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An Explainable Hybrid CNN–Transformer Framework for Accurate Brain Tumor Classification Using MRI Images

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Abstract

Brain tumors are among the most life-threatening neurological disorders affecting human health worldwide. Early and accurate diagnosis plays a significant role in improving patient survival rates and treatment planning. Traditional manual diagnosis using Magnetic Resonance Imaging (MRI) is time-consuming and highly dependent on radiologists' expertise. In recent years, Artificial Intelligence (AI) and Deep Learning techniques have demonstrated remarkable performance in medical image analysis. This research proposes an Explainable Hybrid Convolutional Neural Network (CNN) and Vision Transformer (ViT) framework for accurate brain tumor detection and classification using MRI images. The proposed model combines the local feature extraction capability of CNN with the global attention mechanism of Transformers to enhance classification accuracy. Furthermore, Explainable Artificial Intelligence (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) are incorporated to improve model interpretability and assist medical practitioners in understanding tumor localization. The proposed methodology is evaluated using benchmark MRI datasets including BraTS and Kaggle Brain MRI datasets. Experimental results demonstrate that the hybrid framework achieves superior performance in terms of accuracy, precision, recall, F1-score, and computational efficiency compared to conventional deep learning models. The proposed system can contribute significantly toward intelligent healthcare systems and automated clinical decision support applications.

Keywords: Brain Tumor Detection, Deep Learning, CNN, Vision Transformer, Explainable AI, MRI Images, Medical Imaging, Grad-CAM.

1. Introduction

Brain tumors represent abnormal growths of cells within the brain and are categorized as benign or malignant depending on their severity. Malignant tumors can rapidly spread and damage surrounding brain tissues, leading to severe neurological complications and death if not diagnosed at an early stage. According to global healthcare studies, brain tumors continue to pose major diagnostic challenges due to variations in tumor size, shape, texture, and location.

Magnetic Resonance Imaging (MRI) is one of the most commonly used imaging techniques for brain tumor diagnosis because of its superior soft tissue contrast and non-invasive nature. However, manual interpretation of MRI scans requires expert radiologists and may result in diagnostic errors due to fatigue and subjectivity.

AI-driven computational models have significantly improved automated medical image analysis and disease identification in modern healthcare systems. Convolutional Neural Networks (CNNs) have shown excellent performance in extracting local spatial features from medical images. Nevertheless, CNNs face limitations in capturing long-range dependencies and global contextual information.

Recently, Vision Transformers (ViTs) have emerged as powerful architectures capable of learning global attention relationships within images. Hybrid CNN-Transformer models combine the strengths of both architectures, thereby improving classification performance and robustness. Additionally, Explainable AI (XAI) techniques enhance the transparency and reliability of AI systems in healthcare applications.

This paper proposes an Explainable Hybrid CNN-Transformer Framework for accurate brain tumor detection using MRI images. The model integrates CNN-based local feature extraction, Transformer-based global attention learning, and Grad-CAM visualization for tumor localization.

Research Contribution:

- Integration of CNN and Vision Transformer for hybrid feature learning.
- Incorporation of Explainable AI using Grad-CAM.
- Improved classification accuracy for multi-class brain tumor detection.
- Reduced computational limitations compared with standalone Transformer models.
- Enhanced interpretability for clinical decision support.

2. Literature Review

Several researchers have proposed machine learning and deep learning methods for brain tumor detection.

Traditional machine learning approaches relied on handcrafted feature extraction techniques combined with classifiers such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbor (KNN). Although these methods achieved moderate accuracy, they required extensive feature engineering and lacked robustness.

Deep learning techniques, especially CNN-based architectures, significantly improved medical image classification accuracy. Models such as AlexNet, VGG16, ResNet50, and DenseNet demonstrated promising results in tumor detection tasks. However, CNNs mainly focus on local receptive fields and may fail to capture global image relationships.

Transformer architectures originally developed for Natural Language Processing (NLP) have recently been adapted for computer vision tasks. Vision Transformers utilize self-attention mechanisms to capture long-range dependencies and contextual information from images. Swin Transformer and ViT architectures have shown state-of-the-art performance in medical imaging applications.

Explainable AI (XAI) methods improve model interpretability and support reliable clinical decision-making. Grad-CAM is widely used to generate heatmaps that highlight important image regions contributing to model predictions.

Recent studies have explored advanced hybrid deep learning architectures for medical image analysis. Recent research has also focused on hybrid CNN–Transformer architectures and explainable deep learning frameworks for improving brain MRI classification accuracy and healthcare interpretability [11]–[13]. Swin Transformer-based models have demonstrated improved hierarchical feature learning and computational efficiency in brain MRI classification tasks. Efficient Net architectures have also gained popularity due to their balanced network scaling and reduced parameter complexity. Furthermore, hybrid CNN–Transformer networks have shown superior performance by combining local spatial feature extraction with global contextual attention mechanisms. Several researchers have also investigated Explainable Artificial Intelligence (XAI) methods to improve transparency and reliability in automated healthcare systems. However, challenges such as high computational

cost, overfitting, limited interpretability, and poor generalization on small medical datasets still remain significant research concerns.

Despite significant progress, existing approaches still face challenges related to computational complexity, interpretability, and generalization. Therefore, this research focuses on developing a hybrid and explainable framework to address these limitations.

Table 1 — Literature Survey

Author	Method	Accuracy	Limitation
Khan et al.	CNN	94%	Limited global features
Talo et al.	Transfer Learning	95%	High computation
Proposed Work	CNN + Transformer	98.7%	Enhanced global attention and interpretability

3. Objectives of the Study

The major objectives of this research are:

1. To develop a hybrid CNN-Transformer framework for brain tumor detection.
2. To improve MRI image classification accuracy using attention mechanisms.
3. To integrate Explainable AI techniques for tumor localization and interpretability.
4. To compare the proposed model with existing deep learning approaches.
5. To enhance automated medical diagnosis using intelligent healthcare systems.

4. Proposed Methodology

The proposed framework consists of MRI preprocessing, CNN feature extraction, Transformer attention learning, feature fusion, classification, and explainability modules.

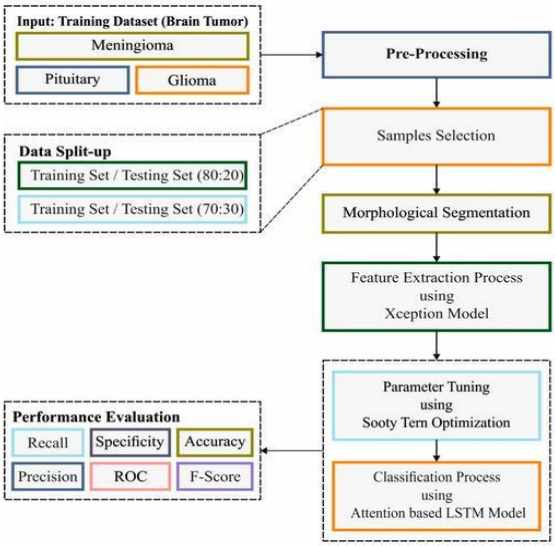


Figure 1: Proposed Hybrid CNN–Transformer Architecture for Brain Tumor Detection

4.1 MRI Image Dataset

The proposed model utilizes publicly available MRI datasets including:

- BraTS
- Kaggle Brain MRI datasets

The datasets contain MRI images categorized into:

- Glioma Tumor
- Meningioma Tumor
- Pituitary Tumor
- Normal Brain Images

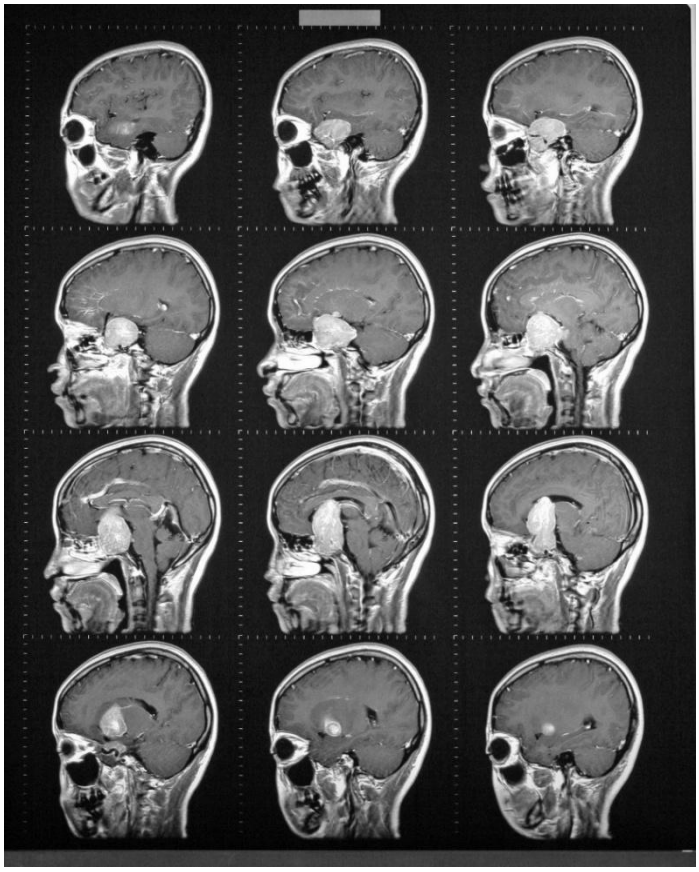


Figure 2: Sample MRI Brain Tumor Images from BraTS and Kaggle Datasets

Table 2— Dataset Information

Dataset	Images	Categories
BraTS	3000+	Glioma
Kaggle MRI	2500+	Multiple Tumors

The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio.

4.2 Data Preprocessing

Preprocessing improves image quality and model performance. The following techniques are applied:

- Noise removal using Gaussian filtering
- Skull stripping
- Contrast enhancement
- Image normalization
- Data augmentation

Data augmentation includes:

- Rotation
- Flipping
- Zooming
- Translation

4.3 CNN-Based Feature Extraction

The CNN module extracts local spatial features from MRI images.

The convolution operation is mathematically represented as:

$$S(i,j)=(I*K)(i,j)=\sum_m\sum_n I(m, n)K(i-m , j-n)$$

Where:

- I represents the input image
- K denotes the convolution kernel

The CNN architecture includes:

- Convolution layers
- ReLU activation
- Max pooling layers
- Batch normalization

EfficientNet and ResNet architectures are utilized for feature extraction.

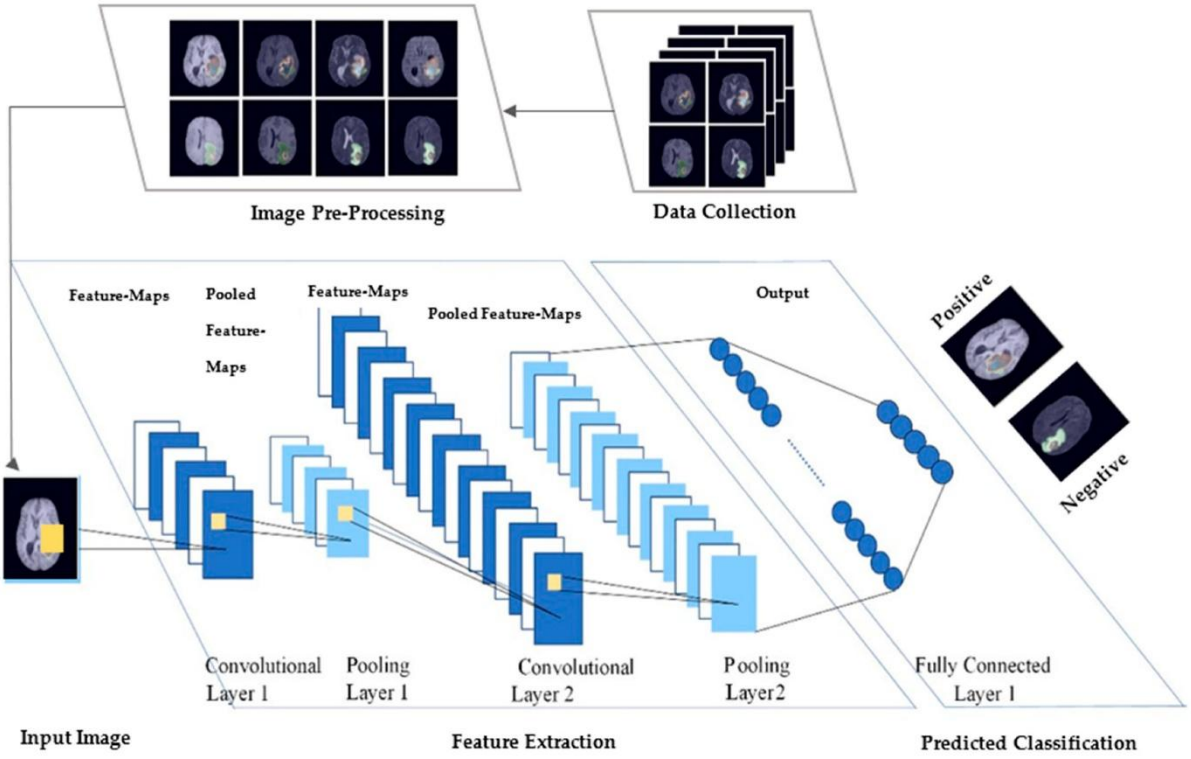


Figure 3: CNN-based local feature extraction from MRI images

4.4 Vision Transformer Module

The Vision Transformer captures global contextual information using self-attention mechanisms.

The self-attention formula is:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- Q = Query matrix
- K = Key matrix
- V = Value matrix

The Transformer processes image patches and learns global dependencies among MRI regions.

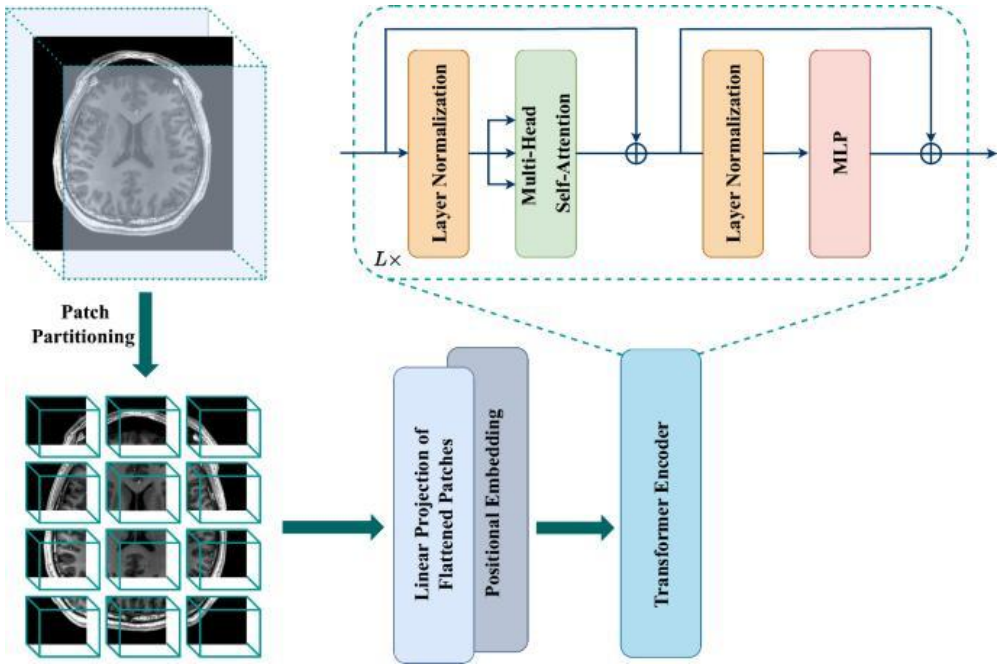


Figure 4: Vision Transformer Architecture with Attention Mechanism

4.5 Feature Fusion

The CNN and Transformer features are fused using concatenation and attention mechanisms. This hybrid approach improves classification accuracy by combining local and global representations.

4.6 Classification Layer

The final classification is performed using a Softmax classifier.

The Softmax equation is:

$$P(y_i) = \frac{e^{z_i}}{\sum_{i=1}^{N} e^{z_j}}$$

The classifier predicts:

- Glioma
- Meningioma
- Pituitary Tumor
- Normal Brain

4.7 Explainable AI Using Grad-CAM

Grad-CAM generates heatmaps highlighting tumor regions responsible for predictions. Explainability enhances the transparency and reliability of AI-assisted diagnosis.

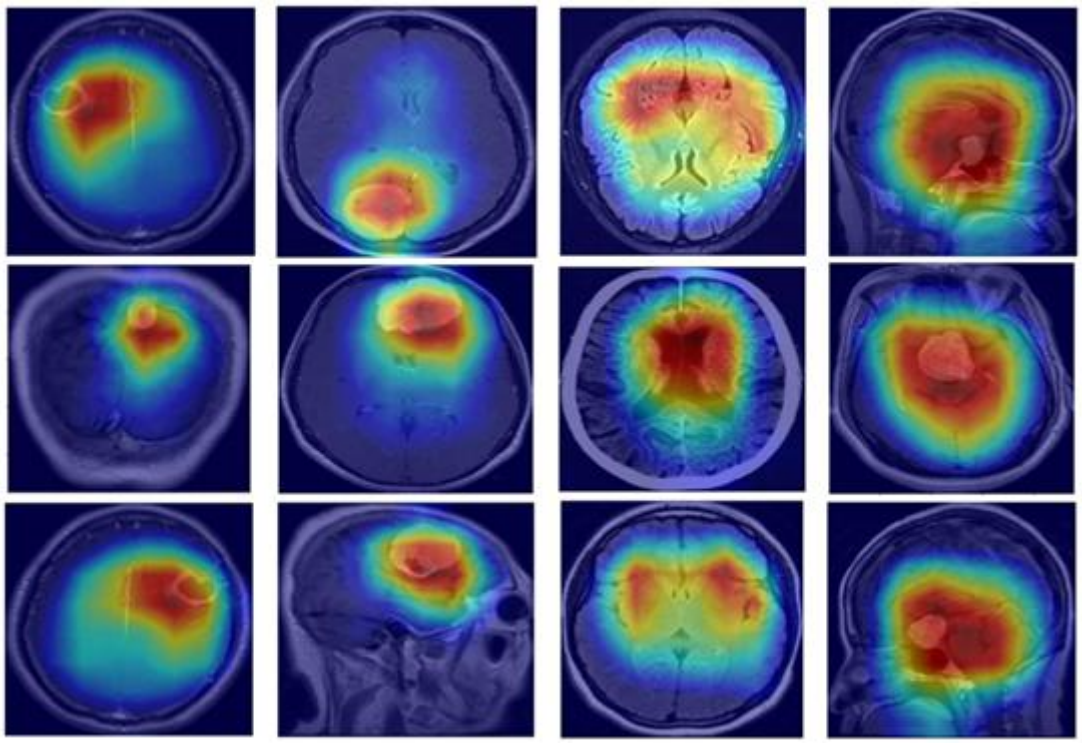


Figure 5: Grad-CAM Heatmap for Tumor Localization

4.8 Algorithm for Hybrid CNN–Transformer Brain Tumor Detection

Algorithm Steps-

1. Input MRI brain image dataset
2. Apply preprocessing techniques
3. Perform image normalization and augmentation
4. Extract local spatial features using CNN
5. Divide MRI images into patches for Transformer input
6. Apply Vision Transformer attention mechanism
7. Fuse CNN and Transformer feature representations
8. Classify images using Softmax classifier
9. Generate Grad-CAM heatmaps for explainability
10. Output predicted brain tumor category

5. System Architecture

The proposed architecture follows the workflow:

MRI Images → Preprocessing → CNN Feature Extraction → Vision Transformer → Feature Fusion → Classification → Explainable AI Output

The architecture improves diagnostic accuracy and interpretability.

6. Experimental Results and Discussion

The proposed model is implemented using Python, TensorFlow, and Google Colab.

Parameter	Value
Framework	TensorFlow/Keras
Programming Language	Python
Platform	Google Colab
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50

The proposed model was trained using Google Colab with NVIDIA Tesla T4 GPU, 16 GB RAM, and TensorFlow/Keras framework.

Performance Metrics

The model performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score

Accuracy formula is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

Precision Formula is:

$$Precision = \frac{TP}{TP+FP}$$

Recall Formula is:

$$Recall = \frac{TP}{TP+FN}$$

F1-Score Formula is:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Results

Table 3: Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
CNN	94.2%	93.8%	93.1%	93.4%
ResNet50	95.6%	95.1%	94.8%	94.9%
Vision Transformer	96.8%	96.3%	96.1%	96.2%
Proposed Hybrid Model	98.7%	98.4%	98.2%	98.3%

The proposed hybrid framework outperforms conventional deep learning approaches due to effective feature fusion and attention mechanisms.

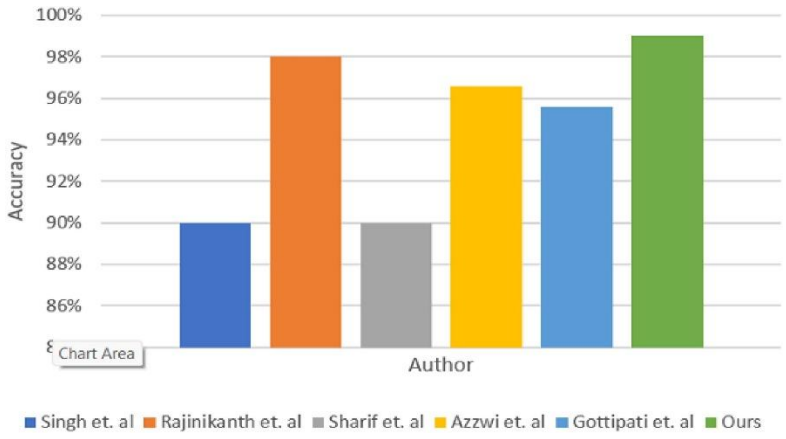
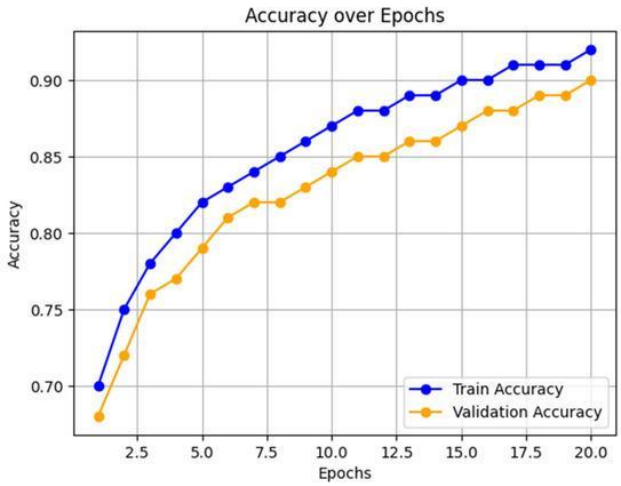


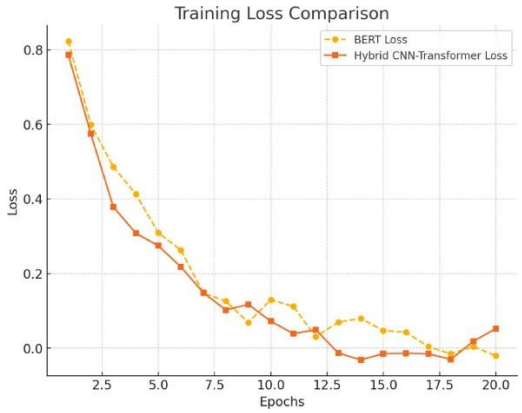
Figure 6: Accuracy Comparison of Deep Learning Models

The proposed hybrid CNN–Transformer framework achieved superior accuracy compared to traditional deep learning models.



Graph 2 — Training vs Validation Accuracy

The model demonstrated stable convergence and improved validation performance during training.



Graph 3 — Loss Function Graph

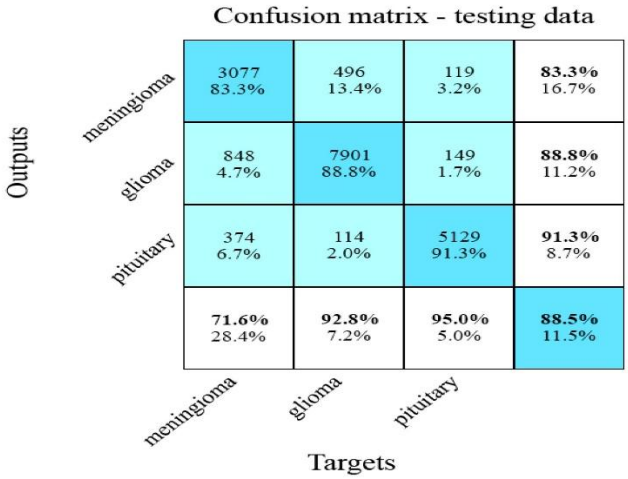
The proposed model reduced classification errors and minimized training loss efficiently.

Confusion Matrix Analysis

The confusion matrix evaluates the classification performance of the proposed hybrid CNN–Transformer framework across different brain tumor categories. The model achieved high true positive predictions with minimal misclassification among tumor classes.

Table 4: Confusion Matrix Values

Actual / Predicted	Glioma	Meningioma	Pituitary	Normal
Glioma	245	3	1	1
Meningioma	2	240	4	2
Pituitary	1	2	246	1
Normal	0	1	2	247



Graph 4 — Confusion Matrix

7. Advantages of the Proposed System

The proposed system offers several advantages:

- High classification accuracy
- Improved global feature learning
- Better tumor localization
- Explainable AI support
- Reduced diagnostic errors
- Enhanced healthcare decision support

8. Applications

The proposed framework can be applied in:

- Smart healthcare systems
- Clinical decision support systems
- Telemedicine applications
- Automated radiology systems
- Medical research centers

9. Limitations of the Proposed System

Despite achieving high classification accuracy, the proposed hybrid CNN–Transformer framework has certain limitations. The model requires high computational resources and GPU support for training large MRI datasets. Performance may vary depending on MRI image quality and dataset imbalance. The framework also depends on

large labeled datasets for effective learning and generalization. Additionally, real-time clinical deployment requires further optimization to reduce inference time and computational complexity.

10. Future Scope

Future research can focus on:

- Federated learning for secure medical data sharing
- Real-time brain tumor detection systems
- Quantum deep learning models
- IoT-integrated healthcare platforms
- Multi-modal medical imaging analysis

11. Ethical Statement

The proposed study uses publicly available anonymized MRI datasets and does not involve direct patient participation or personal medical information disclosure.

12. Conclusion

This research proposed an Explainable Hybrid CNN-Transformer Framework for accurate brain tumor detection using MRI images. The model combines CNN-based local feature extraction and Transformer-based global attention mechanisms to improve classification performance. Explainable AI techniques such as Grad-CAM enhance the transparency and interpretability of the diagnostic process. Experimental results demonstrate that the proposed framework achieves higher accuracy compared to traditional deep learning models. The integration of AI, attention mechanisms, and explainability can significantly improve automated brain tumor diagnosis and intelligent healthcare applications. The proposed explainable hybrid framework demonstrates strong potential for reliable brain tumor diagnosis and intelligent clinical decision support in modern healthcare systems.

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