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A Hybrid Framework-Integrating a Radiomatic Features with CNN for Brain Tumor Detection

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***Abstract*— Brain tumors are life-threatening diseases, and early diagnosis using MRI is crucial for effective treatment. This study presents an interpretable framework for brain tumor detection using MRI images. A lightweight Convolutional Neural Network (CNN) is used to classify images as tumor or non-tumor, while a traditional Gray Level Co-occurrence Matrix (GLCM) with Support Vector Machine (SVM) serves as a baseline model. The CNN achieves higher accuracy than the GLCM+SVM approach. To improve transparency, Grad-CAM is applied to generate heatmaps that highlight the regions influencing the CNN's predictions. The results demonstrate that combining deep learning with explainable AI can enhance both diagnostic accuracy and model interpretability in MRI-based brain tumor detection.**

***Keywords*— Brain tumor detection; magnetic resonance imaging (MRI); convolutional neural network (CNN); explainable artificial intelligence (XAI); Grad CAM.**

I. INTRODUCTION

Medical imaging has evolved from simple visual interpretation to a data-driven analytical discipline, largely due to advancements in radiomics, which extract high-dimensional quantitative features from images to characterize tumor phenotype noninvasively [1], [11]. These developments have been strengthened by rapid progress in artificial intelligence and computer vision, enabling more accurate and automated medical image analysis for clinical decision support [2]. MRI-based brain tumor classification, in particular, has gained significant attention, supported by publicly available datasets such as the Brain Tumor Classification (MRI) dataset hosted on Kaggle [3], [18].

Deep learning approaches especially convolutional neural networks (CNNs)—have proven highly effective in learning discriminative spatial features from MRI, outperforming traditional machine-learning pipelines [4], [5]. Several studies have demonstrated strong performance of CNN-based and deep transfer learning models for classifying different brain tumor types [6], [7]. More recently, lightweight CNN architectures have been proposed to maintain high accuracy even when training data are limited, addressing a common challenge in medical imaging [8]. Beyond deep learning, hybrid frameworks that integrate handcrafted radiomic features such as GLCM and LBP with deep features have shown substantial improvements in classification robustness and generalizability [12], [13], [14], contributing to ongoing advancements in radiomics-based tumor analysis [15].

As deep neural networks continue to grow in complexity, interpretability has become a critical requirement for clinical trust and deployment. Methods such as Grad-CAM provide visual explanations by highlighting salient image regions that influence the model's decision-making process [9], [10].

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Likewise, model-agnostic interpretability techniques such as SHAP enhance transparency by quantifying feature importance, enabling clinicians to better understand AI-driven predictions [16]. Recent surveys on explainable artificial intelligence emphasize that interpretability is essential for integrating AI models into real-world medical practice safely and responsibly [17].
Building upon these advancements in radiomics, deep learning, and explainability, this study aims to develop an accurate and interpretable framework for automated brain tumor classification using MRI data.

II. Methodology

A. Dataset Collection

The study utilizes the Brain Tumor Classification (MRI) dataset, which consists of T1-weighted axial Magnetic Resonance Imaging (MRI) scans of the brain. The images are categorized into two classes: Tumor and Non-Tumor, enabling binary classification. This publicly available dataset is widely used in medical image analysis research for developing and evaluating brain tumor detection models.

B. Data Preprocessing

- Image Resizing: All MRI images are resized to 128 × 128 pixels with three color channels to maintain a uniform input size.
- Normalization: All MRI images were normalized by dividing pixel values by 255, scaling them from the range 0–255 to 0–1. This improves training efficiency, model convergence, and overall classification performance
- Feature Engineering: New features were derived to capture the relationship between variables and market behaviour.

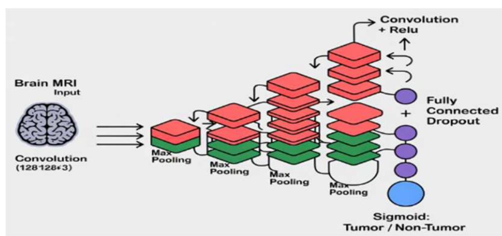

Fig. 1. Flowchart of the model

These include:

- MRI Input Image: Brain MRI images resized to 128 × 128 × 3 pixels and normalized before processing.
- Convolution Layer: Extracts important features such as edges, textures, and tumor patterns from MRI images.
- ReLU Activation: Introduces non-linearity, enabling the model to learn complex image representations.
- Max Pooling Layer: Reduces feature map dimensions while retaining the most significant information, improving computational efficiency.
- Deep Feature Extraction: Multiple convolution and pooling layers progressively capture high-level tumor-related features.
- Fully Connected Layer with Dropout: Combines extracted features for classification while reducing overfitting through dropout regularization.
- Sigmoid Output Layer: Produces a probability score and classifies the MRI image as Tumor or Non-Tumor.

C. Dataset Splitting

- Training Dataset (80%): Used to train the CNN model and optimize its parameters.
- Testing Dataset (20%): Used to evaluate the model's performance and classification accuracy on unseen MRI images.

III. Model Development

A. Proposed CNN Model

The proposed Convolutional Neural Network (CNN) model begins with an input layer that accepts MRI images resized to 128 × 128 × 3. The architecture consists of three convolutional layers followed by ReLU activation and max-pooling layers to extract important features and reduce spatial dimensions. After feature extraction, the output is passed through two fully connected layers with dropout regularization to prevent overfitting. The final output layer contains a single neuron with a sigmoid activation function for binary classification (Tumor/Non-Tumor). The model was trained using the Adam optimizer with a learning rate of 0.001, binary cross-entropy loss, a batch size of 32, and a fixed number of epochs.

B. ResNet50 Transfer Learning Model

The ResNet50 transfer learning model utilizes a pre-trained ResNet50 network trained on ImageNet. MRI images are resized to 224 × 224 pixels before being fed into the model. The pre-trained backbone is frozen, and additional layers including Global Average Pooling, a Dense layer with 128 neurons and ReLU activation, and a sigmoid output layer are added for classification.

IV. Results and Discussion

In this section, the performance of the proposed Convolutional Neural Network (CNN) model is evaluated and compared with the traditional GLCM + SVM radiomics baseline for brain tumor detection using MRI images. The models are assessed using Accuracy, Precision, Recall, and F1-Score metrics. Additionally, Grad-CAM visualizations are used to interpret model predictions. The detailed results are presented below.

A. CNN Performance

TABLE I. Comparative Performance Metrics of ANN and LSTM for Bsoft

Class	Accuracy	Precision	Recall	R^2
Non-Tumor	0.82	0.90	0.53	0.67
Tumor	0.82	0.80	0.97	0.88
Macro Avg	0.82	0.85	0.75	0.88
Weighted Avg	0.82	0.83	0.82	0.81

The proposed CNN model achieved an overall accuracy of 82% on the validation dataset. The model demonstrated excellent tumor detection capability with a recall of 97% and an F1-score of 88%, indicating high sensitivity toward tumor cases. However, the lower recall for non-tumor images suggests the presence of some false-positive predictions.

B. GLCM + SVM Base

TABLE II. Performance Metrics of GLCM + SVM Model

Class	Accuracy	Precision	Recall	F1-Score
Non-Tumor	0.61	0.00	0.00	0.00
Tumor	0.61	0.61	1.00	0.76
Overall	0.61	0.47	0.50	0.38

The traditional radiomics-based GLCM + SVM model achieved an overall accuracy of 61%. Although it successfully identified most tumor cases, it failed to classify non-tumor images effectively, resulting in poor precision and recall values. These findings indicate that handcrafted texture features alone are insufficient for capturing the complex patterns present in MRI scans.

C. Grad-CAM Visualization Analysis

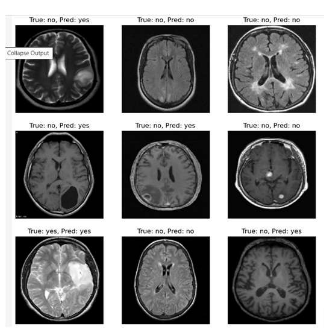

Fig. 3. Grad-CAM Explanation for Correctly Classified Tumor MRI

The Grad-CAM heatmap shown in Figure 3 highlights the tumor region that contributed most to the CNN's prediction. The activation map is concentrated around the visible lesion, demonstrating that the model learns clinically relevant features rather than relying on irrelevant image regions. This improves transparency and trustworthiness of the deep learning model.

A. Correct and Incorrect Predictions

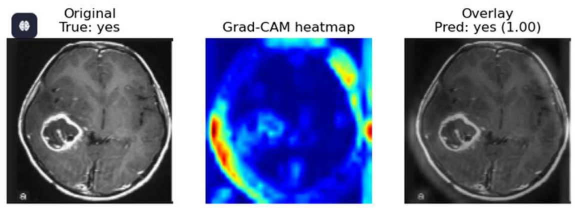

Fig. 4. Correct and Incorrect Predictions for Tumor and Non-Tumor MRIs

Figure 4 presents examples of correctly and incorrectly classified MRI images. Most tumor cases were classified correctly, while a few non-tumor images were incorrectly predicted as tumors. These misclassifications explain the lower recall observed for the non-tumor class and indicate areas where future improvements can be made

B. Confusion Matrix Analysis

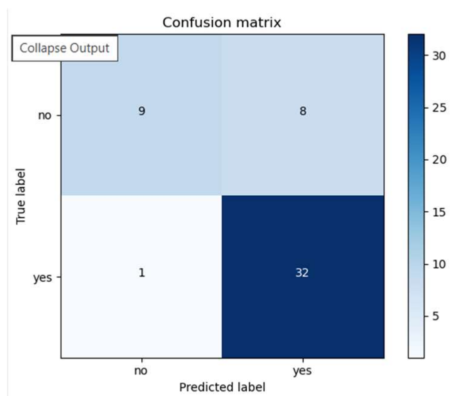

Fig 5. Confusion Matrix of the Proposed CNN

The confusion matrix in Figure 5 summarizes the classification performance of the CNN model. Out of 50 validation images, 32 tumor images were correctly identified, while only 1 tumor image was missed. For non-tumor cases, 9 images were correctly classified and 8 images were incorrectly labeled as tumors. These results confirm the model's strong sensitivity toward tumor detection while revealing a tendency toward false-positive predictions.

This work is original in its detailed comparative analysis between Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models in the Indian technology sector companies. The research deals with the comparison of individual model performance and directly compare traditional feed forward neural networks with advanced sequential models such as LSTM using the same dataset as well. Our work is core to this area in that it highlights the way that ANN networks are constantly better than LSTM models in capturing short-term patterns in the highly volatile Indian tech sector. Our study also underlines the idiosyncratic behaviour of the market and recognizes that the model's performance may be affected by the region and industry it is applied.

V. Conclusion

The results of this study demonstrate that the proposed CNN model performs effectively for brain tumor detection using MRI images, achieving an overall accuracy of 82% and a high tumor recall of 97%. Compared with the traditional GLCM + SVM radiomics approach, the CNN provided superior classification performance by learning complex spatial features directly from MRI scans. The integration of Grad-CAM further enhanced model interpretability by highlighting the image regions that influenced predictions, increasing confidence in the model's decision-making process. The findings suggest that deep learning combined with explainable AI can serve as a valuable decision-support tool for radiologists. Future work will focus on improving specificity for non-tumor cases, reducing false positives, and validating the framework on larger and more diverse datasets to improve robustness and clinical applicability.

FUTURE SCOPE

Future work can focus on improving the performance and reliability of the proposed brain tumor detection framework by training it on larger and more diverse MRI datasets collected from multiple medical institutions. Advanced deep learning architectures such as EfficientNet, Vision Transformers (ViT), and attention-based CNNs can be explored to enhance classification accuracy. The study can also be extended from binary classification (tumor/non-tumor) to multi-class brain tumor classification, including glioma, meningioma, and pituitary tumors. Furthermore, integrating additional explainable AI techniques alongside Grad-CAM may provide deeper insights into model decisions. Finally, deploying the model as a real-time clinical decision-support system could assist radiologists in faster and more accurate brain tumor diagnosis.

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