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Dual Path CNN for Brain Tumor Segmentation

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A B S T R A C T

Accurate and reliable segmentation of brain tumors from MRI scans remains a significant challenge due to the variability in tumor size, shape, location, and intensity. This study proposes a Dual-Path Convolutional Neural Network (CNN) for precise and automated brain tumor segmentation. The model employs two parallel feature extraction pathways to simultaneously capture high-level global context and low-level fine-grained details, thereby enhancing segmentation accuracy. Multi-modal MRI data, including T1-weighted, T2-weighted, and FLAIR images, are integrated to improve the model's robustness in detecting tumors with irregular boundaries and heterogeneous structures.Building upon established CNN architectures such as U-Net and 3D convolutional networks, this approach incorporates an optimized loss function, advanced data augmentation techniques, and a tailored training strategy to further improve performance. The proposed system aims to support early diagnosis, treatment planning, and patient monitoring by delivering reliable, automated segmentation results. Future work includes refining the model architecture, incorporating additional imaging modalities, and expanding its applicability to other neurological disorders. The project demonstrates the potential of deep neural networks as powerful tools in medical image analysis and personalized healthcare.

Keywords: Brain Tumor Segmentation, Convolutional Neural Network (CNN) , Dual-Path CNN , MRI Brain Imaging, Deep Learning

1. INTRODUCTION

The human brain governs essential functions such as cognition, memory, and motor control, making it highly susceptible to disorders like brain tumors. These tumors, whether benign or malignant, can severely disrupt neurological activity. With over 3,500 pediatric cases reported annually, early and accurate diagnosis of brain tumors is critical for effective treatment and improved outcomes. Magnetic Resonance Imaging (MRI) plays a vital role in brain tumor detection due to its high-resolution imaging capabilities. However, manual interpretation of MRI scans is time-intensive and prone to subjective errors. The rise of artificial intelligence (AI), particularly deep learning, offers promising solutions for automated medical image analysis. Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are two prominent AI models used in image classification. ANNs mimic the human brain's neural structure, learning patterns through adjustable parameters. CNNs, designed for spatial data, utilize convolutional layers to extract hierarchical features, making them highly effective for image-based diagnoses. This study presents a comparative analysis of ANN and CNN models for brain tumor classification using MRI data. Custom architectures are developed and evaluated to identify the more accurate and efficient model, ultimately supporting clinical decision-making through intelligent diagnostic tools**.**

2.LITERATURE SURVEY

2.1 Dual Trans: A Dual-Path Encoder Network with Multi-View

Zhang et al. (2024) proposed **Dual Trans**, a dual-path encoder network designed for brain tumor segmentation. The model integrates a **multi-view dynamic fusion** mechanism to effectively capture both global and local features from MRI cans. One path focuses on spatial encoding, while the other captures semantic information, enabling more precise tumor boundary detection. The fusion module dynamically weights multi-view features, enhancing contextual understanding across different imaging perspectives. Experimental results demonstrate that Dual Trans outperforms existing segmentation models in accuracy and robustness, highlighting its effectiveness in handling complex tumor structures with varied shapes and textures.

2.2 DPAF Net: Residual Dual-Path Attention-Fusion CNN

Li et al. (2022) introduced DPAF Net, a Residual Dual-Path Attention-Fusion Convolutional Neural Network aimed at enhancing brain tumor segmentation performance. The network employs two parallel paths to extract detailed spatial and semantic features, which are then fused using an attention mechanism. The residual connections ensure effective gradient flow and improved feature reuse. The attention-fusion module adaptively emphasizes relevant tumor regions while suppressing background noise, leading to more accurate and refined segmentation. Experimental evaluations show that DPAFNet achieves superior performance compared to conventional CNN models, particularly in delineating irregular tumor boundaries and preserving fine structural details.

3.SYSTEM STUDY

3.1 EXISTING SYSTEM

Existing systems for brain tumor detection often rely on manual segmentation of MRI scans, followed by rule mining techniques. This process involves mapping, confidence learning, and correction of image shape and texture, which are later transformed into spatial features. These features are processed using association rule mining, making the system accurate but time-consuming and complex. Texture analysis is essential since tissue classification based solely on shape is insufficient. Although such approaches have shown robustness using public datasets, their limitations lie in their labor-intensive workflows and dependency on traditional data mining tools.To overcome these limitations, recent advancements focus on enhancement and segmentation through deep learning techniques, particularly using Artificial Neural Networks (ANNs). ANNs simulate the brain's processing structure and classify MRI images to detect normal and abnormal brain tissues. These networks use multiple layers—input, hidden, and output—where neurons apply weights, biases, and activation functions to learn features from MRI data. The use of deep learning allows for faster, more accurate predictions, supporting radiologists in early diagnosis and decision-making. This shift from manual to automated learning significantly enhances performance, enabling real-time, intelligent tumor detection systems that aid in timely and effective treatment planning

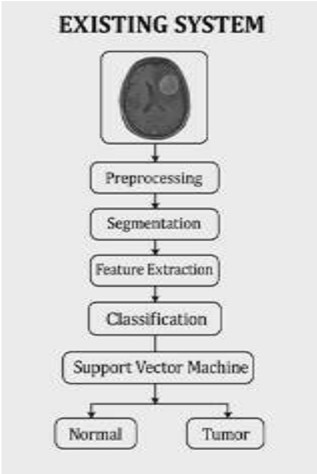

Figure 3.1.1: Existing system

3.2 PROPOSED SYSTEM

The proposed system focuses on the automated classification of brain tumors using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) applied to MRI images. Unlike traditional methods that rely on manual segmentation and rule mining, this model leverages deep learning to efficiently and accurately detect brain abnormalities. MRI scans are preprocessed through steps like denoising, background removal, resampling, and normalization to prepare clean and structured data. The neural network architecture includes input, hidden, and output layers, where weights and biases are adjusted during training to learn from image features. CNN further enhances performance through convolution, max pooling, dropout, flattening, and dense layers, reducing image dimensions while preserving critical information. The system extracts texture and spatial features to improve classification accuracy between normal and tumor-affected brain regions. By segmenting the MRI into slices and feeding them into the network, the model autonomously learns patterns, reducing manual effort and improving diagnostic speed. The work includes a custom ANN and CNN model, with comparative evaluation using publicly available MRI datasets. The main objective is to enable faster, unsupervised segmentation of brain lesions while maintaining high accuracy. This automated approach aids radiologists by providing timely, precise insights for effective treatment planning.

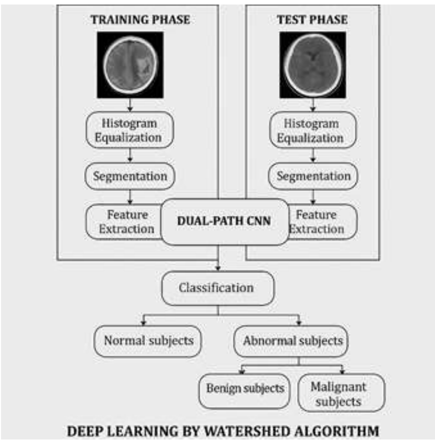

Figure 3.2.1 : Proposed System

4.METHODOLOGY

4.1 Data Preprocessing and Visualization

MRI images are collected and preprocessed through background removal, denoising, resampling, and intensity normalization. Data visualization is used to understand image structure, dimensions, and slice count. These cleaned datasets are vital for effective model training.

4.2 Model Definition Using Dual-Path CNN

A custom architecture combining Two-Path CNN and Cascaded CNNs is developed. This structure includes multiple convolution layers to extract deep features from image patches. It improves spatial understanding and enhances tumor localization**.**

4.3 Segmentation and Feature Extraction

Segmentation separates tumor regions from normal tissues using deep learning techniques. Feature extraction employs Discrete Wavelet Transform (DWT) and Gray-Level Co-occurrence Matrix (GLCM) to retrieve texture and spatial information for classification.

4.4 Training, Testing, and Deployment

The model is trained and validated using labeled MRI datasets on Google Colab. Performance is evaluated using accuracy metrics and confusion matrices. Once validated, the trained model is deployed for real-time brain tumor classification.

5. MODULES IMPLEMENTATION

5.1 LIST OF MODULES

- Data Visualization
- Image Preprocessing
- Model Definition
- Image Segmentation
- Feature Extraction module
- Training and testing Module
- Deployment module

5.2 MODULES DESCRIPTION

5.2.1 DATA VISUALIZATION

This module helps us in gaining valuable information such as the format of the data, dimensions of the image, number of slices present in each image. The observations that are got from this module play a vital role in the Model definition phase. The library used for visualization is “Matplotlib”.

5.2.2 IMAGE PREPROCESSING:

This module involves exploring the data to identify any missing values, outliers, or inconsistencies. It then handles missing values by either imputing or deleting them, depending on the amount and nature of the missing data.

5.2.3 MODEL DEFINITION

This model is based on a Two-Path CNN, Cascaded CNN’s. These CNN’s are used to reduce the image into patches and finally make the model learn from them.

5.2.4. IMAGE SEGMENTATION

Segmentation is a medical image analysis task that involves the separation of brain tumors from normal brain tissue in magnetic resonance imaging (MRI) scans.

5.2.6.TRAINING AND TESTING MODULE

The Training module is responsible for training the model using the preprocessed data and extracted features. The Testing module is responsible for evaluating the performance of the trained model on a validation or test dataset

5.2.6 FEATURE EXTRACTION MODULE

The feature extraction module is responsible for selecting and extracting relevant features from the raw data that will be used to train the model.

5.2.7 DEPLOYEMENT MODULE:

This module is responsible for deploying the trained model into a productive environment, such as a web application or mobile app to be used by the medical professionals.

SYSTEM ARCHITECTURE

The architecture for brain tumor segmentation using image processing involves collecting the MRI images, collection of the datasets, preprocessing the images by using data mining rules.pre processing techniques also includes registration, background removal, normalisation.Next, the segmentation process and feature extraction process are done for visualizing and prediction by using convolution neural networks algorithms, deep learning algorithms and evaluating the models performance by using the datasets.

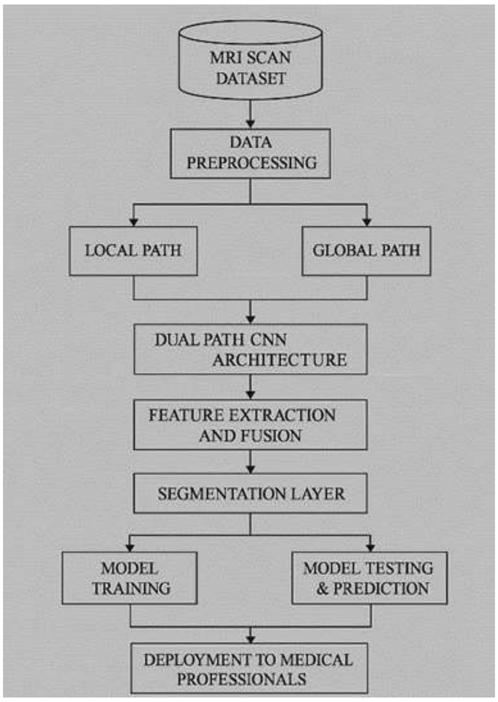

Figure : System Architecture

EXPERIMENTAL RESULT

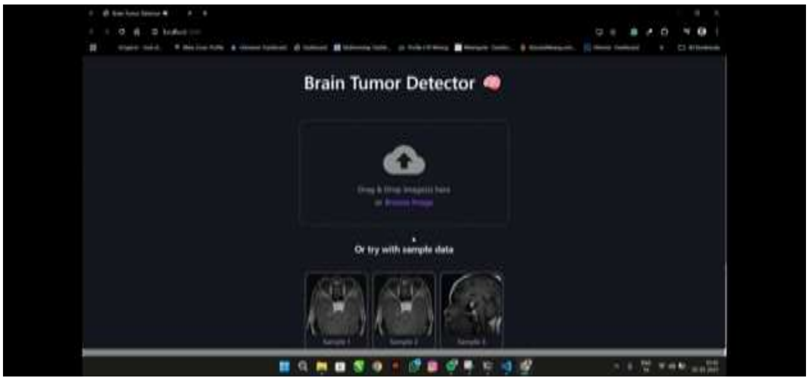

Figure 6.1 Home Page

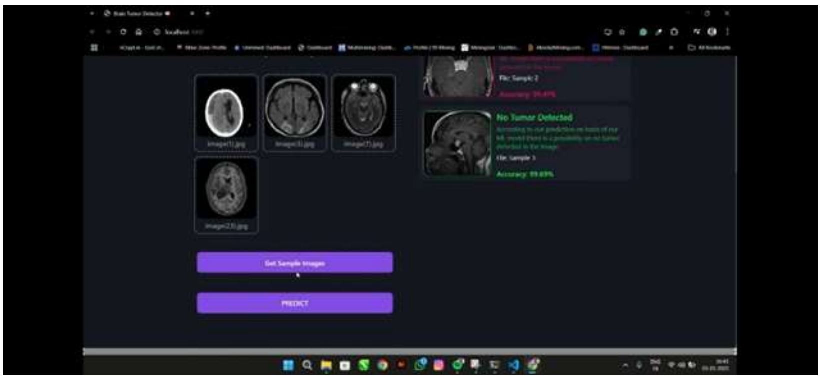

Figure 6.2 Sample Images To Detect Brain Tumor

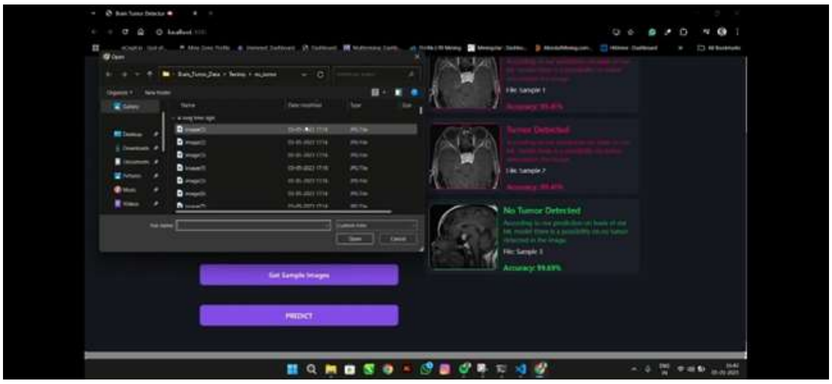

Figure 6.3 Selecting MRI Images

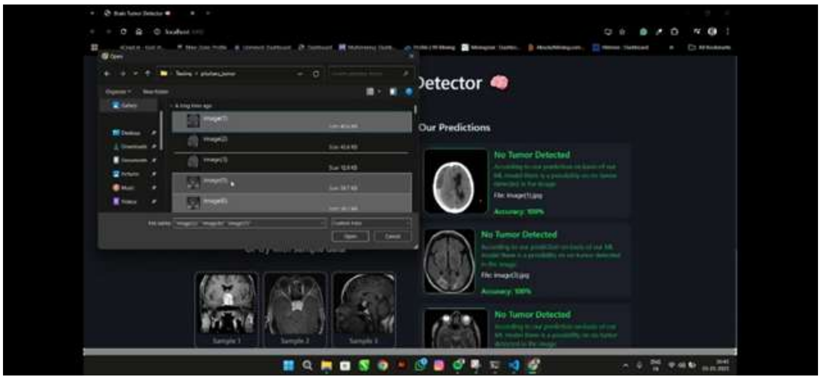

Figure 6.4 Uploading MRI Images

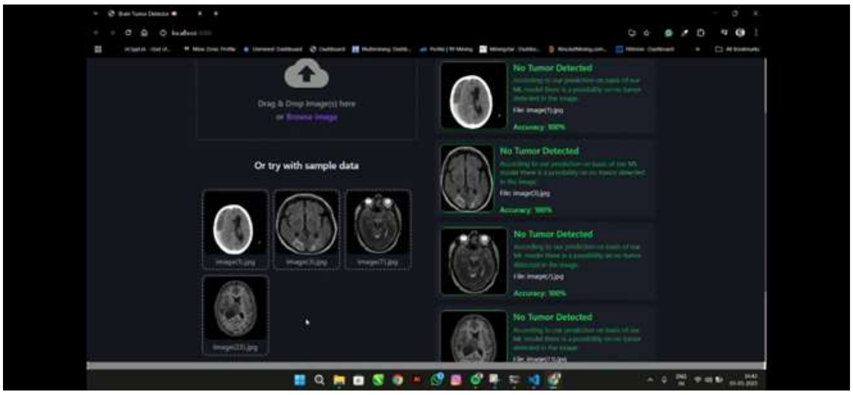

Figure 6.6 Result Page

CONCLUSION AND FUTURE ENHANCEMENT

The Accurate brain tumor detection is still very demanding because of tumor appearance, variable size, shape, and structure. Although tumor segmentation methods have shown high potential in analyzing and detecting the tumor in MRI images, still many improvements are required to accurately segment and classify the tumor region. It will be helpful for the researchers to develop an understanding of doing new research in a short time and correct direction. The deep learning methods have contributed significantly but still require a generic technique. These methods provided better results when training and testing are performed on similar acquisition characteristics however, a slight variation in the training and testing images directly affects the robustness of the methods

FUTURE ENHANCEMENT

In future research it is important to better model prior information by more suitable geometric modeling of tumor closeness which codes classification errors in those areas more accurately

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