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Development of a Brain Tumor Classification System using a Convolutional Neural Network Model with Explainable Artificial Intelligence

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ABSTRACT

Brain tumors are abnormal cell growths in the brain that require accurate and timely diagnosis, where Magnetic Resonance Imaging (MRI) plays a critical role in detection. However, interpreting MRI scans is challenging due to their complexity and the limited availability of expert radiologists. This challenge is further compounded by the lack of interpretability in many deep learning-based diagnostic systems. Therefore, this study developed an automated and interpretable brain tumor classification system using MRI images. The model, based on a Convolutional Neural Network (CNN), was developed to classify brain tumors into glioma, meningioma, pituitary tumor, and no-tumor categories, while providing visual explanations using Grad-Class Activation Mapping (Grad-CAM). The system was evaluated using accuracy, precision, specificity, recall, F1-score, false positive rate, and ROC-AUC. Results show an overall classification accuracy of 90.6% and an AUC of 0.9892, indicating strong performance. The Grad-CAM visualizations consistently highlighted tumor-affected regions in the MRI images, confirming that the model based its predictions on clinically relevant anatomical structures. The developed model demonstrated effective classification performance and improved interpretability, making it suitable as a reliable decision-support tool for automated brain tumor diagnosis.

INTRODUCTION

Brain tumors are among the most severe neurological disorders due to their aggressive nature, complex treatment, and high mortality rates. These tumors arise from abnormal cell growth in the brain or Central Nervous System (CNS) and can be classified into malignant and Benign tumors.

Malignant tumors are fast-growing and invasive (e.g., glioblastomas), while benign tumors are slow-growing but may still cause significant damage due to pressure on brain structures (e.g., meningiomas). Brain tumor diagnosis relies primarily on the interpretation of Magnetic Resonance Imaging (MRI) scans, which is typically done by trained radiologists. Manual analysis of MRI images is time-consuming, error-prone, and often limited by variability in tumor appearance and radiologist expertise (Bi *et al.*, 2019).

Although several automated techniques have been developed to support diagnosis, many existing approaches are limited in scope and require substantial manual intervention. Recent studies have applied Convolutional Neural Networks (CNNs) for brain tumor classification, demonstrating promising results in accuracy and speed. Aamir *et al.* (2024) and Shawon *et al.* (2023) implemented CNN-based models for brain tumor classification and reported strong performance on publicly available MRI datasets. However, these models often generalize poorly to unseen data and offer little insight into how decisions are made, reducing clinical trust in their predictions. Other studies have attempted to improve interpretability using visualization techniques, yet challenges remain in combining high accuracy with reliable, explainable outputs.

To address these limitations, this study developed a brain tumor classification system using a CNN integrated with Explainable Artificial Intelligence (XAI) techniques, specifically Gradient-weighted Class Activation Mapping (Grad-CAM). The model was trained on a diverse, multi-source MRI dataset obtained from Kaggle and Figshare, incorporating data augmentation to enhance generalization. By providing both accurate predictions using CNN and visual explanations through Grad-CAM, the system aims to support radiologists in clinical decision-making, reduce diagnostic errors, and improve overall confidence in automated brain tumor diagnosis.

REVIEW OF RELATED WORK

In an effort to improve the accuracy and efficiency of brain tumor diagnosis using medical imaging, several researchers have explored automated classification techniques based on Magnetic Resonance Imaging (MRI). Traditional diagnosis relies heavily on radiologists' expertise; it is often time-consuming and prone to human error. As a result, machine learning and deep learning approaches have been widely investigated to assist in brain tumor detection and classification.

Mohsen *et al*. (2018) developed a deep neural network-based brain tumor classification system using MRI images obtained from Harvard Medical School. The problem addressed was the limitation of traditional machine learning methods in capturing complex tumor features. The methodology combined Fuzzy C-Means clustering for segmentation, Discrete Wavelet Transform (DWT) for feature extraction, Principal Component Analysis (PCA) for dimensionality reduction, and a Deep Neural Network for classification. The model achieved 96.97% classification accuracy, demonstrating improved performance over conventional approaches. However, the system lacked interpretability mechanisms and was evaluated on a limited dataset, raising concerns regarding generalization.

Liu and Zhao (2022) developed an enhanced CNN-based model for brain tumor classification from MRI images to improve recognition accuracy and robustness. The study addressed limitations of conventional CNN architectures in capturing detailed tumor features. The methodology involved a modified CNN structure with multiple convolutional and pooling layers, utilizing 3×3 and 5×5 kernels, along with preprocessing techniques such as normalization and data augmentation. The model was trained and tested using an 80:20 data split and achieved a classification accuracy of 98.87%, outperforming Support Vector Machine, K-Nearest Neighbors, and baseline CNN models. However, the evaluation was conducted on simplified benchmark datasets, which are MNIST, Fashion-MNIST, CIFAR-10, Cats and Dogs, and miniImageNet. Also, it was not validated on complex multi-source MRI data, which may affect its generalization in real clinical settings.

Maurya *et al*. (2023) developed an automated glioblastoma detection and segmentation framework using DeepLabv3 and UNet architectures to improve early diagnosis and segmentation precision. The study addressed the need for accurate tumor boundary delineation while maintaining computational efficiency. The methodology involved preprocessing steps such as skull stripping, Gaussian and high-pass filtering, followed by data augmentation techniques, and comparative evaluation of the two deep learning models. UNet demonstrated suitability for real-time applications due to its encoder–decoder structure with skip connections, while DeepLabv3 achieved higher segmentation accuracy using dilated convolutions and feature pyramid networks. However, DeepLabv3 required substantial computational resources and exhibited segmentation inconsistencies in homogeneous tissue regions, limiting its practical deployment in resource-constrained environments.

Musthafa *et al*. (2024) proposed an explainable deep learning framework for brain tumor detection from MRI images by integrating ResNet50 with Grad-CAM to enhance both classification performance and interpretability. The study addressed the lack of transparency in conventional deep learning models by incorporating heatmap-based visual explanations. The model was trained on an augmented MRI dataset and achieved 98.52% classification accuracy, with precision and recall values exceeding 98%. Although the integration of Grad-CAM improved model transparency and clinical relevance, the system was evaluated on a single dataset without multi-source validation, limiting its generalization across diverse imaging conditions.

Filvantorkaman *et al*. (2025) developed a fusion-based CNN framework for MRI brain tumor classification by integrating deep learning, explainable AI, and rule-based reasoning to improve diagnostic reliability.

The study addressed the need for enhanced classification performance and clinical interpretability. The methodology combined MobileNetV2 and DenseNet121 using a soft-voting ensemble, with image resizing and normalization as preprocessing steps and stratified 5-fold cross-validation for robust evaluation. Grad-CAM was incorporated for visual explanations, while a Clinical Decision Rule Overlay was applied to align predictions with radiological guidelines. The ensemble model achieved an overall accuracy of 91.7%, outperforming individual CNN architectures. However, the study was restricted to a single-source dataset, excluded normal cases, and introduced high computational complexity due to ensemble and rule-based components, limiting real-time deployment in low-resource settings.

METHODOLOGY

The study developed a brain tumor classification system based on a Convolutional Neural Network (CNN) using Magnetic Resonance Imaging (MRI) scans with explainable AI. The overall workflow of the proposed system is illustrated in Figure 1,it shows the major stages: image acquisition, preprocessing, CNN-based classification, and explainable output generation.

Data Collection

A total of 10,287 brain MRI images were obtained from publicly available Kaggle and Figshare repositories. The dataset comprised four categories: Glioma, Meningioma, Pituitary tumor, and No tumor. After merging both sources, the class distribution is 400 glioma images, 421 meningioma images, 374 pituitary tumor images, and 510 no-tumor images. The combined dataset was split into training and testing subsets in an 80:20 ratio for model development and evaluation. Figure 2 shows a sample of MRI images obtained, showing the typical structure and format of the data used for model training and evaluation.

Data Preprocessing

To ensure uniformity and improve model learning, Brain MRI images obtained from Kaggle and Figshare were first preprocessed. All images were resized to 220 × 220 pixels to maintain consistent input dimensions across the dataset. Grayscale conversion was applied to reduce computational complexity and emphasize structural intensity features relevant to tumor detection.

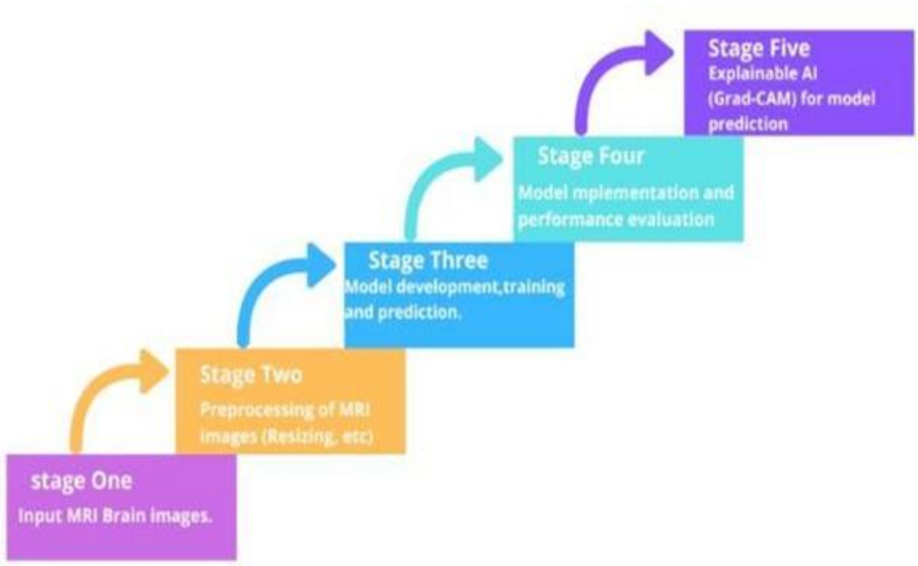

Figure 1: Framework for the Brain Tumor classification system

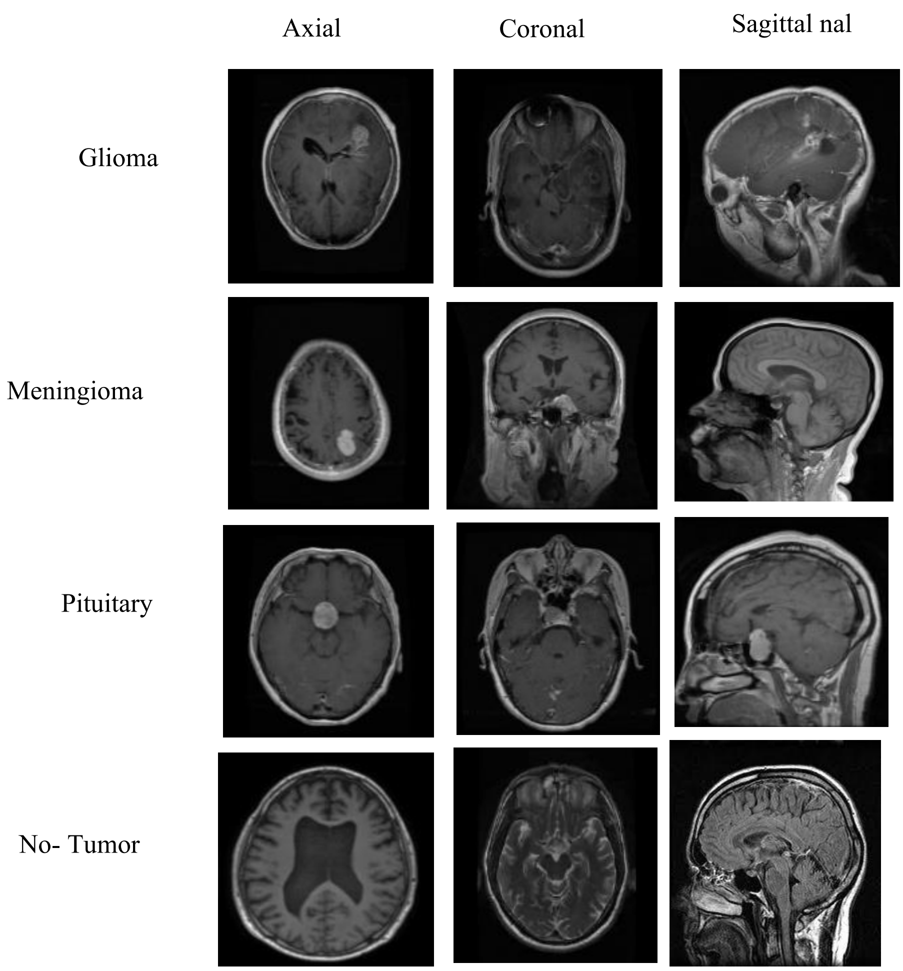

Figure 2: Sample of MRI Images obtained

Data Preprocessing

To ensure uniformity and improve model learning, Brain MRI images obtained from Kaggle and Figshare were first preprocessed. All images were resized to 220 × 220 pixels to maintain consistent input dimensions across the dataset. Grayscale conversion was applied to reduce computational complexity and emphasize structural intensity features relevant to tumor detection. Pixel normalization was performed by scaling intensity values to the range 0 to 1 to stabilize gradient updates during training. To enhance dataset variability and improve model generalization, real-time data augmentation techniques including rotation, horizontal and vertical flipping, and zoom transformations were applied during training. This procedure standardized input data, enabling effective feature learning, while data augmentation increased variability in the training set, thereby reducing overfitting. Figure 3 shows the preprocessed MRI images.

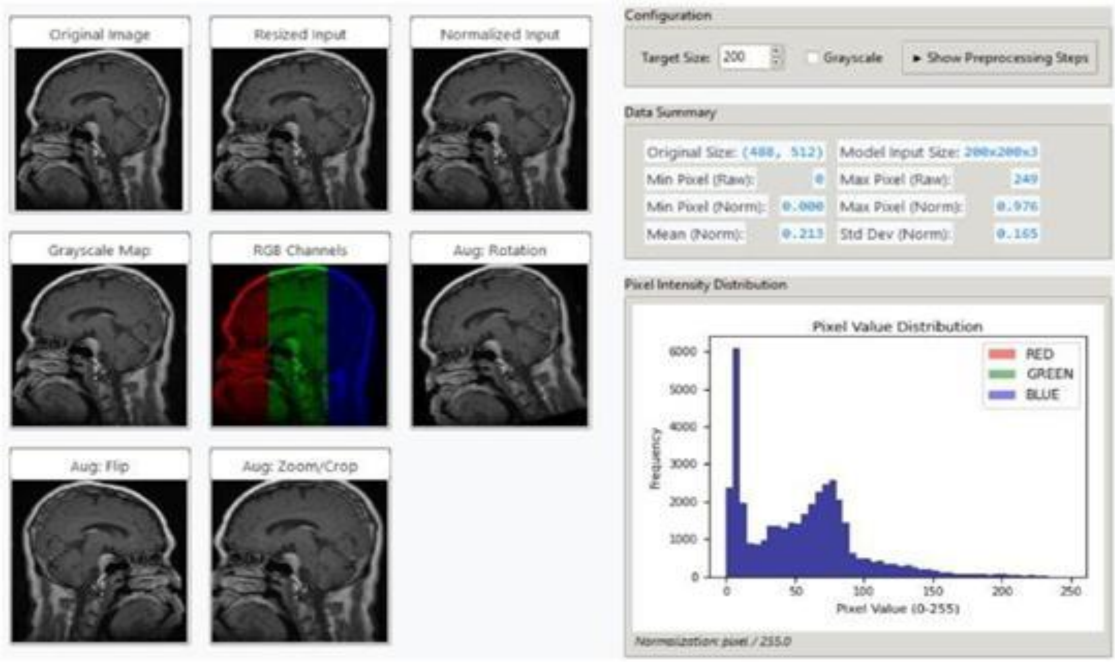

Figure 3: Histogram of the Preprocessed MRI Dataset

Formulation of CNN Model

The brain tumor classification system was developed using a convolutional neural network (CNN) architecture. The model was structured to extract spatial and hierarchical features from MRI images for effective tumor classification. The architecture consists of multiple convolutional layers followed by activation functions, Rectified Linear Unit, pooling layers for dimensionality reduction, and fully connected layers for classification. The final layer applies a softmax activation function to produce probability scores across the tumor classes. The CNN architecture was designed using the Sequential Application Programming Interface (API). The logical workflow of the brain tumor classification process is illustrated in Figure 4.

Model Implementation and Training

The brain tumor classification system was implemented using Python with TensorFlow and Keras deep learning frameworks. Model training and evaluation were performed in a GPU-enabled computational environment to accelerate convergence. The CNN architecture was trained using the Adam optimization algorithm with categorical cross-entropy as the objective function for multi-class classification. The dataset was partitioned into 80% for training and 20% for testing to evaluate model performance. During training, hyperparameters including learning rate, batch size, and number of epochs were defined to control optimization and convergence behavior. Supporting libraries were utilized to facilitate the workflow: NumPy for numerical operations, OpenCV and Pillow for image preprocessing, and Matplotlib for performance visualization, including accuracy and loss curves, confusion matrices, and ROC–AUC analysis. For interpretability, Grad-CAM was integrated into the trained CNN model to generate class-specific activation maps, highlighting tumor-relevant regions in MRI images. To enhance usability, a Graphical User Interface (GUI) was developed using Tkinter, enabling model training, MRI image upload, prediction, and visualization of Grad-CAM outputs. The system supports both single-image inference and batch evaluation, producing class probabilities alongside visual explanations. The overall system workflow is shown in Algorithm 1. The application follows a multi-stage algorithmic process for training, prediction, and evaluation, centered on a Convolutional Neural Network (CNN).

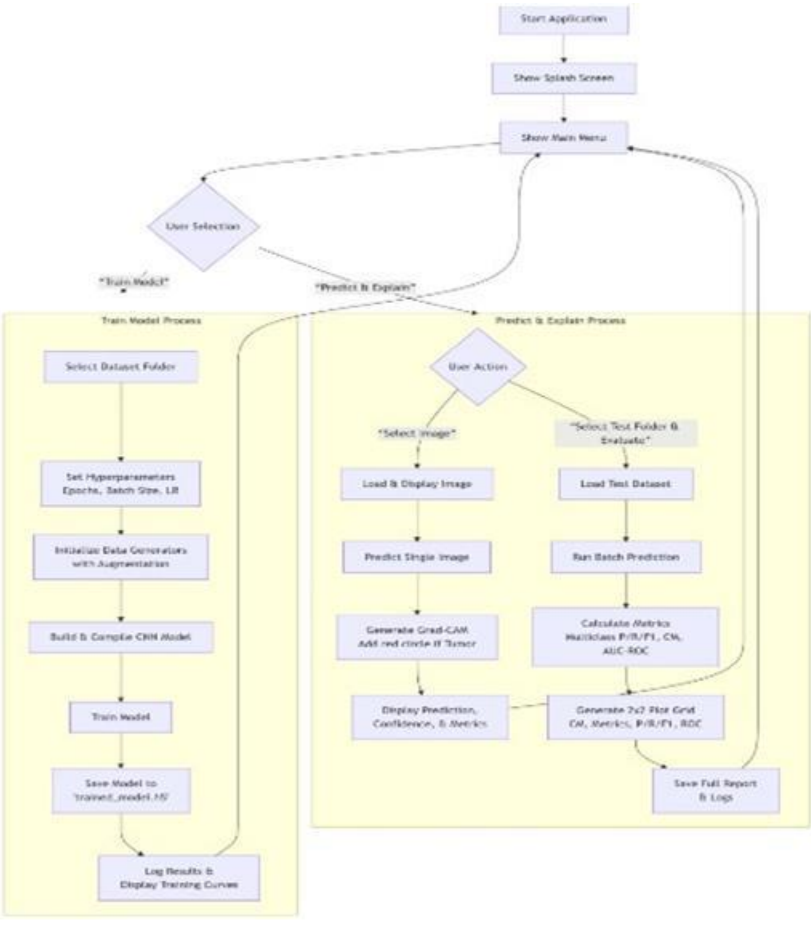

Figure 4: The system's logical process flow for brain tumor classification

Model Performance Evaluation Metrics

The performance of the developed CNN-based brain tumor classification model was evaluated using several standard classification metrics to ensure a comprehensive assessment of the model's predictive capability. The evaluation metrics used in this study include Accuracy, Precision, Recall (Sensitivity), Specificity, F1-score, False Positive Rate (FPR), and Receiver Operating Characteristic–Area Under Curve (ROC–AUC).

Algorithm 1: System workflow for Brain Tumor Classification

Application Start and GUI Setup

Initialize the Tkinter GUI using the Brain Tumor App class.

1. Create the main application frames: Splash Screen, Main Menu, Train Page, and Predict Page.
2. Display the Splash Screen and transition to the Main Menu.

Model Training Procedure (Train Page)

1. Receive user inputs: dataset path, epochs, batch size, and learning rate.
2. Prepare the dataset using Image Data Generator with augmentation and rescaling.
3. Split the dataset into training and testing sets (80/20).
4. Construct a Sequential CNN with three Convolutional layers: MaxPooling blocks, Flatten, and Dense layers with Dropout.
5. Compile the model using the Adam optimizer and categorical cross-entropy loss.
6. Train the model using the prepared generators.
7. Save the trained model as trained_model.h5.
8. Save the training history and display accuracy/loss curves.

Single-Image Prediction and Explanation (Predict Page)

1. Receive a single uploaded image.
2. Load the trained model if not already in memory.
3. Preprocess the image (resize, normalize, batch).
4. Generate prediction probabilities and select the highest-scoring class.
5. Create a Grad-CAM explanation by computing gradients from the last convolutional layer.
6. Produce and overlay the heatmap on the original image.
7. Display the original image, Grad-CAM heatmap, class confidence, and metrics.
8. Save the prediction log.

Test Set Evaluation (Predict Page)

1. Receive a test folder containing class-labelled subdirectories.
2. Load and preprocess all test images using Image Data Generator.
3. Predict class probabilities for the entire test set.
4. Generate evaluation metrics: classification report, confusion matrix, and per-class TP, FP, FN, TN.
5. Compute binary AUC-ROC (tumour vs. non-tumour).
6. Generate performance visualisations: confusion matrix, class metrics bar chart, AUC-ROC curve.
7. Save all evaluation results and plots to the logs directory.

These metrics provide insight into the model's ability to correctly classify tumor and non-tumor MRI images while minimizing misclassification.

Accuracy: measures the overall correctness of the classification model

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision represents the proportion of correctly predicted positive cases among all samples predicted as positive by the model.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Specificity: measures the ability of the model to correctly identify non-tumor MRI images.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (3)$$

Recall (Sensitivity) is also known as the True Positive Rate (TPR). It measures the model's ability to correctly identify all tumor cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

False Positive Rate (FPR)

The False Positive Rate measures the proportion of non-tumor images that were incorrectly classified as tumor images.

$$\text{FPR} = \frac{\text{FP}}{\text{FP+TN}} \quad (5)$$

F1-score: The F1-score provides a balance between precision and recall

$$\text{F1\_score} = 2 \text{ x } \frac{\text{precision x recall}}{\text{precision+recall}} \quad (6)$$

ROC–AUC

The Characteristic (ROC) curve illustrates the trade-off between sensitivity and specificity at different classification thresholds, while the Area Under the Curve (AUC) measures the model's ability to distinguish between different tumor classes.

Explainable Artificial Intelligence and Graphical User Interface

Explainable Artificial Intelligence (XAI) techniques were integrated into the CNN model to enhance the interpretability of the brain tumor classification system, to understand the model's decision-making process so as to improve clinical trust, support diagnosis validation, and assist in medical decision-making. The focus was on using Gradient-weighted Class Activation Mapping (Grad-CAM) due to its compatibility with CNN-based architectures and its ability to provide intuitive visual explanations.

Grad-CAM worked by extracting gradients from the last convolutional layer. A single MRI image was passed to the trained CNN model to analyze its prediction and generate a corresponding heatmap using Grad-CAM. The gradients of the predicted class with respect to the feature maps of the final convolutional layer were extracted and globally pooled to obtain weights that indicated the importance of each feature map. By combining these weighted feature maps, a class-discriminative localization heatmap was produced, highlighting the most influential regions for the model's decision. This heatmap was then resized and superimposed onto the original MRI image to visually indicate which areas contributed most to the classification. The Grad-CAM heatmap LcGrad-CAM for class c is computed using equation 1 (Selvaraju *et al*., 2017).

$$L^{c}_{Grad-CAM} = \mathrm{Re}LU(\sum k\alpha_k{}^{c} A^{k}) \quad (7)$$

Where A^k is the activation map of unit k in the selected convolutional layer, $\alpha_k{}^{c}$ is the important weight for feature map k, calculated by:

$$\alpha_k{}^{c} = \frac{1}{Z}\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{\partial y^{c}}{\partial A_{ij}{}^{c}} \quad (8)$$

Where Z is the number of pixels in the feature map, $\frac{\delta y^{c}}{\delta A^{k}_{ij}}$ is the **gradient of** the score for class **c** with respect to the activation at position (i, j) in the k-th feature map A^k (i.e., Z=width×heightandReLU is the **Rectified Linear Unit** function, applied to retain only the positive values in the final heatmap (i.e., parts that positively influence the class).

RESULT AND DISCUSSION

The training and validation performance of the model at 30 and 50 epochs, respectively, are illustrated in Figure 5, showing stable convergence during training.

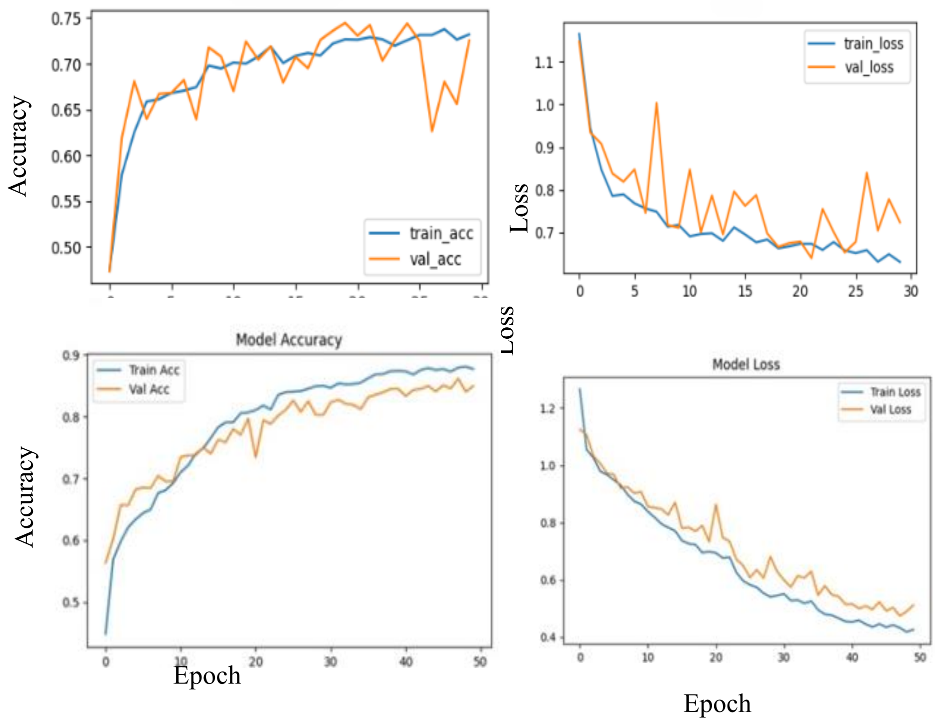

Figure 5: Training and Validation Curve at 30 and 50 epochs, respectively

Model Performance Evaluation Result

For glioma test images, the model achieved an accuracy of 92.4%, precision of 95.9%, specificity of 99.01%, recall of 70.7%, F1-score of 81.4%, and an FPR of 0.92%. The classification performance for meningioma images showed an accuracy of 94.66%, precision of 84.9%, specificity of 94.47%, recall of 95.2%, F1-score of 89.75%, and an FPR of 5.53%. For pituitary tumor images, the model attained an accuracy of 98.47%, precision of 97.8%, specificity of 99.39%, recall of 95.1%, F1-score of 96.43%, and an FPR of 0.60%. The no-tumor class achieved an accuracy of 95.54%, precision of 87.8%, specificity of 94.14%, recall of 98.8%, F1-score of 92.97%, and an FPR of 5.85% as shown in Table 1. Overall, the CNN model achieved a classification accuracy of 90.6% and an AUC score of 0.9892. The confusion matrix presented in Figure 6 shows the overall classification performance of the CNN model on the testing dataset. It shows how well the model predicted each tumor class: Glioma, Meningioma, Pituitary, and No-Tumor. From the matrix, the diagonal values represent the correctly classified samples for each class, while the off-diagonal values indicate misclassified samples.

Table 1: Performance Evaluation Metrics of CNN Model for Each Tumor Category.

Tumor types	**Glio ma**	**Meningoma**	**Pituitary**	**No Tumor**
No of Testing data	400	421	374	510
TP	283	401	356	504
FN	117	20	18	6
FP	12	71	8	70
TN	1293	1213	1323	1125
FPR(%)	0.92	5.53	0.60	5.85
SPEC(%)	99.01	94.47	99.39	94.14
RECALL(%)	70.70	95.20	95.10	98.80
PREC(%)	95.90	84.90	97.80	87.80
ACC(%)	92.40	94.66	98.47	95.54
F1-SCORE (%)	81.40	89.75	96.43	92.97

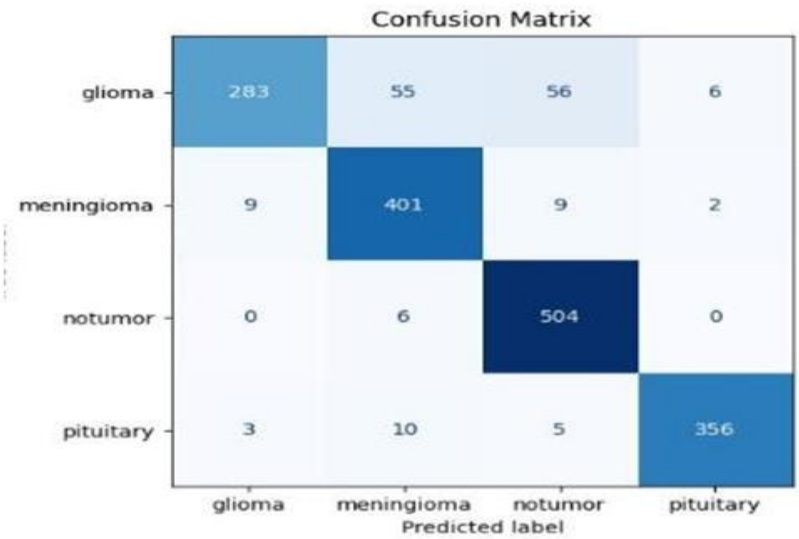

Figure 6: Confusion Matrix of CNN Model

Figure 7 shows the prediction metrics chart for each tumor class in terms of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN). The figure provides a clear comparison of the model's prediction outcomes across the four tumor categories. It can be observed that the number of True Positives and True Negatives is consistently high, with relatively low False Positives and False Negatives, indicating that the model made only a few misclassifications. Figure 8 presents the per-class Precision, Recall, and F1-score values of the CNN model. The results show that the model achieved high performance across all classes, particularly for pituitary and no-tumor, where both precision and recall exceeded 95%.

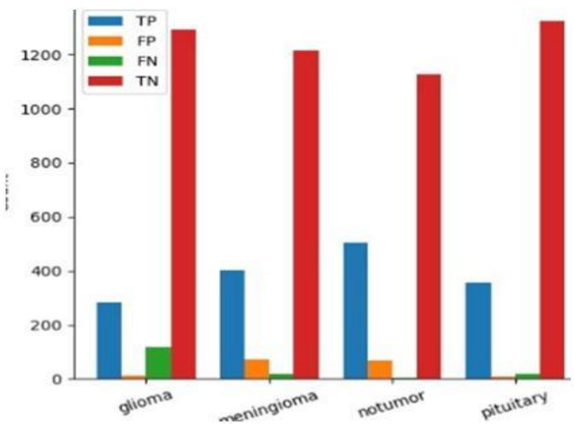

Figure 7: Prediction Metrics Chart

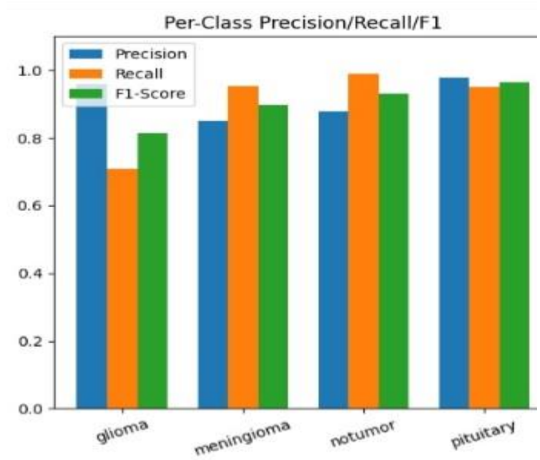

Figure 8: Per-class Precision, Recall, and F1-score chart

Figure 9 presents the Receiver Operating Characteristic (ROC) curve of the CNN model. The model achieved an Area Under the Curve (AUC) value of 0.9892, indicating excellent discriminative capability. An AUC value close to 1.0 reflects the model's strong ability to correctly distinguish between tumor and non-tumor MRI images. Specifically, an AUC of 0.9892 implies a 98.92% probability that the classifier ranks a randomly selected tumor case higher than a randomly selected non-tumor case.

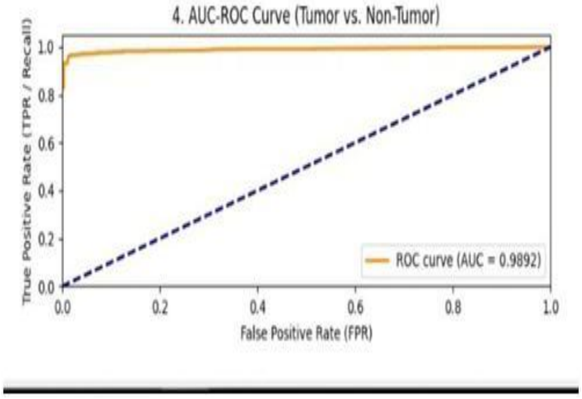

Figure 9: Result of the ROC-AUC Curve of CNN classification

Grad-CAM Result

The Grad-CAM results are shown in Figures 10, 11, 12, and 13 for each tumor class**,** highlighting the specific regions of an MRI image that influenced the model's prediction and verifying whether the model focused on the actual tumor area. The model accurately predicted the image as the tumor class specified, and the Grad-CAM heatmaps emphasized important regions associated with the classification, thereby identifying discriminative regions influencing the model's decision and not explicitly performing tumor segmentation.

Figure 10 shows the Grad-CAM visualization for a glioma MRI image. The model predicted the glioma class with a probability score of 99.36%, indicating strong certainty in its decision. The corresponding heatmap shows concentrated activation over the abnormal mass region within the brain tissue, with minimal response in surrounding healthy areas. The alignment between high prediction confidence and focused tumor localization demonstrates that the model based its decision on clinically relevant structural features rather than background intensity variations.

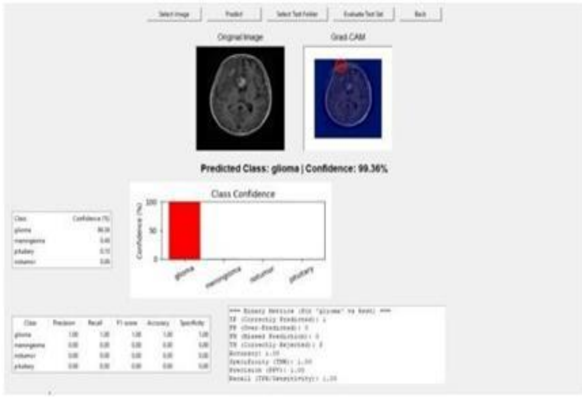

Figure 10: Grad-CAM result for the predicted glioma MRI image

Grad-Cam Result Analysis for Meningioma Test Image

As illustrated in Figure 11, the model classified the MRI image as meningioma with a high probability value. The Grad-CAM heatmap highlights activation primarily along the peripheral tumor boundary, consistent with the typical anatomical presentation of meningioma. The probability score of 98.45%, combined with spatially localized activation, indicates that the model effectively captured shape-based and boundary-specific features characteristic of the tumor type.

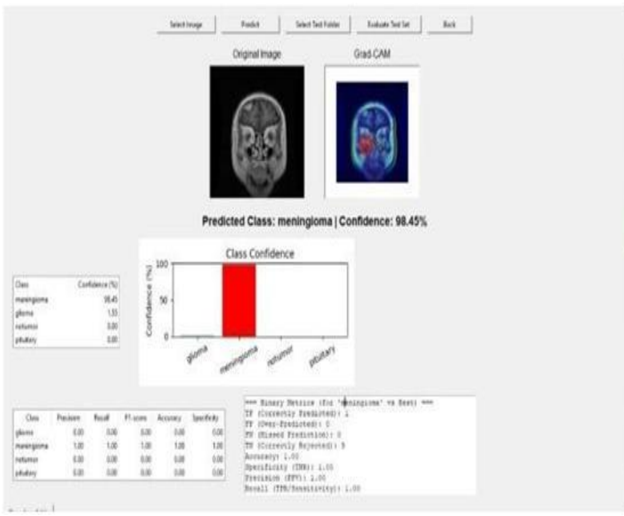

Figure 11: Grad-CAM result for the predicted meningioma MRI image

Grad-Cam Result Analysis for Pituitary Test Image

Figure 12 shows the Grad-CAM output for a pituitary tumor image. The model predicted the pituitary class with a probability score of 99.89%, and the activation map concentrates in the sellar region of the brain. This alignment suggests that the model focuses on spatially relevant regions when making predictions. This observation is based on qualitative visual interpretation.

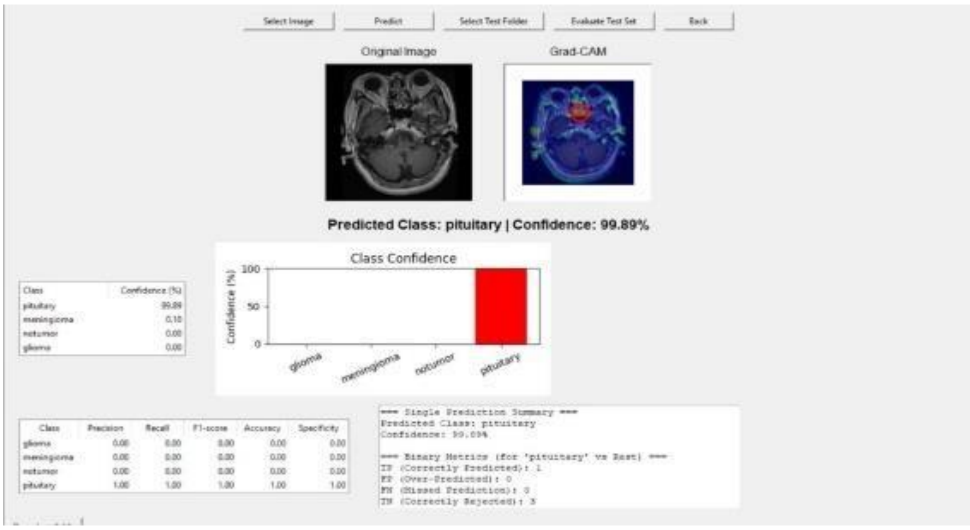

Figure 12: Grad-CAM result for the predicted pituitary MRI image

Figure 13 presents the Grad-CAM result for a non-tumor MRI image. The model predicted the no-tumor class with a probability score of 99.89%. The probability score for each predicted class was generated using the Softmax activation function in the output layer of the CNN model. The softmax activation function in the output layer of the CNN model. The softmax layer is mathematically defined by equation 9.

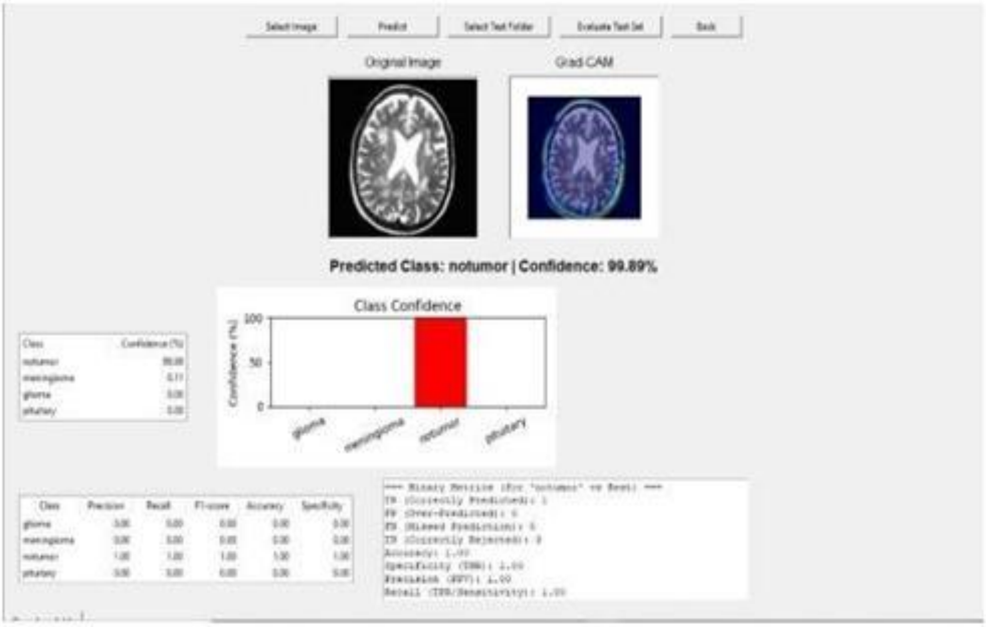

Figure 13: Grad-CAM result for the predicted No-tumor MRI image

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{c} e^{z_j}} \qquad (9)$$

Where P(yi) is the probability of class i, Zi and Zj are output scores for class i and j, respectively,

where c is the total number of classes. The heatmap shows no concentrated pathological activation; instead, low-intensity distributed attention is observed across normal brain structures. This suggests that the model does not falsely identify tumor-like features in healthy scans, reinforcing its reliability in distinguishing pathological and normal cases.

CONCLUSION

This study developed a CNN-based brain tumor classification system using MRI images integrated with Explainable Artificial Intelligence through Grad-CAM. The developed model was capable of classifying MRI images into glioma, meningioma, pituitary tumor, and no-tumor categories while providing visual explanations that highlight the image regions influencing the model's predictions. The integration of Grad-CAM improved the transparency and interpretability of the system, making the prediction process more understandable and clinically meaningful. In addition, the use of a large multi-source MRI dataset enhanced the robustness and generalization capability of the model. A Graphical User Interface (GUI) was also implemented to support real-time image classification and visualization of Grad-CAM outputs, thereby improving the practical usability of the system. Therefore, the study presents an effective and interpretable deep learning framework that can serve as a reliable decision-support tool for automated brain tumor classification.

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