UNIVERSITY COLLEGE OF ENGINEERING VILLUPURAM
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Brain Tumor Detection Using Machine Learning & Deep Learning

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Agenda

- Abstract
- Introduction
- Literature review
- Existing Architecture
- Existing Work
- Problem Statement
- Proposed Architecture
- Proposed Work
- Output & Results
- Existing Work Vs Proposed Work
- Conclusion & Future Enhancements
- Reference

Abstract

Accurate brain tumor detection in MRI scans is essential for diagnosis and effective treatment planning. This paper introduces a hybrid classification framework that combines traditional image processing techniques, deep learning-based feature extraction, and machine learning to improve brain tumor identification. The pipeline begins with MRI preprocessing , Features are extracted using four pre-trained CNNs. These features are concatenated into a unified representation and classified using an XGBoost model. The system is evaluated on both custom and publicly available brain tumor datasets, demonstrating superior performance in terms of Accuracy, Precision, Recall, and F1-Score.

Introduction

Overview

•Utilizes MRI scans and Convolutional Neural Networks (CNNs) for automated brain tumor detection, minimizing manual diagnosis.

•Processes images through techniques like cropping, grayscale conversion, and sharpening to enhance quality and create structured datasets.

•Builds and trains CNN models on labeled image data to detect and classify various tumor types.

•Ensures balanced datasets and handles image preprocessing efficiently throughout the pipeline.

•Evaluates model performance using metrics such as accuracy, precision, and recall.

•Designed for scalability to support larger datasets or real-time diagnostic applications.

Objectives

- Automate the detection of brain tumors from MRI images using deep learning.
- Enhance Accuracy by minimizing human error through algorithmic diagnosis.
- Preprocess Images with techniques like cropping, sharpening.
- Design a CNN Model capable of classifying tumor types based on MRI scans.
- Split Data Strategically using stratified sampling for balanced learning.
- Improve Speed of diagnosis through real-time or near-real-time processing.
- Evaluate Performance using relevant metrics like accuracy, recall, and F1-score.

Goals

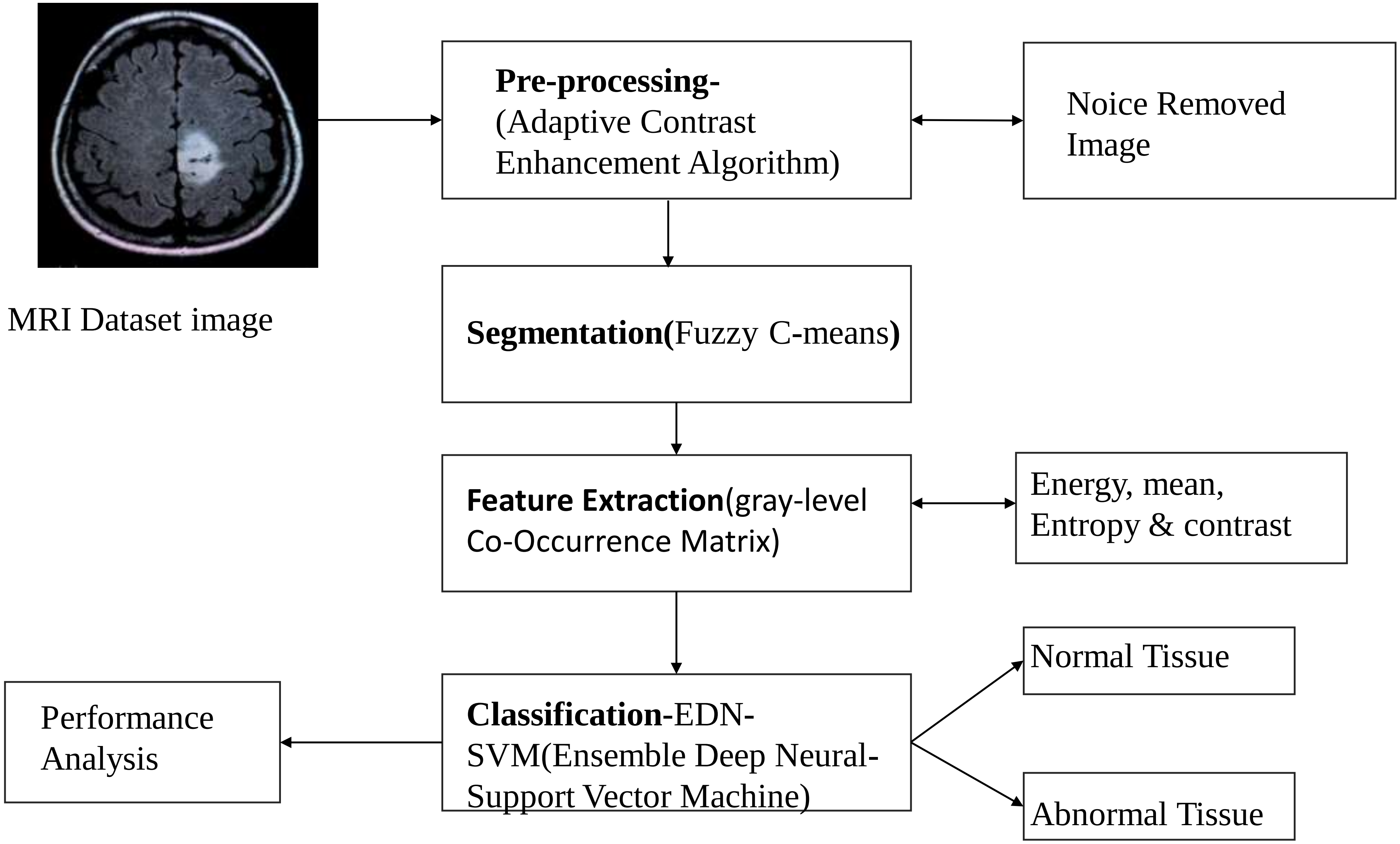
- Achieve high classification accuracy for different types of brain tumors.
- Reduce diagnostic time through fast and automated analysis.
- Support radiologists and doctors in early and accurate tumor identification.
- Build a scalable model adaptable to larger datasets and real-time applications.
- Integrate effective preprocessing techniques to improve model input quality.
- Lay the foundation for future research and real-world clinical deployment.

Literature Review

S .No	Paper Title	Authors	Models/Algorithms	Drawbacks
01	MRI brain tumor detection using deep learning and machine learning approaches	Shenbagarajan Anantharajan, Shenbagalakshmi Gunasekaran, Thavasi Subramanian, Venkatesh R	Adaptive Contrast Enhancement and Median Filtering are used for MRI image preprocessing.Fuzzy C-Means segmentation and GLCM feature extraction identify tumor characteristics.The proposed Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifies healthy and tumorous tissues.	Overfitting, Dependence on Image Quality and Preprocessing, Model Complexity.
02	Image Segmentation for MR Brain Tumor Detection Using Machine Learning	Toufique A.,Soomro,Lihong Zheng,Ahmed J. Afifi,Ahmed Ali ,Shafiullah Soomro,Ming Yin,Junbin Gao.	Supervised (e.g., SVM, Random Forest, Decision Trees) Unsupervised (e.g., K-means, Fuzzy C-means, SOM) **Deep Learning Models**: CNN (Convolutional Neural Networks),FCNN (Fully Convolutional Neural Networks),U-Net,DenseNet, ResNet, VGGNet, Inception-v3,GANs,Autoencoders	Low Image Quality, Annotation Issues, Generalization, Data Imbalance, Tumor Variability.

03	Brain Tumor Image Identification and Classification on the Internet of Medical Things Using Deep Learning	B. Raghuram and Bhukya Hanumanthu	Support Value-Based Deep Neural Network (SDNN) K-Means Clustering (KMC) **Feature Extraction Techniques**: Grey-Level Co-occurrence Matrix (GLCM) . Geometric features. Entropy measures. **Preprocessing Techniques** Contrast-Restricted Adaptive Histogram Balancing (CRAHB)	Dependence on Image Quality, Segmentation Challenges, Generalizability Concerns.

Existing Architecture



Existing Work

Input Stage

•MRI brain scan from dataset.

Pre-processing

•Adaptive Contrast Enhancement.

•Enhances contrast & removes noise.

•Outputs noise-free image.

Segmentation

•Fuzzy C-means clustering.

•Segments image into meaningful regions.

Feature Extraction

•Gray-Level Co-Occurrence Matrix (GLCM).

•Key features: Energy, Mean, Entropy, Contrast.

Classification

•Model: EDN-SVM (Ensemble Deep Neural - SVM).

•Combines neural networks with SVM.

•Output: Normal or Abnormal Tissue.

Performance Analysis

•Metrics: Accuracy, Sensitivity, Specificity, AUC.

•Evaluates model effectiveness.

Disadvantages

•Uses GLCM for extracting statistical features like entropy and contrast, which limits the model’s ability to learn complex tumor patterns.

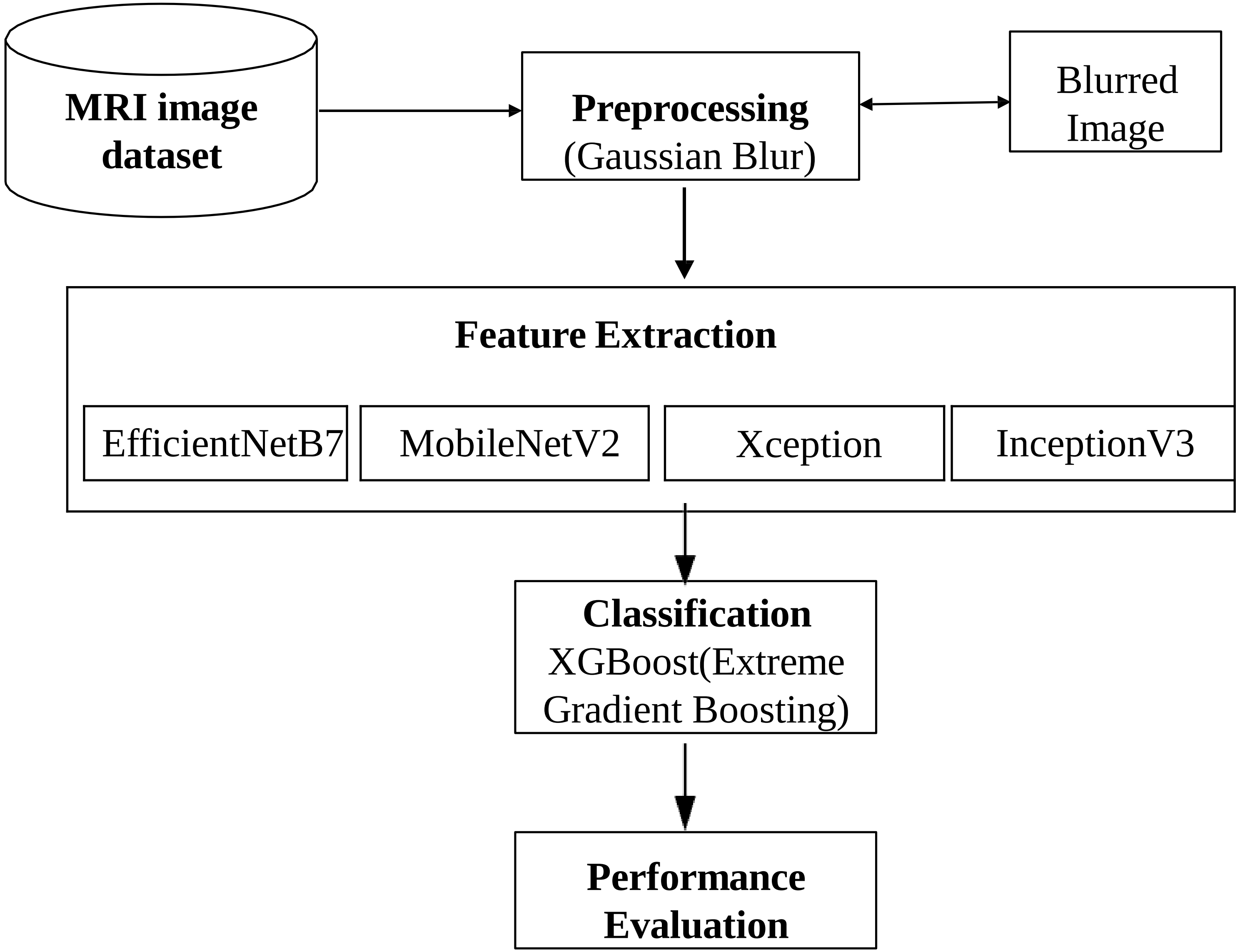
•Feature extraction and classification are done separately (GLCM → EDN-SVM), preventing the system from optimizing performance holistically.

•GLCM features are sensitive to noise and variations in MRI quality, making the system less reliable for diverse or noisy clinical images.

Problem Statement

- Manual diagnosis of brain tumors through MRI image analysis is time-consuming, prone to human error, and requires specialized medical expertise.
- With the growing volume of medical imaging data and increasing demand for accurate diagnosis, there is a critical need for an automated system that can assist healthcare professionals in detecting and classifying brain tumors efficiently.
- This project aims to develop a deep learning-based solution that can analyze MRI images, identify the presence and type of brain tumors, and provide fast, reliable, and scalable support for clinical decision-making.

Proposed Architecture



Proposed Work

1. Dataset Preparation

- The dataset comprises brain MRI images categorized into different classes such as **glioma**, **meningioma**, **pituitary tumor**, and **no tumor**.
- Images are loaded from a structured directory where each subfolder represents a tumor class.

2. Image Preprocessing Pipeline

- **Cropping**: Each MRI image is processed to extract the brain region by detecting and isolating the largest contour.

- **Grayscale Conversion**: The images are converted to grayscale to reduce dimensionality and focus on intensity features.
- **Sharpening & Blurring**: Sharpening filters enhance tumor boundaries, while Gaussian blurring reduces background noise.
- **Edge Detection**: Canny edge detection highlights the boundaries of tumors.
- **Contour Extraction**: Contours are drawn on images to visually emphasize the affected region, aiding the model in learning structural features.
- **Resizing** : All processed images are resized to a standard shape (e.g., 256×256).

3. Data Labeling and Splitting

- The images are labeled based on their parent directory (tumor type).
- The dataset is divided into **training** and **testing** sets using stratified sampling to preserve class balance.

4. Model Development

- We use pre-trained CNNs (EfficientNetB7, MobileNetV2, Exception ,Inception) for automatic, deep feature extraction from MRI images, enabling end-to-end learning.
- XGBoost is employed as a fast, scalable classifier supporting multi-class tumor detection with high accuracy and efficiency.

- The final dense layers are adapted for binary or multi-class classification based on the dataset.

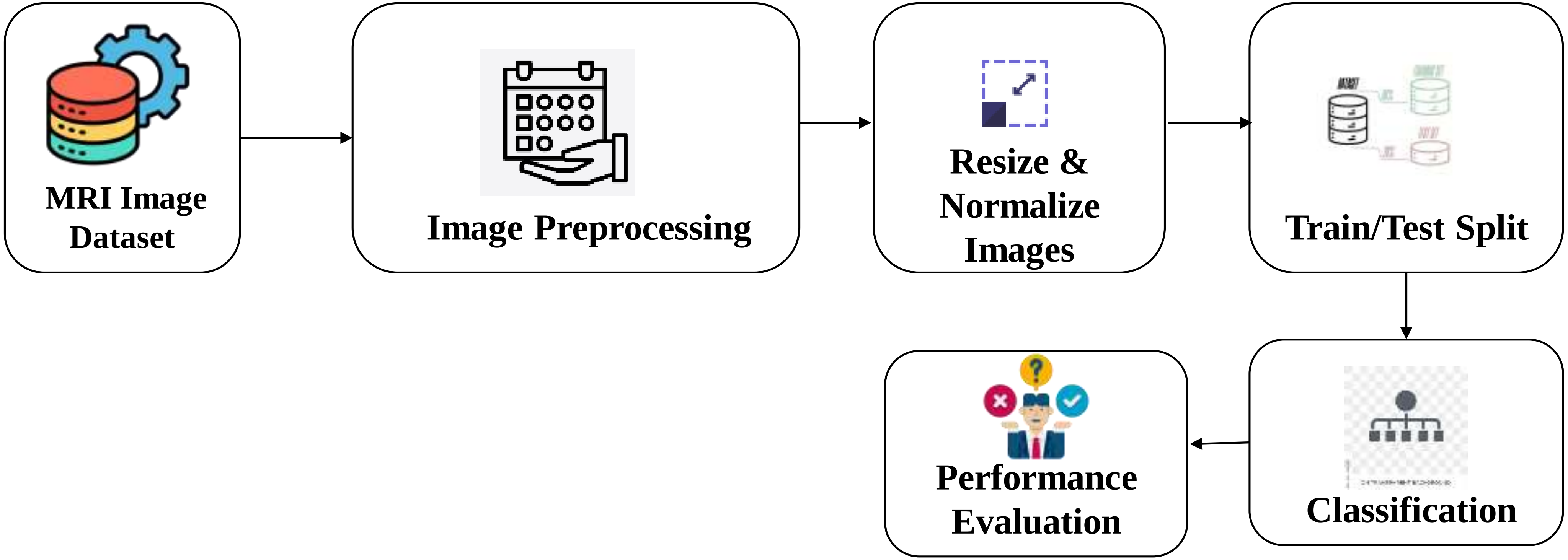
5. Model Training

- The model is compiled with suitable loss functions (binary or categorical cross-entropy) and optimized using the Adam optimizer.
- The training is conducted over several epochs, and validation is performed concurrently to monitor overfitting and generalization.

6. Evaluation and Prediction

- The trained model is evaluated using performance metrics like **accuracy**, **precision**, **recall**, and **F1-score**.

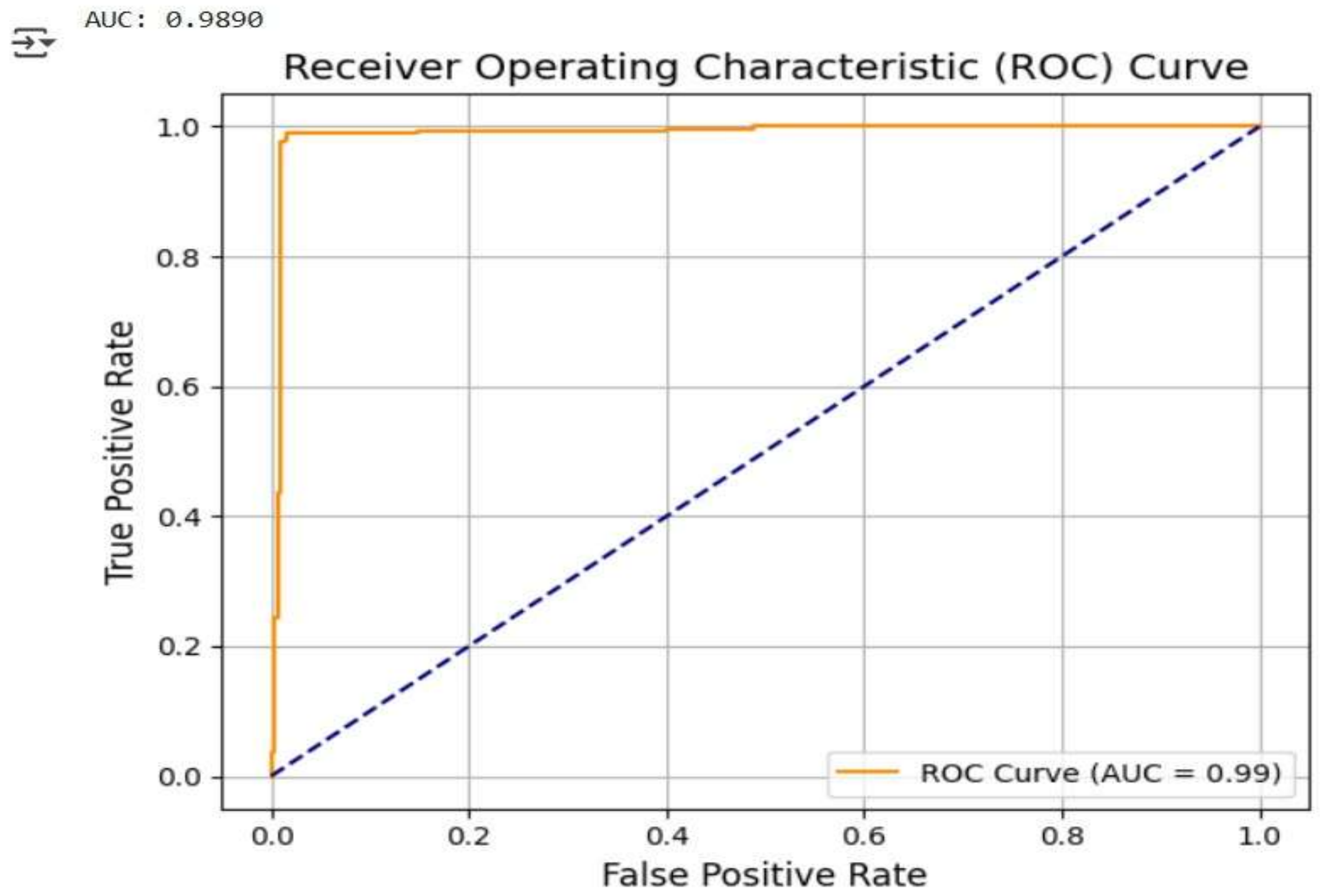
- The model provides **prediction outputs** along with **confidence scores** for each class.



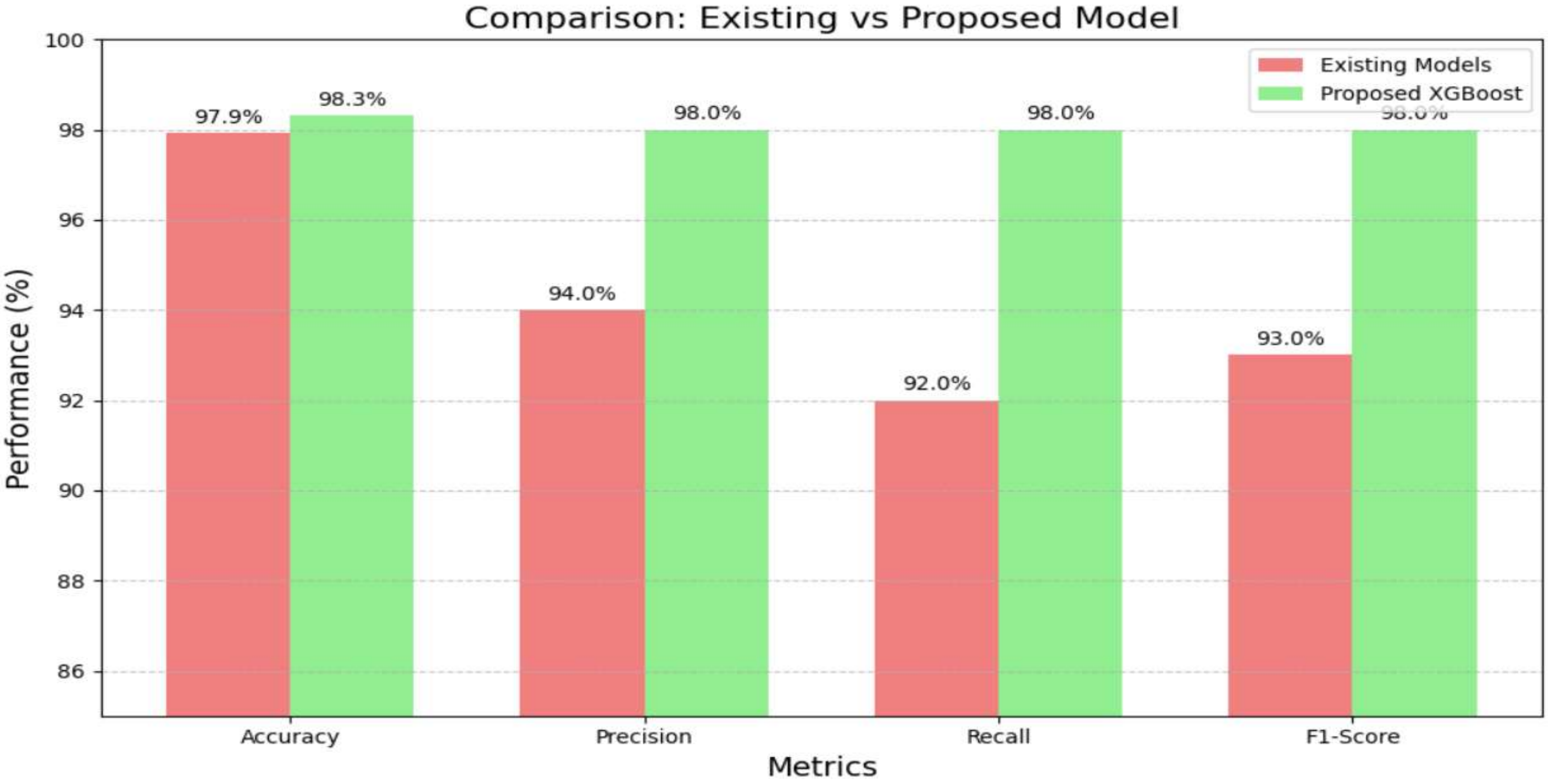
Output & Results

```
Accuracy: 98.33%
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       305
           1       0.98      0.98      0.98       295

    accuracy                           0.98       600
   macro avg       0.98      0.98      0.98       600
weighted avg       0.98      0.98      0.98       600
```

ROC Curve


AUC: 0.9890
Receiver Operating Characteristic (ROC) Curve
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
ROC Curve (AUC = 0.99)

Existing Work Vs Proposed Work



Tools Required

Category	Tools & Libraries	Purpose
Programming	Python	Main Language for implementation
Data Handling	Pandas , NumPy	Processing and storing extracted features
Image Processing	OpenCV , Scikit-Image	Loading , resizing , and extracting MRI features
Machine Learning	XGBoost	Training a Classifier for brain tumors detection
Visualization	Matplotlib	Displaying MRI images and feature distributions

Conclusion

- This project developed a brain tumor detection system using deep learning and machine learning.
- Features were extracted using pre-trained CNNs like EfficientNetB7, Xception, MobileNetV2 and Inception.
- An XGBoost classifier was trained on combined features for binary classification of MRI images.
- The model achieved high accuracy, supported by metrics like ROC-AUC and confusion matrix.
- This hybrid approach shows promise for clinical decision support in early tumor diagnosis.

Future Enhancements

•Expand to multi-class classification (e.g., glioma, meningioma) for finer tumor type prediction.

•Utilize 3D MRI volumes to capture spatial tumor features more accurately.

•Add explainable AI tools like Grad-CAM to improve model interpretability.

•Integrate into real-time clinical systems or mobile health applications for practical use.

Reference

1.Shenbagarajan A., Shenbagalakshmi G., Thavasi S., & Venkatesh R. (2024). ***MRI Brain Tumor Detection Using Deep Learning and Machine Learning Approaches****. Measurement: Sensors, 31, Article 101026. DOI: [10.1016/j.measen.2024.101026](https://doi.org/10.1016/j.measen.2024.101026)*

2. . Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., ... & Menze, B. H. (2017). Identifying the Best Machine Learning Algorithms for Brain Tumor Segmentation, Progression Assessment, and Overall Survival Prediction

3. Raghuram, B., & Hanumanthu, B. (2023). Brain tumor image identification and classification on the Internet of Medical Things using deep learning. Measurement: Sensors, 30, 100905.

Thank You!