OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbreviated Tittle- Ind J Multi Res
ISSN *(Online)*- 2583-3820
Journal Homepage Link- https://indianapublications.com/Journals/IJMR
DOI: https://doi.org/10.5281/zenodo.21609568

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Article

Volume-06|Issue-04|2026

NeuroScope: AI-Powered Brain Tumor Detection

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Article History
Received: 05.05.2026
Accepted: 22.06.2026
Published: 25.07.2026

Citation
Chandrakala, B. M., Sandyal, K. S., Radhika, T. V., Chetan, T., Sudiksha, P. & Umesh, A. (2026) NeuroScope: AI-Powered Brain Tumor Detection. *Indiana Journal of Multidisciplinary Research, 6*(4), 314-322.

Abstract: This study introduces NeuroScope, an artificial intelligence (AI) system that analyzes magnetic resonance imaging (MRI) data to detect brain tumors. The system is built around a convolutional neural network (CNN) trained to differentiate between MRI scans indicating the presence or absence of a tumor. A labeled dataset from Kaggle containing a variety of brain MRI images was preprocessed using techniques such as normalization, skull stripping, resizing, and data augmentation to ensure consistency. Once trained, the model generates a simple prediction of tumor or no tumor, enabling radiologists to evaluate scans more quickly and efficiently. To enhance the interpretability of the predictions, a fuzzy logic module assigns a confidence level (low, moderate, or high) to each outcome. The system's performance was evaluated using accuracy, precision, recall, and F1-score. The results demonstrate that NeuroScope is a reliable and scalable approach for the rapid detection of brain tumors.

Keywords: Normalization, Convolutional Neural Network, Magnetic Resonance Imaging, Preprocessing, Segmentation

INTRODUCTION

Brain tumors represent a serious and potentially life-threatening health condition, requiring swift and accurate diagnosis to facilitate effective treatment and improve patient survival rates [1]. These tumors, whether malignant or benign, can disrupt vital neurological functions and, in advanced stages, pose severe health risks or even lead to fatal outcomes. Magnetic resonance imaging (MRI) remains the preferred non-invasive technique for brain tumor detection, offering high-resolution images that enable detailed visualization of brain structures [2]. Despite its effectiveness, manual interpretation of MRI scans can be time-consuming and subjective, relying heavily on the expertise and experience of radiologists. This subjectivity increases the risk of diagnostic errors, particularly in early-stage cases where visual abnormalities may be subtle [3].

With the rapid growth of medical imaging data in hospitals and diagnostic centers, there is an increasing demand for intelligent systems that can assist radiologists in delivering faster and more consistent diagnoses [4]. In this regard, artificial intelligence (AI), particularly deep learning, has significantly transformed medical image analysis. Convolutional neural networks (CNNs), a widely adopted class of deep learning models, have demonstrated outstanding performance in image classification, object recognition, and semantic segmentation tasks, making them highly suitable for brain tumor detection [5].

This paper presents NeuroScope, an AI-based diagnostic framework developed to automatically detect and classify brain tumors from MRI images using CNNs. The proposed model incorporates a U-Net architecture to accurately segment the tumor region, followed by a classification module to determine the presence or absence of tumors. To improve interpretability and effectively manage prediction uncertainty, a fuzzy logic layer is integrated into the system. This component categorizes the model's confidence into low, moderate, or high levels, making the predictions more intuitive and clinically meaningful. NeuroScope aims to provide a scalable, non-invasive, and clinically applicable tool that supports healthcare professionals in the early detection of brain tumors, particularly in under-resourced settings where expert radiological assessment may not always be readily available. By bridging clinical needs with advanced AI technologies, this work contributes to the growing field of computer-aided diagnosis, promoting earlier intervention and improved patient outcomes.

LITERATURE SURVEY

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Sl. No.	Title	Authors	Algorithms Used	Merits	Demerits	Year
1	"The Multimodal Brain Tumor Image Segmentation Benchmark"	Menze et al.	CNN-based segmentation	High-quality annotated dataset	Dataset only, no model proposed	2015
2	"U-Net: Convolutional Networks for Biomedical Segmentation"	Ronneberger et al.	U-Net architecture	High segmentation accuracy, simple architecture	Necessitates bulky datasets for generalization	2015
3	"Brain Tumor Type Classification via Capsule Networks"	Afshar et al.	Capsule Networks	Maintains spatial hierarchy, robust to rotation	High computational cost	2020
4	"Brain Tumor Detection Using GoogLeNet"	Kumar et al.	Transfer Learning (GoogLeNet)	Achieved 90%+ accuracy, reduced training time	Limited interpretability	2019
5	"Brain Tumor Segmentation with Deep Neural Networks"	Havaei et al.	Two-pathway CNN	Combines local and global features	Limited scalability	2015
6	"Deep Learning for Head CT Scan Analysis"	Chilamkurthy et al.	Deep CNN	Segmentation accuracy 94%; accuracy in real-time finding detection	Only applied to CT scans	2018
7	"nnU-Net: Self-configuring Biomedical Segmentation"	Isensee et al.	Automated CNN configuration	Outperformed hand-tuned models	Resource intensive	2021
8	"Res-BRNet: Brain Tumor Classification"	Zahoor & Khan	Hybrid CNN + Residual Learning	Improved accuracy, good spatial attention	Training complexity	2022
9	"VGG16 and ResNet50 in Brain Tumor Detection"	Praveen & Santika	Transfer Learning	Achieved over 92% accuracy	Requires large data and fine-tuning	2022
10	"Glioma Grading using Deep Radiomics"	Banerjee et al.	CNN for multi-class classification	87% accuracy in low/high grade glioma detection	Requires more interpretability	2019
11	"UNet++: Nested U-Net for Medical Segmentation"	Zhou et al.	Nested U-Net	Improved boundary segmentation (2–3% gain over U-Net)	Slightly more complex than U-Net	2018
12	"Multi-grade Brain Tumor Classification"	Sajjad et al.	Custom CNN	91% accuracy on T1-weighted MRIs	Less generalized architecture	2019
13	"Classification of Brain MRI Using Hybrid CNN"	Rehman et al.	CNN + PCA + SVM	Accuracy improved by 4% over CNN alone	Hybrid models are harder to train	2021
14	"GAN-Based Data Augmentation for Tumor Detection"	Saha et al.	GAN + CNN	Improved accuracy by 6% using synthetic data	GANs are complex and resource-intensive	2020
15	"Brain Tumor Classification with CNN and Wavelets"	Swati et al.	CNN + Discrete Wavelet Transform	Combines spatial and frequency features; 89% accuracy	Complexity in feature extraction	2019
16	"Automatic Brain Tumor Detection Using Genetic CNN"	Anaraki et al.	CNN + Genetic Algorithm	92% accuracy, optimized architecture	Time-consuming optimization process	2019

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Sl. No.	Title	Authors	Algorithms Used	Merits	Demerits	Year
17	"CNN-based Brain Tumor Segmentation and Detection"	Noreen et al.	Deep CNN	Fast processing with low false positives	May need fine-tuning for specific tumor types	2021
18	"Brain Tumor Classification Using ResNet"	Deepak & Ameer	ResNet + Softmax	94% recall in multi-class detection	Requires powerful GPU for training	2019
19	"Brain Tumor Classification Using Ensemble CNN"	Muhammad et al.	Ensemble of CNNs	Accuracy improved by 3% with higher robustness	Model complexity and longer training time	2021
20	"Real-time Brain Tumor Detection"	Gupta & Yadav	Lightweight CNN + App Interface	88% accuracy on mobile with real-time predictions	Slightly lower accuracy than full CNNs	2022

PROPOSED STRUCTURE

This system uses a well-organized pipeline to provide an efficient brain tumor detection solution, starting with the collection of high-quality MRI data and concluding with the delivery of precise and comprehensible predictions. In the process of developing a model that is both technically sound and clinically beneficial, each step is crucial.

Dataset Collection

The starting point of our approach is a diverse and comprehensive dataset of brain MRI scans. This includes images of individuals diagnosed with different types of brain tumors as well as images of healthy individuals. We used publicly available Kaggle datasets [6], which contain annotated images across different MRI modalities such as T1-weighted, T2-weighted, and FLAIR. This diversity ensures that the model is trained on rich and representative brain structures, helping it generalize well across different cases.

Image Processing

To ensure consistency and improve the quality of the MRI scans, several preprocessing techniques are applied. Skull stripping is performed to isolate the brain from the surrounding tissue [7], and pixel intensity values are normalized to a common scale [8]. Additionally, the images are resized to fit the model's required input size. Furthermore, we generate additional training examples by applying data augmentation techniques such as rotation, flipping, and zooming, which reduce overfitting and improve the model's ability to learn meaningful features [9][10].

Tumor Segmentation

After preprocessing, a U-Net-based deep learning model is used to identify and segment tumor regions in the MRI images [11]. This model performs pixel-level classification to accurately outline the tumor and its sub-regions, such as the enhancing core, surrounding edema, and necrotic tissue [12]. The result is a visual map showing the tumor's location and shape, which is important for both classification and interpretation [13].

Feature Extraction

Once the tumor region is segmented, key features are extracted from that area. These features include the shape, texture, intensity, and boundary characteristics of the tumor [14]. The resulting region of interest (ROI) is then provided to the classification model. The neural network learns to recognize complex visual patterns in order to distinguish between different tumor types or identify the absence of a tumor [15].

Model Development

We use two well-known deep learning architectures, VGG16 and ResNet50, for classification. Transfer learning enables these models to adapt to the brain tumor detection task without requiring training from scratch [16]. Their performance is enhanced using additional dense layers, dropout layers for regularization, and a softmax layer for multi-class classification. The final model is trained to classify the input MRI images as either tumorous or non-tumorous [17].

Model Evaluation

The model's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) [18]. In addition, k-fold cross-validation is performed to assess the consistency of the model across different subsets of the dataset [19][20]. The proposed deep learning model is also compared with conventional machine learning classifiers to highlight the advantages of the proposed approach [21].

Fuzzy Logic Implementation

To improve interpretability and support decision-making under uncertain conditions, a fuzzy logic inference module is integrated after the classification stage [22]. The confidence scores generated by the CNN are provided as inputs to a Mamdani-type fuzzy inference system implemented in MATLAB. Linguistic rules based on tumor characteristics, such as size, texture consistency, and classification confidence, are used to evaluate the overall likelihood and severity of tumor presence. The system generates fuzzy confidence levels categorized as low, moderate, or high, providing a more intuitive representation of diagnostic risk.

Defuzzification & Deficiency Prediction

The fuzzy system's linguistic outputs are converted into crisp numerical values through the defuzzification process. These values represent the final confidence level of the system's prediction. If a tumor is detected, the output includes the predicted tumor type, its location, and the corresponding confidence score. This information is presented in a well-structured report along with annotated MRI images, enabling medical professionals to validate and interpret the results more effectively.

System Integration & Validation

The CNN model and fuzzy logic module are integrated into a unified framework that can be deployed through a user-friendly web or mobile application. The complete system is validated using real-world MRI cases and cross-checked with clinical diagnoses to ensure its reliability. After thorough testing and optimization, the tool is made available to medical professionals to support faster and more consistent brain tumor diagnosis, particularly in settings where expert radiologists may not always be readily available.

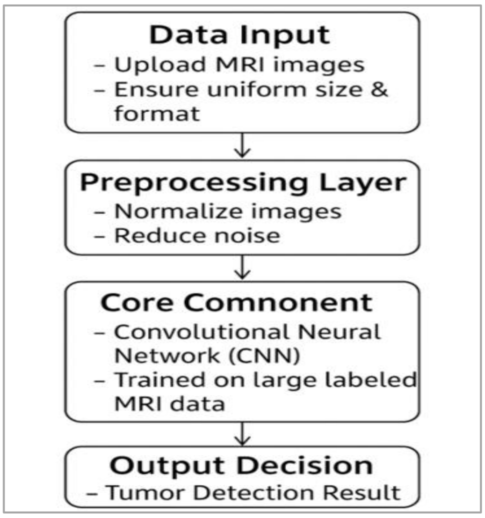

Fig. 1. Proposed Method

MATHEMATICAL FORMULA

We replaced the conventional Sigmoid activation function with the Rectified Linear Unit (ReLU) activation function to improve the speed and performance of the CNN for brain tumor detection. ReLU is particularly effective because it eliminates negative values, which generally represent less significant or irrelevant information in MRI scans. By focusing only on the most important features that indicate the presence of a tumor, the network becomes more efficient. In addition to accelerating the training process, this filtering introduces sparsity into the network, which can improve its generalization capability. Furthermore, by incorporating a bias term into the weighted input, the model gains greater flexibility in detecting subtle patterns within complex brain images. This improves the model's ability to identify early signs of abnormalities, making it more accurate and responsive in real-world diagnostic scenarios.

The expression of the weighted sum is equation 1:

$$z = \sum_{i=1}^{n} w_i x_i + b$$

where:

- w_i= Weight of input i
- x_i= Input feature i
- b= Bias term
- z= Output of the linear combination before activation

The **ReLU** activation method is represented by equation 2:

$$f(z) = \max(0, z)$$

where:

- z= Input from the previous layer (weighted sum)
- $f(z)$= Output of **ReLU** — returns **0** if $z < 0$; returns $z$if $z \geq 0$

1. Image Normalization

Before feeding images into the model, each pixel is normalized to **[0,1]**.

Equation 3:

$$x_{\text{normalized}} = \frac{x_{\text{pixel}}}{255}$$

where:

- **pixel_value** = Original grayscale pixel (0 to 255)
- **normalized_pixel** = Scaled value between 0 and 1 for neural network input

2. Binary Cross-Entropy Loss

Since the **neuroscope** model performs binary classification (tumor vs. no tumor), it utilizes binary cross-entropy loss to measure how well the model performs by comparing predicted probabilities with true binary labels, forming Equation (4).

$$\mathcal{L} = -[y \cdot \log(p) + (1 - y) \cdot \log(1 - p)]$$

Where:

- y= True label (0 or 1)
- p= Predicted probability of Class 1

3. Sigmoid Activation Function

For binary classification, the output layer uses the sigmoid activation function to convert the logits into a probabilistic score, as shown in Equation (5).

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

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Where:

- z= Input from the final layer (logit)
- $\sigma(z)$= Output probability ranging between 0 and 1

4. Learning Rate Scheduler (ReduceLROnPlateau)
The learning rate is automatically reduced when the validation loss stagnates, helping to avoid overshooting during training and improving convergence stability, as represented in Equation (6).
$lr_{\text{new}} = lr_{\text{current}} \times \text{factor}$

Where:

- **factor** is typically set to **0.5**.
- **Patience** refers to the number of epochs without improvement before the learning rate is reduced.

5. Adam Optimizer
Adam is employed as the optimizer to update model weights using momentum and adaptive learning rates, combining the advantages of RMSProp and SGD with momentum which gives us equation 7.

$$\theta = \theta - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon} \cdot \hat{m}_t$$

Where:

- θ= weights
- α= learning rate
- $\hat{m}_t$= first moment estimate (momentum)
- $\hat{v}_t$= second moment estimate (adaptive gradient)
- ϵ= small constant to avoid division by 0

ALGORITHMS
To categorize brain tumor images into two groups—tumor and no tumor—the model use a CNN. In order to scale the data to a range amid 0 and 1, the input photos are first shrunk to a fixed dimension and normalized by dividing each pixel value by 255. Training becomes more stable as a result. Following that, training and validation sets make up the dataset.

Convolution and max pooling are used in multiple layers to construct the CNN. In order to extract significant spatial information such as edges and textures, Convolutional planes apply filters to an image. A ReLU activation function is used to add non-linearity following each convolution. The model learns more quickly and efficiently thanks to this function, which merely sets all negative values to zero and retains the positive ones.

The image gradually gets smaller as it moves through successive levels, but it gains more significant details. The output is flattened into a one-dimensional vector after this feature extraction is complete. The final classification is performed by feeding this vector into fully connected layers. Using a sigmoid activation algorithm, the final layer's value returns a probability within 0 and 1, indicating the likelihood that the image contains a tumor.

Binary cross-entropy, which gauges how closely the model's predictions match the actual labels, is used as the loss function during model training. Adam, the optimizer in use, uses both the variance and the average of previous gradients to change the learning rate through training. This facilitates the model's effective learning.

A learning rate scheduling is used to increase performance with new data while avoiding overfitting. For example, if the validation loss does not improve after a specified number of periods, the Reduce LROn Plateau approach decreases the learning rate. After the model has been trained, it is evaluated using the validation set of data. In order to make predictions, the model calculates a probability; if the value is greater than 0.5, the image is classified as having a tumor; otherwise, it is classified as not having one.

IMPLEMENTATION

In this study, brain MRI images are classified as **tumor** or **non-tumor** using a convolutional neural network (CNN). A collection of MRI scans is first assembled, and the images are pre-processed to ensure consistency. Pixel values are normalized by dividing them by 255, and each image is resized to a fixed dimension. This normalization process accelerates training and improves the model's learning efficiency by scaling pixel values to a range between 0 and 1. The dataset is then divided into training and validation sets for model training and evaluation. To improve the model's ability to generalize to unseen data, data augmentation techniques such as rotation, zooming, and horizontal flipping are applied. These transformations increase the diversity of the training data and reduce the risk of overfitting.

The CNN consists of several layers. Each convolutional layer applies filters to detect meaningful patterns and features within the images, such as edges, textures, and shapes. These layers are followed by ReLU activation functions, which introduce non-linearity and enable the model to learn complex patterns. Max-pooling layers reduce the spatial dimensions of the feature maps, improving computational efficiency and helping to control overfitting. After passing through the convolutional and pooling layers, the extracted feature maps are flattened into one-dimensional feature vectors. These vectors are then passed through one or more dense, fully connected layers, which interpret the learned features and perform the final classification. The output layer uses a sigmoid activation function to generate a probability value between 0 and 1, representing the model's confidence in the presence of a tumor.

Brain Tumors

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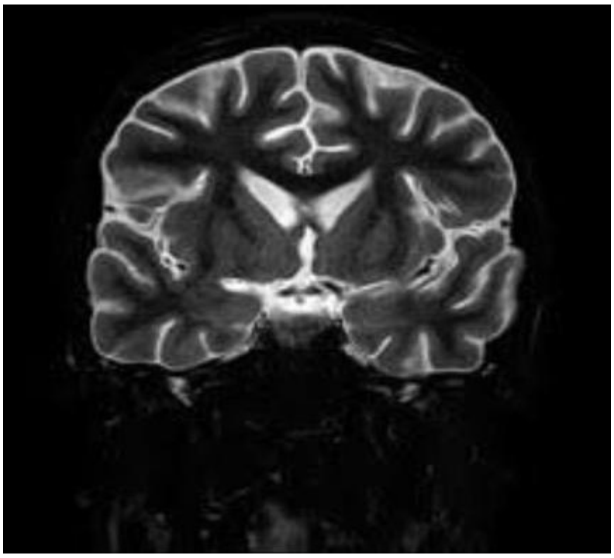

Fig. 2. Image of Brain with No Tumor

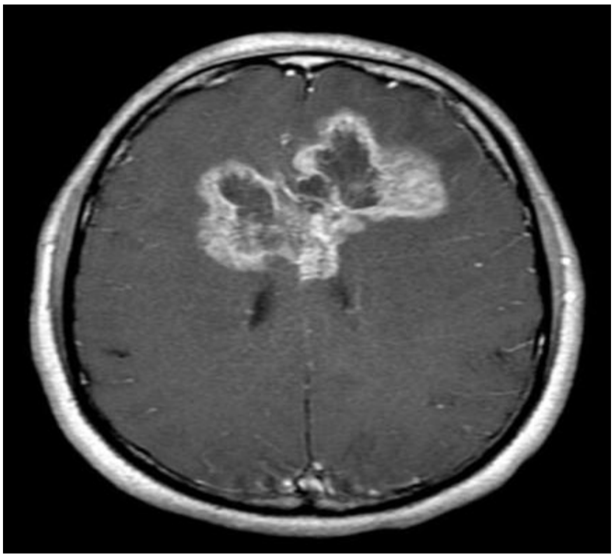

Fig. 3. Image of Brain with a Tumor

Screenshots of Model Output

Fig. 4. Image of Brain with Tumor

Fig. 5. Image of Brain with No Tumor

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For training, the model uses the binary cross-entropy loss function, which is well-suited for binary classification tasks. The Adam optimizer is employed because it combines adaptive learning rates with momentum, enabling efficient weight updates during training. Additionally, the ReduceLROnPlateau learning rate scheduler is used to improve training performance. This scheduler automatically reduces the learning rate whenever the validation loss stops improving, allowing the model to converge more smoothly.

Training is performed over multiple epochs using mini-batches of data. Validation accuracy and validation loss are continuously monitored to track the learning process. After training, the model is evaluated using the validation dataset. During inference, the model outputs a probability score for each image. If the probability is greater than 0.5, the image is classified as **tumor**; otherwise, it is classified as **non-tumor**.

RESULTS AND DISCUSSION

A convolutional neural network (CNN) model was developed to distinguish between tumor and non-tumor brain MRI images. The model's performance was evaluated using several important metrics, including accuracy, precision, recall, F1-score, and validation loss.

During training, the model demonstrated strong learning behavior, with rapid convergence and validation accuracy stabilizing after a few epochs. The final validation accuracy reached approximately **90.43%**, indicating that the model is effective at identifying tumor-related patterns in brain MRI images. Furthermore, the model achieved high precision and recall values, which are particularly important in medical diagnosis, where minimizing both false positives and false negatives is essential.

Our CNN performed competitively compared with similar models reported in the literature. This performance was influenced by several architectural and training strategies. Data augmentation significantly improved the model's ability to generalize to previously unseen data by increasing the diversity of the training dataset. The ReLU activation function accelerated training by mitigating the vanishing gradient problem, while the Adam optimizer ensured stable and efficient weight updates during backpropagation. The ReduceLROnPlateau learning rate scheduler dynamically adjusted the learning rate whenever the validation loss reached a plateau, helping the model escape local minima and improving overall convergence. Finally, the sigmoid activation function in the output layer generated clear and interpretable probability scores, enabling straightforward classification using a threshold value of 0.5.

Overall, the results confirm that the proposed CNN architecture is effective for detecting brain tumors from MRI images and demonstrates strong potential for integration into clinical decision support systems.

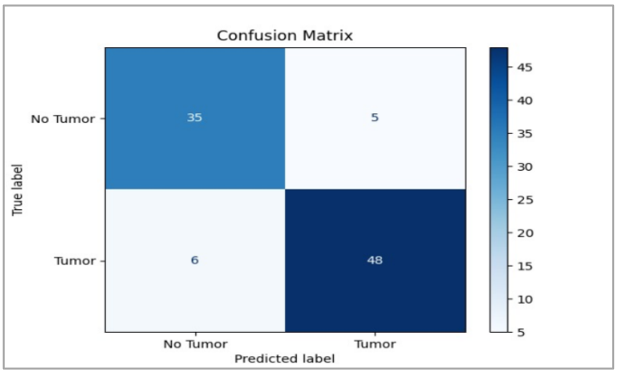

Fig. 6. Confusion Matrix

CONCLUSION

Convolutional neural networks (CNNs) have demonstrated promising results in developing an automated brain tumor classification system, serving as a reliable tool for the early and accurate detection of brain tumors. The proposed model, trained using MRI image datasets, successfully distinguishes between tumor and non-tumor cases with high accuracy. This achievement has significant potential for medical diagnostics, where early detection can substantially improve patient outcomes.

The model architecture was optimized using convolutional layers, ReLU activation functions, dense layers, and a sigmoid output layer. The Adam optimizer and a learning rate scheduler further improved model performance by accelerating convergence, reducing overfitting, and enhancing validation accuracy. Additionally, image normalization contributed to improved model stability and interpretability.

The evaluation results confirm the robustness of the proposed model for binary classification tasks. However, its performance is closely dependent on the quality, size, and diversity of the input dataset. Since the current study utilized a relatively limited dataset, the model's ability to generalize across more diverse populations and imaging conditions remains constrained. Addressing this limitation will be an important focus of future research.

In the future, the proposed system can be extended to support multi-class brain tumor classification, tumor grading, and prediction of treatment outcomes. Incorporating larger and more diverse datasets, along with advanced deep learning techniques such as attention mechanisms, could further enhance the model's predictive performance and clinical applicability.

FUTURE SCOPE

Classifying Various Tumor Types and Grades

At present, the model only determines whether a brain tumor is present. A logical next step would be to train the

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model to identify specific brain tumor types and grades, thereby providing more detailed diagnostic information and supporting more informed treatment decisions.

Using Larger and More Diverse Datasets
To improve reliability in real-world clinical settings, the model should be trained on a larger and more diverse collection of MRI images obtained from different hospitals, imaging devices, and patient populations. This diversity would improve the model's ability to generalize across varying imaging conditions.

Applying Transfer Learning
Transfer learning offers an effective approach to improving model performance while reducing the amount of training data and computational time required. By utilizing pre-trained deep learning models, a more accurate and robust brain tumor classifier can be developed.

Real-Time Deployment
A key future objective is to integrate the proposed model into real-world applications such as web-based platforms or mobile applications that clinicians can use during patient evaluation. Such deployment would make brain tumor detection faster, more accessible, and especially valuable in healthcare settings where experienced radiologists are limited.

Incorporating Explainable AI
For AI-assisted diagnosis to gain widespread clinical acceptance, healthcare professionals must understand how predictions are generated. Integrating explainable AI techniques, such as attention maps or heatmaps highlighting influential image regions, would improve transparency, interpretability, and trust in the model.

Supporting Clinical Decision-Making
The proposed system is intended to assist radiologists rather than replace them. By serving as a reliable decision-support tool within existing clinical workflows, it can function as a second opinion, helping clinicians make faster and more accurate diagnoses while ultimately improving patient care.

Overall, the proposed model demonstrates significant potential for accurate and efficient brain tumor detection, providing a reliable tool to support healthcare professionals in early diagnosis and treatment planning.

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