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Transfer Learning Driven Brain Tumor Detection via Deep CNN Architectures

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Abstract: In today's medical imaging field, the classification of brain tumors plays a crucial role in determining the treatment plan, course of therapy, and survival rate. Our approach introduces a new technique that utilizes image-based deep learning models, specifically pre-trained neural networks, combined with a stacking algorithm for improved classification of brain tumors. Here, our method begins by processing T1-weighted images from MRI brain scans using multiple pre-trained CNNs. These neural networks extract visual features from the images, capturing intricate details crucial for accurate classification. To enhance accuracy, we employ an ensemble technique where the extracted image features serve as inputs to a single-layer stacking algorithm. This method integrates predictions from multiple base classifiers to make a final, more robust decision. Through its use of transfer learning, our approach leverages CNNs trained on extensive image datasets, ensuring that the extracted features are highly relevant for brain tumor classification. The combination of various base classifiers with a stacking algorithm further enhances classification accuracy. Our evaluation on two publicly available brain MRI image datasets demonstrates that this method significantly improves lesion detection, making it a promising step forward in medical imaging and healthcare.

Keywords: *Brain Tumor Classification; MRI; Deep Learning; Convolutional Neural Networks (CNN); Transfer Learning; Stacking Algorithm; Ensemble Learning; Medical Imaging; T1-weighted Images; Feature Extraction.*

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I. INTRODUCTION

A brain tumor is an abnormal growth in the brain that can be dangerous if not detected early. Doctors use MRI scans to find these tumors, but analyzing these scans manually takes a lot of time and can sometimes lead to mistakes. A faster and more accurate way to detect brain tumors is needed. A brain tumor is a growth of cells in the brain or near it. Brain tumors can happen in the brain tissue. Brain tumors also can happen near the brain tissue. Nearby locations include nerves, the pituitary gland, the pineal gland, and the membranes that cover the surface of the brain. This project uses Convolutional Neural Networks (CNNs), a type of deep learning model that analyze images and find patterns automatically. Instead of training a new model from scratch, we use Transfer Learning, which means we take a pre-trained model and fine-tune it to detect brain tumors. This helps improve accuracy and reduces training time. The goal of this project is to create a system that can quickly and accurately detect brain tumors from MRI images. This will help doctors make better decisions and provide faster treatment to patients. Treatment options for brain tumors depend on the type, location, and size of the tumor, as well as the patient's overall health. Common treatments include: Surgery, Radiation therapy, Chemotherapy, Targeted therapies, and Clinical trials Convolutional Neural Networks (CNNs) are a powerful tool for detecting brain tumors from medical images like MRI scans. CNNs excel at recognizing patterns in images, allowing them to identify subtle anomalies indicative of tumors. Research has shown high accuracy rates in brain tumor detection using CNNs, with some studies achieving close to 100% accuracy.

II. METHODOLOGY

The process of brain tumor detection using Convolutional Neural Networks (CNN) and transfer learning follows a systematic approach to ensure accurate and reliable classification of brain tumors from MRI images. It begins with data collection, where MRI images are gathered from publicly available datasets such as BRATS (Brain Tumor Segmentation) or Kaggle datasets. These images typically include various categories, such as normal brain scans, benign tumors, and malignant tumors. Since raw medical images often contain noise and variations in resolution, preprocessing is a

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crucial step before feeding them into the CNN model. Preprocessing techniques include resizing images to ensure consistency in input dimensions, normalizing pixel values to improve model convergence, and applying noise reduction techniques to enhance image clarity. Data augmentation methods such as rotation, flipping, zooming, and brightness adjustments are applied to artificially expand the dataset and improve the model's generalization capability. Rather than training a CNN model from scratch, transfer learning is employed to leverage pretrained deep learning models such as VGG16, ResNet, InceptionV3, or MobileNetV2. These models, which have been trained on large-scale image datasets like ImageNet, already possess strong feature extraction capabilities. The initial layers of these pre-trained networks are frozen to retain their learned features, while custom fully connected layers are added on top to adapt the model for brain tumor classification. The final output layer is designed according to the classification task, whether it is binary (tumor vs. no tumor) or multi-class (normal, benign, malignant). The model undergoes fine-tuning, where deeper layers of the pre-trained network are adjusted to better capture tumor specific patterns in MRI images. Once the modified CNN model is ready, it is trained using the preprocessed MRI dataset. The dataset is typically divided into training, validation, and test sets to ensure a robust evaluation of the model's performance. During training, the model is optimized using loss functions such as categorical cross-entropy (for multi-class classification) or binary cross-entropy (for two-class classification). Optimization algorithms like Adam or Stochastic Gradient Descent (SGD) are used to update the model's parameters iteratively. Overfitting is prevented by implementing techniques such as dropout layers, learning rate scheduling, and early stopping. The training process continues for multiple epochs, where the model continuously learns and refines its ability to distinguish between tumor and non-tumor images. After training, the model is evaluated using a separate test dataset to measure its performance in real-world scenarios. Key performance metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (AUC-ROC) curve are used to assess the model's effectiveness. To ensure interpretability and trust in the system, Grad-CAM (Gradient weighted Class Activation Mapping) visualization is applied. This technique highlights the regions in an MRI scan that influenced the model's prediction, allowing medical professionals to understand the reasoning behind each classification decision. Finally, once the CNN model has demonstrated reliable performance, it is deployed for real-time use in clinical or research settings. Deployment can be achieved through a web-based application using frameworks like Flask or Django, allowing users to upload MRI scans and receive automated tumor predictions. Alternatively, the model can be integrated into mobile applications using TensorFlow Lite or deployed on cloud platforms like Google Cloud, AWS, or Azure for scalable processing. The final system not only provides an accurate classification of brain tumors but also enhances decision-making by offering visual explanations of predictions, making it a valuable tool in medical diagnostics.

The methodology for the brain tumor detection web application involves integrating deep learning techniques with a user-friendly interface for real-time MRI image classification. Initially, a dataset of labeled brain MRI images is collected and preprocessed through resizing, normalization, and augmentation techniques such as rotation, zooming, and flipping to improve model generalization and robustness. Transfer Learning using pre-trained models like VGG16 and ResNet50 is applied, where the top layers are removed and replaced with custom dense layers suited for multiclass tumor classification. Additionally, a custom Convolutional Neural Network (CNN) is also designed with multiple convolutional, pooling, and dropout layers to extract relevant features from input images. The model is trained using the Adam optimizer with categorical cross-entropy loss over several epochs, with performance evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Grad-CAM (Gradient-weighted Class Activation Mapping) is used to visualize and interpret the regions of the brain where the tumor is most likely located. The trained model is then saved and integrated into a Flask-based Python web server. The front-end is developed using HTML, CSS, and Bootstrap, enabling users to upload MRI images through a clean and intuitive interface. Once an image is uploaded, the backend processes it, performs prediction using the deep learning model, and returns the results in real-time, including the predicted tumor type and heatmap visualization. The complete system is designed to aid doctors and users in early and efficient brain tumor detection, making it accessible via local or cloud-based deployment.

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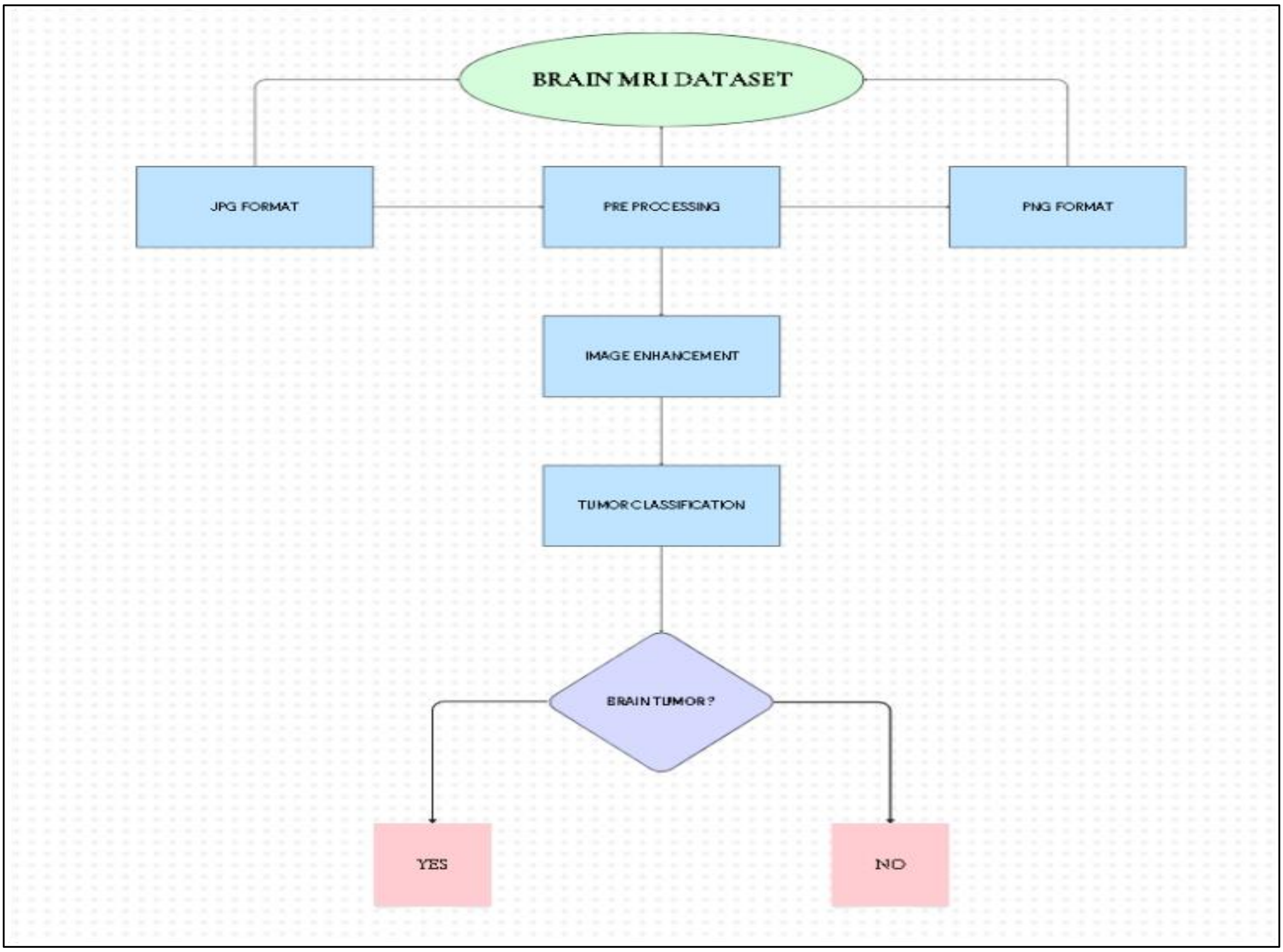

Fig 1 Flowchart

III. MODULES AND ITS IMPLEMENTATION

A. System Operations:

➢ *Image Preprocessing:*

To achieve a more accurate interpretation, the MRI images undergo a series of preprocessing phases. The fig 3 shows the Image preprocessing and This procedure involves the following steps: normalization to ensure that pixel intensity values remain consistent, resizing of images for standardization, thresholding to segment regions of interest, interpolation to align spatial dimensions, sharpening techniques to enhance edges, and denoising to reduce image noise.

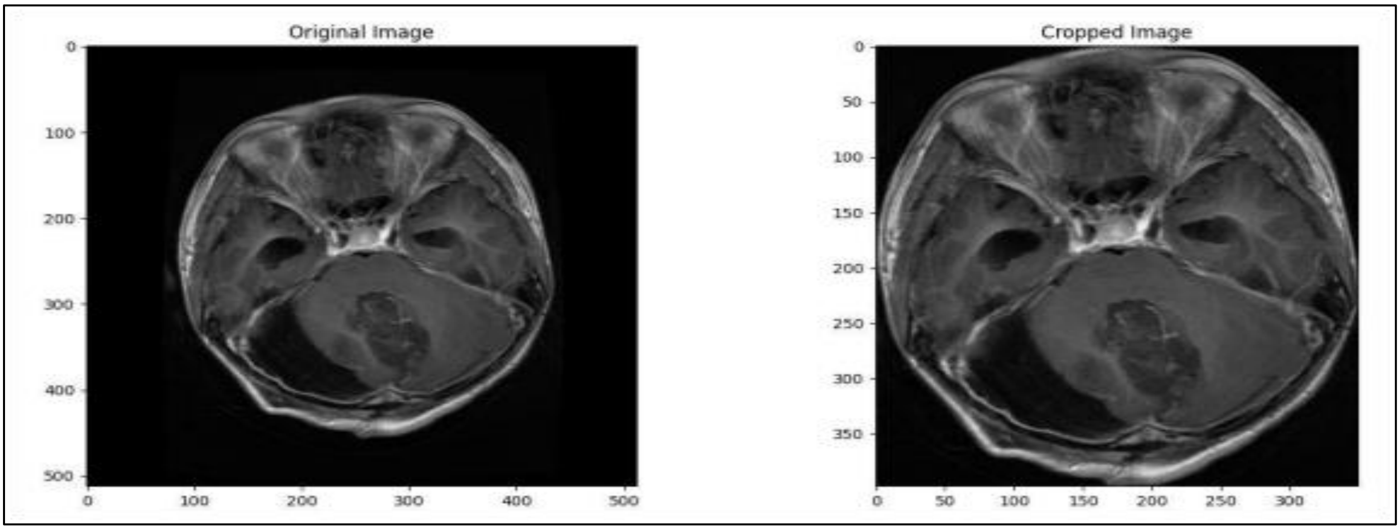

Fig 2 Image Preprocessing

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➢ *Image Enhancement:*

In addition to preprocessing, image enhancement methods are implemented to enhance the diagnostic value and visual lucidity of MRI images.he fig 4 shows the Image Enhancement and this method was further improved by Histogram Adaptive Equalization and Adaptive Equalization, which responded to local picture properties, resulting in a more effective enhancement.

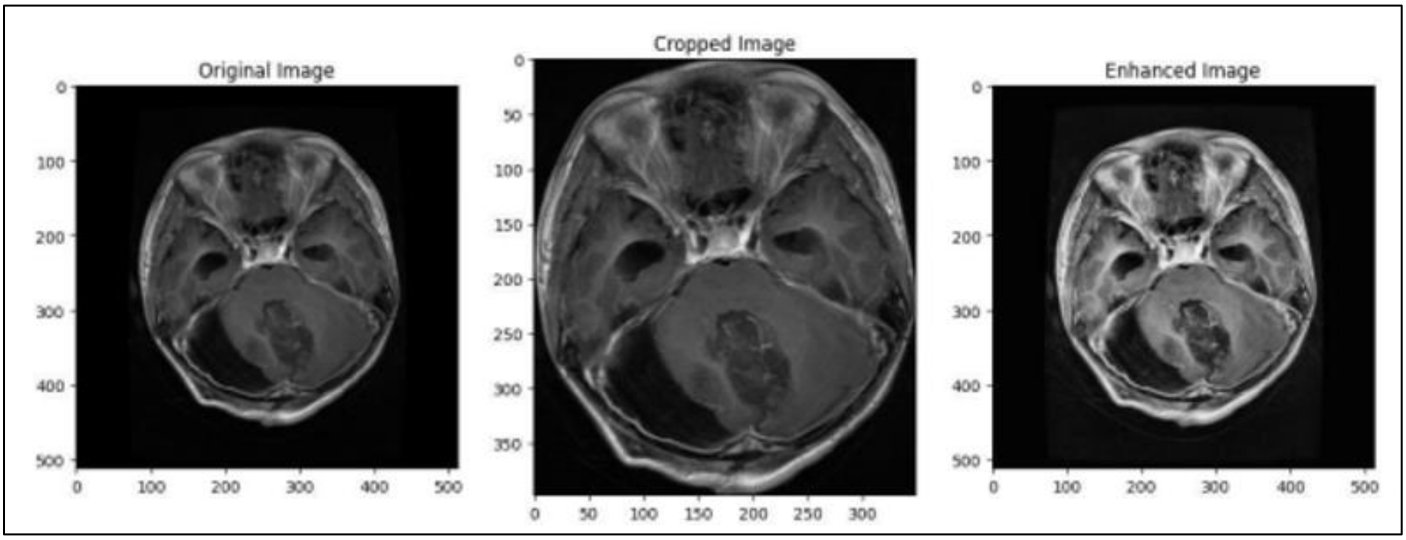

Fig 3 Image Enhancement.

➢ *Feature Extraction:*

The MRI images are analyzed to extract significant characteristics that suggest the presence of a brain tumor after undergoing preprocessing and enhancement. The objective of feature extraction methods is to recognize distinctive patterns and properties within the visuals, including intensity, texture, and form. These methods are essential for the identification and classification of tumor

➢ *Feature Reduction:*

Feature reduction (also known as dimensionality reduction) is an important technique in brain tumor detection and classification using Convolutional Neural Networks (CNNs). It helps improve model performance, reduce computational complexity, and avoid overfitting by focusing on the most informative features extracted from MRI images.

B. User Interface:

➢ *MRI Image Upload and Detection:*

Users can upload brain MRI scans directly through the homepage interface. Once an image is uploaded, the system automatically preprocesses the image and uses a trained deep learning model (CNN with Transfer Learning) to detect the presence and type of brain tumor. The result, along with the predicted tumor class (e.g., Glioma, Meningioma, Pituitary), is displayed on the screen. Additionally, a Grad-CAM heatmap is shown to highlight the tumor affected region in the MRI image, providing visual interpretability.

➢ *View Symptoms of Brain Tumors:*

A dedicated section is available where users can read about the common symptoms associated with brain tumors. These may include headaches, vision problems, seizures, memory issues, and changes in behavior. This feature helps users gain awareness and better understand the importance of early diagnosis.

➢ *Explore Types of Brain Tumors:*

Another section in the interface provides detailed information about the different types of brain tumors, such as Glioma, Meningioma, and Pituitary tumors. Each type is explained with its characteristics, severity, and occurrence. This educational content helps users differentiate between tumor types and their typical MRI appearances.

IV. MODELING AND ANALYSIS

➢ *Convolutional Neural Network (CNN):*

CNN is a deep learning model particularly effective for image classification tasks like brain tumor detection. In this project, the CNN automatically extracts spatial features from MRI images through convolutional and pooling layers. It learns hierarchical representations—starting from edges and textures to complex tumor structures. This model effectively identifies subtle differences between tumor types (such as Glioma, Meningioma, and Pituitary) and shows high accuracy due to its ability to capture localized features. With dropout layers and batch normalization, overfitting is minimized. The CNN serves as the core model in the web application, offering fast and precise predictions based on image inputs.

➢ *Support Vector Classifier (SVC):*

SVC is employed as a traditional machine learning baseline to classify tumors using extracted feature vectors from preprocessed images. It finds the optimal decision boundary that maximizes the margin between different tumor classes. For non-linear classification, kernels like Radial Basis Function (RBF) are applied. Although SVC performs well on small to medium datasets, its computational cost increases with high-dimensional image data. In this project, SVC is used for benchmarking, showing competitive performance but limited scalability in comparison to CNN.

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➤ *Grad-CAM (Gradient-weighted Class Activation Mapping):*

Grad-CAM is integrated to enhance model interpretability by generating heatmaps that highlight the regions of the MRI image that most influenced the CNN's classification decision. This visual explanation helps medical professionals and users verify if the network is focusing on the tumor region, thereby increasing trust in the AI model. Grad-CAM does not function as a classifier but complements CNN by adding transparency and explainability to the predictions.

➤ *Decision Tree:*

The Decision Tree classifier is used for comparison due to its simplicity and interpretability. It splits the data based on feature thresholds derived from extracted image data (e.g., average intensity, texture features). Each node represents a decision based on a feature, and the leaves indicate the predicted tumor type. Decision Trees are easy to visualize and explain, making them useful for quick rule-based insights. However, due to their tendency to overfit on noisy or high-dimensional image data, their standalone performance is weaker than CNN.

➤ *Random Forest:*

Random Forest is an ensemble of multiple Decision Trees trained on random subsets of the data and features. For tumor classification, it improves generalization by aggregating predictions from all trees through majority voting. It is robust against overfitting and handles noisy data better than a single tree. In this project, Random Forest shows better accuracy and stability than standalone Decision Trees, making it suitable for structured feature inputs extracted from MRI images.

➤ *K-Nearest Forest:*

KNN is a simple yet effective classifier that predicts tumor type based on the majority class of the 'k' closest feature vectors in the dataset. For this project, it is applied using flattened or feature-extracted image data. Although KNN offers high accuracy in some cases, it becomes computationally expensive as the dataset grows and is sensitive to the choice of 'k' and feature scaling. Despite its limitations, it serves as a good benchmark model in the comparison study.

V. RESULTS AND DISCUSSION

The process of brain tumor detection using Convolutional Neural Networks (CNN) and transfer learning follows a systematic approach to ensure accurate and reliable classification of brain tumors from MRI images. The **fig 4** shows the accuracy analysis and loss analysis of model RESNET v2.It begins with data collection, where MRI images are gathered from publicly available datasets such as BRATS (Brain Tumor Segmentation) or Kaggle datasets.

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Once the modified CNN model is ready, it is trained using the preprocessed MRI dataset. The dataset is typically divided into training, validation, and test sets to ensure a robust evaluation of the model's performance. During training, the model is optimized using loss functions such as categorical cross-entropy (for multi-class classification) or binary cross-entropy (for two-class classification).

Optimization algorithms like Adam or Stochastic Gradient Descent (SGD) are used to update the model’s parameters iteratively. Overfitting is prevented by implementing techniques such as dropout layers, learning rate scheduling, and early stopping. The training process continues for multiple epochs, where the model continuously learns and refines its ability to distinguish between tumor and non-tumor images.

➤ *ResNet(Residual Learning) V2*:

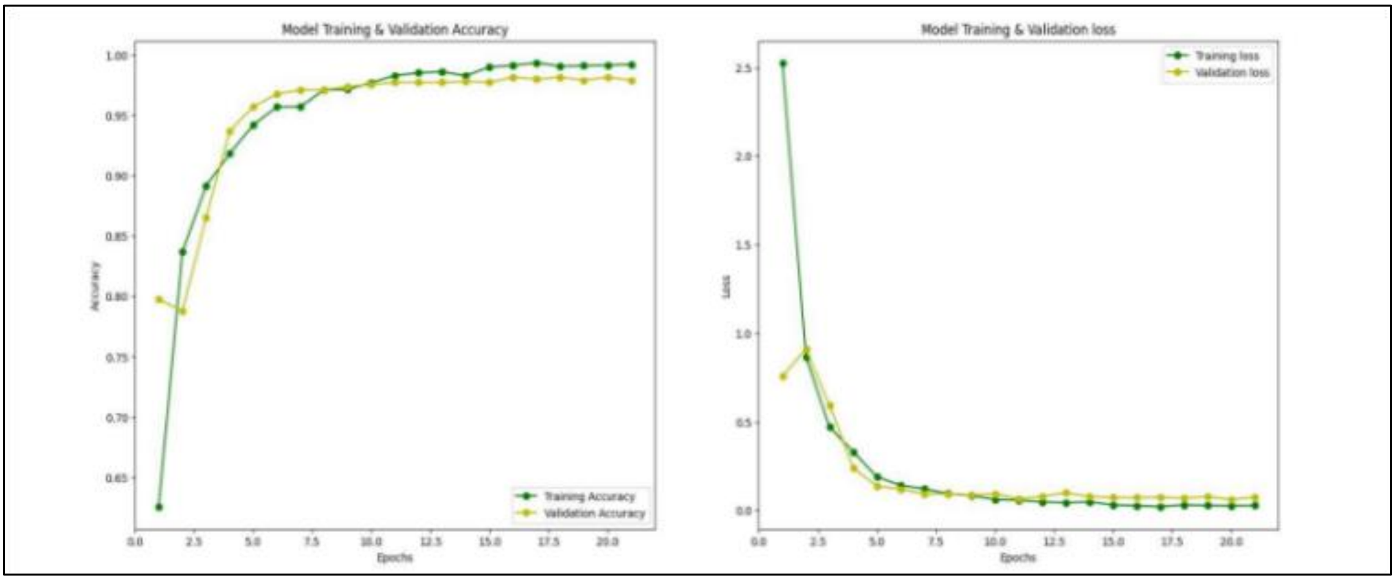

Fig 4 Model Accuracy and Loss Analysis

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Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.99	0.99	0.99	300
1	0.98	0.98	0.98	306
2	0.99	1.00	1.00	405
3	1.00	0.99	0.99	300

Fig 5 Tumor Image Classification Report

Metric	Precision	Recall	F1-Score	Support
Accuracy			0.99	1311
Macro Avg	0.99	0.99	0.99	1311
Weighted Avg	0.99	0.99	0.99	1311

Fig 6 Accuracy Metrics

In the given classification report generated by the **ResNet v2 model**, the **accuracy** value is **0.99**, or **99%**. This means that out of the total **1311** test samples, the model correctly predicted the class labels for **99%** of them. Accuracy is calculated using the formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} = \frac{Correct}{1311}$$

An accuracy of 0.99 indicates that the model made only a very small number of incorrect predictions (approximately 13 errors), demonstrating excellent overall performance in classifying the input data correctly.

VI. CONCLUSION

The research demonstrates the effectiveness of deep learning techniques, particularly the ResNet v2 model, in achieving highly accurate brain tumor detection and classification, reaching up to 99% accuracy. Despite the impressive performance, several challenges persist. Medical datasets are often limited and imbalanced, which can hinder the training of robust models. Additionally, the variability in MRI scan quality across different sources and institutions introduces inconsistencies in the data. Overfitting remains a concern, especially when working with small datasets, and the requirement for high computational resources can limit accessibility in resource-constrained environments.

However, the advantages offered by deep learning models significantly outweigh these challenges. The ResNet v2 model delivers high accuracy, faster training times, and automated feature extraction without the need for manual intervention. Its consistent and unbiased predictions enhance diagnostic reliability, and its scalability allows it to handle large volumes of MRI data efficiently. Moreover, these models can be wrapped into user-friendly interfaces and integrated into clinical workflows, enabling non-technical users, including hospital staff, to utilize them effectively. This research confirms that deep learning, when applied thoughtfully and with proper data handling strategies, holds substantial promise for advancing medical diagnostics and improving patient outcomes.

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