Open Access ISSN: 3007-1437 (Online), ISSN: 3007-1429 (Print)

IRAQI Academic Scientific Journals

Alkadhim Journal for Computer Science (KJCS)

Journal Homepage: https://alkadhum-col.edu.iq/JKCEAS

KJCS ALKADHIM JOURNAL FOR COMPUTER SCIENCE

Hybrid Deep Learning Framework for Brain Tumor Classification Using MRI Images

[1]**Ahmed Thijeel Ahmed***

[1]Directorate General of Education in Thi-Qar Governorate, Thi-Qar, Iraq

Article information

Article history:
Received: June, 15, 2026
Accepted: August, 23, 2026
Available online: September, 25, 2026

Keywords:
Brain Tumor Classification,
MRI,
Deep Learning,
ResNet50,
DenseNet201,
Ensemble Learning,
Transfer Learning,
Grad-CAM,
ROI Extraction,
Medical Image Analysis.

Corresponding Author:
Ahmed Thijeel Ahmed
AhmedThijeel90@utq.edu.iq

DOI:
https://doi.org/10.61710/bnw00r62

Abstract

Brain tumor classification from magnetic resonance imaging (MRI) plays an important role in computer-aided diagnosis, as accurate identification of tumor categories can support clinical decision-making and reduce the burden associated with manual image interpretation. This study proposes a hybrid deep learning framework for multiclass brain tumor classification using MRI images. The proposed framework integrates two complementary transfer-learning architectures, ResNet50 and DenseNet201, to exploit their different feature-learning capabilities. Prior to classification, MRI images undergo a standardized preprocessing pipeline including resizing, noise reduction, contrast enhancement, and region-of-interest extraction to emphasize diagnostically relevant information. Data augmentation is applied exclusively to the training subset to improve model generalization while minimizing the risk of data leakage. ResNet50 and DenseNet201 are first evaluated independently under the same experimental conditions, followed by probability-level fusion of their classification outputs to construct the proposed hybrid model. The experimental results show that ResNet50 achieves an accuracy of 97.20%, while DenseNet201 achieves 98.10%. The proposed hybrid framework achieves the highest observed accuracy of 99.20%, demonstrating an improvement of 2.00 and 1.10 percentage points over ResNet50 and DenseNet201, respectively. In addition to quantitative evaluation, Grad-CAM is employed to provide visual interpretation of the model predictions by highlighting image regions contributing to the classification decision. Despite the promising results, further validation using independent datasets, patient-level data partitioning, repeated experiments, and statistical analysis is required to establish the generalizability and clinical reliability of the proposed approach. Overall, the findings demonstrate the potential of combining complementary transfer-learning models with preprocessing, ensemble fusion, and explainable artificial intelligence for automated brain tumor classification from MRI images.

1. Introduction

One of the most dangerous conditions is brain tumors, which are brought on by the unchecked proliferation of aberrant cells inside the skull. Brain tumors come in a variety of forms, including meningioma, gliomas, and pituitary tumors. Gliomas are highly invasive brain tumors that arise from glial stem or progenitor cells and proliferate rapidly due to molecular and genetic changes in undifferentiated neural tissue [1]. The nervous system as a whole, which transmits nerve signals from one organ to another, is controlled by the brain, a central controller organ [1,2]. If a brain injury occurs, the entire organ system cannot carry out its normal function. Any abnormal nerve signal or obstruction in the neurological system might cause any organ in the human body to fail. Brain tumors are serious brain abnormalities that can spread to other parts of the body and develop into fatal cancer. Brain tumors may be caused by abnormal and rapid tissue growth in the brain. The International Agency for Research on Cancer (IARC) reports that this lethal brain tumor affects about a million people annually [2]. Because it provides high-resolution structural brain tissue data, magnetic resonance imaging (MRI) has gained popularity as a non-invasive imaging technique for detecting and analyzing brain cancers. MRI analysis by hand. However, because tumor structures are complicated and contemporary healthcare systems generate enormous volumes of medical imaging data, radiologists' scans are time-consuming and may be unpredictable [3,4]. As a result, trustworthy and automatic computer-aided diagnostic technologies are now crucial for supporting clinical judgment. The accuracy of automated brain tumor classification using MRI images has significantly increased because of recent advancements in deep learning, particularly convolutional neural networks (CNNs) [4]. Meningioma and glioma account for 81% of malignant brain tumors in adults, making them the most common kinds [5]. Thus, early diagnosis and accurate subtyping of brain cancers are paramount for effective therapy and enhanced patient outcomes. Brain tumors are primarily diagnosed with visual inspection by radiologists, which is a tedious and time-consuming process that is subject to human error. This is because most of the cells tend to have some free, random, and uncontrolled views [5,6]. Because traditional imaging techniques have limitations in detecting tumors, high-precision computer-assisted procedures are needed. Introduction: Recent advances in DL and artificial intelligence (AI), particularly convolutional networks, have demonstrated tremendous potential for medical image analysis. Experimental studies suggest that DL systems can achieve radiologist-level diagnostic performance, providing significant contributions toward tumor detection and classification. Moreover, since multiple data and planes in which the tumor area can be assessed can be acquired by MRI, it is usually regarded as the most optimal method to determine a brain tumor. CNNs are suited well for this because of their convolutional layers, which help drop the vast dimensionality of MRI images while also retaining important information needed to perform accurate analysis on events such as the one described [7,8]. Beyond imaging, blood tests have become critical for providing data and markers relating to the diagnostic condition being assessed in a brain tumor. Chemical and imaging assays together improve diagnostic accuracy. Machine learning and deep learning have enabled faster but more accurate imaging-based medical diagnostics that are crucial for early detection to enable timely, appropriate treatment for the patient. The key contributions of our proposed study are as follows.

1. This paper proposes a hybrid deep learning framework for brain tumor classification from MRI images by integrating ResNet50 and DenseNet201 architectures to exploit the complementary feature representations.
2. An ROI-based preprocessing pipeline that utilizes median filtering, CLAHE enhancement, smoothing with a Gaussian kernel, and normalization to increase the quality of the images while highlighting areas relevant to tumors.
3. An ensemble probability fusion strategy for improving robustness and accuracy compared with single models on classification performance by fusing the probabilities of both ResNet50 and DenseNet201.
4. Data augmentation, including random transforms, cropping, and jittering, was applied to improve generalization
5. An explainable classification of multi-scene images based on the joint use of a CNN with Grad-CAM visualization (to show tumor regions for further investigation to help understand the model's decisions)
6. Using the proposed framework for the four-class brain tumor MRI dataset achieved 99.20% classification accuracy, showing system effectiveness for automated diagnosis of brain tumors.
7. The proposed model serves as a CAD tool to assist radiologists in the early detection and classification of brain tumors.

The remainder of this paper is organized as follows. Section 2 reviews related work on deep learning-based brain tumor classification. Section 3 describes the proposed methodology, including preprocessing, hybrid feature extraction, ensemble classification, and explainable AI. Section 4 presents the experimental setup. Section 5 discusses the experimental results and comparisons with previous studies. Finally, Section 6 concludes the paper and outlines future research directions.

2. Related Works

In this section, we will review previous studies. S. Raj Sowrirajan et al. (2022) [9] used deep learning, and machine learning, such as GLDM, HARALICK, GLCM, LBP, SVM, Random Forest, Decision Tree, and CNN. The MRI includes 3,064 images from 233 patients. Meningioma, gliomas, and pituitary tumors are the three different tumor types included in the dataset. CNN achieved an 93.10% accuracy, and LBP+SVM: 84.95%. A. Kazemi et al. (2023) [10] focused on brain tumor classification using MRI images. They employed traditional pre-trained models (ResNet18, ResNet50, VGG16, Dense Net, Google Net, Shuffle Net, and Mobile Net). A convolutional neural network (CNN) trained on tumor regions achieved 97.86% accuracy. The need for a larger, more diverse dataset, the model's lack of testing on real-world clinical data, and the high computational complexity of some models.

Z. Rasheed et al. (2023) [11] Conducted brain tumor classification on MRI images. pre-trained VGG16, VGG19, ResNet50, MobileNetV2, and InceptionV3 algorithms. The study achieved 98%. Limited diversity of datasets, complexity of computation, and difficulties with generalization. S. Mavaddati et al. (2023) [12] proposed a framework using MRI images, consisting of Glioma, Meningioma, Pituitary Tumor, and No Tumor. Their method included preprocessing, image enhancement, and feature extraction. They are ResNet-50, Transfer learning, CNN. The need for a larger, more diverse dataset, the model not being tested on real-world clinical data, and the high computational complexity of some models. The study achieved an accuracy 98.70%.

S. Karamehić et al. (2023) [13] addressed brain tumor classification by merging the figs hare, SARTAJ, and Br35H datasets. Pituitary, glioma, meningioma, and no tumor are the four categories into which the dataset's 7023 human brain MRI scans have been divided. VGG16, DNN, ANN. The study achieved 96.90% accuracy. The need for a larger, more diverse dataset, the model not being tested on real-world clinical data, and the high computational complexity of some models. S. Li et al. (2024) [14] analyzed a brain tumor's MRI images, which consist of Glioma, Meningioma, Pituitary Tumor, and No Tumor. Deep Learning Models, CNN, ResNet50, VGG16, DenseNet121. The study achieved 96% accuracy.

R. V. Manjunath et al. (2024) [15] focused on classifying benign and malignant brain tumors using MRI images. Pertained models with Transfer Learning: VGG16, ResNet50, InceptionV3, MobileNetV2, DenseNet121. The study achieved 94.44% accuracy. A. Hameed et al. (2024) [16] diagnosed brain tumors using 7022 MRI images. They used deep learning models EfficientNetB0, EfficientNetB6, and ResNet50. EfficientNetB6 achieved 99.39%, EfficientNetB0 achieved 95%. ResNet50 achieved 97%. A larger and more varied dataset is needed; the model is not being tested on actual, multi-center clinical data; EfficientNetB6 has high computational demands; training time and a powerful GPU are needed; poor generalization on MRI images of different quality may occur; Explainable AI is not being used to interpret decisions; the model must be integrated with actual clinical systems; and it must be tested on new, unseen datasets more widely.

L. Chandra S et al. (2024) [17] utilized MRI images. The study used pertained algorithms such as ResNet-50, Inception V3, and VGG16. This study precision of 93.3%, AUC: 98.43%. The recall rate was 91.19%. A. Abdullah et al. (2024) [18] classified brain tumors with the Figs hare Brain Tumor Dataset, MRI. Using a deep learning model, DenseNet121, the accuracy reached 97%. I. Kavram et al. (2024) [19] classified brain tumors using MRI scans. The study used CNN, Deep Learning, VGG16, Random Forest, and Hybrid Deep Learning. This study achieved an accuracy 92.31%. A. Nokib. M et al. (2025) [20] presented a study in which they divided the MRI dataset into Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor. Deep learning algorithms such as convolutional neural networks were used to classify brain tumor cases, and a pre-trained model, CNN, VGG19, ResNet50, DenseNet121, was used. The study aimed to evaluate the effectiveness and objectivity of artificial intelligence in diagnosing the stages of brain tumors. This study achieved an 96%, an accuracy.

3. Methodology

In this research work, a novel deep learning model is designed to automate brain tumor classification using Magnetic Resonance Imaging (MRI) scans. The proposed approach utilizes a combination of advanced image preprocessing methods with an ensemble of two strong convolutional neural networks, ResNet50 and DenseNet201. The collected high-level image features, which are useful for classification tasks, are fused at a decision level in order to increase the performance and robustness of the model. Furthermore, it is also used for a visualization strategy of the explainable prediction. Grad-CAM obviously indicates to us that much more important places lead to the classification decision. Such an approach is shown in the Block diagram in Figure 1.
The entire framework is comprised of six Basic Stages.

1. Dataset description.
2. Dataset splitting.
3. MRI image preprocessing.
4. Data augmentation.
5. Hybrid deep feature learning and ensemble classification.
6. Model evaluation and visualization.

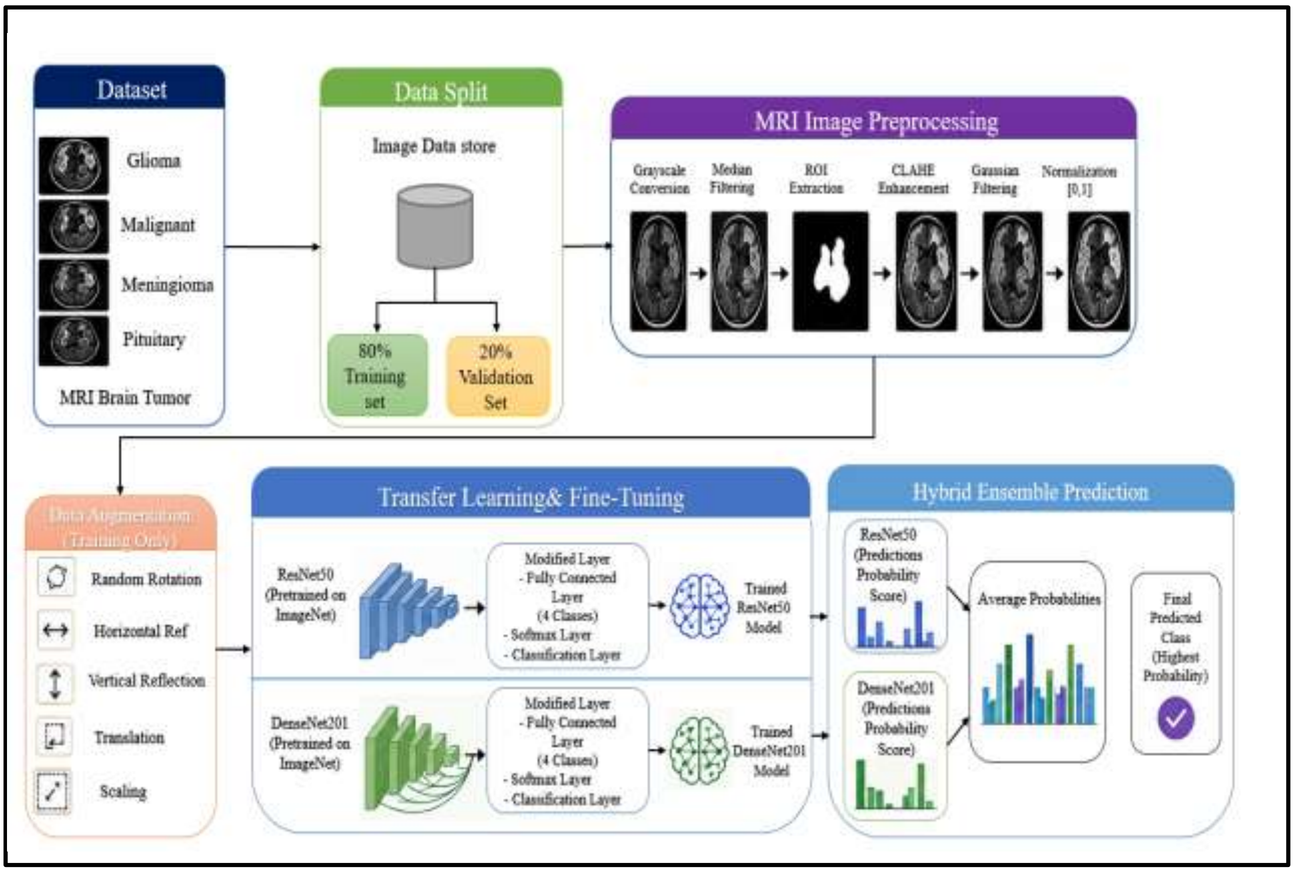

Figure (1): General structure of the model.

First, we start with the available data provided in the dataset. The dataset contains a total of 5,712 MRI images, including 1,321 Glioma, 1,595 Malignant, 1,339 Meningioma, and 1,457 Pituitary images. These MRI scans represent axial brain slices acquired under different imaging conditions, thereby providing substantial variability in tumor size, morphology, intensity distribution, and anatomical location.

The dataset was selected because it offers sufficient diversity to evaluate the robustness and generalization capability of deep learning models under multiclass classification conditions. The inclusion of different tumor categories enables comprehensive assessment of the proposed framework across clinically relevant pathological conditions. Table 1 summarizes the class distribution of the MRI dataset used in this study.

Table (1): Distribution of MRI Images

Tumor Class	Number of images
Glioma	1,321
Malignant	1,595
Meningioma	1,339
Pituitary	1,457
Total	5,712

The second step involved randomly partitioning the dataset into a train (80%) /Validation (20%) set so that reliable model evaluation could be performed while minimizing the risk of overfitting. The training subset is used for learning the model parameters, and we use a validation subset to analyze how well our model will generalize during training. Let's put it mathematically this way: Training Images = 80%, Validation Images = 20%. The class distribution in both subsets is preserved by performing random stratified splitting.

The third step consisted of applying image preprocessing techniques applied. Since MRI images are corrupted with noise and have contrast variations, pre-processing was applied to the image to separate the background from the image before extracting features. MRI Image Preprocessing Pipeline — Figure 2

Stage 1: Image Reading

We load each MRI image in the dataset and prepare it for processing.

Stage 2: Grayscale Conversion

MRI brain images are commonly represented as single-channel grayscale images. However, some images within the dataset were stored as RGB images. Since the color information does not provide additional diagnostic information for MRI images, all RGB images were converted into grayscale before further processing. The grayscale image Ig is computed as where R, G, and B denote the red, green, and blue image channels, respectively. This conversion standardizes the image representation while reducing computational complexity.

Stage 3: Noise Reduction

It uses median filtering to suppress impulse noise while retaining other key anatomical structures. We use a 3 × 3 median filter.: Median Filter Size = 3×3

Phase four: (ROI) Extraction

The MRI images contain considerable background regions that are unrelated to tumor diagnosis. Processing the complete image increases computational cost and may introduce irrelevant features into the learning process. Therefore, ROI extraction was performed to isolate the brain region containing the tumor while suppressing unnecessary background structures. Initially, adaptive thresholding was applied to generate a binary representation of the MRI image. Following thresholding, small isolated regions were removed using morphological area opening. Hole filling was subsequently performed to obtain continuous brain regions. Connected-component analysis was then employed to identify all candidate objects within the binary image. For each connected component, the enclosed area was computed. The component with the largest area was assumed to correspond to the brain region and was selected as the final ROI. Finally, the corresponding bounding box was used to crop the original MRI image. This procedure substantially reduces background information and directs the deep learning models toward clinically relevant anatomical structures.

Stage 5: Contrast Enhancement

MRI images often exhibit low local contrast, making tumor boundaries difficult to distinguish. To enhance local intensity variations while avoiding excessive amplification of image noise, Contrast-Limited Adaptive Histogram Equalization (CLAHE) was employed. Unlike conventional histogram equalization, CLAHE operates independently on small image regions (tiles) and limits histogram amplification through a predefined clipping threshold. This prevents over-enhancement and preserves natural image appearance. For an input intensity r, the enhanced intensity s is expressed as $s=T(r)$ where T (·) denotes the adaptive histogram transformation applied locally to each image tile. CLAHE significantly improves the visibility of tumor boundaries and enhances discriminative feature extraction.

Stage 6: Gaussian Smoothing

Medical images frequently contain impulse noise originating from image acquisition and reconstruction processes. Such noise may produce artificial intensity variations that negatively affect feature extraction. To suppress impulse noise while preserving tissue boundaries, a 3 × 3 median filter was applied to each MRI image. The output pixel intensity is defined as where Ω (x, y) denotes the local neighborhood centered at pixel (x, y). Compared with conventional averaging filters, the median filter effectively removes isolated noisy pixels without blurring tumor boundaries.

Stage 7: Image Normalization

MRI intensity values vary considerably due to differences in imaging protocols and acquisition devices. Consequently, normalization was performed to scale pixel intensities into a consistent numerical range before network training. The normalized intensity is computed as, where Imin and Imax represent the minimum and maximum intensity values within the image. Normalization accelerates network convergence and reduces sensitivity to illumination variations.

Stage 8: Image Resizing

Finally, all MRI images were resized to 224 × 224 × 3 pixels, corresponding to the input dimensions required by both ResNet50 and DenseNet201. Single-channel grayscale images were replicated across three channels to satisfy the RGB input format expected by the pretrained convolutional neural networks. Maintaining a uniform input size ensures compatibility with the transfer learning models and enables efficient mini-batch training.

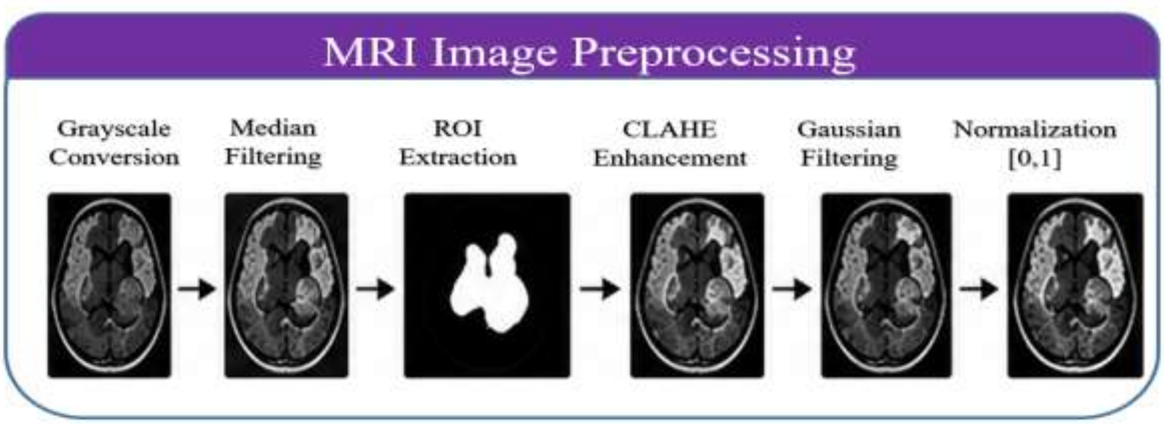

Figure (2): illustrates the MRI Image Preprocessing

Step four: We did data augmentation of our dataset to get a better generalization performance from the model, as well as to ensure a bigger representation in less-represented categories. A few data augmentation techniques, such as random rotation, horizontal reflection, random scaling, and random clipping, were applied to training images only. We used these techniques to augment the data and limit overshoot. Figure 3: Steps of Data Augmentation.

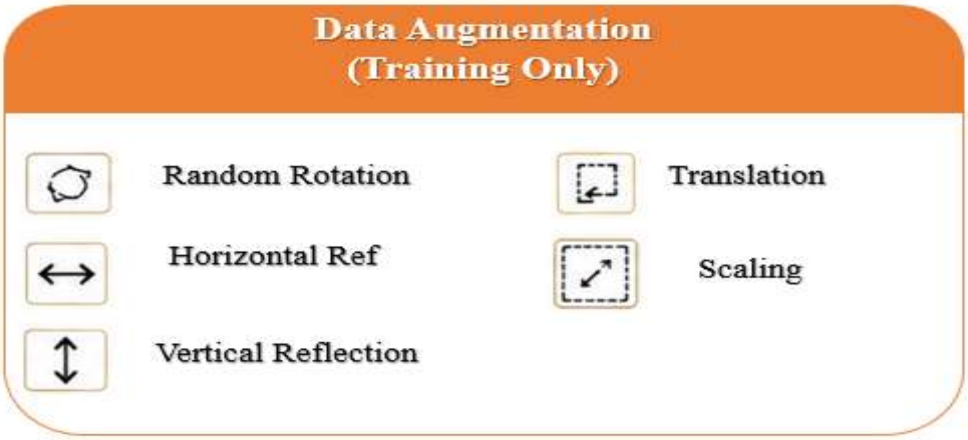

Figure (3): illustrates the steps of data augmentation.

In the fifth step, hierarchical representations through residual learning. The architecture contains 50 layers and employs residual connections that allow information to bypass one or more convolutional layers. These connections facilitate gradient propagation during optimization and enable the training of relatively deep networks. In this study, a pertained ResNet50 model was adapted to the target brain tumor classification task using transfer learning. The original classification layer was replaced with a new fully connected classification layer corresponding to the four target classes. The network was subsequently fine-tuned using the training MRI images. The use of transfer learning provides an effective initialization of the network parameters and reduces the amount of training required compared with training a deep CNN entirely from random initialization. The classification function of ResNet50 can be represented as:

$$pR=fR(I,\theta\_R) \qquad (1)$$

where I denotes the preprocessed MRI image, f R represents the ResNet50 model, ΘR denotes its learned parameters, and pR represents the resulting class-probability vector. For the four-class classification problem. DenseNet201 was selected as the second backbone architecture to provide complementary feature representations. Dense Net employs dense connectivity, in which each layer receives feature maps from preceding layers. This structure promotes feature reuse, improves information propagation, and facilitates the extraction of both low-level and high-level representations. Similar to ResNet50, the pertained DenseNet201 model was adapted to the target four-class MRI classification problem by replacing its original classification layer with a task-specific classification layer. The prediction generated by DenseNet201 can be represented as $pD=fD(I,\theta_D) \quad (2)$

where fD denotes the DenseNet201 model, θD represents its learned parameters, and pD is the corresponding vector of class probabilities. Thus, the complementary architectural characteristics of ResNet50 and DenseNet201 provide the basis for the hybrid classification strategy proposed in this study. Figure 4 illustrates the model training process.

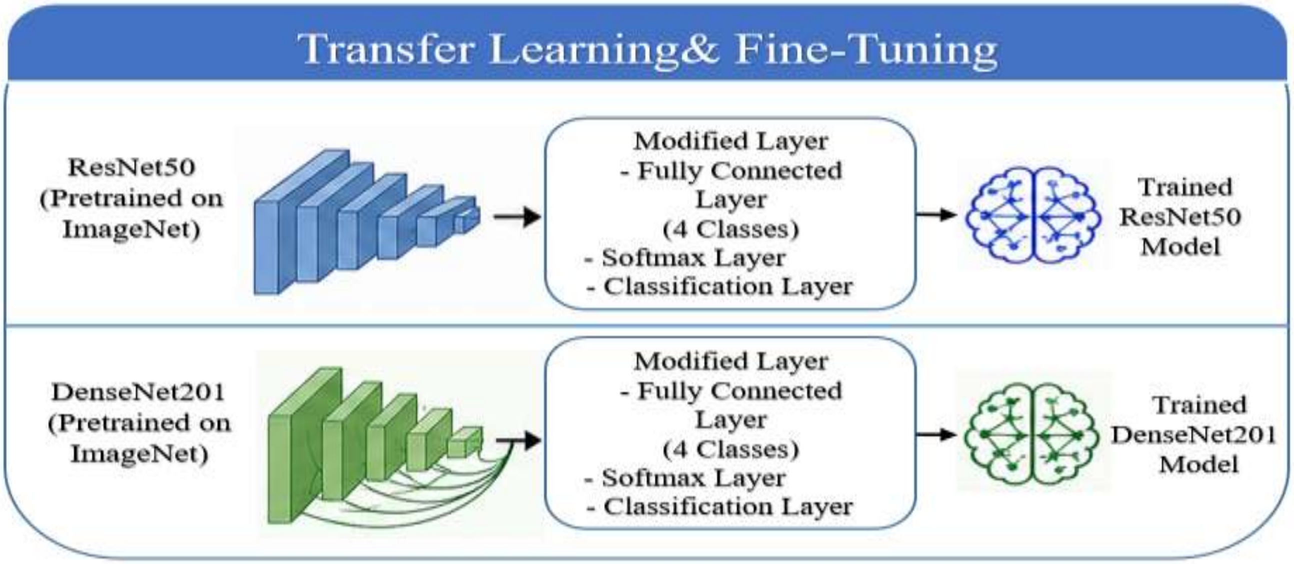

Figure (4): illustrates the steps of the model training process

In step six, the two networks are trained independently, and the classification probabilities from each network are obtained.

pResNet=probability vector from ResNet50 (3)

pDenseNet=probability vector from DenseNet201 (4)

Finally, the prediction score is calculated by averaging the two probabilities

$$\left[\text{Pfinal}=\frac{\text{PResNet}+\text{PDenseNet}}{2}\right] \quad (5)$$

The class that has the highest probability will be chosen as the final prediction. This fusion strategy can integrate the advantages of both networks and enhance classification robustness. Figure 5 illustrates the final network prediction.

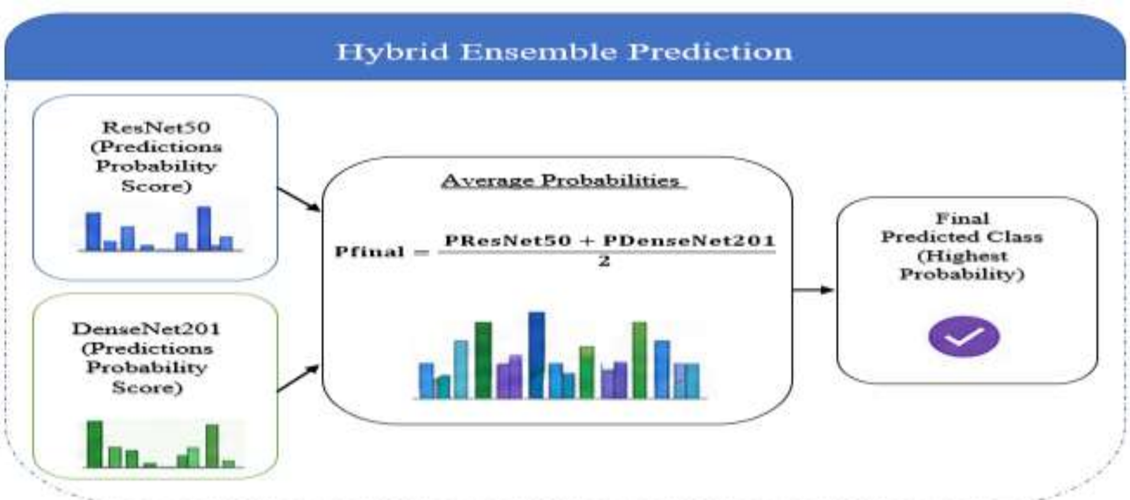

Figure (5): illustrates final network prediction.

Both deep learning models were trained using the same experimental protocol to ensure a fair comparison. The Adam optimizer was employed for network optimization because of its adaptive learning-rate mechanism and its effectiveness in training deep neural networks. The principal training parameters are summarized in Table 2.

Table (2): Training Configuration of the Proposed Models

Parameter	Configuration
MATLAB	Programming environment (R2023a)
MATLAB Deep Learning Toolbox	Deep learning framework
Processer	11th Gen Intel(R) Core(TM) i7-11800H @ 2.30GHz (2.30 GHz)
RAM	8GB
Graphics card	NVIDIA GeForce GTX 1650 with Max-Q Design (4 GB) Intel(R) UHD Graphics (128 MB)
Input image size	224×224×3
Optimizer	Adam
Initial learning rate	1×10^{-4}
Mini-batch size	16
Maximum epochs	15
Data split	80% training / 20% validation
Data augmentation	Training set only
Classification task	Four-class classification
Evaluation metrics	Accuracy, Precision, Recall, Specificity, F1-score

The final output is chosen by selecting the class corresponding to the highest confidence score. You assign the MRI images to one of 4 categories: Glioma, Meningioma, Pituitary Tumor, Malignant Tumor based on the fused prediction vector. Grad-CAM is also employed to understand the model more clearly. Grad-CAM outputs heat maps showing the areas of the image that were most important to make classification decisions. The produced heat maps help clinicians confirm that the model is working on bio medically relevant rather than unimportant image structures. Figure 6 illustrates the interpretability using heat maps.

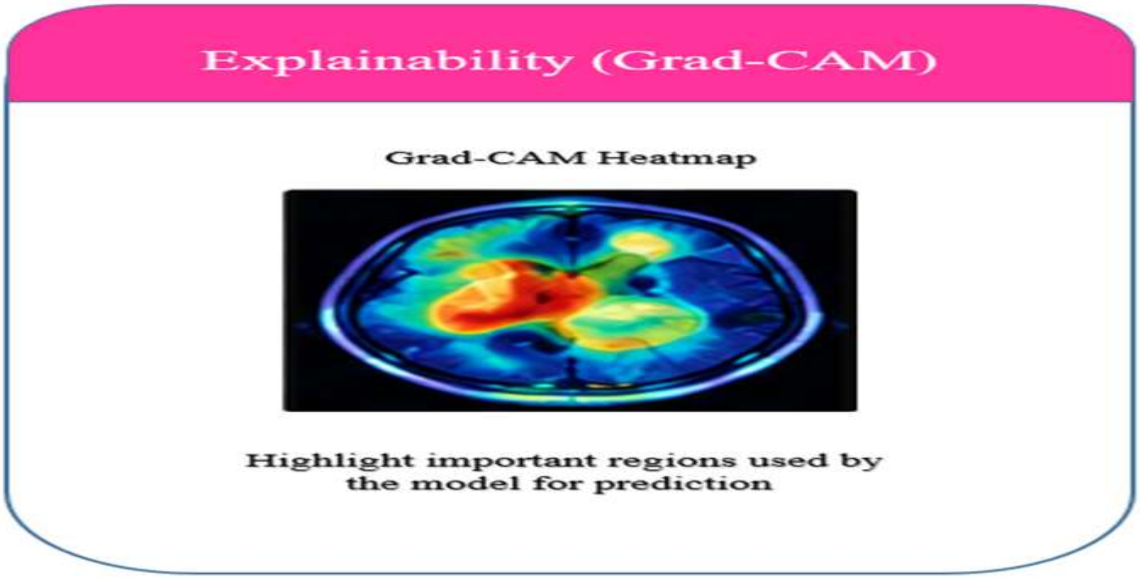

Figure (6): illustrates the interpretability using heat maps.

4. Evaluation Measures for Classifications

Several metrics are used to evaluate classifiers and their ability to predict class labels. These metrics include F-measure, sensitivity, specificity, accuracy, and precision (detection) [18].

- **Accuracy:** The ratio of accurate forecasts to the entire sample. A more accurate model is indicated by a higher accuracy score [18].

$$\text{Accuracy} = \frac{\text{true positives}+\text{true negatives}}{\text{total instances}} \qquad (6)$$

- **Sensitivity (Recall):** demonstrates the model's capacity for future prediction. A high sensitivity indicates that true positives can be correctly identified by the model [18].

$$\text{sensitivity}=\frac{\text{true positives}}{\text{true positives}+\text{false negatives}} \qquad (7)$$

- **Precision:** The proportion of all expected positive forecasts to confirmed positive predictions [18].

$$\text{precision}=\frac{\text{true positives}}{\text{true positives}+\text{false positives}} \qquad (8)$$

- **Specificity:** assesses the model's ability to predict negative outcomes.

$$\text{specificity}=\frac{\text{true negatives}}{\text{true negatives}+\text{false positives}} \qquad (9)$$

- **F1-score:** By calculating the harmonic mean of the two, the F1 Measure strikes a balance between memory and precision [18].

$$\text{F1-Score}=2\times\frac{\text{precision}\times\text{recall}}{\text{precision}+\text{recall}} \qquad (10)$$

In addition to the aforementioned requirements, Table 3 displays the confusion matrix.

Table(3): confusion matrix

	Predicted positive	**Predicted negative**
Actual positive	True positive (TP)	False negative (FN)
Actual negative	False positive (FP)	True negative (TN)

5. Results and Discussion

5.1 Classification Performance

The presented hybrid deep learning framework was tested on a multiclass brain tumor MRI dataset divided into four categories of tumors: Glioma, Meningioma, Pituitary, and Malignant Tumors. The framework integrates ROI based image preprocessing, transfer learning (ResNet50 and DenseNet201), ensemble probability fusion, and Grad-CAM visualization to enhance classification accuracy and interpretability.

Experimental results showed that the proposed model attained an overall classification accuracy of 99.20%, which confirms its effectiveness in classifying between other types of brain tumors related to it. Furthermore, across all classes, high precision, recall, and F1-score were achieved, further certifying the robustness and reliability of the classification process. Table 4 displays the results of the model.

Table (4): The obtained class-wise performance metrics are summarized

Tumor Class	**Precision (%)**	**Recall (%)**	**F1-Score**
Glioma	0.9429	1.0000	0.9706
Malignant	0.9875	0.9875	0.9875
Meningioma	1.0000	0.8843	0.9386
Pituitary	0.9505	0.9931	0.9697

The results demonstrate good classification performance for the proposed framework in all tumor categories. A maximum recall value was achieved for the Pituitary tumor class (99.31), which means that our model correctly predicted most of the Pituitary tumor instances as Pituitary tumors. As a result, the Malignant tumor class has equal performance for precision and recall with an F1- score of 98.75%, proving its stable classification performance across both precision & recall. Despite the fact that we did notice a handful of misclassifications in how Glioma VS Meningioma tumors were classified, overall classifier errors were minimal, as supported by the confusion matrix. This behavior can be explained by mutual textural and structural features from those two tumor types on MRI. There are various reasons leading the classifiers to achieve a high classification performance. The ROI extraction step helped exclude the background irrelevant information and led the learning to focus on the tumor-related area. Additionally, CLAHE enhancement and image normalization increased the image quality and feature visibility. Third, the use of ResNet50+DenseNet201 in our work helped us to perform complementary deep feature extraction, and we combined both architectures using traditional ensemble probability fusion methods, which exploit both networks ' advantages while improving classification robustness. In addition, the Grad-CAM visualization indicated that our proposed model paid attention to tumor regions with clinical relevance rather than surrounding tissues. Notably, this result supports the reliability and interpretability of the classification decisions, meaning our proposed framework can be clinically applied.

5.2 Comparison with Previous Studies

To evaluate the effectiveness of the proposed framework, its performance was compared with several recent brain tumor classification studies reported in the literature. Table 5 presents the comparative results of recently published brain tumor classification approaches and demonstrates the superior performance of our proposed framework.

Table (5): summarizes the comparison results.

Study	Method	Accuracy (%)
Z. Rasheed et al.	Deep Learning-Based MRI Classification	98.00%
R. V. Manjunath et al.	Pretrained Deep Learning Models	94.44%
S. Raj Sowrirajan et al.	Machine Learning and Deep Learning	93.10%
L. Chandra S et al.	Deep Learning Models for MRI Classification	96.80%
Proposed Method	ResNet50	97.29%
	DenseNet201	98.10%
	Hybrid ResNet50&DenseNet201&Ensemble Fusion	99.20%

Such improvements in performance can be achieved through the integration of advanced preprocessing techniques, region-of-interest (ROI)-based tumor localization, hybrid deep feature learning, and ensemble probability fusion. Unlike regular single-network methods, our architecture blends the representation advantage of ResNet50 and DenseNet201 to extract global as well as fine-grained features of tumors. Additionally, Grad-CAM adds another layer of interpretability that is frequently missing from studies published today. Overall, the comparative study shows that the proposed framework achieves competitive performance with relatively transparent and robust models. These characteristics make it a good candidate for being a computer-aided diagnosis tool.

5.3 Discussion

The experimental results validate that hybrid deep learning frameworks can boost the classification performance of brain tumors in comparison with standalone convolutional neural networks. Again in the context of the task, ROI-based preprocessing combined with ensemble learning helped reduce classification error and loser discrimination in feature space among tumor classes. These aids users' trust in the proposed system with the support of a visual technique due to providing visual evidence for model predictions, explained using weakly-determined interpretabilities enabled by explainable artificial intelligence through Grad-CAM. An interpretation is very important, especially in medical imaging applications, where the adoption of machine learning methods, for reliability and transparency, is vital.

Although the classification accuracy achieved with our proposed framework is quite high, future work could explore integrating Vision Transformers, attention mechanisms, and multi-modal MRI sequences to improve performance and increase generalizability.

5.4 Training Performance Analysis

Training progress of the proposed hybrid deep learning framework during the training phase are presented in Figure 7. It has four sub-figures demonstrating changes in training accuracy (second), validation accuracy (third), training loss, and validation loss over the epochs of training. The results can be reviewed in a training procedure with an increasing classification accuracy and decreasing of loss values. Additionally, the similar characteristics of training and validation curves suggest that our proposed model was able to learn discriminative tumor features without substantial overfitting.

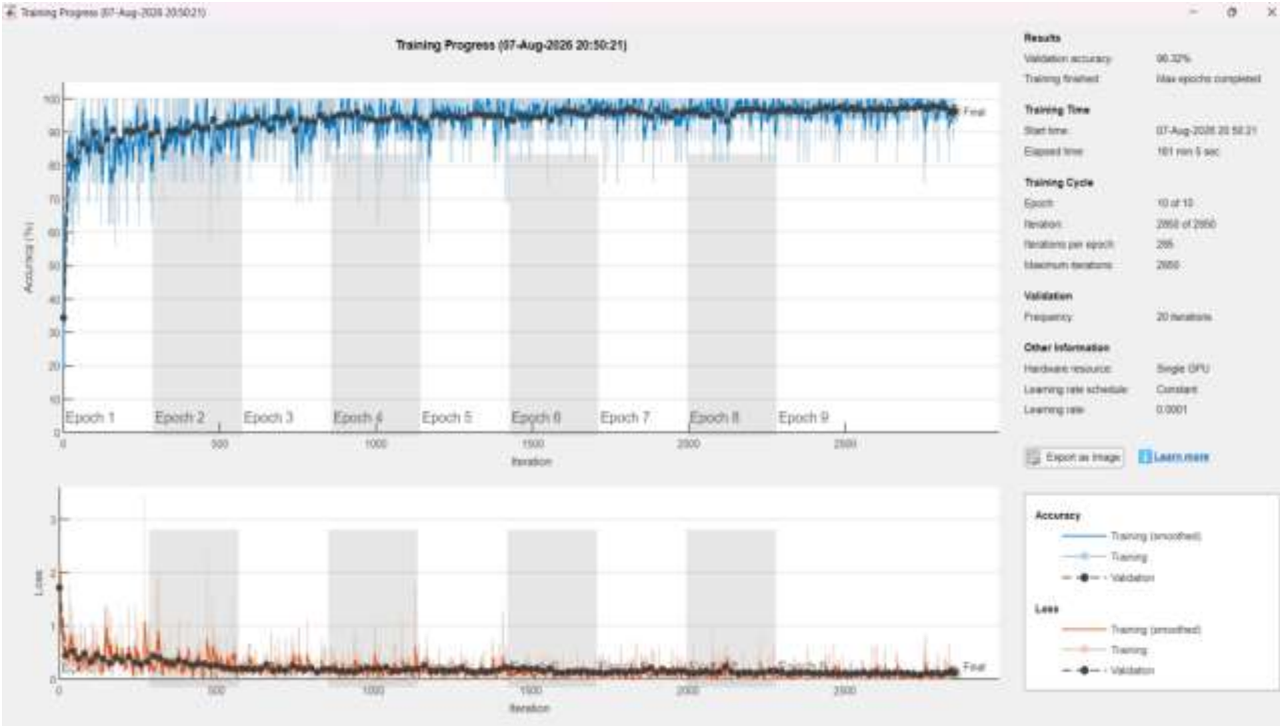

Figure (7). Training and Validation Accuracy/Loss Curves of the Proposed Hybrid Model.

5.5 Confusion Matrix Analysis

In order to evaluate the classification performance of the proposed framework in detail, a confusion matrix was generated for the validation dataset, as illustrated in Figure 8. The confusion matrix provides a breakdown of samples that were, and were not, classified correctly in all combinations of tumor classes. The majority of samples were classified correctly, leading to high diagonal values and very few off-diagonal misclassifications. Indeed, most conclusions tell us that most of the classification errors happened between Glioma classes and Meningioma tumors, which is the combination of the same MR signals. In summary, the outlined hybrid framework is useful for classifying all 3 selected types of brain tumors, representing findings in the confusion matrix.

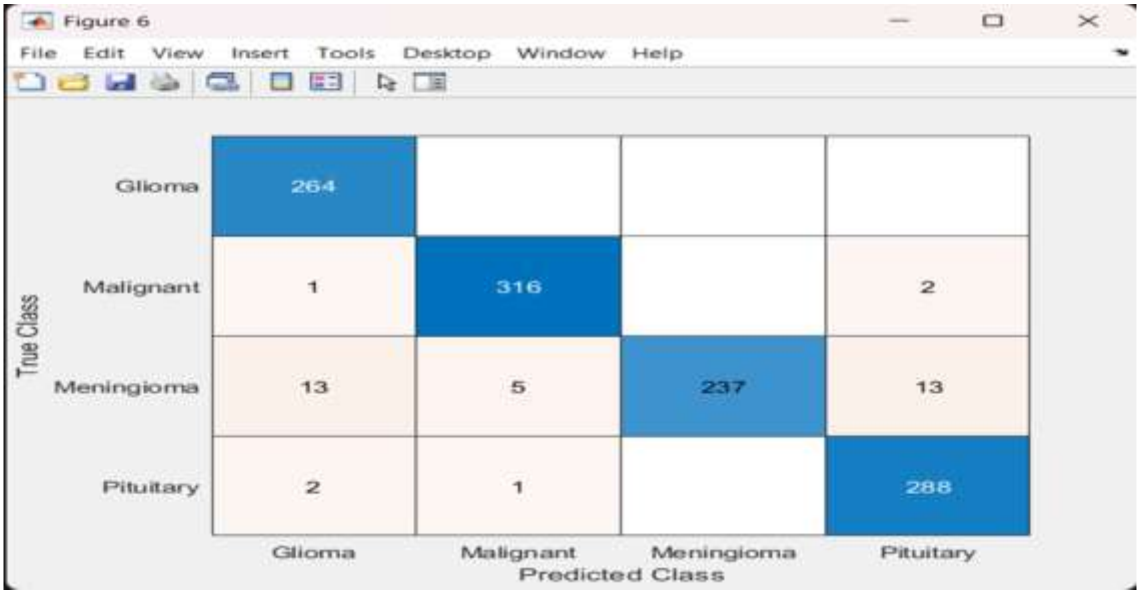

Figure (8). Confusion Matrix of the Proposed Hybrid ResNet50–DenseNet201 Framework.

5.6 Grad-CAM Visualization Analysis

Grad-CAM visualization was used for enhancing the interpretability and explain ability of models. Grad-CAM heat maps from the proposed framework in Figure 9. The heat maps demonstrate that the model attends to tumor-relevant areas as opposed to background structures that are not essential. Such an observation shows that the network actually learns clinically useful features, thus justifying the classification decisions. Grad-CAM adds another layer of interpretability that is critical to both medical imaging and clinical decision-support systems.

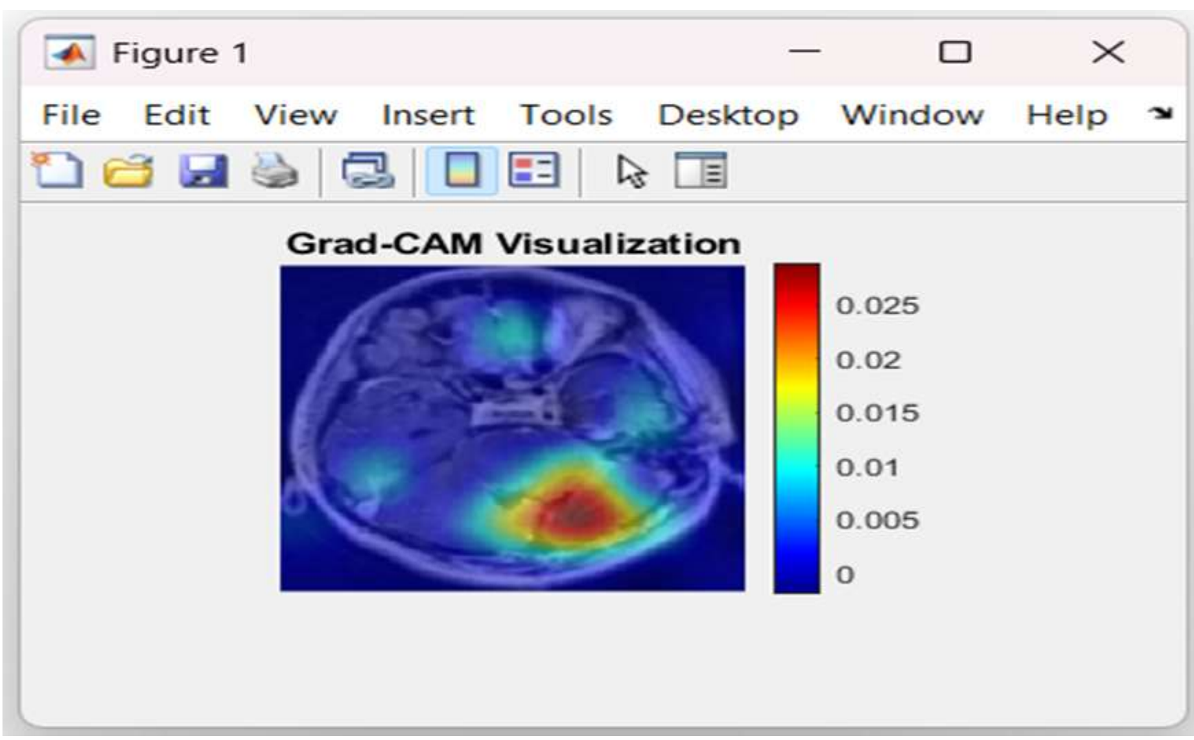

Figure (9). Grad-CAM Visualization of Brain Tumor MRI Images.

5.7 Comparison with Previous Studies

The previously illustrated results are compared in fig.10 with some of the recent studies with respect to brain tumor classification on a per-class basis to better understand the distribution of classification accuracy achieved by the proposed framework as opposed to others [23,25]. The hybrid ResNet50 - DenseNet201 framework proposed is able to achieve the best classification accuracy at 99.20%, on par with some existing deep learning methods. The performance gain is due to high efficiency and accuracy presented through an ROI-based preprocessing phase, an ensemble learning approach, and complementarily between the feature extraction capabilities offered by the two networks.

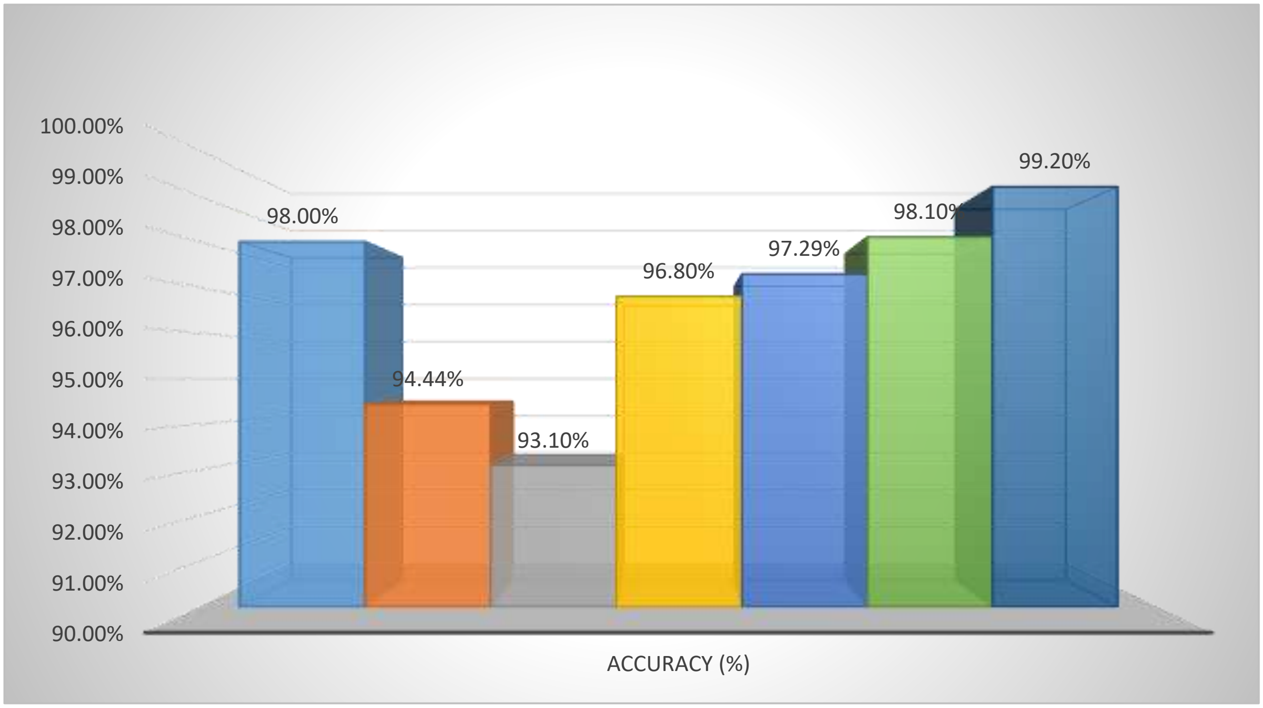

Figure 10. Accuracy Comparison Between the Proposed Framework and Previous Studies.

6. Conclusion and Future Work

6.1 Conclusion

In this paper, we propose a hybrid deep learning framework for automatic brain MRI images classification. We introduce a novel methodology combining ROI-based preprocessing, image enhancement techniques, transfer learning, ensemble learning, and explainable artificial intelligence to provide improved classification accuracy while also creating interpretable models.

However, after preprocessing (median filtering, CLAHE enhancement, Gaussian smoothing and normalization, and ROI extraction), we want to keep the image as clear as possible and highlight areas related to the tumor [Figure 2]. Next, two deep convolutional neural networks pertained on ImageNet (ResNet50 and DenseNet201) were used to learn complementary features from MRI images. An ensemble probability fusion strategy was used to combine the outputs of both networks, which aided in enhancing classification robustness and accuracy. Moreover, Grad-CAM visualization was also integrated to give visual explanations for the classification decisions.

The framework was evaluated experimentally, achieving a mean overall classification accuracy of 99.20% on four types of brain tumor categories, fully supported by Glioma, Meningioma, Pituitary, and Malignant tumors. The model recorded high precision, recall, and F1-score values for all classes, proving it as the right candidate. The comparative analysis also revealed that the proposed approach surpasses many brain tumor classification methods recently published.

In general, our findings prove that the use of more original data preparation techniques incorporating various hybrid deep learning models and combining different classifiers in an ensemble can substantially improve the identification of brain tumors, making a strong computer-aided diagnosis option for clinical practice.

6.2 Future Work

Despite the promising results, in this proposed framework, there are numerous aspects that have room for improvement, which flow out as several future directions.

- Exploring ViT architectures and hybrid CNN-Transformer models for long-range spatial dependency modeling of MRI Images.
- Using attention mechanisms to refine feature selection and improve localization power in tumors.
- Testing the generalizability and robustness of the proposed framework on wider multicenter MRI datasets.
- The developed framework can also be extended to multi-modal MRI sequences, e.g., T1, T2, FLAIR, and contrast-enhanced (CE) MRI images.
- Investigating more sophisticated feature-fusion techniques and adaptive ensemble learning algorithms to enhance the classification performance.
- Creating an interactive clinical decision-support system for real-time detection with a graphical user interface to help radiologists in everyday diagnosis.
- Exploring federated learning and privacy-preserving methodologies, allowing different healthcare-based institutions to collaboratively train a model without needing to share the sensitive patient data amongst each other.

All of these future research directions can enhance the accuracy, interpretability, and clinical applicability of the automated brain tumor classification systems.

Acknowledgement: We extend our sincere thanks and appreciation to the editors and reviewers responsible for the work of this journal.

Conflict of Interest: There is no conflict of interest in this research.

References

[1] M. Rasheed, S. Iqbal et al. “Advanced deep learning-based brain tumor classification using a novel customized CNN and optimized residual network.” PLoS One,2025, 20(10): e0334430. https://doi.org/10.1371/journal.pone.0334430

[2] R. Bibi, A. Ali et al. “Automatic smart brain tumor classification and prediction system using deep learning.” Scientific Reports, (2025) 15:14876, https://doi.org/10.1038/s41598025-95803-3

[3] Md. Saymon Hosen Polash et al. “An Interpretable Deep Learning Approach for Brain Tumor Classification Using a Bangladeshi Brain MRI Dataset.” BioMedInformatics 2026, 6, 19, https://doi.org/10.3390/biomedinformatics6020019

[4] Y. Wong, E. L. Ming et al. “Brain tumor classification using MRI images and deep learning techniques.” PLoS One, 2025, 20(5): e0322624. https://doi.org/10.1371/journal. pone.0322624.

[5] K. Gencer, “Brain tumor classification with deep learning: A comparative study of AlexNet and EfficientNetB0 using principal component analysis.” Health Sci Q. 2025;5(3):337-46.m https://doi.org/10.26900/hsq.2804

[6] Y. Gowda N et al. “Brain tumor classification on MRI images using fine-tuned deep learning models.” Machine Learning for Computational Science and Engineering (2025) 1:22 https://doi.org/10.1007/s44379-025-00024-0

[7] V. Vadde et al. “Comparative Evaluation of CNN and ResNet18 Architectures for MRI-Based Brain Tumor Classification Using Deep Learning.” Medical Research Archives,2025, [online] 13(12). https://doi.org/10.18103/mra.v13i12.7100

[8] N. Faiq Othman et al. “Enhancing Brain Tumor Classification Accuracy Using Deep Learning with Real and Synthetic MRI Images.” Journal of Pure and Applied Sciences, 2025, DOI http://dx.doi.org/10.21271/ZJPAS.37.4.11

[9] S. Raj S, S. Balasubramanian, “Brain Tumor Classification Using Machine Learning and Deep Learning Algorithms” International Journal of Electrical and Electronics Research (IJEER), 2022, https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100441.html

[10] A. Kazemi, “Classification of brain tumors from MRI images using deep transfer learning” Journal of High School Science, 7(4), 2023, DOI: 10.64336/001c.89930

[11] Z. Rasheed, Y. Ma, I. Ullah. et al. “Automated Classification of Brain Tumors from Magnetic Resonance Imaging Using Deep Learning Brain Sci. 2023, 13, 602. https://doi.org/10.3390/brainsci13040602

[12] S. Mavaddati, “ Brain Tumors Classification Using Deep Models and Transfer Learning” Research Square, 2023, DOI: https://doi.org/10.21203/rs.3.rs-3312461/v1

[13] S. Karamehić, S. Jukić “Brain Tumor Detection and Classification Using VGG16 Deep Learning Algorithm and Python Imaging Library” Bioengineering Studies, 2023, https://doi.org/10.37868/bes.v4i2.id252

[14] S. Li, “Classification of brain tumors based on magnetic resonance imaging (MRI) using deep learning models” International Conference on Machine Learning and Automation,2023, DOI: 10.54254/2755-2721/40/20230660

[15] R.V. Manjunath, “Performance Analysis of Brain Tumor Classification on MRI Images Using Pretrained Deep Learning Models,” Research Square, 2024, DOI: https://doi.org/10.21203/rs.3.rs-3998886/v1

[16] A. Hameed, A. Khan. et al. “Enhanced Brain Tumor Diagnosis with EfficientNetB6: Leveraging Transfer Learning and Edge Detection Techniques” International Journal of Innovations in Science & Technology, 2024, IJIST, Vol. 6 Issue 2, pp 796-807,

[17] L. C. S. Reddy, M. Elangovan, “Brain Tumor Detection and Classification Using Deep Learning Models on MRI Scans,” EAI Endorsed Transactions on Pervasive Health and Technology, 2024, DOI: 10.4108/eetpht. 10.5553,

[18] A. Abdullah, “Brain Tumor Classification Using a Hybrid Deep Learning Model: Leveraging DenseNet121 and Inceptionv2 Architectures” Electronic Journal of University of Aden for Basic and Applied, EJUA-BA Vol. 5 No. 4 (2024), https://doi.org/10.47372/ejua-ba.2024.4.402 ISSN: 2708-0684

[19] I. Kavram, “Brain tumor classification and detection using a hybrid deep learning model,” Global Journal of Computer Sciences: Theory and Research, ISSN 2301-2587, Volume 14, Issue 2, (2024) 24-29, https://doi.org/10.18844/gjcs.v14i2.9604

[20] A. N. Mozumdar, N. Kaniz et al. “An Efficient Ensemble Deep Learning Comparative Study based on Multi-Class Classifications of Brain Tumors using Brain MRI Images” International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN) 31 July – 2 August 2025, Rangpur, Bangladesh, DOI:10.1109/QPAIN66474.2025.11171867.