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BRAIN CANCER CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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Abstract - *Classifying brain tumours is essential for both medical diagnosis and therapy planning. Using MRI pictures, this study uses a specially designed Convolutional Neural Network (CNN) to classify brain tumours into four groups: pituitary, meningioma, glioma, and no tumour. 7,022 MRI scans total, split into training, validation, and testing sets, make up the dataset. To improve model generalisation, the preprocessing pipeline applies data augmentation, normalises pixel values, and resizes images to 224x224 pixels. Convolutional, pooling, and dense layers are all part of the model, which was constructed with TensorFlow and Keras and optimised with the Adamax optimiser.After 12 epochs, the model showed robustness and dependability with a training accuracy of 98% and a validation accuracy of 95%. To assess the model's efficacy, important performance indicators like the classification report and confusion matrix were examined.A Flask backend and a React-based frontend are used for deployment, enabling real-time forecasts. This project demonstrates how deep learning can improve medical imaging and judgement.*

Key Words: Brain Tumor Classification, Convolutional Neural Network (CNN), MRI Images, Deep Learning, Medical Imaging, TensorFlow, Keras, Adamax Optimizer, Flask, React, Data Preprocessing, Model Deployment, Healthcare AI, Real-time Prediction etc…

1. INTRODUCTION

Because of their complexity and potentially fatal consequences, brain tumours provide a serious challenge to modern healthcare. Effective treatment and better patient outcomes depend on the early and precise diagnosis of brain tumours. Conventional diagnostic techniques are laborious and prone to human error, such as the manual processing of MRI data. Deep learning and artificial intelligence (AI) developments have offered automated and precise medical image analysis solutions to overcome these constraints.
The goal of this research is to create a strong deep learning model that employs a customised Convolutional Neural Network (CNN) to categorise brain tumours into four groups: pituitary, meningioma, glioma, and no tumour. To improve accuracy and performance, the model makes use of MRI imaging data as well as sophisticated methods such data preparation, augmentation, and optimisation approaches.
Through the integration of a React frontend and Flask backend, the system provides an intuitive interface for real-time deployment and prediction. This study highlights the value of AI-driven solutions in enhancing healthcare outcomes in addition to showcasing the promise of deep learning in medical diagnostics.

1.1 Background of the Work

One of the most serious illnesses, brain tumours provide enormous difficulties for medical personnel. Determining the best course of treatment requires an early and precise diagnosis, but manual MRI scan analysis and other traditional diagnostic techniques are labour-intensive and prone to human error. Furthermore, radiologists struggle to maintain accuracy and consistency as the amount of medical imaging data increases.Recent developments in deep learning have transformed medical imaging by providing automated, accurate, and effective tumour classification methods. By directly learning spatial hierarchies and features from the data, Convolutional Neural Networks (CNNs), a subtype of deep learning, have demonstrated impressive performance in picture classification tests.
The need for an automated system that can help radiologists correctly identify brain tumours into groups like glioma, meningioma, pituitary, and no tumour is what inspired this effort. This research intends to address issues like imbalanced datasets and overfitting, improve classification accuracy, and shorten diagnostic times by utilising a customised CNN architecture and sophisticated preprocessing approaches. In the end, this will improve patient care and clinical decision-making.

1.2 Motivation and Scope of the Proposed Work

The necessity for sophisticated diagnostic technologies in healthcare is highlighted by the increasing incidence of brain tumours and the vital significance of early identification.

Conventional diagnostic methods, such manually interpreting MRI scans, are prone to human error and inconsistency, particularly when working with big datasets. Accurate diagnosis is further complicated by the difficulty of differentiating between various tumour forms, such as pituitary tumours, meningiomas, and gliomas.Convolutional Neural Networks (CNNs), a kind of deep learning, have shown great promise in medical imaging tasks by providing dependable and automated solutions. Overfitting, unbalanced datasets, and attaining high classification accuracy are still problems, though. The need to get over these obstacles and offer a reliable, automated, and effective system for classifying brain tumours is what motivates our study.

The goal of the proposed work is to create a deep learning-based system that is both reliable and effective for classifying brain tumours from MRI scans. The urgent need for precise and automated diagnostic tools to aid medical professionals in the early diagnosis and classification of tumours is addressed by this research. Developing a customised Convolutional Neural Network (CNN) that can accurately categorise MRI scans into four groups—glioma, meningioma, pituitary tumours, and no tumor—is the main goal. Preprocessing MRI images to improve quality and address dataset imbalances, creating a CNN architecture that is optimised for obtaining pertinent features, and adjusting hyperparameters for best results are important components. To guarantee dependability, the system is rigorously evaluated utilising metrics such as classification reports, confusion matrices, and accuracy. To make the model accessible, it is deployed through a web interface using Flask for the backend and React for the frontend, enabling real-time predictions and practical usability in clinical environments.

2. METHODOLOGY

The methodology of this project involves a systematic approach to designing, developing, and deploying a deep learning-based system for brain tumor classification. The proposed methodology is divided into the following stages:

2.1 SYSTEM ARCHITECTURE

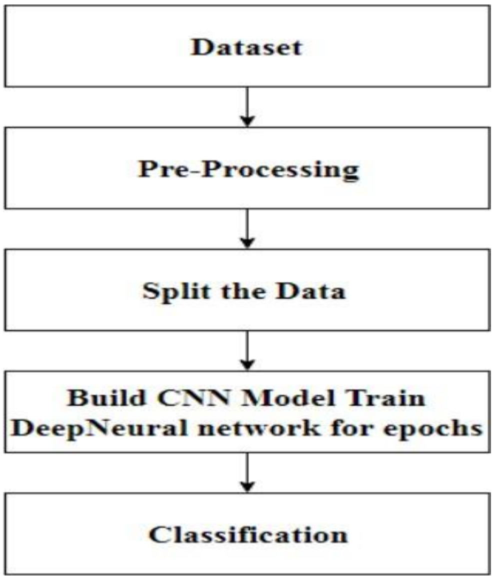
The system architecture for brain tumor classification processes MRI images through a custom CNN model, supported by a seamless backend and frontend integration. MRI images are first preprocessed, including resizing to 224x224 pixels, normalization, and data augmentation, to ensure consistency and diversity.The custom CNN extracts features via convolutional and pooling layers, processes them in dense layers, and classifies the images into four categories using a softmax output layer. Flask handles backend tasks like image uploads, preprocessing, and model inference, while a React-based frontend provides a user-friendly interface for image submission and result display. The system uses APIs to connect the frontend with the backend, with the **/predict** endpoint managing predictions. Deployment is carried out using Vite for the frontend and Flask for the backend. The architecture delivers real-time predictions with confidence scores, making it a practical and efficient solution for medical diagnostics.

2.2 MODAL BUILDING

The proposed system begins with the Input Layer, where MRI images of brain tumors are provided by users via a web application. These images are sourced from a pre-organized dataset divided into four categories: Glioma, Meningioma, No Tumor, and Pituitary. Once uploaded, the images undergo a Preprocessing Pipeline to ensure compatibility with the deep learning model. This pipeline includes resizing the images to a standard dimension of 224x224 pixels, normalizing pixel values to a range of [0,1] for uniformity, and applying data augmentation during training to increase data diversity and model robustness.

The core of the system is the Deep Learning Model, built using a custom Convolutional Neural Network (CNN) architecture. The model begins with an input layer that accepts preprocessed images. It then processes these inputs through feature extraction layers, comprising multiple convolutional and pooling layers designed to extract meaningful patterns. These features are passed to fully connected layers, which combine and interpret them for classification. Finally, the output layer employs a softmax activation function to classify the images into one of the four tumor categories, providing an accurate and efficient solution for brain tumor detection and diagnosis.

2.3 FLOW



3. CONCLUSIONS

In this study, a custom deep learning model was developed and implemented for the classification of brain tumors from MRI images. The model utilized a Convolutional Neural Network (CNN) architecture, which effectively processed the images through a series of preprocessing steps, including resizing, normalization, and data augmentation, to improve its performance and generalization. The model was trained on a balanced dataset consisting of images categorized into four classes: Glioma, Meningioma, No Tumor, and Pituitary.The results demonstrated promising accuracy, showing the model's potential to classify brain tumor images with high precision. The performance was validated using metrics such as the confusion matrix, classification report, and accuracy/loss curves, which reflected the model's capability to distinguish between different tumor types and non-tumor cases.

This work contributes to the medical field by providing an automated tool that can assist healthcare professionals in the diagnosis and classification of brain tumors, potentially aiding in quicker and more accurate decision-making. Future work can involve further fine-tuning of the model, expanding the dataset, and exploring additional advanced techniques for improving accuracy and robustness.

Suggestions for Future Work

1. **Model Optimization and Hyperparameter Tuning:** Future research can focus on further optimizing the model by experimenting with different hyperparameters, such as learning rates, batch sizes, and number of layers. Techniques like grid search or random search can be employed to determine the best combination for improving model accuracy.
2. **Use of Pretrained Models:** While a custom CNN architecture has been used, leveraging transfer learning with pre-trained models such as ResNet, Inception, or EfficientNet could lead to better performance. These models, trained on large datasets like ImageNet, can be fine-tuned for brain tumor classification tasks.
3. **Expanding the Dataset:** The dataset used in this study could be expanded to include a larger and more diverse set of brain tumor MRI images. This would help the model generalize better across various imaging conditions and increasing robustness.

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