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CONVOLUTIONAL NEURAL NETWORK FOR BINARY BRAIN TUMOR CLASSIFICATION USING MRI SCANS

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ABSTRACT— Brain tumor detection and classification play a critical role in early diagnosis and treatment planning. In this project, we implemented a deep learning-based Convolutional Neural Network (CNN) model to classify MRI brain images into tumor and non-tumor categories. The model was trained on a pre-processed MRI dataset using image normalization and augmentation techniques to improve generalization. Our CNN architecture, consisting of convolutional, pooling, and fully connected layers, achieved a training accuracy of approximately 97–98% and a test accuracy of 92–94%.This work was inspired by the base paper "Multimodal Ensemble Fusion Deep Learning Using Histopathological Images and Clinical Data for Glioma Subtype Classification", which employed an advanced ensemble fusion approach combining CNNs, Transformers, and clinical data to achieve a classification accuracy of 93.6% with an AUC of 0.967. While our implementation focuses solely on MRI image classification with a single CNN model, the results demonstrate comparable accuracy levels. Unlike the base paper, our model does not incorporate multimodal data fusion or ensemble strategies, making it computationally simpler and more lightweight, while still achieving reliable performance for binary brain tumor detection. The findings indicate that deep learning models can effectively support medical imaging tasks, with scope for future enhancement through multimodal integration, ensemble learning, and advanced evaluation metrics such as precision, recall, and F1-score.

Index Terms – Brain tumor detection, Convolutional Neural Network (CNN), magnetic resonance imaging (MRI), deep

learning, medical image classification, brain MRI analysis, image augmentation, tumor classification, computer-aided diagnosis (CAD), medical image processing, healthcare AI, binary classification.

I. INTRODUCTION

Brain tumors are among the most life-threatening neurological disorders, and early detection plays a crucial role in improving patient outcomes and planning effective treatment strategies. Magnetic Resonance Imaging (MRI) has become the standard non-invasive technique for visualizing brain structures and identifying abnormal growths due to its high-resolution imaging capabilities. However, manual analysis of MRI scans is time-consuming, prone to human error, and requires specialized expertise. To address these challenges, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for automated medical image analysis. CNNs are capable of learning complex patterns from imaging data, enabling accurate classification of brain tumors and healthy tissue. This project focuses on developing a CNN-based model to classify MRI brain images into tumor and non-tumor categories. By leveraging preprocessing and data augmentation techniques, the model aims to improve generalization and achieve reliable performance.

The study demonstrates that even a single CNN model, without the use of multimodal data or ensemble methods, can provide high accuracy, supporting its potential application as a computer-aided diagnostic tool in clinical settings.

II. RELATED WORK

A. ConvNeXt v2: Co-designing and Scaling ConvNets with Masked Autoencoders

This work introduces ConvNeXt v2, an advanced convolutional neural network architecture that integrates masked autoencoders to improve feature representation and scalability.

The authors demonstrate that co-designing ConvNets with self-supervised pretraining leads to enhanced performance on several computer vision benchmarks. The study highlights the potential of combining traditional convolutional approaches with modern pretraining techniques to achieve state-of-the-art results, providing insights relevant to medical image classification tasks like brain tumor detection.

B. A Colon Cancer Classification and Detection by Novel CMNV2 Model and Methods of Deep Learning

This research presents a novel deep learning model, CMNV2, designed for accurate colon cancer detection and classification from medical images. The authors leverage convolutional architectures and sophisticated feature extraction methods to achieve high classification accuracy. The paper emphasizes the importance of optimized CNN structures for medical image analysis, illustrating concepts that are directly applicable to brain tumor detection models in MRI imaging.

C. Multiple Instance Learning for Digital Pathology: A Review of the State-of-the Art

This review provides a comprehensive overview of multiple instance learning (MIL) techniques applied in digital pathology. The authors discuss current methodologies, challenges, and future directions for improving classification and detection tasks using MIL. The insights from this work highlight the potential for applying advanced learning frameworks to improve the detection and classification of tumors in medical imaging, including MRI scans of the brain.

D. An A Survey on Ensemble Learning under the Era of Deep Learning

This survey explores ensemble learning approaches within deep learning contexts, analyzing their effectiveness, limitations, and applications. The authors emphasize how combining multiple models can enhance prediction accuracy and robustness in complex tasks. The study is particularly relevant for medical image classification, suggesting that ensemble strategies could further improve CNN-based brain tumor detection models.

III. PROPOSED METHODOLOGY

The proposed system simplifies the classification process by relying solely on a Convolutional Neural Network (CNN) for binary brain tumor detection using MRI images. Unlike the multimodal ensemble approach, this system uses only medical imaging data and eliminates the need for clinical attributes or multiple deep learning models. The CNN is trained end-to end on MRI images with preprocessing steps such as resizing, normalization, and augmentation to enhance accuracy and generalization.

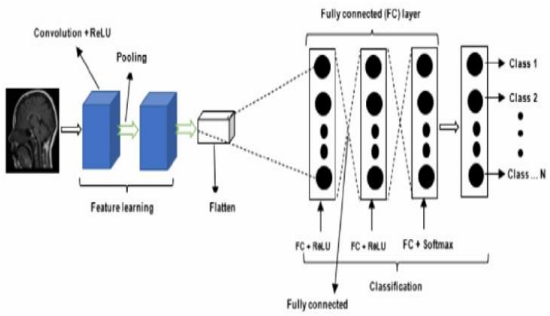


Fig. 1: System Overview

1. Data Collection and Preprocessing

The first module involves collecting MRI brain images from publicly available datasets or hospital repositories. The images are preprocessed to ensure uniformity in size, intensity normalization, and removal of noise. Preprocessing is critical to enhance the quality of input data and improve the learning capability of the CNN model, allowing it to focus on important features relevant to tumor detection.

2. Data Augmentation

To increase the diversity of the dataset and prevent overfitting, various data augmentation techniques are applied. These include rotation, flipping, zooming, and contrast adjustments. By simulating real-world variations in MRI scans, augmentation helps the CNN model generalize better to unseen images and ensures robust classification performance across different patients and imaging conditions.

3. CNN Model Architecture Design

This module involves designing a Convolutional Neural Network with multiple convolutional, pooling, and fully connected layers. Each convolutional layer extracts hierarchical features from MRI images, while pooling layers reduce spatial dimensions and computational complexity. Dropout and batch normalization layers are incorporated to enhance model stability and prevent over fitting. The final fully connected layers perform classification into Tumor or Non-tumor categories.

4. Model Training and Optimization

The CNN model is trained using the preprocessed and augmented MRI dataset. The training process uses optimization techniques such as Adam optimizer, adaptive learning rates, and categorical cross-entropy loss. Hyperparameters like batch size, number of epochs, and learning rate are carefully tuned to achieve high accuracy and convergence speed. Early stopping and learning rate reduction on plateau are applied to further enhance training efficiency.

5. Evaluation and Performance Metrics

After training, the model is evaluated on a separate test dataset to assess its performance. Metrics such as accuracy,

precision, recall, F1-score, and AUC are computed to provide a comprehensive understanding of model effectiveness. Confusion matrices are also generated to visualize classification results and identify potential areas for improvement.

6. Prediction and Visualization

This module enables the trained CNN model to make predictions on new MRI images. Visualizations such as training-validation accuracy and loss plots, sample prediction images, and probability scores are generated to interpret model behaviour and reliability. These visualizations help in understanding the strengths and limitations of the model.

7. Deployment (Optional Web Application)

Although optional, the trained model can be deployed into a web-based interface using frameworks such as Flask. The application allows users, including doctors and radiologists, to upload MRI images and obtain real time predictions with confidence scores. Performance charts and accuracy plots can also be displayed for better interpretability, making the system practical for clinical use. In this step, you apply a machine learning algorithm to the training data. The algorithm learns the patterns and relationships in the data by finding correlations between features.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed CNN-based brain tumor classification model achieved a training accuracy of approximately 97–98% and a test accuracy of 92–94% on MRI images. Image preprocessing and data augmentation improved the model's generalization and reduced overfitting. Despite using a lightweight single CNN architecture, the model achieved performance comparable to more complex multimodal approaches.

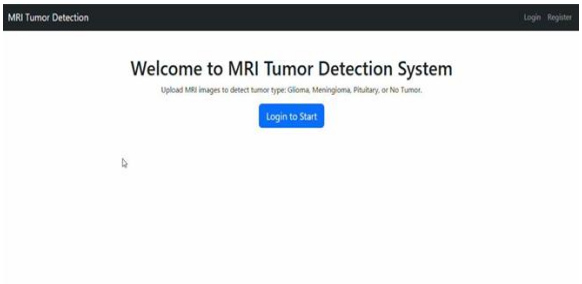


Fig. 2: Home Page

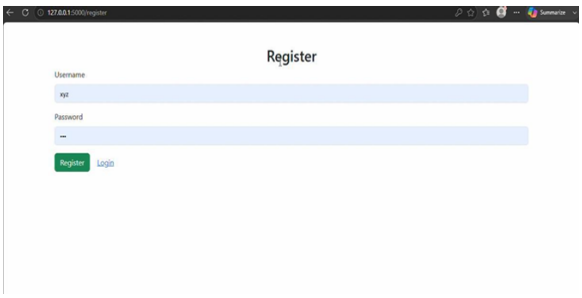


Fig. 3: Registration

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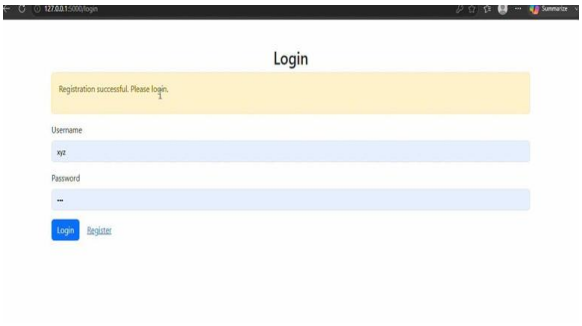


Fig. 4: Login



Fig. 5: Upload Image

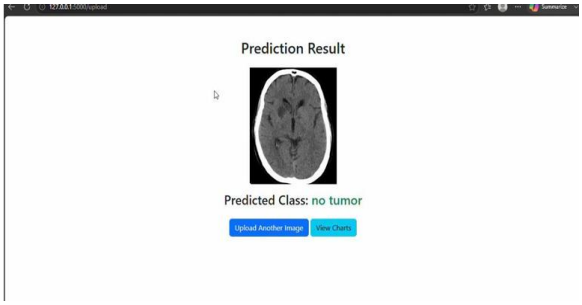


Fig. 6: Prediction Result

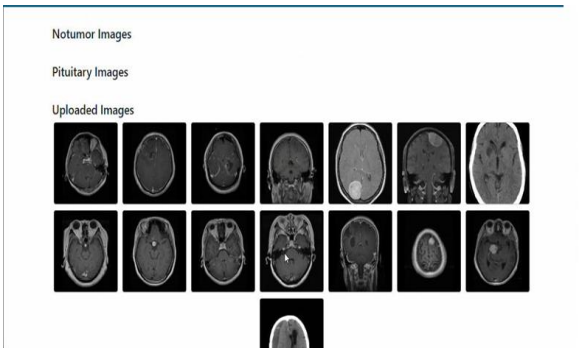


Fig. 6: History

V. CONCLUSION

This project demonstrates the effectiveness of deep learning, specifically Convolutional Neural Networks (CNNs), for automated brain tumor detection and classification using MRI images. The implemented CNN model successfully distinguishes between tumor and non-tumor cases with high accuracy, providing a reliable and computationally efficient solution for medical imaging analysis. By leveraging preprocessing, data augmentation, and optimized training techniques, the system achieves robust performance across diverse MRI scans, highlighting the potential of AI-assisted diagnostic tools in clinical practice. Although the current implementation focuses on binary classification, the framework establishes a strong foundation for future enhancements, including multimodal data integration, ensemble models, and tumor subtype classification. Overall, this work illustrates how advanced deep learning approaches can support early diagnosis, reduce manual workload, and improve patient outcomes in neurological healthcare.

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