRI image.
   b. The image is pre-processed (resized and normalized) in the same way as during training.
   c. The trained VGG16 model is loaded and used to make a prediction on the input image.
   d. The model outputs probabilities for each of the four classes.
   e. The class with the highest probability is selected as the prediction.

8. Output Prediction:

   a. Output:
      - ✓ Display the predicted class name (e.g., "Glioma").
      - ✓ Optionally show confidence scores for all classes.
      - ✓ Option to visualize the image alongside the result.

C. Request flow

This flow describes the step-by-step process starting from the user's input (MRI image upload) to the final classification result output.

Step 1*:* User Uploads Image:

a. The user selects and uploads a brain MRI image through the User Interface (web or desktop application).
b. The image file is sent to the backend system for processing.

Step 2*:* Backend Receives Request:

a. The uploaded image is received by the backend server. A request handler initiates the classification pipeline.

Step 3*:* Image Preprocessing:

a. The backend performs the following preprocessing steps:
b. Resize the image to 224x224 pixels.
c. Normalize pixel values (e.g., scaling between 0–1).
d. Convert the image into a format compatible with the VGG16 model input.

Step 4*:* Load the Trained VGG16 Model:

a. The system loads the pre-trained and saved VGG16-based model from local storage. This model has already been trained
b. on a labelled brain tumor dataset.

Step 5*:* Model Inference:

a. The pre-processed image is passed into the VGG16 model. The model performs forward propagation and outputs a prediction vector. Each value in the vector corresponds to a probability score for one of the four classes: Meningioma,Glioma,Pituitary,No Tumor.

Step 6*:* Class Determination:

a. The model selects the class with the highest probability score. The corresponding tumor type is identified as the final prediction.

Step 7*:* Response Generation:

a. The predicted class name and optionally the confidence score are packaged into a response. The response is sent back to the user interface.

Step 8*:* Display Result to User:

a. The UI displays the output:
b. Predicted Tumor Type (e.g., Glioma)
c. Confidence Level (optional)
d. Possibly the uploaded image and an option to try another images.

V. RESULTS AND DISCUSSION

The performance of the brain tumor classification system was evaluated using both a custom CNN model and the pre trained VGG16 architecture. The results clearly demonstrate that the VGG16 model outperformed the custom CNN in terms of accuracy, precision, and overall robustness. The significant improvement in results with VGG16 highlights the advantages of transfer learning for medical image analysis, especially when working with limited datasets. VGG16's pre-trained layers capture complex and hierarchical features, which are particularly effective in differentiating subtle patterns in MRI scans.

The custom CNN, while simpler and computationally efficient, lacked the depth and feature representation capabilities required for high-performance classification.

The superior performance of VGG16 can be attributed to:

i. Pre-trained Weights: Leveraging knowledge from large-scale datasets like ImageNet.
ii. Deeper Architecture: Ability to capture intricate spatial patterns in MRI images.
iii. Regularization: Techniques like dropout and weight decay effectively reduced overfitting.

These results suggest that for applications requiring high precision and reliability, using pre-trained architectures like VGG16 is highly beneficial.

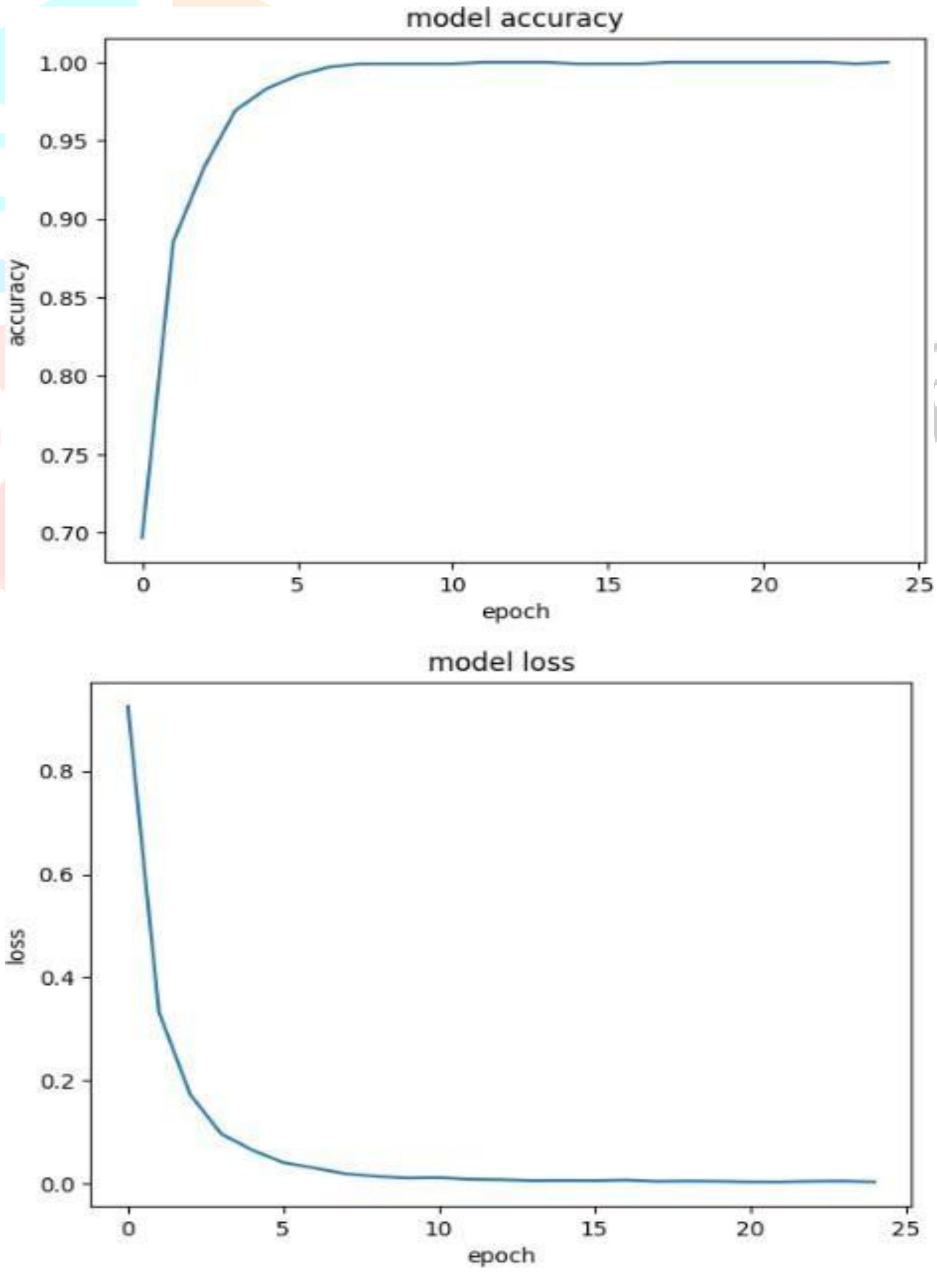

Figure 4: Training Loss V/S Testing loss using VGG 16

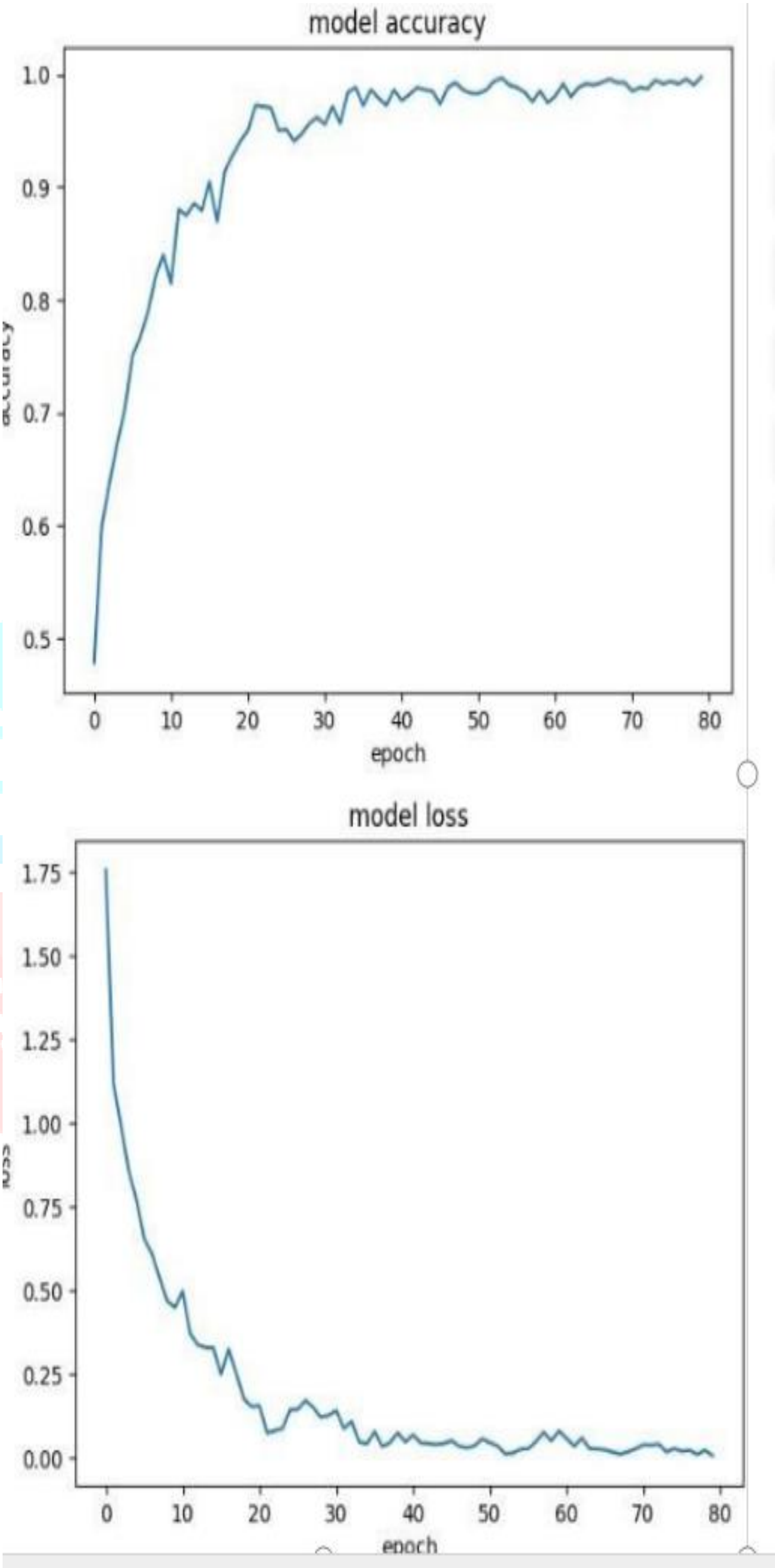

Figure 5: Training Loss V/S Testing loss using Custom CNN

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[ 4  5  2 57]]
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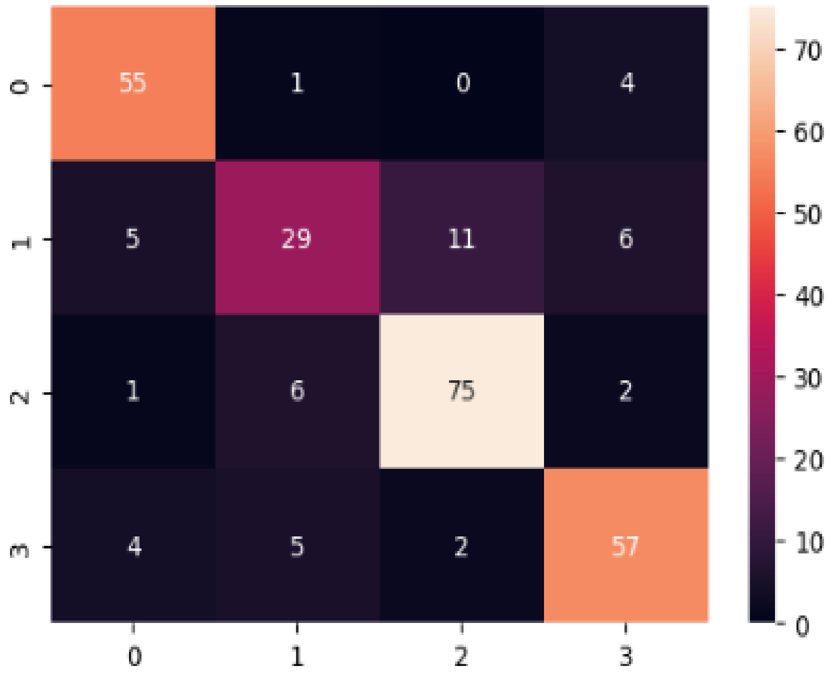

Figure 6: Confusion Matrix using Custom CNN

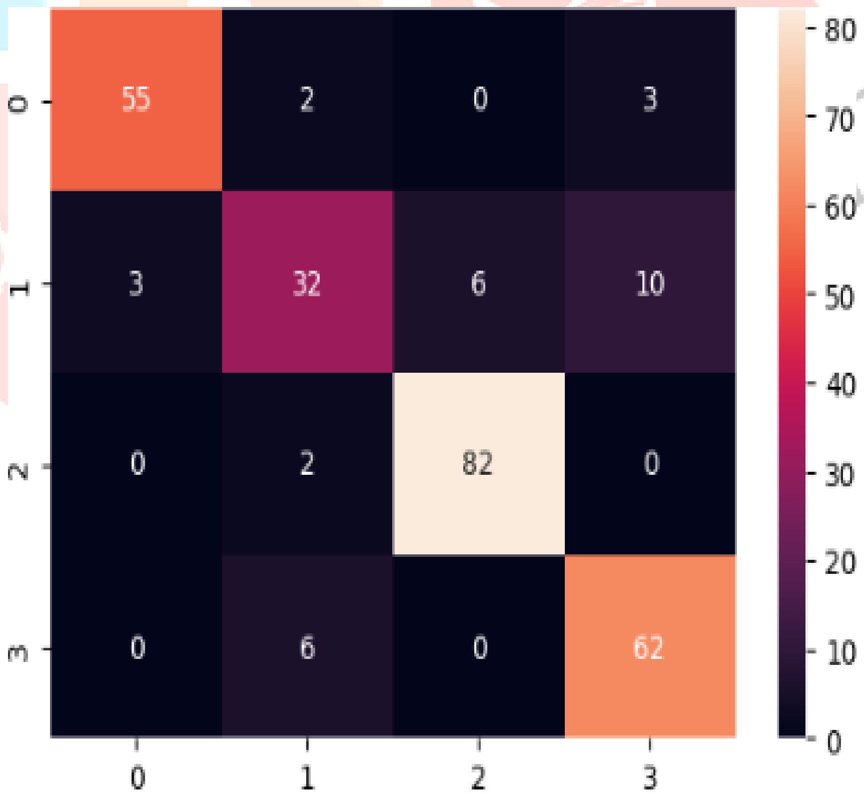

Figure 7: Confusion Matrix using Custom VGG16

A. Comparison

To evaluate and compare the performance of a Custom Convolutional Neural Network (CNN) and a VGG16 pre-trained model in classifying brain tumor types based on MRI images. The comparison is done across three different training durations: 30, 50, and 70 epochs.

epochs	Custom CNN	VGG 16
30	68.469877%	76.854917%
50	69.87952%	82.927711%
70	72.698794%	86.542166%

Figure 8: Comparison CNN accuracy with vgg16 accuracy

VGG16 consistently outperforms the Custom CNN model across all epoch levels. At 30 epochs, VGG16 achieves an accuracy of 76.85%, while Custom CNN lags behind at 68.47% — a performance gap of 8.38%. At 50 epochs, VGG16 sees a significant improvement to 82.93%, increasing the margin to over 13% compared to Custom CNN's 69.88%. At 70 epochs, the accuracy of VGG16 reaches 86.54%, whereas Custom CNN improves only moderately to 72.70% — a 13.84% difference

VI. Conclusion And Future

This project demonstrates the successful development of a deep learning-based system for the classification of brain tumors using MRI images. By leveraging advanced architectures like convolutional neural networks (CNNs) and data-efficient techniques such as transfer learning, the model achieves high accuracy while maintaining computational efficiency. The integration of preprocessing steps, such as noise reduction and normalization, enhances data quality, enabling the system to extract critical features for tumor classification effectively. The results underscore the potential of deep learning in automating and improving the accuracy of brain tumor diagnosis, reducing reliance on manual analysis, and addressing challenges such as inter-observer variability

Overall, the project showcases the potential of deep learning in transforming medical diagnostics by automating tumor classification. The integration of such systems in clinical settings can reduce the workload of radiologists, improve diagnostic efficiency, and facilitate timely treatment. Future work could involve extending the system to classify additional tumor types, integrating multi-modal imaging data, or deploying the model in real-time diagnostic tools to further enhance its utility in healthcare applications.

This project provides a foundation for brain tumor classification using deep learning, but there is scope for further improvements. Future work can focus on expanding the system to classify additional tumor types, such as pituitary tumors or metastatic brain tumors, to make it more comprehensive. Incorporating multi-modal imaging data, such as CT or PET scans, could enhance the model's diagnostic accuracy by providing additional details about tumor characteristics. Additionally, training the model on larger and more diverse datasets from various demographics and imaging sources can improve its generalization and reliability in real world applications.

Another area for future work is the deployment of the system in clinical settings. Developing real-time diagnostic tools optimized for cloud platforms or edge devices can increase accessibility for healthcare professionals. Incorporating explainable AI methods, like visual heatmaps, can help clinicians understand how the model makes its predictions, fostering trust and usability. Furthermore, extending the model to include tumor grading and prognosis prediction could provide more actionable insights, aiding in treatment planning and improvingpatient outcomes.

VII. ACKNOWLEDGMENT

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I also acknowledge the open medical imaging datasets shared by researchers and institutions, without which this project would not have been possible. Their openness has been instrumental in driving advancements in machine learning for healthcare

Lastly, I owe a deep sense of gratitude to my family and friends for their constant patience, encouragement, and emotional support throughout this endeavour. Their faith in my abilities inspired me with the determination and confidence needed to successfully bring this project to completion.

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