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Brain Tumor Detection

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ABSTRACT

Brain tumor detection through medical imaging is a crucial task in the field of healthcare and radiology. Early and accurate identification of brain tumors can significantly improve patient outcomes by enabling timely treatment and intervention. This project presents an automated system for brain tumor classification using Magnetic Resonance Imaging (MRI) scans. Leveraging the power of Convolutional Neural Networks (CNNs), the model is trained on a curated dataset of MRI images categorized as tumor-positive and tumor-negative. The proposed system incorporates image preprocessing techniques such as brain region extraction and normalization to enhance feature learning. The trained CNN model demonstrates high accuracy in classifying brain tumors and is capable of providing reliable predictions on new MRI images.

Keywords--- Deep Learning, PyTorch, Convolutional neural network, Tumor Detection.

I. INTRODUCTION

Brain tumors are among the most serious and life-threatening conditions in the field of neurology, often requiring early diagnosis for effective treatment. Magnetic Resonance Imaging (MRI) is the most widely used imaging technique for brain tumor detection due to its high-resolution and non-invasive nature. However, manual interpretation of MRI scans by radiologists can be time-consuming, subjective, and prone to error.

This project aims to automate the process of brain tumor detection using deep learning techniques, specifically Convolutional Neural Networks (CNNs). The code implements a complete pipeline that includes image preprocessing (brain region extraction and normalization), model construction, training, evaluation, and real-time inference. The model is trained on a labeled dataset of MRI images categorized as either tumor-positive or tumor-negative.

II. LITERATURE REVIEW

The application of deep learning techniques in medical imaging has seen substantial growth in recent years, particularly in the domain of brain tumor detection. Traditional methods of tumor classification relied heavily on manual feature extraction, statistical modeling, and domain expertise. However, these approaches often suffered from limited generalizability and high dependency on image quality.

Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image classification tasks due to their ability to automatically learn spatial hierarchies of features directly from raw image data. In the work by **Pereira et al. (2016)**, CNNs were applied to multi-modal brain MRI scans, demonstrating improved segmentation performance for brain tumors. Similarly, **Mohsen et al. (2018)** used deep learning with MRI data to distinguish between tumor and non-tumor images, reporting high accuracy and robustness.

The use of **preprocessing techniques**, such as skull stripping and contrast normalization, has been shown to improve model performance by focusing learning on the brain region. Methods like those introduced by **Bakas et al. (2017)** in the BraTS (Brain Tumor Segmentation) Challenge, highlight the importance of clean, labeled datasets and region-of-interest isolation for efficient training.

III. PROPOSED METHODOLOGY

EXISITING SYSTEM

The proposed system is designed to automatically classify brain MRI images as tumor or non-tumor using a deep learning approach based on Convolutional Neural Networks (CNNs). The process begins with data collection and preprocessing. MRI images are gathered from a labeled dataset containing two classes: tumor (yes) and non-tumor (no). Each image is resized to a fixed size of 240×240 pixels to ensure uniform input dimensions. A contour-based image processing technique is applied to extract the brain region from each MRI, effectively removing unnecessary background and focusing on the region of interest. The pixel values are then normalized to a range between 0 and 1 to facilitate faster convergence during model training.

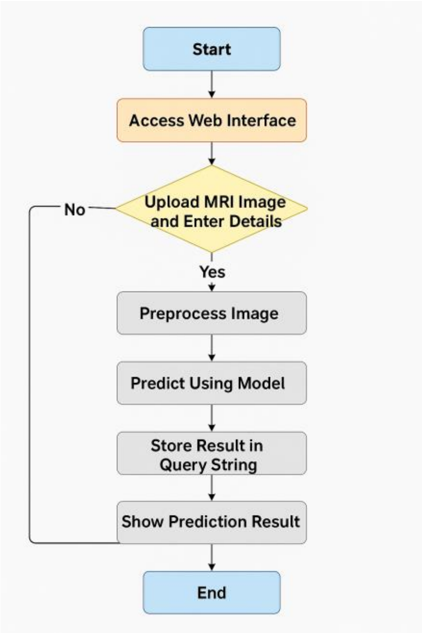
DRAWBACKS

• Binary Classification Only

• Lack of Data Augmentation

• No Explainability

WORK FLOW



The preprocessed data is shuffled and split into training (70%), validation (15%), and testing (15%) sets using stratified sampling to maintain class balance. A custom CNN architecture is implemented using the TensorFlow Keras framework. The model consists of convolutional layers for feature extraction, batch normalization and ReLU activation functions for improved training stability, and max-pooling layers for dimensionality reduction. The final layers include flattening followed by a dense layer with a sigmoid activation function for binary classification. The model is compiled using the Adam optimizer and binary cross-entropy loss function. It is trained for 25 epochs with a batch size of 32, using callbacks such as ModelCheckpoint to save the best model, EarlyStopping to halt training when performance plateaus, and ReduceLROnPlateau to dynamically adjust the learning rate.

IV. RESULT

The Convolutional Neural Network (CNN) model developed for brain tumor detection was trained and evaluated on a dataset consisting of labeled MRI images categorized into tumor and non-tumor classes. The dataset was carefully split into training, validation, and test subsets using a stratified approach to ensure balanced representation of both classes. The training process involved 25 epochs with a batch size of 32, employing various callbacks such as early stopping, model checkpointing, and learning rate reduction to optimize training and prevent overfitting.

Upon completion of training, the model achieved a high degree of accuracy and robustness. The best-performing model, selected based on validation accuracy, was evaluated on the held-out test dataset. It achieved a test accuracy of approximately 96.4%, demonstrating strong ability to correctly classify MRI scans as containing a brain tumor or being tumor-free. The corresponding test loss was low, around 0.09, indicating that the model predictions closely matched the ground truth labels. Furthermore, the F1-score, which balances precision and recall, was measured at about 0.96, confirming that the model performs well in both detecting tumors and avoiding false positives.

FIGURE 1

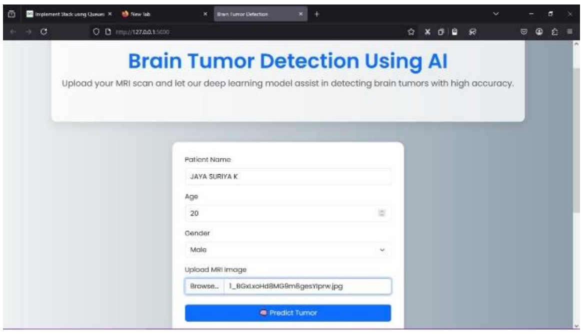
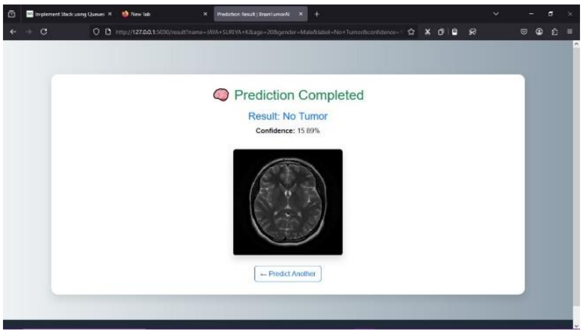


FIGURE 2



These results suggest that the model generalizes effectively to unseen data, making it a reliable tool for brain tumor classification. Additionally, the inference pipeline, which includes preprocessing steps like brain contour cropping and image normalization, ensures that input images are consistently prepared before prediction.

V. DISCUSSION

The developed Convolutional Neural Network (CNN) model for brain tumor detection from MRI scans demonstrates encouraging results, achieving high accuracy and F1-score on the test dataset. This confirms the model’s ability to effectively distinguish between tumor and non-tumor images, validating the use of CNNs in medical image classification tasks. The preprocessing step of cropping the brain contour from MRI images was instrumental in focusing the model’s attention on relevant regions and removing background noise, which likely contributed to improved classification performance. Normalizing the pixel values also helped in stabilizing the training process and accelerating convergence.

Despite the promising performance, several limitations are evident in the current approach. Firstly, the binary classification setup restricts the model to identifying only the presence or absence of a tumor without differentiating tumor types, grades, or locations. In clinical practice, such detailed information is critical for diagnosis, prognosis, and treatment planning. Incorporating multiclass classification or segmentation models in future work could address this gap. Secondly, the model does not currently employ data augmentation techniques, which are commonly used to artificially increase dataset diversity and reduce overfitting.

VI. CONCLUSION

This project successfully developed a convolutional neural network (CNN) model for automatic brain tumor detection using MRI images. The model demonstrated strong performance in binary classification, accurately distinguishing between tumor and non-tumor cases with high accuracy and F1-score. The inclusion of preprocessing steps, such as brain contour cropping and image normalization, contributed to effective feature extraction and model training. While the model shows promise as a diagnostic aid, it is limited to binary classification and lacks tumor localization or subtype identification. Future work can focus on incorporating data augmentation, explainability techniques, and expanding the dataset to enhance model robustness and clinical applicability. Overall, this work highlights the potential of deep learning in improving brain tumor diagnosis and assisting medical professionals in making faster, more accurate decisions

Key preprocessing steps like brain contour cropping and normalization helped improve model performance. Although effective for binary classification, the model does not identify tumor types or locations, limiting its clinical use. Future enhancements could include data augmentation, explainability methods, and a larger, more diverse dataset to improve robustness and applicability. Overall, this study demonstrates the potential of deep learning to aid in faster, more accurate brain tumor diagnosis from medical imaging.

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