**BRAIN TUMOR DETECTION LEVERAGING THE RESNET ARCHITECTURE**

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**Abstract**

Brain tumors pose severe health risks due to abnormal cell growth, necessitating accurate and early detection. Deep learning, particularly ResNet50, has shown significant advancements in medical imaging analysis. This study proposes a ResNet50-based classification model trained on MRI images to distinguish among pituitary tumors, meningioma, glioma, and non-tumor patients. The prototype achieves an accuracy of 99%, outperforming conventional approaches. A real-time classification system using Streamlit UI is deployed for user-friendly interaction. This research shows how deep learning may be used to automatically detect brain tumors.

**Keywords:** ResNet-Model, MRI Scans, Tumor, Brain, Detection, Glioma, Meningioma.

**1. Introduction**

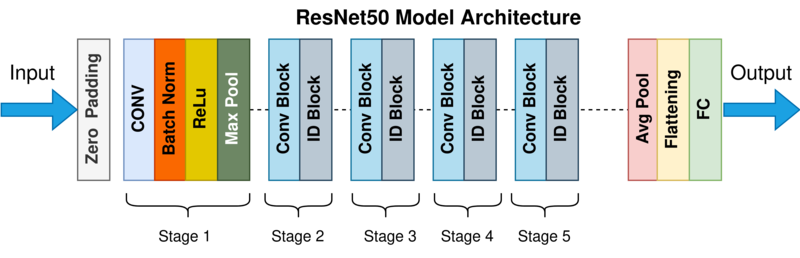
A brain tumor is life-threatening because of their invasive nature and influence on neurological functions. A common diagnostic technique is magnetic resonance imaging (MRI), but manual classification is error-prone and time-consuming. Models for deep learning, specifically Medical image analysis has been transformed by Convolutional Neural Networks (CNNs). ResNet50, a deep residual network, is employed in this study to increase tumor categorization accuracy. This paper presents the methodology, evaluation, and the model's real-time deployment interface.

**2. Related Work**

In clinical trials, precise categorisation of brain tumour magnetic resonance imaging (MRI) pictures is essential for prompt detection and successful therapy. Numerous artificial intelligence (AI)-supported models have been put out in these research as expert assistant systems. Specifically,Brain MRI image categorisation has successfully employed cutting-edge models for deep learning (DL) that have demonstrated their effectiveness within several domains. Researchers continue to carry out various investigations in this area despite the low accuracy of multiple classification of these photos. In particular, models that accomplish great precision of the original photos must be developed, hence it is thought that both DL models and traditional machine learning (ML) algorithms can satisfy this demand. However, for the hybrid use of ML techniques with DL models, it is crucial to select the hyperparameters appropriately[1]. Among the main reasons for death is brain tumors in people. If it is not treated effectively and quickly, it has a high chance of turning into cancer. Early diagnosis of brain tumours is therefore essential. In this work, the brain surface extraction (BSE) approach is used to remove the skull first. To improve segmentation, the image with the skull removed is subsequently fed into particle swarm optimisation (PSO). Subsequently, segmented images' deep features and local binary patterns (LBP) are retrieved, and the best characteristics are chosen a genetic algorithm (GA) is used[2]. Radiology is a broad field, and in medical research, precise tumour diagnosis requires greater knowledge and comprehension. Thus, the lack of qualified radiologists is solved by the necessity for a tumour detection system. Brain tumour identification and localisation Biomedical image processing makes them easier that uses Imaging using Magnetic Resonance (MRI). This article describes A technique for brain segmentation and detection tumours that defines the tumor zone using MRI sequence images as input images. This procedure is challenging because tumour tissue composition varies greatly amongst patients, and the work is sometimes complicated by similarities among normal tissues [3]. A brain tumor is among cancers that have significantly raised the incidence of morbidity and mortality among people worldwide. Effective preventive measures depend on the early identification and characterisation of gliomas. At the moment, BT diagnosis and therapy using Transformers, a deep learning model, is getting a lot of attention. For effective processing and analysis, the transformer self-attention mechanism automatically discovers the relationships between the input data. Studies reveal that Transformers might be crucial for MRI image segmentation using BT, brain cancer grading based on MRI and histopathology, BT molecular expression prediction, primary brain metastasis site classification, voxel-level dose and BT radiotherapy outcome prediction, synergistic prediction, and drug combination pathway deconvolution[4]. Millions of people are impacted by depression, one of the most common mental illnesses in the modern world. The symptoms of depression are varied and frequently coexist with those of other ailments such as Parkinson's disease, bipolar illness, schizophrenia, etc. It is a severe mental disorder that, if addressed, can result in other health issues [5].Even with the proper capture of brain imaging, segmenting brain tumours in a reliable and accurate manner remains a difficult task. Correct diagnosis and treatment planning require Magnetic Resonance Imaging (MRI) is used for tumour grading and segmentation. Different regions of the tumor can be identified using different MRI sequence pictures (T1, Flair, T1ce, T2, etc.). Different information and features can be gleaned from each input modality due to the variations in lighting of each brain imaging mode[6]. We begin by demonstrating the architectural features of Machine learning and deep learning (DL and ML)/radiomics methodologies. For ML/radiomics, the phases of feature selection, training, validation, and testing are described. Direct image processing is made possible by DL models, which are artificial/convolutional neural networks with several layers. Technical procedures like data harmonization, picture labelling, and image annotation (with segmentation being a crucial stage in radiomics) as well as federated learning are all included in the data curation section. After that, we devote particular parts to: calculating the sample size [7]. Long-term brain injury results from aberrant proliferation of either malignant or nonmalignant brain tissues. One of the most used techniques for identifying brain tumors is magnetic resonance imaging (MRI). After being obtained, MRI filters are physically inspected by specialists to ascertain whether a patient has a brain tumor. Since experts create assessments in different ways, it is likely that MRI scans analyzed by several specialists will yield conflicting conclusions[8]. The field of brain tumour computer-aided diagnosis (CAD) has changed in the role of result of advancements in artificial intelligence and medical imaging. In this study, Explainable AI (XAI) techniques are used to increase the classification accuracy and interpretability of brain tumours. For the patient to receive the best care and treatment possible, a prompt thus it is essential to accurately identify brain tumors. On the other hand, standard machine learning models frequently lack interpretability and transparency, which makes it challenging for clinicians to trust their judgement. This study develops a comprehensible and interpretable CAD system for brain tumour classification using the Grad-Cam algorithm [9]. One of the leading causes of dementia globally is Alzheimer's disease (AD), which impairs the ability of an individual to perform daily duties on their own as it progresses from mild to severe. For clinical intervention to be successful, AD must be diagnosed accurately and promptly. Even seasoned radiologists may find it difficult to interpret AD from medical imaging. In order to overcome this difficulty, researchers have looked into the possibility of applying Artificial Intelligence (AI) methods, especially deep learning models, to the autonomous diagnosis of AD [10].

**3. Proposed System**

**3.1 ResNet Architecture**



*Fig 1: ResNet-50 Architecture*

**ResNet architecture**, a deep neural network using convolutions used for image classification. It begins with **Zero Padding** to maintain spatial dimensions, followed by a **Convolution (CONV) layer** that extracts key features. **Batch Normalization** ensures stable training, while the activation function of ReLU introduces non-linearity. A Spatial dimensions are decreased using the Max Pooling layer to retain essential features. The core of ResNet consists of **Residual Blocks (Conv and Identity Blocks)** that enable deep learning by allowing gradient flow through skip connections, preventing the vanishing gradient problem. Finally, an **Average** The pooling layer decreases dimensionality before the **Flattening and** layer that is fully connected (FC), which maps the traits that were extracted to classification outputs. This architecture enhances accuracy while preserving the effectiveness of computing.

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**3.2. Methodology**

The proposed system uses a pre-trained ResNet50 model optimized for classifying brain tumors. The dataset comprises MRI scans categorized into Glioma, Meningioma, Pituitary tumor, and No Tumor are the four categories. Preparation includes data augmentation, standardization, and scaling to enhance generalization. The Categorical cross-entropy loss and the Adam optimizer are used to train the model for 45 epochs.

**4. Implementation and Training**

The training script (resnet\_train.py) initializes ResNet50 without its top layers, incorporating totally connected layers for classification. To train the model, a dataset of MRI images with a 32 batch size and a 0.0001 learning rate. The model that has been trained is preserved as brain\_tumor\_model.h5 for deployment in a real-time classification system.

**5. Deployment & User Interaction**

A user-friendly interface is created with Streamlit (main.py), enabling users to upload MRI images for real-time classification. The model predicts the tumor type and its stage with high confidence. This ensures accessibility and practical usability for medical professionals.

**6. Evaluation & Results**

The model achieves 99% accuracy on training as well as validation datasets. Evaluation metrics include precision (98.35%), recall (98.32%), and F1-score (98.31%). A confusion matrix highlights classification performance, with no tumor and pituitary tumors achieving 100% accuracy. The Area Under Curve (AUC) score reaches 0.999, confirming the model's reliability.

**7. Conclusion & Future Work**

This study was successfully demonstrates the effectiveness of ResNet50 in brain tumor classification. With 99% accuracy, the model surpasses traditional diagnostic methods. Future enhancements include multi-tumor detection within a single MRI scan and integration with clinical diagnostic systems.

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