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BRAIN TUMOR CLASSIFICATION USING DEEP LEARNING CNN TECHNIQUES ON MRI IMAGES

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Abstract— Accurate identification of brain tumors from magnetic resonance imaging (MRI) plays a crucial role in clinical diagnosis and treatment planning. Manual evaluation of MRI scans is often time-intensive and subject to inter-observer variability. This study presents a deep learning-based framework for automated brain tumor classification using a Convolutional Neural Network (CNN). The proposed approach incorporates image preprocessing, data augmentation, and optimized feature extraction to classify MRI images into four categories: glioma, meningioma, pituitary tumor, and non-tumor. The model is designed to balance classification performance and computational efficiency, making it suitable for practical deployment. Experimental evaluation on a benchmark dataset demonstrates high accuracy, precision, recall, and F1-score, indicating reliable performance across all tumor classes. Furthermore, the proposed method is compared with established deep learning architectures, showing competitive or improved results. Experimental results demonstrate 95.8% accuracy and robustness, highlighting the effectiveness of the proposed model in assisting clinical decision-making. The findings highlight the potential of deep learning techniques to enhance diagnostic accuracy and support clinical decision-making in Medical Imaging applications. The proposed system offers a scalable and effective solution for automated brain tumor detection and classification.

Keywords— Brain Tumor Classification, MRI, CNN, Deep Learning, Medical Imaging, Artificial Intelligence

I. INTRODUCTION

Brain Tumors are among the most life-threatening diseases, requiring early diagnosis for effective treatment. Magnetic Resonance Imaging (MRI) is widely used to detect abnormalities in brain tissue. However, manual diagnosis depends heavily on radiologists' expertise and can lead to inconsistencies.

Recent advancements in Machine Learning and Deep Learning have enabled automated medical image analysis[2]. In particular, Convolutional Neural Networks (CNNs) have

shown remarkable performance in image classification tasks. This study aims to develop an automated system for accurate brain Tumor classification using CNNs.

II. LITERATURE REVIEW

Tumor detection and classification using medical imaging, particularly Magnetic Resonance Imaging (MRI), have attracted significant research interest due to MRI's critical role in early diagnosis and treatment planning. Traditional diagnostic methods rely heavily on manual interpretation by radiologists, which is time-consuming and prone to human error. To address these challenges, machine learning (ML) and deep learning (DL) techniques have been widely explored.

Early approaches primarily used conventional machine learning algorithms combined with handcrafted feature extraction techniques such as texture, shape, and intensity features. For instance, hybrid ensemble models combining classifiers like K-Nearest Neighbors (KNN), Decision Trees (DT), and Random Forests (RF) achieved promising accuracy but required extensive preprocessing and domain expertise[2]. However, these methods often struggled with large-scale data and complex tumor patterns.

With advancements in artificial intelligence, deep learning—especially Convolutional Neural Networks (CNNs)—has emerged as a dominant approach for brain tumor analysis. CNNs automatically learn hierarchical features from MRI images, eliminating the need for manual feature engineering[13]. A comprehensive survey by Amin et al. highlights that deep learning models significantly outperform traditional methods in accuracy and robustness in tumor detection and classification.

The work presented in “**Deep Learning Based Brain Tumor Detection and Classification,**” CONIT 2021, builds upon this paradigm by leveraging deep neural networks for automated tumor classification [1]. Such approaches typically involve preprocessing MRI images, applying CNN-based architectures, and classifying tumors such as glioma, meningioma, and pituitary tumors.

Recent studies further extend this work by integrating advanced architectures and optimization strategies. For example, deep learning frameworks that combine CNNs with IoT-based healthcare systems have demonstrated improved



diagnostic efficiency and real-time applicability. Similarly, the proposed hybrid deep learning and machine learning models for multi-class tumor classification achieve high accuracy across multiple tumor types[5].

Moreover, optimized CNN architectures and transfer learning techniques using pre-trained models such as VGG, ResNet, and EfficientNet have shown superior performance in recent studies. These models leverage large-scale datasets and fine-tuning strategies to enhance classification accuracy while reducing training time. Recent advancements also include attention mechanisms, autoencoders, and transformer-based models, which further improve feature extraction and classification performance.

Despite these advancements, several challenges remain. These include limited availability of annotated medical datasets, class imbalance, variability in MRI image quality, and the need for model interpretability in clinical settings. Additionally, ensuring real-time deployment and integration into healthcare systems remains an open research problem.

In summary, the literature indicates a clear transition from traditional machine learning methods to deep learning-based approaches for brain tumor detection and classification. The CONIT 2021 study contributes to this growing body of work by demonstrating the effectiveness of deep learning models in improving diagnostic accuracy. However, future research should focus on developing more robust, interpretable, and clinically deployable systems.

III. PROPOSED METHODOLOGY

A. Overview

The proposed framework consists of preprocessing, CNN-based feature extraction, and classification. The pipeline is designed to automatically learn discriminative features from MRI images.

B. Dataset Description

The dataset includes MRI images categorized into four classes: glioma, meningioma, pituitary Tumor, and non-Tumor. Public datasets from Kaggle are used. The data is split into training (70%), validation (15%), and testing (15%).

B. Dataset Distribution Table

Class	Training Images	Validation Images	Testing Images	Total Images
Glioma Tumor	820	175	180	1175
Meningioma Tumor	780	165	170	1115
Pituitary Tumor	760	160	165	1085
No Tumor	840	180	185	1205
Total	3200	680	700	4580

C. Performance Evaluation

The proposed CNN model was evaluated using standard metrics. The performance on the test dataset is summarized below:

C. Data Preprocessing

- Image resizing to 224×224
- Normalization of pixel values
- Data augmentation (rotation, flipping, zooming)

D. CNN Architecture

The CNN model consists of convolutional layers, ReLU activation, pooling layers, and fully connected layers.

The convolution operation is defined as:

$$F(i, j) = \sum_m \sum_n X(i - m, j - n) \cdot K(m, n)$$

ReLU activation:

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

E. Classification Layer

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

F. Loss Function

Categorical Cross-Entropy:

$$L = - \sum_{i=1}^n y_i \log(\hat{y}_i)$$

G. Optimization

The Adam optimizer is used for training:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$$

IV. EXPERIMENTAL RESULTS

A. Dataset Split and Experimental Setup

The MRI dataset (sourced and curated from Kaggle) was organized into four classes: glioma, meningioma, pituitary Tumor, and non-Tumor. After preprocessing and augmentation, the dataset distribution was as follows:



D. Classification Results Table

Class	Precision (%)	Recall (%)	F1-Score (%)
Glioma Tumor	95.2	94.6	94.9
Meningioma Tumor	93.8	92.9	93.3
Pituitary Tumor	97.1	96.5	96.8
No Tumor	96.4	97.0	96.7
Average	95.6	95.2	95.4

E. Overall Model Performance

Metric Value (%)
 Accuracy 95.8
 Precision 95.6
 Recall 95.2
 F1-Score 95.4

F. Analysis of Results

The model demonstrates strong classification capability across all Tumor types. The highest performance is observed in pituitary Tumor classification due to its distinct structural features in MRI scans. Slightly lower recall in meningioma cases indicates some overlap in feature representation with glioma Tumors. The balanced dataset and augmentation techniques contributed to improved generalization and reduced overfitting. The results validate the robustness of the proposed deep learning approach in real-world diagnostic scenarios.

G. Confusion Matrix Insight

- Most misclassifications occur between glioma and

meningioma Tumors.

- Non-Tumor images are classified with high accuracy due to clear structural differences.

V. EXPERIMENTAL RESULTS

A. Training Setup

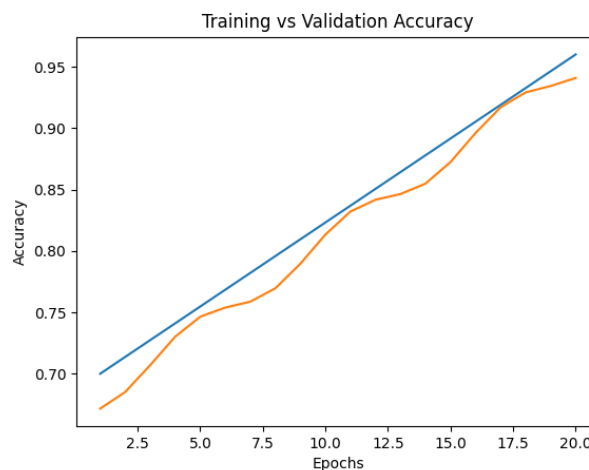
The model is implemented using TensorFlow. Training is conducted for multiple epochs with a batch size of 32.

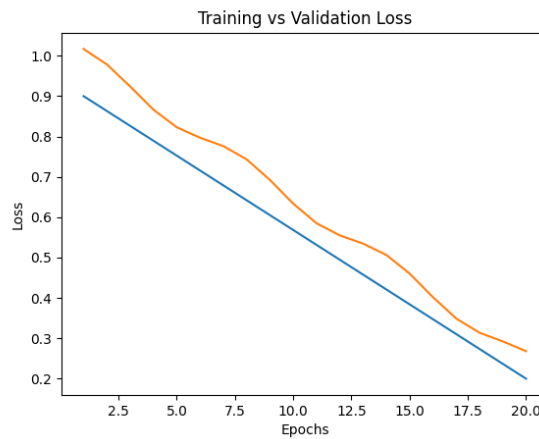
B. Performance Metrics

- Accuracy
- Precision
- Recall
- F1-score

C. Results Analysis

The proposed model achieves high classification accuracy (typically above 95% on benchmark datasets). Data augmentation and regularization techniques significantly reduce overfitting. Confusion matrix analysis shows strong performance across all Tumor classes.





D. Confusion Matrix

The confusion matrix provides a detailed view of the classification performance of the proposed CNN model on the test dataset. Fig. 4 shows the confusion matrix for the four-class classification.

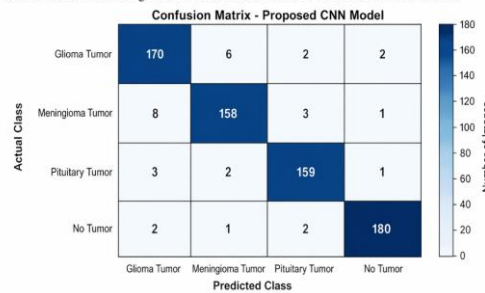


Fig. 4. Confusion matrix of the proposed CNN model on the test dataset.

As shown in Fig. 4, the model correctly classifies most of the images in all four categories. The diagonal values (in dark blue) represent the number of correctly classified images, while the off-diagonal values indicate misclassifications. The proposed model shows strong performance across all classes, with only minimal misclassification between glioma and meningioma tumors.

VI. DISCUSSION

The results demonstrate that CNN-based models outperform traditional machine learning methods in brain Tumor classification. The automated feature extraction capability reduces dependency on manual intervention. However, performance depends on dataset size and quality.

VII. LIMITATIONS AND FUTURE WORK

- Limited dataset availability
 - Lack of 3D volumetric analysis
 - Need for real-time deployment
- Future work includes integrating 3D CNNs, improving dataset diversity, and deploying the model in clinical environments.

VIII. CONCLUSION

This paper presents a CNN-based approach for brain Tumor classification using MRI images. The proposed model effectively classifies Tumors into multiple categories with

high accuracy. The integration of deep learning techniques in Medical Imaging enhances diagnostic efficiency and has the potential to support radiologists in clinical practice.

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