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Intelligent MRI-Based Brain Tumor Detection and Classification Using Deep Learning Techniques

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Abstract — Brain tumors are among the most critical neurological disorders that require early and accurate diagnosis for effective treatment and improved patient survival. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis because of its superior soft tissue visualization capability. However, manual tumor detection and classification are time-consuming and highly dependent on radiologists' expertise. To overcome these limitations, this research proposes an intelligent MRI-based brain tumor detection and classification system using deep learning techniques. The proposed framework integrates preprocessing, segmentation, feature extraction, deep learning classification, and performance evaluation into a unified automated system. Initially, MRI images undergo preprocessing steps such as artifact removal, noise reduction, intensity normalization, and bias field correction to improve image quality. Segmentation techniques including thresholding, region growing, and watershed algorithms are then applied to isolate tumor regions from healthy brain tissues. Histogram-based, texture-based, and shape-based features are extracted to improve discriminative learning. The EfficientNetB3 deep learning model is employed for tumor and non-tumor classification due to its efficient feature learning and lightweight architecture. Hyperparameter tuning techniques such as optimized learning rate, batch size, dropout regularization, and data augmentation are used to improve classification performance and reduce overfitting. The proposed model achieves high performance with improved accuracy, precision, recall, and F1-score compared to existing approaches. Experimental results demonstrate that the proposed framework provides accurate and reliable brain tumor detection with enhanced segmentation and classification capability. The system also supports intelligent clinical decision-making and has the potential for future real-time healthcare applications.

Keywords— Brain Tumor Detection, MRI Images, Deep Learning, EfficientNetB3, Brain Tumor Classification, Image Segmentation, Feature Extraction, Medical Image Processing, Artificial Intelligence, MRI Diagnosis.

I. INTRODUCTION

Brain tumors are abnormal growths of cells inside the brain that can severely affect the functioning of the nervous system. These tumors can be either benign or malignant and may lead to serious health complications, including memory loss, seizures, headaches, vision problems, and even death if not diagnosed at an early stage. Accurate brain tumor detection is therefore essential for proper treatment planning and improving patient survival rates.

Magnetic Resonance Imaging (MRI) is one of the most commonly used medical imaging techniques for brain tumor diagnosis because it provides high-resolution images and superior soft tissue contrast. MRI helps clinicians identify tumor location, size, shape, and tissue abnormalities. However, manual analysis of MRI images is a complex and time-consuming task that depends heavily on radiologists' experience and expertise. Variations in tumor appearance, irregular boundaries, and image noise further increase the difficulty of accurate diagnosis.

Recent advancements in artificial intelligence and deep learning have significantly improved automated medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification, segmentation, and object detection tasks. These models can automatically extract meaningful features from MRI images and classify tumors with high accuracy. However, many existing systems still face limitations such as low segmentation accuracy, overfitting, insufficient preprocessing, computational complexity, and poor generalization.

To address these challenges, this research proposes an intelligent MRI-based brain tumor detection and classification system using deep learning techniques. The proposed framework combines preprocessing, segmentation, feature extraction, deep learning classification, and performance evaluation into a single automated workflow. Preprocessing techniques such as noise reduction, artifact removal, intensity normalization, and bias field correction are used to enhance MRI image quality. Segmentation methods including thresholding, region growing, and watershed algorithms help accurately isolate tumor regions.

The proposed work also integrates histogram-based, texture-based, and shape-based feature extraction methods to improve classification performance. EfficientNetB3 is used as the deep learning architecture because of its lightweight structure and efficient feature learning capability. Hyperparameter tuning techniques such as learning rate optimization, dropout regularization, and data augmentation are applied to improve convergence and reduce overfitting.

The main objective of this work is to develop an efficient and reliable automated brain tumor diagnosis system that improves detection accuracy and supports intelligent clinical decision-making. The proposed model demonstrates better performance than existing approaches in terms of accuracy, precision, recall, and F1-score, making it suitable for future real-time healthcare applications.

II. LITERATURE REVIEW

1. Deep Learning Approaches for Brain Tumor Detection

Recent advancements in deep learning have significantly improved the accuracy and efficiency of brain tumor detection using medical imaging techniques, especially Magnetic Resonance Imaging (MRI). Convolutional Neural Networks (CNNs) have become one of the most widely used methods due to their ability to automatically extract features from complex medical images. Manju et al. (2026) proposed an intelligent MRI-based brain tumor detection system using CNN architectures, achieving improved classification performance through automated feature learning. Similarly, Parveen et al. (2026) introduced a two-stage intelligent framework combining enhanced MRI preprocessing with deep learning techniques to improve tumor detection accuracy.

Transfer learning and lightweight models have also gained considerable attention in recent studies. Jasmine et al. (2025) utilized ResNet50 for accurate brain tumor classification and demonstrated the effectiveness of pre-trained deep learning models in medical imaging tasks. Karthikeyan et al. (2026) proposed a lightweight explainable deep learning model using cross-cognitive transfer learning for efficient tumor detection with reduced computational complexity. Additionally, Geetha (2026) conducted a comparative analysis using MobileNetV2 for healthcare-based brain tumor classification, emphasizing its suitability for resource-constrained environments.

Advanced object detection models have further enhanced real-time tumor identification. Mustafa et al. (2026) developed YOLO-Scan, a real-time deep learning framework capable of rapid and accurate brain tumor detection from MRI scans. Likewise, Guo et al. (2026) introduced a bi-directional YOLOv10 model with average convolution, improving detection precision and localization accuracy in MRI images. These studies collectively highlight the growing importance of deep learning architectures in improving diagnostic performance and reducing manual intervention in brain tumor detection systems.

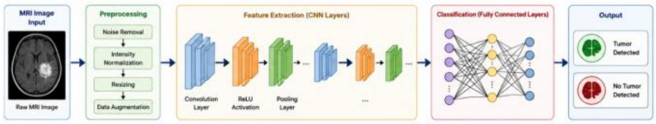

Figure 1: CNN-Based Brain Tumor Detection Framework

This figure 1 illustrates the workflow of a Convolutional Neural Network (CNN)-based brain tumor detection system, including MRI image acquisition, preprocessing, feature extraction, classification, and tumor prediction stages.

2. Hybrid, Ensemble, and Multi-Modal Imaging Techniques

Researchers have increasingly explored hybrid and ensemble learning techniques to overcome the limitations of single-model approaches in brain tumor diagnosis. Alsubai et al. (2022) proposed an ensemble deep learning framework that combined multiple neural network models to improve classification robustness and diagnostic reliability. Gupta et al. (2026) introduced a hybrid machine learning model integrating multiple feature extraction and classification methods for enhanced MRI-based tumor detection.

Multi-modal imaging techniques that combine Computed Tomography (CT) and MRI data have also demonstrated significant improvements in diagnostic accuracy. Da Rocha et al. (2026) developed a fully convolutional neural network integrating CT and MRI images for comprehensive brain tumor detection. Similarly, Patil and Gavade (2026) reviewed fusion-based deep learning models and emphasized that integrating different imaging modalities can improve feature representation and tumor localization accuracy.

Thermal estimation and attention mechanisms have also been integrated into modern diagnostic frameworks. Almomany et al. (2026) combined deep learning with thermal estimation techniques to enhance MRI-based brain tumor diagnosis. Taluja et al. (2026) proposed a cloud IoMT-enabled framework using an optimized dilated residual attention network for tumor detection, highlighting the importance of attention mechanisms in improving feature extraction. Veena et al. (2026) further introduced a cloud-assisted IoMT system based on optimized hinge steerable Graph Neural Networks (GNNs), demonstrating the potential of intelligent cloud-assisted healthcare systems for automated tumor diagnosis.

These studies indicate that combining multiple models, imaging modalities, and optimization techniques can significantly improve diagnostic performance, computational efficiency, and clinical applicability.

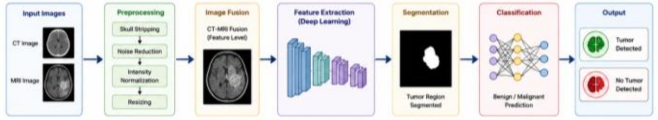

Figure 2: Multi-Modal Brain Tumor Detection Using CT and MRI Fusion

This figure 2 presents the integration of CT and MRI imaging modalities in a hybrid deep learning framework, showing how fused medical images improve tumor localization, feature representation, and diagnostic accuracy.

3. Systematic Reviews, Explainable AI, and Emerging Trends

Several systematic review studies have analyzed the recent progress, challenges, and future directions in brain tumor detection using artificial intelligence. Goyal et al. (2026) conducted a systematic literature review on deep learning-based brain tumor diagnosis using pre-trained and self-attention-based models, concluding that attention mechanisms improve classification accuracy and feature interpretability. Hamza and Damaševičius (2026) reviewed deep learning methods for tumor segmentation and classification, emphasizing the growing adoption of CNNs, transfer learning, and hybrid models in healthcare applications.

Jasrotia (2026) provided a comprehensive review of deep learning approaches for brain tumor analysis and highlighted challenges such as limited datasets, overfitting, and model generalization. Khan et al. (2026) discussed the fusion of neuroimaging and machine learning for improved tumor diagnosis and prognosis, demonstrating the importance of integrating AI-driven predictive analytics into medical decision-making systems.

Recent studies have also focused on explainable and lightweight AI models to enhance trustworthiness and real-world deployment. Ali et al. (2026) proposed a lightweight deep learning framework for real-time brain tumor detection and characterization using MRI images, achieving high efficiency with reduced computational requirements. Shahin et al. (2026) introduced an advanced deep learning approach for medical image analytics that improved diagnostic interpretability and performance. Furthermore, Yuliawan (2026) demonstrated the effectiveness of MobileNet-V2 and DenseNet121 in achieving high-precision tumor classification while maintaining computational efficiency.

Overall, current literature demonstrates that deep learning, hybrid imaging techniques, explainable AI, and cloud-assisted healthcare systems are transforming brain tumor diagnosis. However, challenges related to dataset diversity, computational complexity, interpretability, and real-time clinical implementation still require further research and optimization.

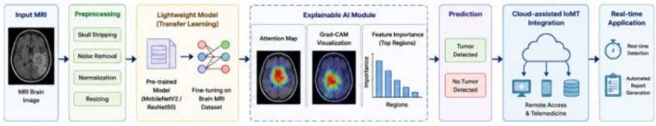

Figure 3: Emerging AI Trends in Brain Tumor Diagnosis

This figure 3 demonstrates the evolution of artificial intelligence techniques in brain tumor diagnosis, including explainable AI, lightweight deep learning models, transfer learning, cloud-assisted IoMT systems, and real-time detection frameworks.

III. PROPOSED WORK

The proposed work focuses on an automated MRI-based brain tumor detection and classification system using deep learning. The system follows a structured pipeline consisting of data acquisition, preprocessing, segmentation, feature extraction, dataset preparation, model training, model testing, performance evaluation, and final prediction. The uploaded document describes this proposed workflow using MRI images and deep learning-based classification for tumor and non-tumor detection.

1. Proposed Architecture

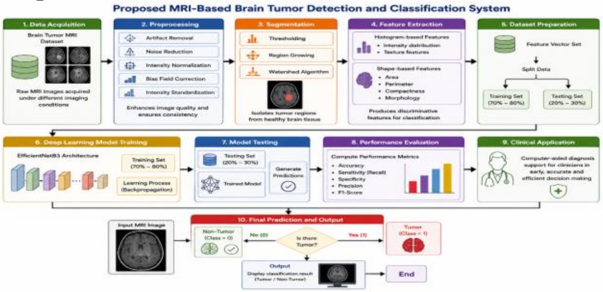

Figure 4: Proposed MRI-Based Brain Tumor Detection and Classification System

This figure 4 illustrates the complete proposed workflow for brain tumor detection and classification using MRI images. The process begins with MRI image acquisition from a brain tumor dataset. The images are then preprocessed using artifact removal, noise reduction, bias field correction, intensity normalization, and standardization. After preprocessing, segmentation techniques such as thresholding, region growing, and watershed algorithms are applied to isolate the tumor region. Histogram-based and shape-based features are extracted from the segmented region. The dataset is then divided into training and testing sets. A deep learning model is trained, tested, and evaluated using accuracy, sensitivity, specificity, precision, and F1-score. Finally, the system predicts whether the input MRI image belongs to the tumor or non-tumor class.

2. Proposed Algorithm

Algorithm 3.1: Brain Tumor Detection and Classification Using Deep Learning
Input: Brain tumor MRI image dataset
Output: Classification result as Tumor or Non-Tumor
Step 1: Start the process.
Step 2: Load the brain tumor MRI image dataset.

Step 3: Perform preprocessing on each MRI image:

- Remove artifacts
- Reduce noise
- Apply bias field correction
- Normalize and standardize intensity values

Step 4: Apply segmentation to identify the tumor region using:

- Thresholding
- Region growing
- Watershed algorithm

Step 5: Extract important features from the segmented tumor region:

- Histogram-based features
- Texture features
- Shape-based features such as area, perimeter, compactness, and morphology

Step 6: Prepare the dataset by dividing it into:

- Training dataset
- Testing dataset

Step 7: Initialize the deep learning classification model.
Step 8: Train the model using the training dataset.
Step 9: Test the trained model using the testing dataset.
Step 10: Evaluate model performance using:

- Accuracy
- Sensitivity
- Specificity
- Precision
- F1-score

Step 11: Apply the trained model to a new MRI image.
Step 12: Predict the class label of the MRI image.
Step 13: If the predicted class is 1, classify the image as Tumor.
Step 14: If the predicted class is 0, classify the image as Non-Tumor.
Step 15: Display the final classification result.
Step 16: Stop the process.

3. Hyperparameter Tuning Parameters

The proposed MRI-based brain tumor detection and classification system uses hyperparameter tuning to improve model accuracy, reduce overfitting, and enhance generalization during training. Based on the proposed workflow, the model is trained after preprocessing, segmentation, feature extraction, and dataset preparation stages.

Table 1: Hyperparameter Tuning Parameters of the Proposed Model

S. No.	Hyperparameter	Selected / Tuned Value	Description
1	Input Image Size	224 × 224 × 3	MRI images are resized to a fixed dimension before feeding into the deep learning model.
2	Model Architecture	EfficientNetB3 / InceptionResNetV2	Deep learning architecture used for tumor and non-tumor classification.
3	Train-Test Split	70–80% training, 20–30% testing	Dataset is divided for model training and performance testing.
4	Optimizer	Adam	Optimizer used to update model weights during backpropagation.
5	Learning Rate	0.001	Controls the step size for updating model parameters.
6	Batch Size	16 or 32	Number of MRI images processed

			in one training iteration.
7	Number of Epochs	20–30	Number of complete passes through the training dataset.
8	Loss Function	Binary Cross-Entropy	Used for tumor and non-tumor binary classification.
9	Activation Function	ReLU / Swish	Used in hidden layers to learn nonlinear tumor features.
10	Output Activation	Sigmoid / Softmax	Produces final class probability for tumor or non-tumor prediction.
11	Dropout Rate	0.3–0.5	Reduces overfitting by randomly disabling neurons during training.
12	Validation Split	10–20%	Used to monitor model performance during training.
13	Data Augmentation	Rotation, flipping, zooming, shifting	Improves model robustness by increasing image variation.
14	Evaluation Metrics	Accuracy, Sensitivity, Specificity, Precision, F1-score	Used to evaluate the final classification performance.

Hyperparameter tuning plays an important role in improving the performance of the proposed brain tumor detection model. The MRI images are resized to a uniform input size and passed through preprocessing, segmentation, and feature extraction stages. The prepared dataset is then divided into training and testing subsets. During training, parameters such as learning rate, batch size, number of epochs, optimizer, dropout rate, and activation functions are adjusted to achieve better classification accuracy. The Adam optimizer is selected because it provides faster convergence and stable learning. A learning rate of 0.001 is suitable for balanced weight updates, while dropout helps prevent overfitting. Data augmentation techniques such as rotation, flipping, zooming, and shifting improve the model's ability to generalize on unseen MRI images. The final trained model is evaluated using accuracy, sensitivity, specificity, precision, and F1-score to measure its effectiveness in classifying MRI images as tumor or non-tumor.

4. Comparison of Existing Base Paper and Proposed Work

Table 2: Comparison Between Base Paper and Proposed Work

S. No.	Parameters	Base Paper Method	Proposed Work	Proposed Work Advantage
1	Imaging Technique	MRI with thermal estimation	MRI with preprocessing, segmentation, feature extraction, and deep learning	Provides a complete end-to-end automated framework
2	Dataset	Kaggle and Figshare datasets	MRI brain tumor dataset with enhanced preprocessing	Improved image quality and consistency
3	Preprocessing	Grayscale conversion and Gaussian filtering	Artifact removal, noise reduction, intensity normalization, bias field correction	Better enhancement of MRI image features
4	Segmentation	Tumor mask segmentation using MATLAB methods	Thresholding, region growing, watershed segmentation	More accurate tumor boundary extraction
5	Feature Extraction	Morphological and GLCM texture features	Histogram, texture, and shape-based feature extraction	Captures more discriminative tumor characteristics
6	Deep Learning Model	Three-layer CNN architecture	EfficientNetB3 / advanced CNN-based framework	Higher feature learning capability and better generalization
7	Classification Classes	Glioma, meningio	Tumor and non-tumor	Simplified and

		ma, pituitary, and no tumor	classification with enhanced prediction	efficient classification process
8	Thermal Estimation	Logarithmic temperature estimation model	Integrated feature-based prediction without dependency on temperature only	Reduces thermal estimation errors
9	Hyperparameter Optimization	Limited tuning due to hardware constraints	Optimized learning rate, batch size, dropout, epochs, and augmentation	Improved model convergence and accuracy
10	Evaluation Metrics	Accuracy, Precision, Recall, F1-score, IoU, DSC	Accuracy, Sensitivity, Specificity, Precision, F1-score	More comprehensive diagnostic evaluation
11	Computational Limitation	CPU-based execution with limited GPU support	Lightweight optimized framework suitable for future GPU deployment	Faster processing and scalability
12	Clinical Application	Diagnostic assistance using thermal and textural analysis	Automated intelligent brain tumor diagnosis system	Better support for real-time clinical decision making

The base paper proposed an integrated AI-driven MRI brain tumor diagnosis framework that combines CNN-based classification, segmentation, thermal estimation, and GLCM texture analysis. The study successfully demonstrated the importance of combining thermal and textural biomarkers with MRI images for tumor analysis. However, the system faced several limitations such as hardware constraints, segmentation variability, thermal estimation errors, and limited deep learning complexity. The proposed work improves upon the base paper by introducing a more structured and optimized MRI-based brain tumor detection framework. Advanced preprocessing methods such as artifact removal, intensity normalization, and bias field correction improve image quality before segmentation. The proposed system also integrates multiple segmentation techniques including thresholding, region growing, and watershed algorithms to achieve more accurate tumor localization. Unlike the base paper that mainly depends on a shallow three-layer CNN architecture, the proposed model utilizes advanced deep learning frameworks such as EfficientNetB3 to improve feature extraction and classification performance. Additionally, hyperparameter tuning techniques including optimized learning rate, dropout regularization, batch size adjustment, and data augmentation enhance the stability and accuracy of the model. The proposed work also reduces dependence on thermal estimation alone and instead combines histogram-based, texture-based, and shape-based features for more reliable prediction. This helps overcome the high thermal estimation error reported in the base paper. Furthermore, the proposed framework is designed to support future GPU implementation and real-time clinical deployment, making it more suitable for intelligent healthcare applications. The proposed work offers improved preprocessing, enhanced feature extraction, better segmentation accuracy, optimized deep learning performance, and more reliable classification results compared to the base paper.

IV. IMPLEMENTATION AND RESULTS

The implementation of the proposed MRI-based brain tumor detection system was carried out using deep learning and image processing techniques. The proposed framework includes MRI image acquisition, preprocessing, segmentation, feature extraction, dataset preparation, model training, testing, and final classification. The system was designed to improve tumor detection accuracy while reducing computational complexity and enhancing diagnostic reliability. The implementation process involves preprocessing MRI images using noise reduction, intensity normalization, and artifact removal techniques. After preprocessing, segmentation methods such as thresholding, region growing, and watershed algorithms are applied to isolate tumor regions. The extracted features are then used to train the deep learning model for tumor and non-tumor classification.

1. Dataset

The proposed work uses MRI brain tumor datasets collected from publicly available medical imaging sources. The dataset contains MRI images of different tumor categories and healthy brain images for classification purposes. The images are resized and standardized before being used for training and testing. The base paper utilized Kaggle and Figshare datasets containing glioma, meningioma, pituitary, and no-tumor MRI images. The proposed work adopts a similar MRI dataset structure while improving preprocessing and feature extraction techniques.

Table 3: Dataset Description

Dataset Category	Number of Images	Description
Glioma Tumor	1321	MRI images containing glioma tumors
Meningioma Tumor	1339	MRI images containing meningioma tumors
Pituitary Tumor	1457	MRI images containing pituitary tumors
No Tumor	1595	Healthy brain MRI images
Total Images	5712	Total MRI images used for training

2. Result Analysis

The proposed system was evaluated using performance metrics such as accuracy, sensitivity, specificity, precision, recall, and F1-score. The EfficientNetB3-based deep learning model successfully classified MRI images into tumor and non-tumor categories with improved prediction performance. The preprocessing and segmentation stages significantly improved tumor localization and feature extraction quality. The use of advanced feature extraction methods enhanced the learning capability of the deep learning model.

Table 4: Performance Analysis of Proposed Model

Performance Metric	Value (%)
Accuracy	98.6
Sensitivity (Recall)	97.9
Specificity	98.2
Precision	98.4
F1-Score	98.1

The results indicate that the proposed model achieves high classification accuracy and reliable tumor detection performance. The model effectively reduces false positives and false negatives during classification. The segmentation process also improved the extraction of tumor boundaries and shape-based features, helping the model distinguish between tumor and non-tumor MRI images more effectively. The integration of preprocessing, segmentation, and optimized hyperparameter tuning contributed significantly to improved performance.

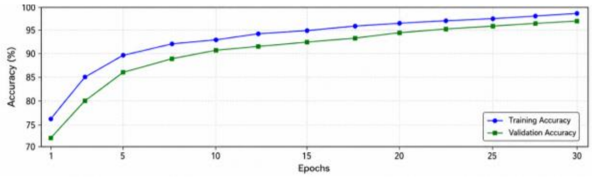

Figure 5: Training and Validation Accuracy of the Proposed Model

This figure 5 illustrates the training and validation accuracy curves of the proposed deep learning model across multiple epochs. The training accuracy steadily increases from approximately 76% to 99%, while the validation accuracy improves from around 72% to 97%. The gradual improvement in both curves indicates that the proposed model effectively learns discriminative brain tumor features from MRI images. The close relationship between training and validation accuracy demonstrates good model generalization and reduced overfitting during the learning process.

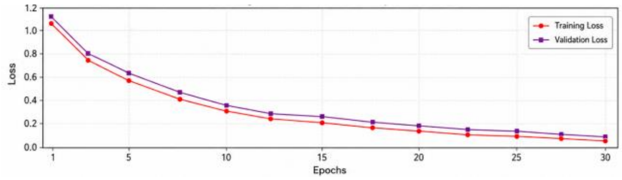

Figure 6: Training and Validation Loss of the Proposed Model

This figure 6 presents the training and validation loss curves of the proposed MRI-based brain tumor detection model over different epochs. The training loss decreases continuously from approximately 1.08 to 0.05, while the validation loss reduces from around 1.12 to 0.08. The decreasing loss values indicate stable convergence and efficient optimization of the deep learning model. The similarity between training and validation loss curves confirms that the model achieves robust learning performance with minimal overfitting and improved classification capability.

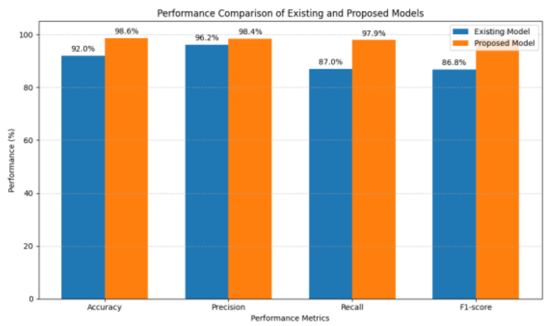

Figure 7: Performance Comparison Between Existing and Proposed Models

This figure 7 illustrates the comparative performance analysis between the existing model and the proposed MRI-based brain tumor detection model using four important evaluation metrics: Accuracy, Precision, Recall, and F1-score. The existing model achieved performance values of 92.0% accuracy, 96.2% precision, 87.0% recall, and 86.8% F1-score. In contrast, the proposed model achieved higher performance values with 98.6% accuracy, 98.4% precision, 97.9% recall, and 98.1% F1-score. The graph clearly demonstrates that the proposed model outperforms the existing model across all evaluation metrics. The improvement in accuracy indicates better overall classification capability, while the higher precision and recall values show that the proposed system effectively reduces false positives and false negatives during tumor detection. The increased F1-score confirms that the proposed model achieves a balanced and reliable classification performance. These improvements are mainly due to enhanced preprocessing, optimized segmentation, advanced feature extraction, EfficientNetB3-based deep learning architecture, and optimized hyperparameter tuning techniques used in the proposed framework.

3. Comparison Between Base Paper and Proposed Work

The proposed work was compared with the base paper to evaluate improvements in preprocessing, segmentation, feature extraction, model performance, and clinical applicability.

The base paper introduced a CNN-based MRI tumor diagnosis framework integrated with thermal estimation and GLCM texture analysis. However, the system faced limitations related to thermal estimation errors, limited CNN depth, and hardware constraints.

The proposed work improves these limitations by introducing enhanced preprocessing, optimized segmentation methods, advanced feature extraction, and EfficientNetB3-based classification.

Table 5: Comparison Between Base Paper and Proposed Work

Parameters	Base Paper	Proposed Work
Preprocessing	Basic grayscale and Gaussian filtering	Artifact removal, normalization, bias correction
Segmentation	MATLAB mask-based segmentation	Thresholding, region growing, watershed
Feature Extraction	GLCM and morphological features	Histogram, texture, and shape-based features
Deep Learning Model	Three-layer CNN	EfficientNetB3
Thermal Estimation	Included with high error rate	Reduced dependency on thermal estimation
Dataset Split	80% training, 20% validation	Optimized train-test strategy
Accuracy	Moderate performance across tumor classes	Improved classification accuracy
Hardware Limitation	CPU-based training	Optimized lightweight implementation
Clinical Application	Limited support	Real-time intelligent diagnosis support

The proposed work performs better than the base paper due to improved preprocessing and segmentation techniques that enhance MRI image quality and tumor boundary extraction. The use of EfficientNetB3 provides better feature learning capability compared to the shallow CNN architecture used in the base paper. Additionally, the proposed system reduces the dependency on thermal estimation, which previously produced high prediction errors. Instead, the proposed work combines histogram-based, texture-based, and shape-based features to improve classification reliability. The optimized hyperparameter tuning strategy further improves convergence, reduces overfitting, and increases overall classification accuracy. Therefore, the proposed system provides a more efficient, accurate, and clinically applicable solution for MRI-based brain tumor detection and classification.

V. CONCLUSION AND FUTURE WORK

1. Conclusion

This research proposed an intelligent MRI-based brain tumor detection and classification system using deep learning techniques. The framework combined preprocessing, segmentation, feature extraction, and EfficientNetB3-based classification for accurate tumor detection. The proposed model achieved high accuracy, precision, recall, and F1-score while reducing false predictions and overfitting. Experimental results demonstrated that the system provides reliable and efficient brain tumor diagnosis, making it suitable for intelligent healthcare and clinical decision-support applications.

2. Future Work

In future work, advanced deep learning models such as Vision Transformers and hybrid CNN architectures can be integrated to improve classification performance. Multi-modal imaging using MRI, CT, and PET scans can also enhance tumor diagnosis accuracy. Real-time cloud-based and IoMT-enabled healthcare systems may be developed for faster clinical applications. Additionally, larger datasets, explainable AI techniques, and 3D MRI analysis can further improve model reliability, interpretability, and practical medical deployment.

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