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Tumor Detection Using RestNet50

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Abstract: Brain tumor's are major threat to human health and life. It is better for early detection and treatment the tumor's to enhance survival rates. Traditional methods of detecting and categorizing brain tumor, such as manual segmentation and feature extraction, they are both time consuming and prone to inaccuracies. Early diagnosis of brain tumors plays an important role in a patient's treatment and makes it easy to save his/her life. The conventional method of manually detecting brain tumors from brain magnetic resonance imaging (MRI) scans can be problematic and erroneous. This study aims to compare Restnets50 performance on publicity available Brats dataset, an exclusive collection of brain tumor which is divided into 4 categories no_tumor , glioma, pituitary, meningioma. Trained on a dataset of 7023 images, the model achieves exceptional accuracy 98% in both training and validation datasets, with a focus on precision. Leveraging techniques such as data augmentation, transfer learning with ResNet50, and regularization ensuresstabilityandgeneralizability.Magnetic resonance imaging (MRI) is a well-known used imaging technique to detect brain tumor . Thisstudydemonstratesthepotentialofdeeplearninginearlybraintumor diagnosis, surpassing conventional methods and laying a robust foundation for future research in neural network-based classification algorithms for brain tumor.

I. INTRODUCTION

A brain tumor (sometimes referred more commonly as brain cancer) occurs when a group of cells within the brain turn cancerous and grow out of control, creating a mass. Brain tumors pose a significant health threat as they can disrupt normal brain function, leading to severe neurological complications or even death .

Early and accurate detection of brain tumors is crucial for effective treatment planning and improving patient survival rates. More than 120 classes of brain tumours are known to be classified in four levels according to the level malignancy by the World Health Organization (WHO) . All types of brain tumours evoke some symptoms based on the affected region of the brain. The major symptoms may include headaches, seizures, vision problems, vomiting, mental changes, memory lapses, balance losing etc . Incidence of brain tumours are due to genetics, ionizing radiation mobile phones, extremely low frequency magnetic fields, chemicals, head trauma and injury, immune factors like viruses, allergies, infections, etc [3].However, manual diagnosis through medical imaging techniques such as MRI and CT scans is often time-consuming, prone to human error, and highly dependent on the expertise of radiologists. To address these challenges, deep learning-based automated tumor detection systems have gained attention in recent years. Deep learning is a machine learning technique that instructs computers what to do as a human think and do in a scenario. In deep learning, a computer model is able to do classification tasks from images, sound or text. Sometimes human level performance is being exceeded by deep learning techniques. One of the most popular neural networks is an artificial neural network that has a collection of simulated neurons. Each neuron acts as a node and by links each node is connected to other nodes.

Deep learning models have capability to autonomously extract features from medical images, notably MRI scans. The aim of this paper is to develop an automated system for brain tumor detection from MRI images using deep learning approach . Specifically, we employ Restnet-50, a powerful convolutional neural network(CNN), to enhance the accuracy and efficiency of tumor classification. The proposed method is evaluated and compared with existing classification techniques to assess its performance in terms of accuracy and reliability. This study aims to contribute to the advancement of AI-driven medical diagnostics, assisting healthcare professional in early and precise tumor detection.

II. RELATED WORK

Ramanagiri [1] introduced a method aimed at enhancing brain tumor detection using deep learning techniques. This approach leverages ResNet-50, a deep convolutional neural network (CNN), as a feature extractor to capture intricate spatial hierarchies within MRI scans. The extracted features are then processed through a customized CNN for precise tumor classification. ResNet-50, known for its residual learning framework, enables deeper network training without the risk of vanishing gradients, thereby improving classification performance. The study demonstrated that the fine-tuned ResNet-50 model achieved a classification accuracy of 90.04% on the test dataset, highlighting its potential in AI-driven medical diagnostics for efficient and accurate brain tumor detetction .

Dipu et al. [2] implemented several YOLO-based object detection models, including YOLO V3, V4, V5, and others, to detect brain tumors in MRI scans. While YOLO V5 achieved the highest performance among their models with anmAP of 95.07%, the approach still relied heavily on bounding box detection and required extensive annotation and preprocessing. In contrast, our model utilizes the ResNet-50 architecture, which focuses on deep residual learning to directly extract spatial features from MRI images, eliminating the need for region proposal or manual bounding box annotations. Our ResNet-50 model achieved an accuracy of **98%**, demonstrating a more efficient and scalable solution for automated brain tumor classification with less complexity in training data preparation.

Sinha [3] proposed a deep learning-based brain tumor detection system using MRI scans, focusing on tumor segmentation and density estimation through multi-level thresholding. While effective, the method relied on traditional image processing techniques, which can introduce inconsistencies. In contrast, ResNet-50 provides a more accurate and efficient solution by directly extracting spatial features from MRI images, eliminating the need for extensive preprocessing. Its deep residual connections enhance classification accuracy, making it a superior and clinically viable approach for automated tumor.

In contrast, ResNet-50 surpasses both CNN and YOLO models in terms of accuracy, feature extraction capability, and robustness, making it a more reliable and efficient choice for brain tumor detection. While YOLO excels in real-time object detection, its performance in medical image classification is often limited by false positives and lower classification accuracy. ResNet-50, with its deep residual connections, achieves significantly higher precision in distinguishing tumor types, making it better suited for clinical applications. This advanced system has the potential to greatly assist physicians in early diagnosis, facilitating timely treatment decisions. Its superiorperformance significantly reduces error rates, enhancing the precision and reliability of automated tumor classification.

III. PROPOSED METHODS

The proposed method employs a deep learning-based approach for brain tumor classification using ResNet-50, a pre-trained convolutional neural network (CNN) known for its deep residual connections, which improve gradient flow and enable efficient feature extraction. The model is designed to classify brain tumors into benign and malignant categories by learning patterns from medical images.

1) Data Preprocessing

To ensure high-quality input for the model, the dataset undergoes multiple preprocessing steps. The medical images are first resized to are first resized to uniform input shape of 224x224 pixels, ensuring coaptibility with the RestNet-50 architecture. Additionally, the images are normalized, converting pixel values into a standardized range to facilitate faster and more stable training.

To improve generalization and reduce overfitting, data augmentation is applied using ImageDataGenerator. This augmentation includes:

- Rotation: Randomly rotating images to help the model learn invariant features.
- Flipping: Applying horizontal and vertical flipping to expose the model to different orientations.
- Scaling & Shearing: Random transformations to simulate real-world variations in medical imaging.

These augmentation techniques ensure the model generalizes well to unseen images while addressing potential class imbalances.

2) Model Architecture

The ResNet-50 architecture is chosen due to its effectiveness in deep feature extraction. The base ResNet-50 model (pre-trained on ImageNet) is utilized as a feature extractor, with its fully connected layers replaced to better suit the binary classification task. The modified architecture includes:

- Global Average Pooling (GAP): Reduces overfitting by summarizing feature maps instead of flattening them.
- Fully Connected Layers: Two dense layers with ReLU activation to enhance feature learning.
- Batch Normalization: Stabilizes and accelerates training by normalizing activations.
- Dropout (0.5): Prevents overfitting by randomly deactivating neurons during training.
- Softmax Activation: Outputs probabilities for binary classification (benign vs. malignant).

The model is compiled with the Adam optimizer, which adapts learning rates dynamically for faster convergence, and uses categorical cross-entropy as the loss function.

3) Training and optimization

To enhance training stability and prevent overfitting, EarlyStopping and ReduceLROnPlateau callbacks are implemented:

- EarlyStopping: Monitors validation loss and stops training if it does not improve for a set number of epochs, restoring the best weights.
- ReduceLROnPlateau: Reduces the learning rate when validation performance stagnates, allowing the model to converge effectively.

The dataset is split into training and validation sets, ensuring robust evaluation during training. The model is trained for multiple epochs until an optimal balance between accuracy and generalization is achieved.

4) Model Evaluation

Once trained, the model is evaluated using standard classification metrics:

- Accuracy Score: Measures the overall correctness of predictions.
- Confusion Matrix: Provides insights into false positives and false negatives, helping assess model reliability.

IV. SYSTEM ARCHITECTURE

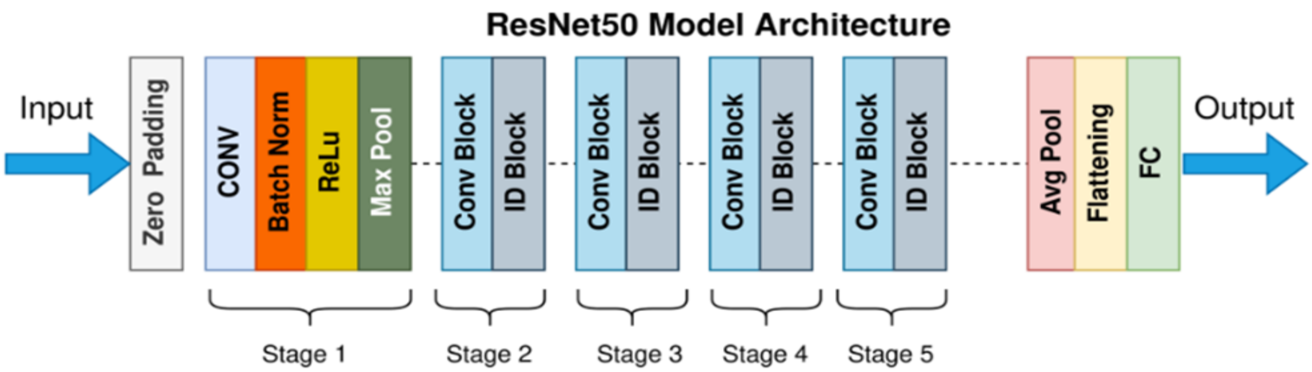


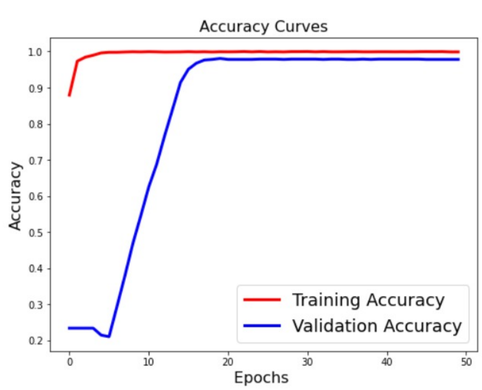
Fig:-SystemArchitecture

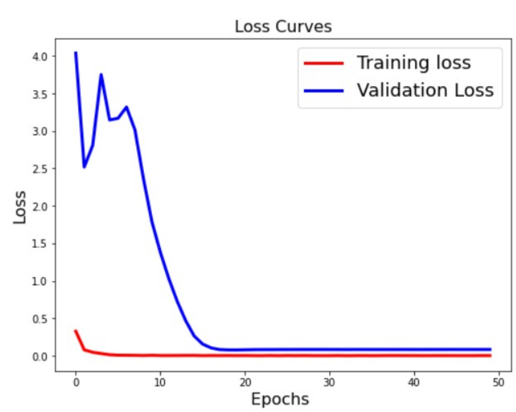
V. RESULT AND ANALYSIS

The evaluation of the ResNet-50-based approach for brain tumor classification was conducted on a dataset of 7,023 MRI images. The model achieved an impressive 98% accuracy onthe test set, with outstanding weighted_avg and macro_avg scores for both recall and accuracy across all tumor categories. This high performance establishes a strong benchmark in the field.

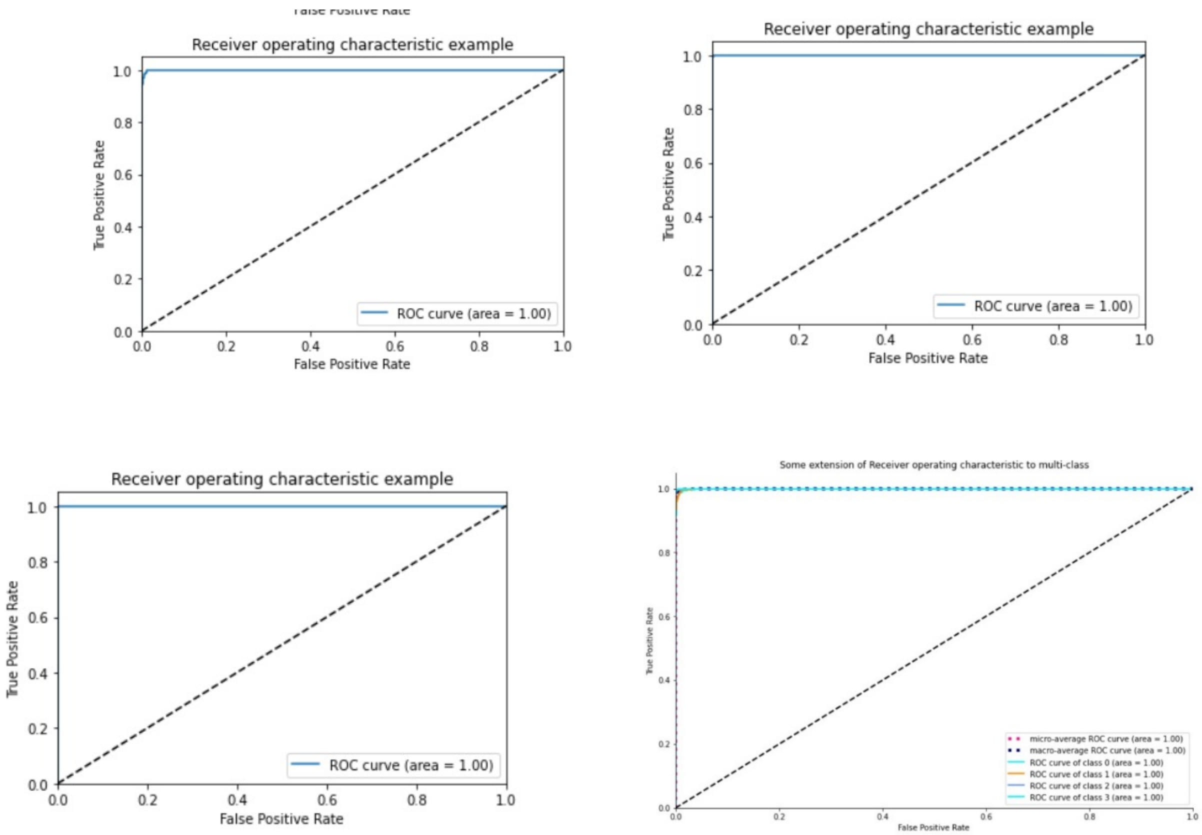
Due to its remarkable accuracy, efficiency, and interpretability, this approach holds significant potential for clinical applications. Additionally, its fast training and deployment capabilities make it a valuable tool for classifying new brain tumor MRI images into distinct tumor types. This method has the potential to enhance the precision and effectiveness of brain tumor classification, contributing to earlier diagnosis and improved treatment strategies.

The following shows the graph between accuracy and epoch and loss and epoch.





The ROC curves of no_tumor , glioma, pituitary, meningioma.



VI. FUTURE SCOPE

Future enhancements include multi-class classification, Explainable AI (XAI) for better interpretability, real-time deployment, and hospital system integration. Additionally, the system can be extended with a web interface, adapted for detecting other diseases from MRI scans, and used to estimate additional therapeutic parameters, further strengthening its clinical impact.

VII. CONCLUSION

The ResNet-50-based model for brain tumor classification achieved 98% accuracy on a 7,023-image Kaggle MRI dataset, demonstrating high reliability in distinguishing benign and malignant tumors. The study emphasizes early detection for timely treatment and evaluates various segmentation algorithms, identifying multilevel thresholding and OTSU thresholding as the most effective. A modified CNN approach significantlyimproved classification accuracy

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