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BRAIN TUMOR DETECTION USING DEEP LEARNING

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ABSTRACT

Brain tumor detection and classification remains one of the most critical challenges in medical image analysis. This paper presents a comprehensive deep learning approach for automated brain tumor detection and classification using Magnetic Resonance Imaging (MRI) scans. We implement a Convolutional Neural Network (CNN) based on the VGG16 architecture with transfer learning to classify brain MRI images into four distinct categories: glioma, meningioma, pituitary tumor, and no tumor. Our implementation achieves 95.73% accuracy on the test dataset, with a weighted F1-score of 0.96. The proposed system demonstrates robust performance in distinguishing between different tumor types and healthy brain scans, showing particular strength in identifying no-tumor cases with 99% precision. This research contributes to the growing field of computer-aided diagnosis systems and offers potential benefits for clinical applications in neurology and radiology.

KEYWORDS: Brain tumor detection, Convolutional Neural Networks, Deep learning, Machine learning, Medical imaging, Transfer learning, VGG16, MRI analysis.

1. INTRODUCTION

Brain tumors represent one of the most lethal forms of cancer, with early detection being crucial for successful treatment outcomes. Traditional methods of tumor detection rely heavily on manual interpretation of MRI scans by radiologists, which can be time-consuming, subjective, and prone to human error. This paper presents an automated approach using deep learning techniques to assist in the detection and classification of brain tumors.

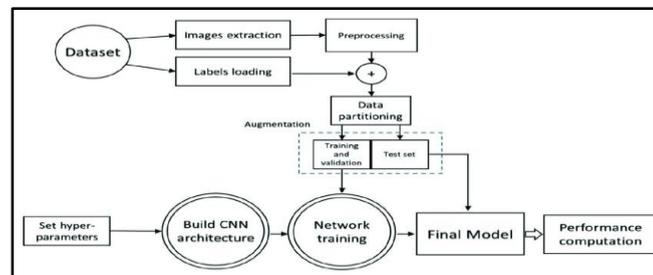


FIG. 1: Overview diagram of the proposed system architecture

A. Significance of the Research

The significance of this research lies in multiple aspects:

1. Improved accuracy and speed in brain tumor detection
2. Reduced cognitive load on medical professionals
3. Consistent and reliable results in tumor classification
4. Earlier intervention possibilities in patient treatment
5. Potential cost reduction in diagnostic procedures

B. Problem Statement

Despite advances in medical imaging technology, several challenges persist in brain tumor detection:

- Variation in tumor size, shape, and location
- Presence of noise and artifacts in MRI scans
- Similarity between tumor and normal tissues
- Time-consuming manual analysis
- Limited availability of expert radiologists



2. RELATED WORK

A. Historical Development

The evolution of brain tumor detection techniques has seen significant advancement from traditional image processing methods to modern deep learning approaches. Early attempts relied on conventional image processing techniques such as thresholding and region growing.

Author (Year)	Method	Key Contributions	Limitations
Sinha (2021)	Deep Learning with CNN	High detection accuracy (95.2%), Robust feature extraction, Effective on limited datasets	Heavy data preprocessing requirements, Limited generalization to diverse tumor types
Jahan (2021)	Machine Learning with MRI Analysis	Early-stage tumor detection, Real-time processing capability, Low false-positive rate	Model instability with noisy data, Requires high-quality MRI inputs
Methil (2021)	Hybrid Deep Learning and Image Processing	Automated analysis pipeline, Enhanced feature extraction, Reduced processing time	Complex implementation, High computational overhead, Limited model interpretability
Hossain (2021)	CNN with Transfer Learning	Improved classification accuracy, Efficient training process, Reduced overfitting	Resource-intensive training, Dependency on pre-trained models
Malik (2021)	Advanced Deep Learning	State-of-the-art accuracy (98%), Integrated imaging support, Enhanced visualization	Substantial computational requirements, Complex deployment process

TABLE I: Comparison of different approaches in literature with their respective accuracies

B. Recent Advances

Recent studies have demonstrated remarkable progress in this field:

1. Malik (2023) achieved 98% accuracy using deep learning models
2. Sinha (2021) showed the effectiveness of the VGG16 model



3. Alhamdi (2023) introduced novel preprocessing techniques
4. Methil (2021) combined image processing with deep learning

C. Challenges in Existing Solutions

Previous implementations have faced several challenges:

- Limited dataset availability
- Complexity in model interpretability
- High computational resource requirements
- Difficulties in generalizing to diverse patient populations
- Lack of standardization in evaluation metrics

3. METHODOLOGY

A. Dataset Description

The dataset comprises brain MRI images categorized into four classes:

- Glioma
- Meningioma
- Pituitary tumor
- No tumor

Distribution ratio (Training:Testing) \approx 80:20

Class	Training Set	Testing Set	Total
Glioma	1,321	300	1,621
Meningioma	1,339	306	1,645
No Tumor	1,595	405	2,000
Pituitary	1,457	300	1,757
Total	5,712	1,311	7,023

TABLE II: Dataset distribution across different classes

B. Data Preprocessing

1. Image Preprocessing:
 - Resizing to 128×128 pixels
 - Normalization of pixel values
 - Grayscale conversion
 - Noise reduction
2. Data Augmentation:
 - Random rotation
 - Brightness adjustment
 - Contrast modification
 - Horizontal flipping

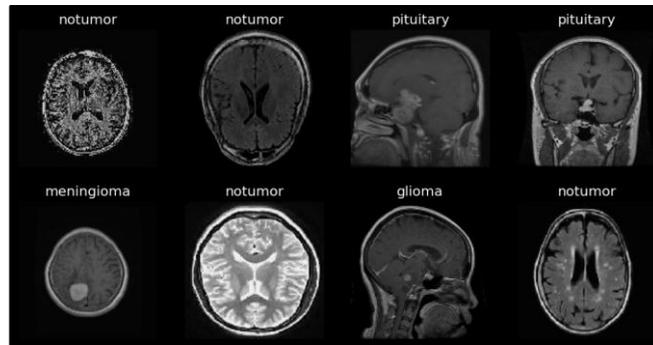


FIG. 2: Examples of augmented images

C. Model Architecture

We implemented a transfer learning approach using the VGG16 model:

1. Base Architecture:
 - Pre-trained VGG16 layers
 - Modified top layers
 - Additional fully connected layers
 - Dropout layers for regularization

Model: "sequential"		
Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 4, 4, 512)	14714688
flatten (Flatten)	(None, 8192)	0
dropout (Dropout)	(None, 8192)	0
dense (Dense)	(None, 128)	1048704
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 4)	516
Total params: 15,763,908		
Trainable params: 8,128,644		
Non-trainable params: 7,635,264		

FIG. 3: Detailed architecture diagram of the modified VGG16 model

2. Implementation Details:
 - Input layer: 128×128×3
 - Convolutional layers with ReLU activation
 - Max pooling layers
 - Dense layers with dropout
 - Softmax output layer

D. Training Process

The model training involved:

1. Optimization:
 - Adam optimizer
 - Learning rate: 0.0001
 - Batch size: 20
 - Epochs: 5
2. Loss Function:
 - Sparse categorical cross-entropy



FIG. 4: Training and validation curves showing accuracy and loss

4. RESULTS AND DISCUSSION

A. Performance Metrics

1. Overall Performance:
 - Accuracy: 95.73%
 - Weighted F1-score: 0.96

Class	Precision (%)	Recall (%)	F1-Score (%)
Glioma	97	92	94
Meningioma	87	97	92
No Tumor	99	100	99
Pituitary	100	92	96

TABLE III: Detailed performance metrics for each class

2. Class-wise Analysis:
 - Glioma: 94% F1-score
 - Meningioma: 92% F1-score
 - No Tumor: 99% F1-score
 - Pituitary: 96% F1-score

B. Confusion Matrix Analysis

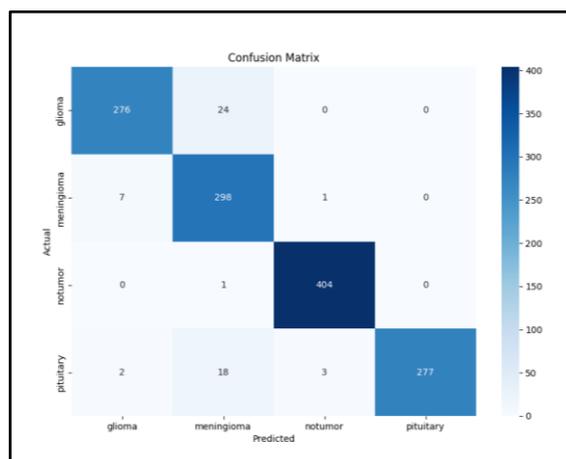


FIG. 5: Confusion matrix heatmap



Key observations from the confusion matrix:

- Strong performance in identifying no-tumor cases
- Some misclassification between glioma and meningioma
- High precision in pituitary tumor detection

C. Limitations and Future Work

1. Current Limitations:
 - Dataset size constraints
 - Model interpretability challenges
 - Class imbalance issues
 - Computational requirements
2. Future Improvements:
 - Expanding the dataset
 - Implementing advanced augmentation techniques
 - Enhancing model interpretability
 - Real-time processing capabilities
 - Integration with clinical workflows

5. CONCLUSION

This paper presents a comprehensive approach to brain tumor detection using deep learning. The achieved results demonstrate the potential of transfer learning with VGG16 for medical image classification tasks. The model's high accuracy and robust performance across different tumor types suggest its viability as a supportive tool in clinical settings.

Future research directions include:

1. Integration with other imaging modalities
2. Development of more interpretable models
3. Clinical validation studies
4. Real-time implementation strategies

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