Deep Neural Framework for Automated Brain Tumor Identification in MRI Scans

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Abstract—**Accurate identification of brain tumors from magnetic resonance imaging (MRI) scans plays a significant role in supporting clinical diagnosis and treatment planning. Manual examination of large volumes of MRI images is time-consuming and may be influenced by inter-observer variability, creating a need for reliable computer-aided diagnostic systems. This study presents a deep learning-based framework for automated brain tumor classification using MRI images. The proposed work investigates the performance of a custom Convolutional Neural Network (CNN) and three transfer learning models, namely ResNet18, VGG16, and ResNet50, for the classification of four categories: glioma, meningioma, pituitary tumor, and no tumor. Image preprocessing techniques, including resizing, normalization, and data augmentation, were applied to improve model robustness and generalization. To enhance transparency in decision-making, Gradient-weighted Class Activation Mapping (Grad-CAM) was incorporated to visualize the image regions that contributed most to the model predictions. Experimental evaluation demonstrated that ResNet18 achieved superior performance compared to the other models, obtaining a test accuracy of 94.39%. The proposed framework not only provides accurate classification results but also offers visual interpretability, making it more suitable for medical imaging applications. Furthermore, a user-friendly Gradio-based interface was developed to facilitate real-time prediction of brain tumor categories from MRI scans. The findings indicate that combining transfer learning with explainable artificial intelligence can contribute to the development of effective and trustworthy computer-aided diagnostic systems for brain tumor analysis.**

Index Terms—**Brain Tumor Classification, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Network (CNN), Transfer Learning, ResNet18, VGG16, ResNet50, Grad-CAM, Explainable Artificial Intelligence (XAI), Medical Image Analysis.**

I. INTRODUCTION

Brain tumors represent one of the most critical neurological disorders, requiring timely diagnosis and appropriate treatment planning to improve patient outcomes. Magnetic Resonance Imaging (MRI) is widely used in clinical practice due to its ability to provide detailed visualization of brain tissues and abnormalities without exposing patients to ionizing radiation. However, the manual interpretation of MRI scans is a challenging task that demands significant expertise and can be affected by factors such as image complexity, workload, and inter-observer variability. These challenges have motivated the development of automated systems capable of assisting medical professionals in the accurate identification of brain tumors. Recent advances in deep learning have significantly transformed the field of medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable capability in automatically extracting discriminative features from medical images, eliminating the need for handcrafted feature engineering. Furthermore, transfer learning techniques have enabled the adaptation of pre-trained deep learning models to specialized medical imaging tasks, often resulting in improved classification performance even when limited training data are available. Despite these advancements, achieving both high classification accuracy and model interpretability remains an important research challenge in healthcare applications. Brain tumor classification involves distinguishing among multiple tumor categories that may exhibit similar visual characteristics in MRI scans. Variations in tumor size, shape, texture, and location further increase the complexity of the classification process. Consequently, robust deep learning models capable of learning representative features from MRI images are essential for reliable diagnostic support. In addition, the ability to explain model predictions is increasingly important in medical environments where transparency and trust are required before automated systems can be integrated into clinical workflows.

This study presents a deep learning-based framework for automated brain tumor classification using MRI images. A custom Convolutional Neural Network (CNN) was developed and evaluated alongside three transfer learning models, namely ResNet18, VGG16, and ResNet50. The classification framework categorizes MRI scans into four classes: glioma, meningioma, pituitary tumor, and no tumor. To improve model robustness, image preprocessing and augmentation techniques were employed during training. Furthermore, Gradient-weighted Class Activation Mapping (Grad-CAM) was incorporated to provide visual explanations of model decisions by highlighting the regions that contributed most to the classification outcome. The experimental results demonstrate the effectiveness of deep learning techniques for brain tumor classification and provide a comparative assessment of different model architectures. By combining accurate classification with explainable artificial intelligence, the proposed framework aims to support the development of trustworthy computer-aided diagnostic systems for medical imaging applications.

II. LITERATURE SURVEY

The application of deep learning techniques in medical image analysis has gained considerable attention due to their ability to learn complex patterns directly from imaging data. In the domain of brain tumor diagnosis, several studies have explored the use of machine learning and deep learning models to improve the accuracy and efficiency of tumor detection and classification from MRI scans.

Early approaches primarily relied on traditional machine learning algorithms combined with handcrafted feature extraction methods. These techniques utilized texture, shape, and intensity-based features obtained from MRI images and employed classifiers such as Support Vector Machines (SVM), Decision Trees, and Random Forests. Although these methods achieved reasonable performance, their effectiveness depended heavily on the quality of manually engineered features, which often limited their ability to generalize across diverse datasets.

The emergence of Convolutional Neural Networks (CNNs) significantly improved the performance of medical image classification systems. CNN-based models automatically learn hierarchical feature representations from raw images, reducing the need for manual feature engineering. Several researchers have reported promising results using deep CNN architectures for brain tumor classification, demonstrating improved accuracy and robustness compared to conventional machine learning methods. These models have proven effective in capturing both low-level and high-level image characteristics associated with different tumor types.

Transfer learning has further enhanced the applicability of deep learning in medical imaging. Pre-trained architectures such as VGG16, ResNet, DenseNet, and Inception have been successfully adapted for brain tumor classification tasks. By leveraging knowledge acquired from large-scale image datasets, transfer learning models can achieve strong performance even when medical datasets are relatively limited in size. Among these architectures, residual networks have gained particular attention due to their ability to facilitate deeper network training while mitigating the vanishing gradient problem.

Despite the high classification accuracy achieved by many deep learning models, the lack of interpretability remains a major concern in healthcare applications. Medical practitioners often require evidence supporting automated decisions before adopting such systems in clinical environments. To address this challenge, explainable artificial intelligence techniques have been introduced to provide visual insights into model behavior. Methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) enable visualization of the image regions that contribute most significantly to a model's prediction, thereby improving transparency and trustworthiness.

Although substantial progress has been made in brain tumor classification, there remains a need for frameworks that combine accurate classification, comparative evaluation of multiple deep learning architectures, and interpretable decision-making mechanisms within a unified system. Motivated by these considerations, the present work investigates the performance of a custom CNN alongside transfer learning models including ResNet18, VGG16, and ResNet50 for multiclass brain tumor classification. In addition, Grad-CAM is incorporated to provide visual explanations of classification outcomes, enabling a more transparent and reliable diagnostic support framework.

III. PROPOSED SYSTEM

3.1 System Architecture

The overall architecture of the proposed framework is designed to perform automated brain tumor classification from MRI images using deep learning techniques while providing visual interpretability of model predictions. The workflow begins with the acquisition of MRI brain images, which are collected from the dataset and organized into four categories: glioma, meningioma, pituitary tumor, and no tumor. The acquired images undergo a preprocessing stage that includes image resizing, normalization, and data augmentation to improve image consistency and enhance the generalization capability of the learning models.

Following preprocessing, the dataset is divided into training, validation, and testing subsets. The training data are utilized to learn discriminative features associated with different tumor categories, while the validation and testing datasets are used to evaluate model performance and generalization. To investigate the effectiveness of different deep learning architectures, a custom Convolutional Neural Network (CNN) and three transfer learning models, namely ResNet18, VGG16, and ResNet50, are employed for classification.

During the training phase, each model learns hierarchical feature representations from MRI images and generates predictions corresponding to the four tumor classes. The trained models are evaluated using performance metrics and comparative analysis to identify the most effective architecture. Based on the experimental results, the best-performing model is selected for further analysis and deployment.

To improve the transparency of the classification process, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated into the framework. Grad-CAM generates visual heatmaps that highlight the image regions contributing most significantly to the model's decision, thereby providing an interpretable explanation of the classification outcome. Finally, a Gradio-based graphical user interface is developed to enable real-time prediction of brain tumor categories from uploaded MRI images. The complete architecture integrates classification accuracy, model comparison, explainable artificial intelligence, and user-friendly deployment within a unified diagnostic support framework.

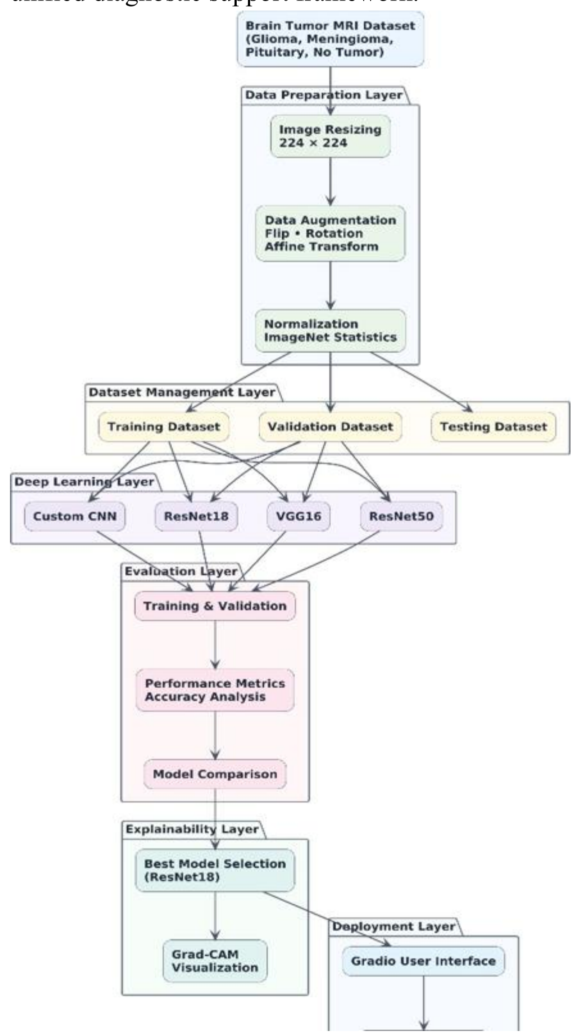

Fig. 1. Architecture of the proposed brain tumor classification framework.

3.2 Dataset Description

The experiments conducted in this study utilize a publicly available Brain Tumor MRI Dataset consisting of magnetic resonance imaging (MRI) scans categorized into four distinct classes: glioma, meningioma, pituitary tumor, and no tumor. These categories represent common brain tumor conditions along with normal brain images, enabling the development of a multiclass classification framework. The dataset contains MRI images acquired from different subjects and exhibits variations in tumor size, shape, location, and intensity characteristics, making it suitable for evaluating the robustness of deep learning models. The dataset is organized into separate training and testing directories, where each class is stored in an individual folder corresponding to its tumor category. During experimentation, image paths and class labels were extracted and converted into a structured format for efficient processing. To reduce computational overhead and accelerate experimentation, a subset of the available images was utilized while preserving the overall class distribution. The selected images were subsequently divided into training, validation, and testing sets to facilitate model development, hyperparameter tuning, and unbiased performance evaluation.

The four tumor categories considered in this work present distinct radiological characteristics. Glioma tumors originate from glial cells and often exhibit irregular structures, while meningioma tumors generally arise from the protective membranes surrounding the brain. Pituitary tumors develop in the pituitary gland region and possess unique anatomical features. The no-tumor category contains normal MRI scans that do not exhibit pathological abnormalities. The inclusion of these classes enables comprehensive evaluation of the proposed classification framework under realistic multiclass diagnostic conditions.

The diversity of the MRI images and the presence of multiple tumor categories provide a suitable benchmark for assessing the effectiveness of deep learning and transfer learning models in automated brain tumor classification.

3.3 Data Preprocessing

Data preprocessing plays a crucial role in improving the quality and consistency of MRI images before they are provided to the deep learning models. Since medical images may vary in resolution, orientation, and intensity distribution, appropriate preprocessing techniques are required to ensure reliable feature extraction and stable model training.

Initially, all MRI images were resized to a fixed resolution of 224×224 pixels to maintain a uniform input dimension across all classification models. Standardizing image dimensions reduces computational complexity and enables compatibility with both the custom CNN architecture and the transfer learning models employed in this study.

To improve the generalization capability of the models and reduce the risk of overfitting, data augmentation techniques were applied to the training images. These augmentations included random horizontal flipping, affine transformations, brightness variations, and small rotational adjustments. Such transformations generate diverse image samples while preserving the underlying anatomical characteristics of the brain structures and tumor regions.

Following augmentation, the images were converted into tensor representations suitable for deep learning frameworks. Image normalization was then performed using standard mean and standard deviation values to ensure that pixel intensities were distributed within a consistent range. Normalization facilitates faster convergence during training and contributes to improved optimization performance.

The preprocessing pipeline was applied differently for training and evaluation phases. While training images underwent both augmentation and normalization, validation and testing images were subjected only to resizing and normalization. This strategy ensures that model evaluation is performed on unaltered images, thereby providing an unbiased assessment of classification performance.

The resulting preprocessed dataset provides standardized and representative input samples, enabling effective learning of discriminative features for brain tumor classification.

3.4 Deep Learning Models

To investigate the effectiveness of different deep learning architectures for brain tumor classification, this study employs a custom Convolutional Neural Network (CNN) along with three widely adopted transfer learning models, namely ResNet18, VGG16, and ResNet50. The objective of utilizing multiple architectures is to compare their classification capabilities and identify the most suitable model for MRI-based brain tumor diagnosis. The custom CNN was designed specifically for this classification task and consists of multiple convolutional layers followed by max-pooling operations, fully connected layers, and dropout regularization. The convolutional layers automatically learn hierarchical image features ranging from low-level edges and textures to high-level tumor-specific characteristics. The inclusion of dropout helps reduce overfitting and improves the model's generalization performance.

In addition to the custom CNN, transfer learning techniques were employed using pre-trained deep neural networks. ResNet18 utilizes residual learning through shortcut connections, enabling effective feature extraction while mitigating the vanishing gradient problem. Its relatively lightweight architecture provides a balance between computational efficiency and classification accuracy, making it suitable for medical imaging applications.

VGG16 is a deep convolutional architecture characterized by a sequence of small convolutional filters and a structured layer design. The model has demonstrated strong feature learning capabilities across various image classification tasks and serves as an important benchmark for performance comparison in this study. ResNet50 extends the concept of residual learning by incorporating a deeper architecture with fifty layers. The increased network depth enables the extraction of highly discriminative image representations and facilitates the learning of complex visual patterns associated with different brain tumor categories. For all transfer learning models, the original classification layers were replaced with new fully connected layers corresponding to the four target classes considered in this work. The models were subsequently fine-tuned using the MRI dataset to adapt their learned representations to the specific characteristics of brain tumor images. The comparative evaluation of these architectures enables a comprehensive assessment of conventional CNN design and transfer learning strategies for automated brain tumor classification.

3.5 Grad-CAM Explainability

Deep learning models often achieve high classification performance; however, their decision-making process is frequently difficult to interpret. In medical image analysis, understanding the rationale behind a prediction is essential for improving transparency and supporting clinical acceptance. To address this challenge, Gradient-weighted Class Activation Mapping (Grad-CAM) was incorporated into the proposed framework as an explainable artificial intelligence technique. Grad-CAM provides visual explanations by identifying the image regions that have the greatest influence on a model's prediction. The method utilizes gradient information obtained from the final convolutional layer of a trained network to determine the importance of spatial features associated with a specific class. These importance values are subsequently combined to generate a localization map that highlights the most influential regions within the MRI image.

In the proposed framework, Grad-CAM is applied after the classification stage to analyze the behavior of the best-performing deep learning model. By examining the activation patterns learned during training, the technique enables visualization of the image areas that contribute most significantly to the final prediction. This process assists in verifying whether the model focuses on clinically relevant tumor regions rather than unrelated image characteristics. The integration of Grad-CAM enhances the interpretability of the classification framework without affecting its predictive performance. As a result, the proposed system not only provides automated tumor classification but also offers an additional layer of transparency that can support the analysis and validation of model decisions in medical imaging applications.

3.6 User Interface Development

To facilitate practical usage of the proposed brain tumor classification framework, a graphical user interface was developed using the Gradio framework. The interface provides a simple and interactive environment through which users can upload MRI images and obtain classification results without requiring direct interaction with the underlying deep learning models.

The developed interface is integrated with the best-performing classification model identified during the experimental evaluation process. Once an MRI image is uploaded, the image undergoes the same preprocessing operations employed during model training, including resizing and normalization. The processed image is then forwarded to the trained model, which generates the predicted tumor category along with the corresponding confidence scores.

The user interface was designed with an emphasis on accessibility and ease of use. The system accepts MRI images as input and presents classification outcomes in a clear and understandable format. This approach enables users to perform inference in real time while abstracting the complexities of deep learning implementation. The integration of a deployment interface demonstrates the practical applicability of the proposed framework beyond experimental evaluation. By providing an intuitive mechanism for image-based prediction, the developed interface serves as a proof-of-concept deployment environment for automated brain tumor classification systems.

IV. RESULTS AND DISCUSSION

4.1 Experimental Setup

All experiments were conducted using the PyTorch deep learning framework within the Google Colaboratory environment. GPU acceleration was utilized to improve training efficiency and reduce computational time. The proposed framework was evaluated using MRI images belonging to four classes: glioma, meningioma, pituitary tumor, and no tumor.

Prior to training, all images were resized to a resolution of 224 × 224 pixels and subjected to normalization to ensure consistency across the dataset. Data augmentation techniques, including horizontal flipping, affine transformations, brightness adjustments, and image rotations, were applied to the training data to improve model generalization and reduce overfitting. The dataset was partitioned into training, validation, and testing subsets to facilitate model development and unbiased performance assessment. Four deep learning architectures were investigated in this study: a custom Convolutional Neural Network (CNN), ResNet18, VGG16, and ResNet50. The transfer learning models were initialized with pre-trained weights and subsequently fine-tuned for the brain tumor classification task. For all models, the final classification layer was modified to produce predictions for the four target categories.

Model training was performed using the Adam optimizer and the Cross-Entropy Loss function. A batch size of 16 was employed throughout the experiments, and each model was trained for 15 epochs. During training, both training and validation accuracies were monitored to evaluate learning behavior and detect potential overfitting. After training, the models were evaluated on the independent test dataset to determine their classification performance. The experimental analysis focused on comparing the effectiveness of the different deep learning architectures using quantitative performance metrics and qualitative visualization techniques. Furthermore, Grad-CAM was utilized to examine the interpretability of the best-performing model, while a Gradio-based deployment interface was developed to demonstrate the practical applicability of the proposed framework.

Table I. Experimental configuration and training parameters used for brain tumor classification.

Parameter	Value
Framework	PyTorch
Development Environment	Google Colaboratory
Input Image Size	224 × 224
Number of Classes	4
Classes	Glioma, Meningioma, Pituitary, No Tumor
Batch Size	16
Optimizer	Adam
Learning Rate	0.0007 (CNN), 0.0003 (Transfer Learning Models)
Loss Function	Cross-Entropy Loss
Number of Epochs	15
Deep Learning Models	CNN, ResNet18, VGG16, ResNet50
Explainability Method	Grad-CAM
Deployment Framework	Gradio
Hardware Accelerator	GPU

4.2 Performance Evaluation

The performance of the developed brain tumor classification models was assessed using standard evaluation metrics commonly employed in multiclass image classification tasks. These metrics provide quantitative insight into the ability of the models to correctly distinguish between glioma, meningioma, pituitary tumor, and no-tumor MRI images.

Classification accuracy was considered the primary evaluation metric and was calculated as the ratio of correctly classified samples to the total number of samples in the dataset. Accuracy provides an overall measure of model effectiveness and enables direct comparison among different deep learning architectures. In addition to accuracy, the learning behavior of each model was analyzed using training and validation performance across multiple epochs. Monitoring these measures helps evaluate convergence characteristics and identify potential overfitting or underfitting during the training process. The validation performance was particularly important for selecting the most suitable model for further analysis and deployment.

To obtain a more detailed understanding of classification behavior, confusion matrix analysis was also performed. The confusion matrix provides class-wise information regarding correct and incorrect predictions, allowing identification of tumor categories that are more challenging to distinguish. This analysis helps reveal strengths and limitations of the classification models beyond overall accuracy values.
Furthermore, comparative evaluation was conducted among the custom CNN, ResNet18, VGG16, and ResNet50 architectures. The comparison was based on training accuracy, validation accuracy, and test accuracy to determine the most effective model for brain tumor classification. The model demonstrating the highest classification performance was subsequently selected for explainability analysis using Grad-CAM and deployment through the developed user interface. The combination of quantitative performance metrics and qualitative analysis techniques provides a comprehensive evaluation of the proposed framework and its effectiveness in automated brain tumor classification.

Table II. Comparative performance of the evaluated deep learning models for brain tumor classification.

Model	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)
Brain Tumor CNN	87.81	84.77	85.20
ResNet18	96.44	93.91	94.39
VGG16	92.18	77.16	86.22
ResNet50	83.66	82.74	84.69

4.3 Model Comparison

A comparative analysis was conducted to evaluate the effectiveness of the four deep learning architectures employed in this study, namely the custom CNN, ResNet18, VGG16, and ResNet50. The comparison was based on training accuracy, validation accuracy, and test accuracy obtained during the experimental evaluation phase. The results are presented in Table II. Among all evaluated models, ResNet18 achieved the highest overall performance with a training accuracy of 96.44%, validation accuracy of 93.91%, and test accuracy of 94.39%. The superior performance of ResNet18 can be attributed to its residual learning mechanism, which enables efficient feature extraction while maintaining stable optimization during training. The model demonstrated strong generalization capability across unseen MRI images and consistently outperformed the other architectures. The custom CNN achieved a test accuracy of 85.20%, indicating its ability to learn meaningful tumor-related features directly from MRI images. Although its performance was lower than that of the transfer learning models, the CNN produced relatively stable results with a smaller gap between training and validation accuracy, suggesting good learning consistency. VGG16 obtained a training accuracy of 92.18% and a test accuracy of 86.22%. While the model demonstrated strong learning capability, fluctuations observed in validation performance indicate a tendency toward overfitting. The considerable difference between training and validation accuracy suggests that the model learned certain dataset-specific patterns that did not generalize effectively to unseen samples.
ResNet50 achieved a test accuracy of 84.69%, which was lower than the performance of ResNet18. Although deeper architectures generally possess stronger representation capabilities, the available dataset size and training configuration may have limited the potential advantages of the deeper network. Consequently, ResNet50 did not provide a significant improvement over the lighter residual architecture.
Overall, the experimental results demonstrate that transfer learning models outperform the custom CNN architecture for brain tumor classification. Among the evaluated approaches, ResNet18 delivered the most balanced and reliable performance, making it the preferred model for subsequent explainability analysis and deployment. The comparative results confirm the effectiveness of residual learning for MRI-based brain tumor classification and highlight the suitability of ResNet18 for practical diagnostic support applications.

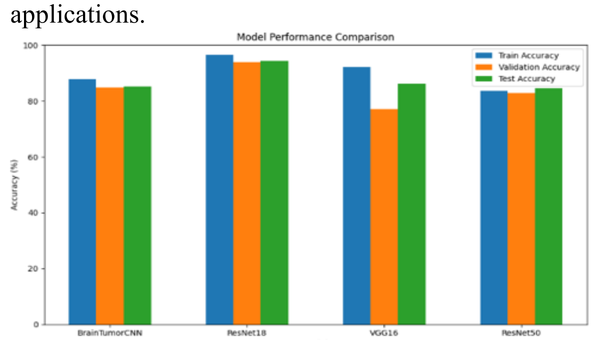

Fig. 2. Comparative performance of CNN, ResNet18, VGG16, and ResNet50 models based on training, validation, and test accuracy.

4.4 Confusion Matrix Analysis

To obtain a detailed understanding of the classification performance of the proposed framework, confusion matrix analysis was performed on the test dataset. The confusion matrix provides class-wise prediction information by comparing the actual labels with the predicted labels generated by the model. Unlike overall accuracy, this analysis highlights the specific categories that are correctly identified as well as the classes that are occasionally misclassified. The results indicate that the model achieved strong classification performance across all four categories. The no-tumor class exhibited the highest level of correct predictions, demonstrating the model's ability to effectively distinguish normal brain MRI images from pathological cases. Similarly, the pituitary tumor category showed a high recognition rate with very few misclassifications, indicating the presence of distinctive image characteristics that were successfully captured by the learning process.

A small degree of confusion was observed between glioma and meningioma images. This behavior can be attributed to similarities in visual appearance and overlapping structural characteristics present in certain MRI scans. Despite these challenges, the majority of samples belonging to both classes were classified correctly, reflecting the effectiveness of the extracted deep features. The confusion matrix further reveals that only a limited number of images were incorrectly assigned to other categories, demonstrating the robustness of the proposed classification framework. Overall, the confusion matrix confirms that the developed model maintains balanced performance across the different tumor classes and is capable of accurately identifying clinically relevant categories. The analysis supports the quantitative evaluation results and provides additional evidence regarding the reliability of the proposed approach for automated brain tumor classification.

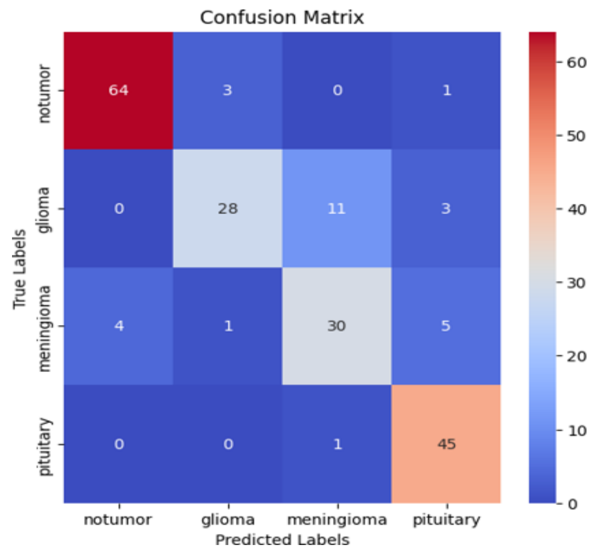

Fig. 3. Confusion matrix illustrating the classification performance of the proposed brain tumor classification model.

4.5 Grad-CAM Analysis

To enhance the interpretability of the proposed brain tumor classification framework, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to visualize the regions that influenced the model's predictions. While deep learning models can achieve high classification accuracy, understanding the basis of their decisions is particularly important in medical imaging applications where transparency and reliability are essential. Grad-CAM analysis was performed using the best-performing model identified during the experimental evaluation. The generated heatmaps were overlaid on the corresponding MRI images to highlight the areas that contributed most significantly to the classification outcome. Regions displayed with higher intensity indicate stronger influence on the prediction, whereas lower-intensity regions represent areas with comparatively less contribution.

The visualization results demonstrate that the model consistently focused on clinically relevant regions associated with tumor structures rather than unrelated background information. For glioma, meningioma, and pituitary tumor images, the highlighted regions were concentrated around the abnormal tissue areas, indicating that the model successfully learned meaningful pathological characteristics during training. Similarly, for no-tumor images, the activation maps exhibited the absence of concentrated pathological regions, supporting the correctness of the model's decision-making process. The Grad-CAM visualizations provide qualitative evidence that the classification framework is capable of identifying informative features from MRI scans while maintaining interpretability. These findings complement the quantitative performance results and demonstrate that the model's predictions are based on relevant anatomical structures. Consequently, the integration of Grad-CAM improves the transparency of the proposed system and strengthens its suitability for computer-aided brain tumor diagnosis.

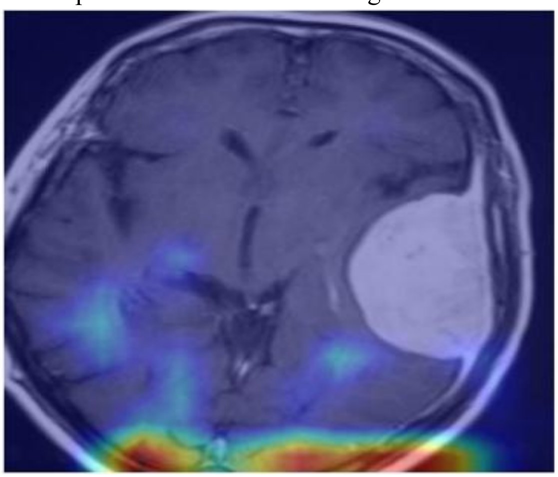

Fig. 4. Grad-CAM visualizations highlighting the MRI regions contributing to brain tumor classification decisions.

V. CONCLUSION AND FUTURE WORK

This study presented a deep learning-based framework for automated brain tumor classification using MRI images. The proposed approach investigated the effectiveness of a custom Convolutional Neural Network (CNN) and three transfer learning models, namely ResNet18, VGG16, and ResNet50, for multiclass classification of glioma, meningioma, pituitary tumor, and no-tumor images. Image preprocessing techniques, including resizing, normalization, and data augmentation, were employed to improve model robustness and learning efficiency.

Experimental results demonstrated that transfer learning models achieved superior performance compared to the custom CNN architecture. Among all evaluated models, ResNet18 produced the best classification results, achieving a test accuracy of 94.39%, thereby outperforming VGG16, ResNet50, and the custom CNN model. Confusion matrix analysis further confirmed the model's ability to accurately distinguish among different tumor categories with minimal misclassification. In addition, Grad-CAM visualizations provided interpretable explanations of model predictions by highlighting the MRI regions that contributed most significantly to the classification outcome. The development of a Gradio-based user interface further demonstrated the practical applicability of the proposed framework for real-time brain tumor prediction.

Although the obtained results are encouraging, several opportunities remain for future improvement. Future work may involve training on larger and more diverse MRI datasets to enhance model generalization across different clinical conditions. Additional deep learning architectures and ensemble learning strategies can also be explored to further improve classification performance. Furthermore, integrating advanced explainable artificial intelligence techniques and developing a web-based or cloud-enabled deployment platform could increase the accessibility and clinical utility of the system. These enhancements may contribute to the development of more reliable and intelligent computer-aided diagnostic tools for brain tumor analysis.

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