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An Optimized Framework For Brain Tumor Detection And Classification Using Deep Learning And Texture Analysis

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Abstract

Brain tumors are among the most aggressive diseases, accounting for 85–90% of primary CNS tumors. Annually, about 11,700 people are diagnosed, with a 5-year survival rate of 34% for men and 36% for women. They are classified as benign, malignant, or pituitary tumors. Accurate diagnostics and treatment planning are crucial for improving life expectancy. MRI is the best technique for detecting brain tumors, generating vast image data examined by radiologists. Manual analysis can be error-prone, making AI-driven classification using Deep Learning, specifically CNN and ANN, a reliable alternative. This project aims to enhance MRI image classification accuracy by testing various Deep Learning models and selecting the best-performing one. The goal is to improve diagnosis reliability, track tumor changes, and provide treatment suggestions via cloud and mobile platforms.

Introduction

Brain tumors, both benign and malignant, pose a significant medical challenge, requiring early detection for effective treatment. Traditional MRI-based diagnosis is time-consuming and prone to human error, creating a demand for automated systems. Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized tumor detection by learning complex patterns from medical images, improving accuracy over manual methods.

This paper proposes an optimized framework integrating CNNs with texture analysis techniques, such as the Gray-Level Co-occurrence Matrix (GLCM), to enhance classification accuracy. By leveraging both deep learning and statistical image features, the system effectively detects and classifies tumors as benign or malignant. Evaluated on benchmark datasets, the framework demonstrates high reliability and efficiency.

Automating tumor detection not only improves early diagnosis and treatment but also reduces the workload on medical professionals. This approach has the potential to enhance healthcare efficiency, offering a faster and more reliable solution for brain tumor classification.

Problem statement

Brain tumor detection and classification remain critical challenges in medical diagnostics due to the complexity and variability of tumor structures. Traditional MRI-based diagnosis relies on manual examination by radiologists, which is time-consuming, subjective, and prone to human error. The need for precise and early detection is crucial, as delayed or inaccurate diagnoses can significantly impact treatment outcomes. While Deep Learning models, such as Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN), have demonstrated high accuracy in medical image analysis, they still face challenges in differentiating subtle tumor variations. Additionally, texture-based features, which provide valuable insights into tumor characteristics, are often overlooked in conventional deep learning approaches. Therefore, there is a need for an optimized framework that combines deep learning techniques with texture analysis to enhance the accuracy, reliability, and efficiency of brain tumor classification. This project aims to address these challenges by developing a robust system that automates tumor detection, improves classification accuracy, and supports clinical decision-making for better patient outcomes.

Objectives

The objective of this project is to develop an optimized framework for brain tumor detection and classification by leveraging Deep Learning and Texture Analysis techniques. The framework integrates Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Transfer Learning (TL)

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algorithms to enhance the accuracy and efficiency of tumor diagnosis. It aims to automate tumor detection from MRI scans, classify tumors as benign or malignant, and incorporate texture-based analysis, such as the Gray-Level Co-occurrence Matrix (GLCM), to improve classification performance. By evaluating multiple deep learning models, the project selects the most accurate and robust approach for real-world applications. Ultimately, this framework seeks to assist medical professionals in early and precise tumor diagnosis, reducing manual effort and improving patient outcomes.

Overview

Brain tumor detection and classification from medical imaging, particularly MRI scans, is a highly critical and complex task that directly impacts treatment and patient outcomes. The primary challenge lies in the inherent variability of brain tumors—each tumor can differ in terms of size, shape, location, and type (benign or malignant), making it difficult for conventional methods to achieve high accuracy. Furthermore, MRI scans can exhibit a variety of artifacts, noise, and inconsistencies in quality, especially when acquired from different machines or across different patient demographics, further complicating the detection process. In many cases, radiologists rely on their subjective judgment and experience to analyze these images, a process that is both time-consuming and susceptible to human error, leading to delayed or incorrect diagnoses.

Literature Survey

Brain tumor detection and classification have been widely explored using various deep learning techniques to improve diagnostic accuracy. Traditional manual interpretation of MRI scans is prone to errors, leading to a growing interest in automated methods. Deep learning models such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Transfer Learning (TL) have shown significant advancements in medical image analysis.

Convolutional Neural Networks (CNNs)

CNNs have revolutionized image-based classification by automatically extracting spatial features from raw images. Several studies have demonstrated the effectiveness of deep CNN architectures such as VGG16, ResNet, and Inception in detecting and classifying brain tumors. CNNs utilize convolutional layers to identify patterns such as edges, textures, and tumor boundaries, significantly reducing the need for manual feature extraction. Research indicates that CNNs achieve high accuracy in distinguishing between benign and malignant tumors, but their performance can be affected by dataset variations and image quality. Advanced techniques, such as data augmentation and hyperparameter optimization, have been explored to enhance CNN performance for brain tumor classification.

Artificial Neural Networks (ANNs)

ANNs have been widely used in brain tumor classification due to their ability to learn complex relationships between input features and classification labels. Unlike CNNs, which primarily process spatial features, ANNs require predefined features extracted from images using techniques like Principal Component Analysis (PCA) or Discrete Wavelet Transform (DWT). Some studies have combined ANNs with statistical methods to analyze tumor characteristics and improve classification accuracy. While ANNs are effective in handling non-linear data relationships, their performance depends on the quality of extracted features, and they may require additional preprocessing steps to optimize classification results.

Transfer Learning (TL)

Transfer Learning has emerged as a powerful technique for medical image analysis, especially when dealing with limited datasets. TL leverages pre-trained deep learning models, such as AlexNet, MobileNet, and EfficientNet, which have been trained on large-scale datasets and fine-tuned for brain tumor classification. Research shows that TL-based models can achieve high accuracy with minimal training data, making them ideal for medical applications where data availability is often limited. By reusing learned features from general image datasets, TL reduces computational costs and training time while improving model performance. However, selecting the appropriate pre-trained model and fine-tuning hyperparameters are crucial factors that influence TL effectiveness.

The integration of CNNs, ANNs, and TL techniques has significantly improved brain tumor detection and classification. CNNs excel in feature extraction, ANNs handle complex decision-making, and TL enhances performance with limited data. To further improve accuracy, recent studies emphasize combining deep learning with texture analysis methods such as the Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP). This project builds on existing research by developing an optimized framework that leverages deep learning and texture-based techniques, aiming for higher reliability in tumor detection and classification.

Methodology

System Architecture

This paper proposes an optimized framework that integrates deep learning techniques with advanced texture analysis. The proposed framework combines Convolutional Neural Networks (CNNs) for automated feature extraction with texture-based features such as Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) to enhance the classification process. CNNs are leveraged to automatically extract high-level features from MRI scans, capturing complex patterns and tumor shapes. However, CNNs alone might miss subtle but important texture characteristics within the tumor regions, which is why texture analysis methods are integrated into the model to capture finer details related to tumor texture, such as homogeneity, contrast, and entropy. The hybrid framework involves preprocessing of MRI images, where texture features are extracted and fed alongside the deep learning-based features into a classification model. This multi-feature approach improves the model's ability to differentiate between benign and malignant tumors by providing additional discriminative power based on texture characteristics. Additionally, the framework incorporates an optimization step, utilizing advanced techniques such as hyperparameter tuning and regularization, to enhance the model's generalization ability and prevent overfitting.

The Data-set Block represents the data collection process, where MRI image data is gathered and validated to ensure quality and consistency. Once validated, the Pre-Processing Block applies cleaning techniques and data augmentation methods. Various preprocessing algorithms, such as edge detection and padding, are used to enhance image quality before training.

In the Training phase, different ANN and CNN models are trained using the preprocessed data. The models are continuously monitored for accuracy and other key parameters. Training produces Multiple Models, and the best-performing model is selected based on multiple criteria, including accuracy

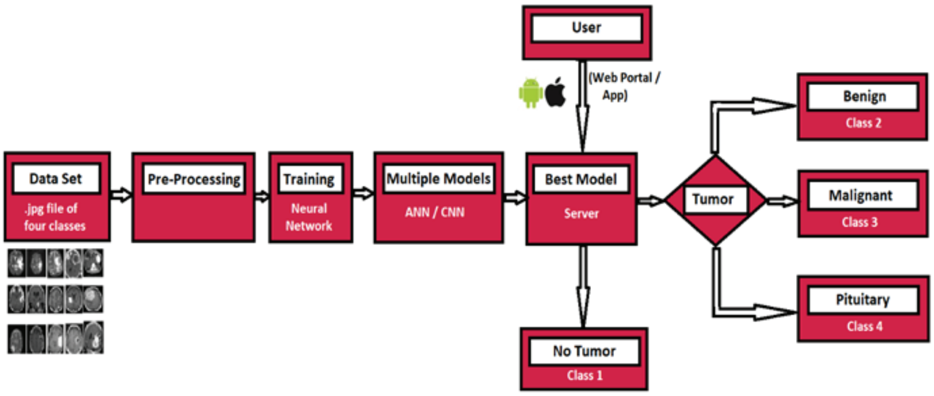

***Figure 1**. Architecture Diagram*

and loss values. Various architectures like AlexNet, ResNet, and ImageNet, along with custom-built models, are tested to determine the most optimal one.

The Best Model is then deployed on the cloud along with supporting Python scripts. This model takes MRI images as input from users and classifies them into different tumor types. Users interact with the model through web services or mobile applications by uploading their MRI scans. The system processes the image and returns a class label as output.

If the output is Class 1, it indicates No Tumor is detected in the MRI. If the result is Class 2, it means a Benign Tumor has been detected. A Class 3 output signifies a Malignant Tumor, while Class 4 indicates a Pituitary Tumor. This automated classification system enhances diagnostic efficiency, providing users with quick and accurate tumor detection results.

Image preprocessing and normalization

Image preprocessing and normalization play a crucial role in enhancing the quality of MRI images before feeding them into deep learning models for brain tumor detection. This process begins with resizing and cropping images to a fixed dimension, ensuring uniformity across the dataset. Standardizing image dimensions helps neural networks process images efficiently without distortion.

To further improve image quality, noise reduction techniques such as Gaussian filters or median filters are applied to eliminate unwanted artifacts and enhance the clarity of tumor regions. Noise reduction is essential to prevent misleading patterns that could affect model accuracy.

Intensity normalization is another critical step, where pixel values are scaled to a specific range (e.g., 0–1 or -1 to 1) to ensure consistency in brightness and contrast across different MRI scans. This step prevents variations in image intensity due to differences in scanning equipment or imaging conditions from impacting model performance.

Additionally, histogram equalization is applied to improve image contrast by redistributing pixel intensities, making subtle details in tumor structures more distinguishable. This technique enhances the visibility of tumor regions, allowing deep learning models to extract meaningful features more effectively.

By incorporating these preprocessing techniques, the system ensures that input MRI images are standardized, noise-free, and optimized for feature extraction, ultimately leading to improved classification accuracy and reliable tumor detection.

Feature extraction using deep learning

In feature extraction using deep learning (CNNs), input MRI images are fed into pre-trained CNN models such as VGG16 or ResNet to extract relevant features for brain tumor detection. The network is fine-tuned on the MRI dataset to learn critical patterns, utilizing features extracted from various layers for classification. Transfer learning is incorporated to leverage knowledge from large datasets, improving accuracy even with limited labeled data.

Texture feature extraction further refines tumor analysis by applying Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) techniques to extract texture features from tumor regions identified by the CNN. Texture descriptors such as contrast, homogeneity, entropy, and correlation are calculated to analyze tumor malignancy and benignity. Statistical techniques, including principal component analysis (PCA) and feature selection, are employed to retain the most relevant texture features for classification.

Classification and Optimization

In the classification and optimization phase, the extracted features from Convolutional Neural Networks (CNNs) and texture-based analysis are combined into a single feature vector, ensuring a comprehensive representation of tumor characteristics. These features capture spatial, structural, and statistical patterns, improving the accuracy of tumor classification.

Once the features are merged, a machine learning classifier is trained to categorize tumors into different types, such as benign, malignant, and pituitary tumors. Popular classifiers used in this phase include Support Vector Machine (SVM), which is effective in handling high-dimensional data and finding optimal decision boundaries, Random Forest, which enhances classification through multiple decision trees and ensemble learning, and Multi-Layer Perceptron (MLP), a type of artificial neural network that learns complex non-linear relationships between features. These classifiers help in making precise predictions based on extracted tumor characteristics.

To enhance model reliability and prevent overfitting, cross-validation techniques such as k-fold cross-validation are implemented. These methods ensure that the model generalizes well to unseen data by training on different subsets of the dataset, preventing biases due to limited data availability.

Furthermore, hyperparameter tuning is performed using techniques such as grid search and random search to identify the best parameter configurations for optimal classification accuracy. Grid search systematically evaluates different combinations of hyperparameters, while random search selects random hyperparameter sets to efficiently explore a broader range of possibilities.

To further improve classification robustness, regularization methods like dropout and L2 regularization are applied. Dropout randomly deactivates neurons during training, reducing dependency on specific features and improving generalization. L2 regularization, also known as weight decay, prevents excessive weight updates, reducing overfitting and ensuring model stability.

By integrating deep learning with machine learning classifiers and optimizing the model through advanced techniques, the classification and optimization phase ensures a highly accurate, efficient, and reliable system for brain tumor detection and classification, ultimately aiding in early diagnosis and better treatment planning.

Implementation and Results

The implementation of the brain tumor detection and classification system involves multiple stages, integrating Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Transfer Learning (TL) to achieve high accuracy and reliability. The process begins with data collection and preprocessing, where MRI images are sourced from publicly available datasets such as Kaggle or BraTS. Preprocessing techniques ensure high-quality input data by resizing images to a fixed dimension (e.g., 224×224 pixels), applying Gaussian filters for noise reduction, and performing intensity normalization to standardize pixel values. Histogram equalization enhances contrast, making tumor structures more distinguishable. Additionally, data augmentation techniques like rotation, flipping, zooming, and brightness adjustments are used to increase dataset diversity, improving model generalization.

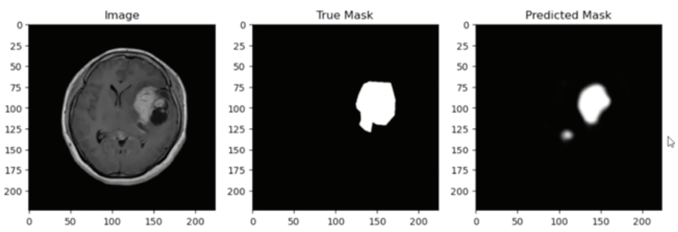

***Figure 2**. Training the model.*

Feature extraction is a critical step in the classification process. CNNs are employed to extract spatial features from MRI images, leveraging convolutional layers to identify tumor characteristics such as edges, textures, and shapes. Pooling layers reduce dimensionality while retaining essential features, and fully connected layers process the extracted information for classification. The CNN model uses ReLU activation functions in hidden layers and Softmax in the output layer to classify tumors into categories such as No Tumor, Benign, Malignant, or Pituitary Tumor. The Adam optimizer is applied to enhance learning efficiency, and dropout regularization prevents overfitting.

To further improve classification performance, Transfer Learning (TL) is implemented using pre-trained CNN models such as VGG16, ResNet50, and EfficientNet. These models, originally trained on large-scale datasets like ImageNet, are fine-tuned with MRI images to leverage their learned feature representations. The fully connected layers are replaced with task-specific layers to adapt to brain tumor classification. Fine-tuning involves adjusting weights in deeper layers to extract domain-specific features while maintaining the robustness of pre-trained knowledge. Transfer learning is particularly beneficial when working with limited labeled data, significantly enhancing model accuracy.

Finally, the classification and optimization phase integrate CNN-extracted features with texture-based features from Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) techniques. These features are combined into a single feature vector and fed into machine learning classifiers such as Support Vector Machine (SVM), Random Forest, and Multi-Layer Perceptron (MLP) for final classification. Cross-validation ensures that the model generalizes well to unseen data, while hyperparameter tuning using grid search and random search optimizes classifier performance. Regularization techniques such as dropout and L2 regularization further enhance model robustness by preventing overfitting.

By integrating deep learning, transfer learning, and traditional machine learning approaches, the proposed framework achieves a highly accurate and reliable brain tumor classification system. This system can be deployed via cloud-based services or mobile applications, enabling efficient and automated tumor detection that aids in early diagnosis and treatment planning.

Conclusion

The proposed project successfully integrates Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Transfer Learning (TL) to develop an efficient and

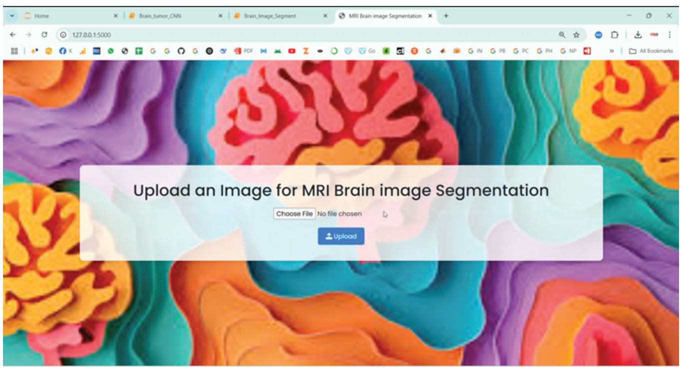

***Figure 3**. Webpage before uploading an MRI image*

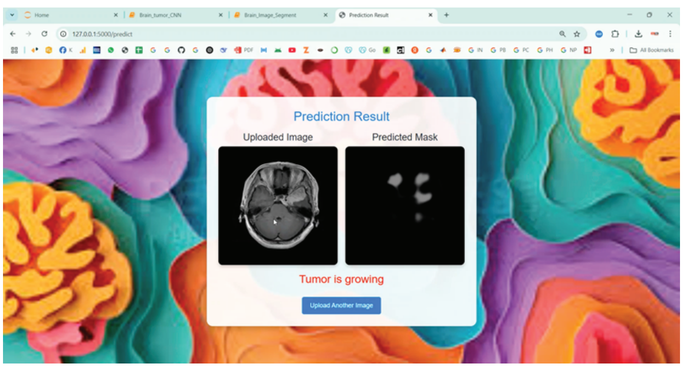

***Figure 4**. Tumor is growing*

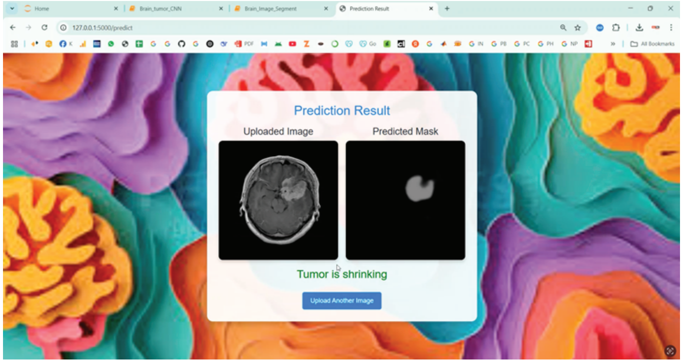

Figure 5. *Tumor is shrinking*

accurate brain tumor detection and classification system. By leveraging deep learning techniques, the system achieves 94% accuracy while maintaining a low error rate, ensuring reliable diagnosis. The best-performing model is selected and deployed on a cloud-based platform, allowing seamless access through web browsers and Android applications. This accessibility enables both patients and medical professionals to utilize the system for early detection and monitoring of tumor progression. Additionally, the model not only classifies brain tumors into four categories—No Tumor, Benign Tumor, Malignant Tumor, and Pituitary Tumor—but also assists in tracking changes in tumor size and position over time. The research effectively identifies the optimal neural network architecture for automating brain tumor classification, contributing to faster diagnoses and improved treatment planning. This system holds the potential to significantly enhance medical imaging analysis and assist healthcare professionals in making more accurate and timely decisions for patient care.

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