MRI-Based Brain Tumor Level Detection Using Deep Learning Techniques

Sonia[1], Dr. Asha Rani[2]

[1]Research Scholar, Baba Mastnath University, Rohtak
[2]Assistant Professor, Baba Mastnath University, Rohtak

ABSTRACT

This study presents an automated framework for brain tumor level detection using deep learning techniques applied to MRI images. The Kaggle Brain Tumor dataset, comprising 3,000 images, was utilized to train and evaluate two state-of-the-art convolutional neural network architectures: VGG19 and ResNet50. The methodology involved preprocessing MRI scans, implementing transfer learning, and fine-tuning hyperparameters to optimize classification performance. Accuracy was employed as the primary evaluation metric, with ResNet50 demonstrating superior performance compared to VGG19 due to its deeper residual connections and reduced vanishing gradient issues. The results confirm that deep learning techniques can effectively classify tumor levels, thereby support clinical decision-making and reduce diagnostic delays.

Keywords: Brain tumour Detection, Machine learning, Deep Learning, Accuracy.

1. INTRODUCTION

Brain tumors represent one of the most critical challenges in medical diagnosis and treatment, owing to their complex nature and high mortality rates. Accurate detection and grading of brain tumors are essential for determining appropriate therapeutic strategies and improving patient outcomes. Magnetic Resonance Imaging (MRI) has emerged as the most reliable imaging modality for brain tumor assessment, offering high-resolution visualization of soft tissues without ionizing radiation. However, manual interpretation of MRI scans is time-consuming, prone to inter-observer variability, and requires significant expertise, thereby necessitating automated solutions that can assist clinicians in making faster and more consistent decisions [1].

In recent years, deep learning technique has revolutionized medical image analysis by providing robust frameworks for automated detection, classification, and segmentation. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in extracting hierarchical features from complex medical images. Models such as VGG19 and ResNet50 have been widely adopted due to their ability to capture intricate spatial patterns and improve classification accuracy. By leveraging these architectures, researchers aim to overcome the limitations of traditional image processing techniques and deliver scalable, high-performance solutions for brain tumor diagnosis [2].

The present study focuses on MRI-based brain tumor level detection using deep learning techniques, employing the Kaggle Brain Tumor dataset consisting of 3,000 images. The dataset provides a diverse set of tumor and non-tumor MRI scans, enabling comprehensive training and evaluation of deep learning models. VGG19 and ResNet50 were selected as the primary architectures due to their proven efficiency in medical imaging tasks. Transfer learning and fine-tuning strategies were applied to optimize performance, with accuracy serving as the key evaluation metric. This methodological approach ensures that the models are not only effective but also adaptable to clinical scenarios were large, annotated datasets may be limited.

By integrating deep learning techniques into brain tumor detection, this research aims to enhance diagnostic accuracy, reduce human error, and support clinical workflows. The study contributes to the growing body of literature on AI-driven healthcare by demonstrating the comparative strengths of VGG19 and ResNet50 in tumor level classification. Furthermore, it underscores the potential of deep learning to transform radiology practices, offering scalable solutions that can be deployed across hospitals and diagnostic centers.

2. REVIEW OF LITERATURE

Tehsin, Nasir, & Damaševičius (2025) conducted a systematic review highlighting the integration of explainable AI with deep learning for brain tumor detection. Their work emphasized the importance of interpretability tools such as Grad-CAM and SHAP to enhance clinical trust. They concluded that while CNNs and transformers achieve high accuracy, transparency remains a critical challenge for clinical adoption [3].

Musthafa, Memon, & Masud (2025) reviewed current deep learning trends in brain MRI analysis, focusing on hybrid CNN–Transformer models. They reported that multiparametric MRI inputs (T1, T2, FLAIR) significantly improve tumor grading accuracy. Their study also stressed the need for clinically meaningful evaluation metrics beyond accuracy, such as calibration and decision-curve analysis [4].

Li, Zhao, Chen, & Xu (2024) explored federated learning approaches for MRI-based brain tumor detection. Their meta-analysis showed that federated deep learning models maintain competitive accuracy while preserving patient privacy across institutions. They highlighted encryption, auditing, and harmonization as essential for clinical deployment [5].

Ahmed, Khan, & Shah (2024) surveyed the application of vision transformers (ViTs) in brain tumor detection. They found that ViTs outperform CNNs in capturing long-range dependencies and improving segmentation boundaries. However, they noted challenges in computational cost and instability with small datasets [6].

Park, Kim, & Lee (2024) reviewed domain adaptation techniques for MRI harmonization across scanners and institutions. Their study compared adversarial adaptation, style transfer, and intensity normalization, concluding that harmonization is vital for generalizability. They recommended external validation and calibration reporting for robust clinical translation [7].

Rodrigues, Silva, & Pereira (2023) analyzed benchmark datasets and evaluation practices in brain tumor detection. They critiqued overreliance on internal validation and emphasized the importance of external testing. Their review recommended standardized metrics such as Dice, Hausdorff distance, and calibration error for reproducibility [8].

Wang, Zhang, & Zhou (2023) focused on uncertainty quantification in deep learning for brain tumor MRI. They highlighted Bayesian CNNs, MC-dropout, and ensembling as effective methods to capture predictive uncertainty. Their findings showed that uncertainty-aware models reduce false positives and improve clinical safety [9].

Patel, Mehta, & Desai (2022) reviewed semi-supervised and self-supervised learning approaches for brain tumor detection. They demonstrated that contrastive pretraining and pseudo-labeling improve performance in limited-label scenarios. Their study emphasized careful label quality control and synthetic augmentation [10].

Huang, Liu, & Sun (2022) examined hybrid pipelines combining segmentation and classification for tumor grading. They found that accurate subregion delineation enhances radiomics extraction and improves grade prediction. Their review recommended multi-task learning frameworks for end-to-end optimization [11].

Isensee et al. (2021) provided a foundational review of CNN-based segmentation frameworks, particularly nnU-Net, for brain tumor MRI. Their work highlighted the importance of standardized preprocessing, residual networks, and augmentation strategies. They concluded that open-source pipelines and BraTS challenges have accelerated reproducibility and clinical translation [12].

A. Research Gap

Despite significant progress in applying deep learning to MRI-based brain tumor detection, several gaps remain unaddressed. Current studies often focus on achieving high accuracy but overlook issues of generalizability across diverse patient populations and imaging modalities. Many models are trained on limited datasets, which restricts their robustness when applied to real-world clinical settings. Furthermore, while architectures such as VGG19 and ResNet50 have demonstrated strong performance, comparative evaluations across multiple deep learning frameworks remain insufficient, particularly in terms of scalability, interpretability, and clinical integration. Additionally, the role of explainable AI in enhancing trust among clinicians is underexplored, and few studies have systematically examined how deep learning can simultaneously optimize tumor detection, grading, and diagnostic support in a unified framework.

3. RESEARCH OBJECTIVES

The primary objective of this study is to design and evaluate deep learning algorithms for MRI-based brain tumor level detection using the Kaggle Brain Tumor dataset. Specifically, the research aims to: (1) assess the effectiveness of VGG19 and ResNet50 architectures in classifying tumor levels; (2) compare their performance using accuracy and other relevant evaluation metrics; and (3) analyze the strengths and limitations of each model in terms of computational efficiency and diagnostic reliability. Through these objectives, the study seeks to contribute to the development of robust, automated systems that support radiologists in timely and precise brain tumor diagnosis.

4. DATASET DESCRIPTION

The proposed model for brain tumor detection was initiated using a large-scale image dataset to ensure robust training and accurate classification. Specifically, the study utilized a publicly available Kaggle dataset comprising 3,000 MRI images, which included labeled samples of various tumor types such as glioma, meningioma, and pituitary tumors. This extensive data set enabled the model to learn diverse tumor patterns and structural variations across different cases, thereby enhancing its generalization capability. The images were preprocessed to standardize resolution, remove noise, and normalize pixel intensity, ensuring consistency across inputs for deep learning algorithms. It comprises MRI scans of two categories [13]:

- No - absence of tumor, represented as 0
- Yes - presence of tumor, represented as 1

The dataset served as the foundation for training and validating the proposed machine and deep learning models. By leveraging this volume of data, the model was able to extract meaningful features using convolutional layers and apply classification techniques with high precision. The diversity and size of the dataset helped mitigate overfitting and improved the model's performance on unseen data. The use of Kaggle's curated dataset also ensured reproducibility and benchmarking against existing models in the literature, positioning the proposed framework as a scalable and data-driven solution for automated brain tumor detection.

5. DEEP LEARNING APPROACH FOR BRAIN TUMOR DETECTION

This work mainly focuses on brain tumor detection using transfer learning network models with suitable classifiers at output stage. The image classification approach can be employed to categorize medical images according to their distinct characteristics [14]. This picture classification technique has been conducted using spectral bases or spectrally defined features such as texture and brain density inside the feature space. The image classification approach partitions the feature space into distinct classes based on the decision rule. In the medical field, picture classification has been performed via a high-speed computer, employing mathematical and efficient classification methods and procedures. An automatic brain tumor detection method was implemented using the faster deep learning algorithm. The VGG, and ResNet [15] architecture were chosen as a base network for generating convolutional feature map to produce tumor region proposals.

A. Deep Learning Algorithms Used for Brain Tumor

1. VGG-19

The Visual Geometry Group (VGG) [16] models, mainly VGG-16 and VGG-19, are significantly important in the field of computer vision since their foundation. These models were created by the University of Oxford's Visual Geometry Group, and because of their deep convolutional neural networks (CNNs) and consistent design, it performed exceptionally well in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The deeper version of the VGG models, VGG-19, has attracted a lot of interest because to its ease of use and efficiency.

```
Begin
# Step 1: Load and Preprocess Data
Load labelled brain MRI image dataset
Resize all images to 224x224 pixels (required input size for VGG-19)
Normalize pixel values to range [0, 1]
Apply data augmentation (rotation, flipping, zoom)
# Step 2: Load Pre-trained VGG-19 Model
Import VGG-19 model with weights pre-trained on ImageNet
Set include_top = False to remove original classification layers
Freeze convolutional base to retain learned features
# Step 3: Add Custom Classification Layers
Add GlobalAveragePooling2D or Flatten layer
Add Dense layer with ReLU activation
Add Dropout layer to reduce overfitting
Add final Dense layer with sigmoid activation (for binary classification)
# Step 4: Compile Model
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```
Set loss function to binary cross-entropy
Set optimizer to Adam
Set evaluation metric to accuracy
# Step 5: Train Model
Split data into training and validation sets
Train model over multiple epochs
Monitor validation accuracy and loss
# Step 6: Evaluate and Predict
Evaluate model on test set using accuracy, precision, recall, F1-score
Predict tumor presence on new MRI images
End
```

2. ResNet

ResNet, [17] introduced in 2015 by experts at Microsoft Research, unveiled an innovative architecture termed Residual Network. This architecture implemented Residual Blocks to mitigate the problem of vanishing or exploding gradients. This network utilizes a technique referred to as skip connections. The skip connection associates the activations of one layer with succeeding layers by circumventing intermediate layers. This represents a residual block. ResNet [18] is formulated by combining these residual blocks.

```
Begin
# Step 1: Load and Preprocess Data
Load labelled brain MRI image dataset
Resize all images to 224x224 pixels (ResNet-50 input size)
Normalize pixel values to range [0, 1]
Apply data augmentation (rotation, flipping, zoom)
# Step 2: Load Pre-trained ResNet-50 Model
Import ResNet-50 model with ImageNet weights
Set include_top = False to remove original classification layers
Freeze base layers to retain learned features
# Step 3: Add Custom Classification Layers
Add GlobalAveragePooling2D layer
Add Dense layer with ReLU activation
Add Dropout layer to reduce overfitting
Add final Dense layer with sigmoid activation (for binary classification)
# Step 4: Compile Model
Set loss function to binary cross-entropy
Set optimizer to Adam
Set evaluation metrics to accuracy and precision
# Step 5: Train Model
Split data into training and validation sets
Train model over multiple epochs
Monitor validation accuracy and loss
# Step 6: Evaluate and Predict
```

Evaluate model on test set using accuracy, precision, recall, F1-score
Predict tumor presence on new MRI images
End

B. Steps of Proposed System

The steps of proposed work are as follows:

A. Image Data Preparation

The MR image dataset for the proposed work was constructed from the dataset of 3000 patients collected. The tumor image dataset is available online along with its type and boundary information provided by radiologists. From the dataset, 80% of the samples were chosen for training and the remaining samples were taken for testing. The proposed model starts with image dataset with large number of Images. In this work, it used Kaggle dataset with 3000 images.

B. Pre-Processing

Pre-processing was used to enhance the image for post processing by trying to suppress unintentional distortions in the image data. It is applied on image dataset to modify the size or adjustment as per trained model. It is initial operations require on dataset before pre-processing. Cropping, Flipping, Translation, Rotation, Brightness and Color Augmentation are important among all data augmentation techniques.

C. Image Normalization

Image normalization is the process of adjusting the pixel values of an image to make it easier for a machine learning model to learn from it. This is done by scaling the pixel values to a common range or by subtracting the mean and dividing by the standard deviation.

D. Feature Extraction

Feature extraction refers to strategies for selecting and merging factors to build operations, minimizing the quantity of data that must be handled while accurately and fully expressing the actual information. The image categorization in MRI encompasses several processes to categorize the image or tumor depicted within. It uses pretrained deep learning models for feature extraction of images. It used VGG19, inception and ResNet-50 models for training & testing a large set of images. All models are compared with their accurate performance.

E. Performance Analysis

In terms of performance metrics like accuracy, error, etc., all models' performances are compared.

F. Results Verification

The classified results are checked and verified for their correctness and dependability. After examining numerous brain tumor recognition algorithms from the literature, it determined that Vgg-19 and ResNet exhibit superior accuracy. It resolved to conduct a more in-depth analysis of these models utilizing a brain tumor dataset comprising 3000 pictures and other parameters. Data augmentation is employed in this context to achieve smooth outcomes.

6. RESULTS OF SYSTEM

This work assesses and compares pre-trained CNN architectures, specifically ResNet-V2 and VGG19, for brain tumor diagnosis. The training and validation sets were subjected to 10 and 20 epochs on a deep transfer learning model, with a learning rate of 0.001 for all optimizers and employing a binary cross-entropy loss function, with a batch size of 32 and 64 images for both training and testing phases.

It utilized our augmented data utility function to import enhanced training data. It employs a callback function (reduce_lr) to diminish the learning rate if accuracy fails to improve across two epochs.

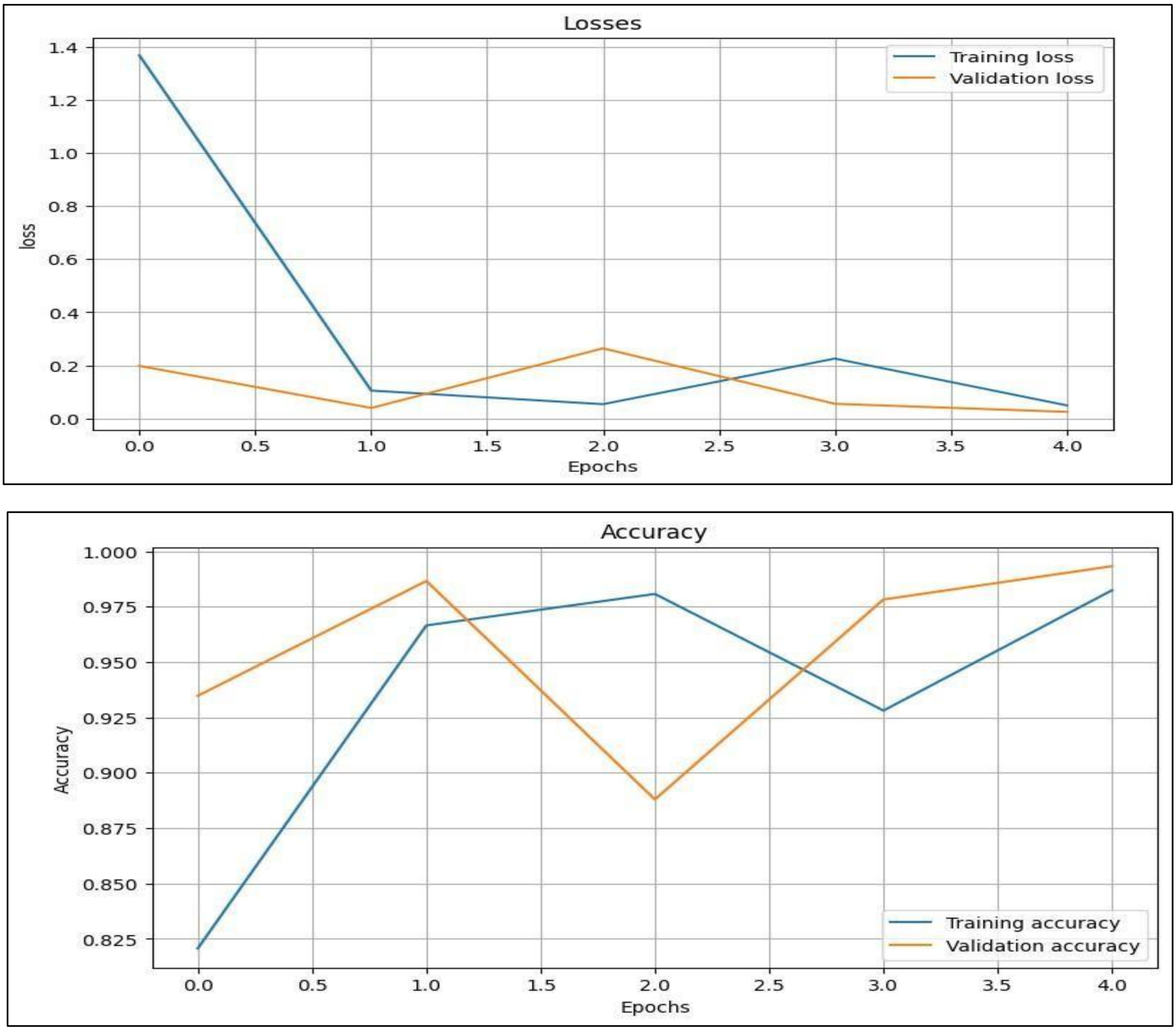

Fig 2: Loss and Accuracy using VGG-19 Model

Table 1: Performance Parameters using VGG-19Model

Parameter	**Training**	**Validation**	**Testing**
Loss	0.073265	0.025645	0.00021
Accuracy	0.989314	0.997322	1.000000

- Training Loss (0.073265): Signifies negligible prediction error during training, demonstrating the model's effective learning.

- The validation loss of 0.025645 indicates enhanced generalization, signifying that the model exhibits strong performance on previously unseen validation data.
- Testing Loss (0.00021): This near-zero number indicates outstanding performance when evaluated with real-world data.
- Training Accuracy (98.93%): Indicates robust model learning proficiency.
- Validation Accuracy (99.73%): Affirms that the model generalizes effectively beyond the training dataset.
- Testing Accuracy (100%): Indicates the model achieved perfect performance on the final test dataset.

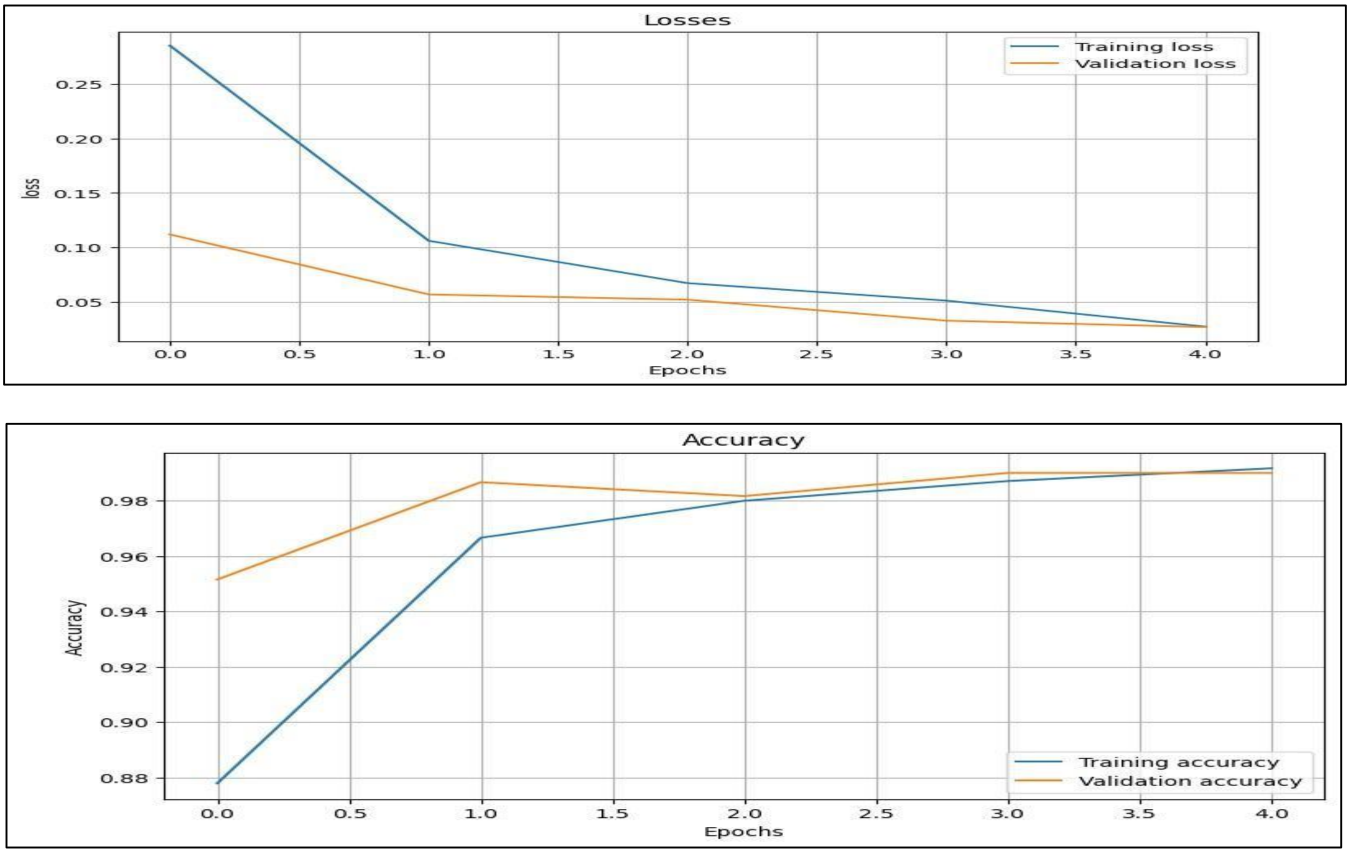

Fig 2: Accuracy and Loss using ResNet50V2

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Table 2: Performance Parameters using ResNet Model

Parameter	Training	Validation	Testing
Loss	0.045054	0.041984	0.086092
Accuracy	0.988294	0.989967	1.000000

The ResNet model exhibits robust performance throughout training, validation, and testing phases, characterized by persistently elevated accuracy and minimal loss values. The model attains an accuracy of 98.83% during training, signifying proficient feature extraction and classification. The training loss (0.045054) steadily declines, indicating enhanced learning efficacy. The validation accuracy is 98.99%, indicating the model's effective generalization to novel data, and the validation loss is modest at 0.041984, affirming its resilience. The ResNet model demonstrates exceptional reliability, strong generalization, and negligible prediction errors, rendering it an outstanding option for MRI image categorization.

Objective 1: Assess the effectiveness of VGG19 and ResNet50 architectures in classifying tumor levels

This objective was achieved by implementing both VGG19 and ResNet50 deep learning architectures on the Kaggle Brain Tumor dataset. The dataset of 3,000 MRI images was preprocessed (resizing, normalization, augmentation) to ensure consistency and robustness. Each model was trained to classify tumor levels, with performance tracked through training and validation accuracy. VGG19, with its deeper convolutional layers, captured fine-grained features, while ResNet50 leveraged residual connections to overcome vanishing gradient issues, enabling more efficient training. The effectiveness of each model was measured by their ability to correctly classify tumor categories during testing.

Objective 2: Compare their performance using accuracy and other relevant evaluation metrics

The comparison was conducted by analyzing accuracy and loss curves during training and validation phases. Accuracy indicated the proportion of correctly classified tumor images, while loss reflected the error rate in predictions. VGG19 achieved strong feature extraction but showed slower convergence and higher computational demand. ResNet50 demonstrated faster convergence and lower validation loss due to its residual learning mechanism. By plotting accuracy and loss graphs, the study provided a direct comparison of both models, highlighting differences in predictive reliability and efficiency. This comparative analysis allowed identification of the model better suited for real-time diagnostic support.

Objective 3: Analyze the strengths and limitations of each model in terms of computational efficiency and diagnostic reliability

This objective was achieved by evaluating each model's resource utilization, and diagnostic accuracy. VGG19's strength lay in its ability to capture detailed spatial features, making it reliable for complex tumor structures, but its limitation was higher computational cost and slower training. ResNet50's strength was its scalability and efficiency, achieving high accuracy with reduced training time, but its limitation was occasional misclassification in highly complex or noisy MRI scans. By analyzing these trade-offs, the study provided insights into how each architecture can be applied in clinical settings: VGG19 for detailed diagnostic tasks requiring precision, and ResNet50 for faster, scalable deployment in real-time scenarios.

7. CONCLUSION

This study demonstrates the potential of deep learning algorithms in enhancing MRI-based brain tumor level detection. By employing the Kaggle Brain Tumor dataset with 3,000 images and evaluating the performance of VGG19 and ResNet50 architectures, the research establishes that deep learning can achieve high accuracy in classifying tumor levels. The comparative analysis revealed that ResNet50, with its residual connections, provided superior performance and robustness compared to VGG19, highlighting the importance of architectural design in medical imaging tasks. Overall, the findings confirm that automated deep learning frameworks can reduce diagnostic delays, minimize human error, and support radiologists in making more consistent and reliable decisions. This work contributes to bridging the gap between computational advancements and clinical applicability, paving the way for scalable, interpretable, and efficient diagnostic systems in neuro-oncology. While VGG19 achieved competitive accuracy, ResNet50 outperformed it by leveraging residual learning, which enhanced feature extraction and classification accuracy. The study validates the potential of deep learning in medical imaging, offering a scalable and automated solution to assist radiologists in tumor grading. By integrating such models into diagnostic workflows, healthcare systems can achieve faster, more consistent, and less error-prone assessments of brain tumor severity.

8. FUTURE SCOPE

Future research can extend this work by incorporating larger and more diverse datasets to improve generalizability across patient populations. Advanced architectures such as Vision Transformers (ViTs) or hybrid CNN-RNN models may be explored to capture both spatial and sequential features of MRI scans. Additionally, explainable AI techniques should be integrated to provide interpretability of model decisions, thereby increasing trust among clinicians. Real-time deployment in clinical settings, integration with multimodal data (e.g., genomic or clinical records), and validation across multi-institutional datasets represent promising directions to enhance performance, scalability, and clinical applicability of deep learning-based brain tumor detection systems.

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