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Brain Tumor Detection Based On Deep Learning Neural Network Using MRI

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KEYWORDS

Magnetic Resonance Imaging, K-Nearest Neighbors, Convolutional Neural Network, brain tumor detection.

ABSTRACT

Brain tumor detection is a critical task in medical imaging, as early and accurate diagnosis significantly improves patient treatment and prognosis. Traditional manual diagnosis of Magnetic Resonance Imaging (MRI) scans is time-consuming, error-prone, and heavily reliant on the expertise of radiologists. To address these challenges, automated machine learning and deep learning methods have been explored. The primary objective of this project is to develop a robust brain tumor detection system capable of accurately classifying tumors as benign or malignant. Initially, the system uses the K-Nearest Neighbors (KNN) algorithm for basic classification based on extracted image features, providing a simple and interpretable baseline. However, KNN has limitations in handling high-dimensional MRI data and complex tumor patterns. To overcome these challenges, a Convolutional Neural Network (CNN) is proposed as the core of the system. CNNs automatically extract hierarchical features from MRI images, including edges, textures, and shapes, and employ convolutional, pooling, and fully connected layers to perform end-to-end tumor detection and classification. The network is trained using backpropagation, optimizing its weights to minimize classification errors. Experimental results demonstrate that the CNN-based system outperforms traditional KNN models in accuracy, robustness, and generalization across diverse datasets. This hybrid approach provides an effective solution for automated brain tumor detection, offering reliable support for clinical decision-making and improving the efficiency of medical diagnosis workflows.

I. INTRODUCTION

Brain tumor is a common lethal illness that affects thousands of people worldwide every day. People over age 50 mostly develop brain tumors, so the number of patients increases daily. Since brain tumors are difficult to detect relative to other diseases, they are considered one of the leading causes of death. The primary cause of detection failure is the small size of the tumor in the early stage. Tumor cells start small but can grow and become malignant over time, making early detection crucial for improving survival rates. Deep learning, a branch of artificial intelligence, plays a key role in automatically identifying tumor and healthy regions using medical images. These models learn from large datasets to detect patterns, correlations, and abnormalities that may not be visible to humans. By enabling accurate and early diagnosis, deep learning supports better treatment planning and improved healthcare outcomes.

Grade I: These tumors do not spread quickly and develop slowly. These are connected to a higher chance of enhanced order and may be surgically eliminated nearly entirely. One such tumor is a pilocytic astrocytoma.

Grade II: Although they may migrate to surrounding tissues and advance to higher grades, these tumors also grow over time. These tumors may detect even though treatment is taken by the patient. An oligodendroglia tumor is an example of an overtime growth tumor.

Grade III: The growth of these tumors has been quicker than grade II malignancies and could spread to adjoining tissues. Such tumors require post-operative chemo or radiotherapy because surgery alone would be insufficient to treat them. Aden squamous astrocytoma is an indication of such a tumor.

Grade IV: The most dangerous and likely to spread malignant tumors are in this category. They might even use blood vessels to speed up their growth. An illustration of one of these tumors is glioblastoma multiform Brain tumors must be detected early and classified accurately to improve treatment outcomes and patient survival. Imaging techniques like Magnetic Resonance Imaging, Computed Tomography, and Positron Emission Tomography are commonly used, with MRI being the most effective due to its detailed, non-invasive imaging. Advanced methods such as Chemical Exchange Saturation Transfer further enhance detection of subtle abnormalities. MRI sequences like T1, T2, and FLAIR provide complementary information for identifying tumor regions. Automated detection systems using AI help improve accuracy, speed, and reliability compared to manual diagnosis.

2. LITERATURE SURVEY

M. J. Lakshmi and S. N. Rao – Brain tumor magnetic resonance image classification: a deep learning approach: Lakshmi and Rao presented an automated deep learning based method for classifying brain tumors from MRI scans. Their work focuses on applying a deep convolutional neural network model to extract multilevel features from brain MRI images, overcoming limitations of traditional feature extraction methods. The Inception v3 architecture was employed to learn rich hierarchical features directly from the data. They optimized learning using an adaptive optimizer (Adam) and trained the model to distinguish between tumor types by minimizing loss during training. After feature extraction, a Soft max classifier was used to assign class labels to the images. The model demonstrates strong classification performance in detecting different tumor categories from MRI inputs. This approach reduces manual intervention and improves diagnostic efficiency compared to conventional algorithms that rely on handcrafted features. Their work also highlights the importance of preprocessing and hyperparameter tuning to achieve higher accuracy in medical image classification. Overall, this research contributes to developing more reliable computer aided diagnostic tools for brain tumor detection using deep learning.

L. Rundo et al. – NeXt for neuro radiosurgery: fully automatic necrosis extraction in brain tumor MRI using unsupervised deep learning: Rundo and collaborators introduced NeXt, an unsupervised deep learning based method for automatic necrosis extraction in brain tumor MRI images. Their technique aims to isolate necrotic (dead) tissue regions within tumors without requiring labeled training data. By leveraging unsupervised representation learning, the model learns characteristic patterns that distinguish necrotic areas, facilitating their extraction from MRI data. This automatic process supports more detailed analysis of tumor composition, which is valuable for treatment assessment in neuro radiosurgery. The unsupervised nature of NeXt allows it to operate effectively even with limited annotated datasets, addressing a key challenge in medical image analysis. The method enhances the interpretability and utility of brain MRI scans by isolating clinically relevant structures, broadening the applications of deep learning in oncology imaging.

3 SYSTEM ARCHITECTURE

The system architecture for brain tumor detection using CNN consists of a structured pipeline that begins with the input layer, where MRI images of the brain are fed into the network. The images pass through multiple convolutional layers, which extract important features such as edges, textures, and shapes. These features are then processed by activation functions like ReLU to introduce non-linearity, followed by pooling layers that reduce the spatial size of feature maps while retaining key information. The high-level features are passed to fully connected layers, which combine them to make predictions about the presence, type, or stage of the tumor.

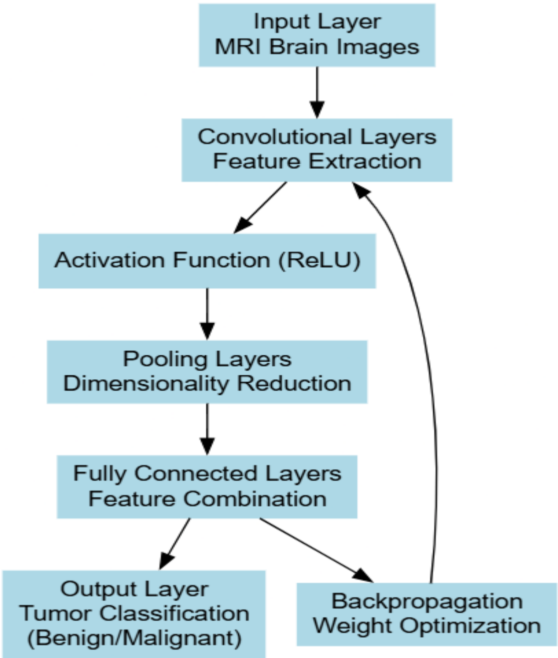

Fig1: **System Architecture**

4.METHODOLOGY

The proposed ML-based Brain Tumor Detection & Analysis system follows a structured deep learning pipeline integrated with Explainable Artificial Intelligence (XAI), as illustrated in the system architecture diagram. The framework consists of preprocessing, customized CNN-based feature extraction, classification, evaluation, and model interpretability.

i.Image Acquisition and Preprocessing

Brain MRI images are collected and passed through a preprocessing stage. The images are resized to 150 × 150 × 3 dimensions to ensure uniform input size. Normalization is applied to stabilize training and improve convergence:

$$I_{norm} = \frac{I - \mu}{\sigma}$$

where $I$is the input image, $\mu$is the dataset mean, and $\sigma$is the standard deviation. The dataset is then split into training (90%) and validation (10%) sets to ensure unbiased performance evaluation.

ii.Customized CNN Architecture

The processed images are fed into a customized Convolutional Neural Network (CNN). The architecture consists of multiple convolutional layers followed by ReLU activation and max-pooling layers for hierarchical feature extraction. The convolution operation is defined as:

$$F(i,j) = \sum_m \sum_n I(i-m, j-n) \cdot K(m,n)$$

where Krepresents the convolution kernel and $F(i,j)$is the generated feature map.

The feature maps progressively reduce in spatial dimension (e.g., 148×148×32 → 74×74×64 → 37×37×128 → 18×18×256 → 9×9×256 → 4×4×256). Fully connected layers (128 → 64 → 1) follow, and a sigmoid activation function is applied for binary classification (Brain Tumor / No Brain Tumor):

$$P(y=1) = \frac{1}{1+e^{-z}}$$

where $z$is the output of the final dense layer.

iii.Model Training and Evaluation

The trained model generates predictions categorized as “Yes Brain Tumor” or “No Brain Tumor.” Performance is evaluated using an evaluation matrix including Accuracy, Precision, Recall, and F1-Score. Binary cross-entropy loss and Adam optimizer are used during training.

iv.Explainable Artificial Intelligence (XAI)

To address the question “Why is this prediction?”, Explainable AI techniques such as LIME, SHAP, and Grad-CAM are integrated. These methods highlight important regions in MRI images influencing the model’s decision. This improves transparency, builds clinical trust, and assists doctors in understanding tumor localization.

5. DESIGN AND CONSTRUCTION

The proposed ML-Based Brain Tumor Detection & Analysis system is designed as a structured deep learning framework integrated with Explainable Artificial Intelligence (XAI) for reliable and interpretable diagnosis. The system architecture consists of dataset preparation, preprocessing, customized CNN construction, classification, evaluation, and explanation modules.

The construction begins with collecting brain MRI images and organizing them into two categories: Brain Tumor and No Brain Tumor. The images are resized to 150 × 150 × 3 dimensions to maintain uniformity. Normalization is applied to scale pixel intensity values, improving training stability. The dataset is then divided into training (90%) and validation (10%) sets to ensure proper model evaluation and to prevent overfitting.

The core component of the system is a customized Convolutional Neural Network (CNN). The architecture consists of multiple convolutional layers followed by ReLU activation functions and max-pooling layers for hierarchical feature extraction. These layers progressively reduce spatial dimensions while increasing feature depth. The extracted features are passed to fully connected layers (128, 64 neurons) and finally to a single output neuron with a sigmoid activation function for binary classification.

For optimization, the model uses the Adam optimizer with binary cross-entropy loss. The trained model generates predictions indicating the presence or absence of a brain tumor. Performance is evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score through an evaluation matrix.

6.RESULTS AND DISCUSSION

The results of the Deep Learning-based Brain Tumor Detection and Analysis system demonstrate significant improvements in diagnostic accuracy and efficiency. Convolutional Neural Networks (CNNs) have proven highly effective in analyzing MRI images and identifying different types of brain tumors, including glioma, meningioma, pituitary tumors, and cases with no tumor. The model shows strong capability in detecting early-stage tumors, which is critical for timely medical intervention and improved patient outcomes.

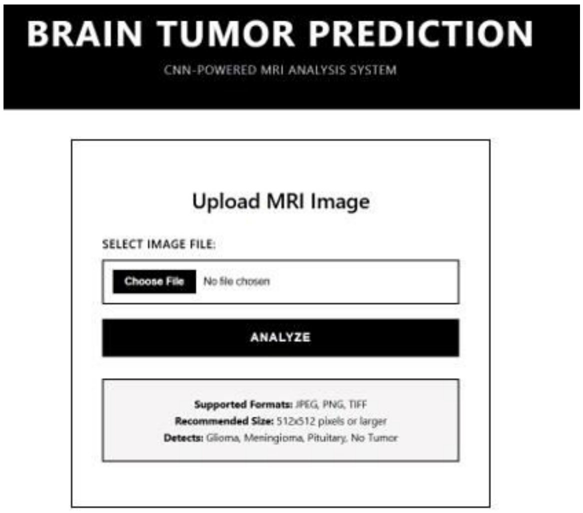

Fig 2: Image Upload Module

The system workflow begins with Figure 2 (Image Upload Module), where MRI images are securely uploaded into the system. This module supports high-resolution images and ensures proper data input for further processing.

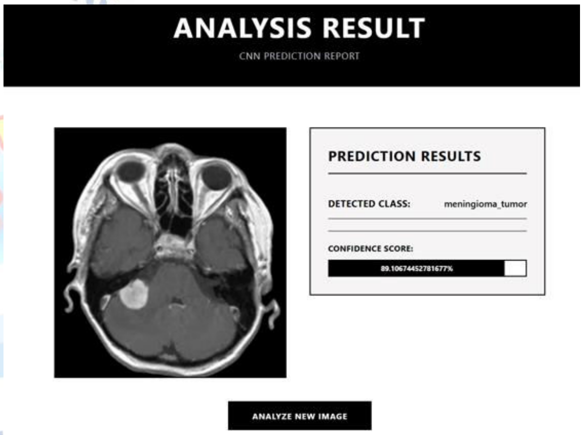

Fig 3: Tumor Prediction Output

The prediction capability of the model is illustrated in Figure, where the CNN processes the MRI scan and accurately identifies the tumor type. In the given case, the model successfully detects a meningioma tumor, demonstrating its effectiveness in real-time diagnostic applications.

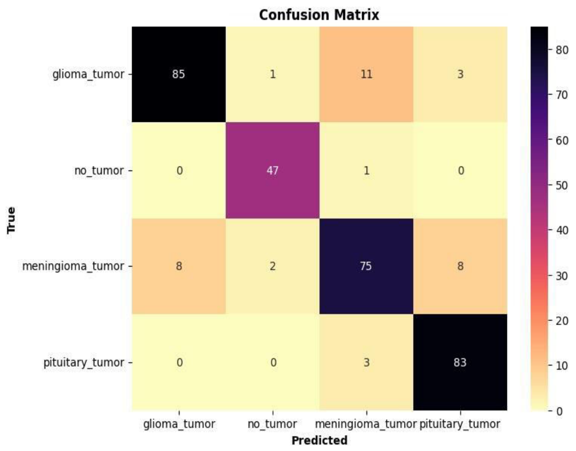

Fig 4: Confusion Matrix Analysis

The performance evaluation of the model is presented in Figure 3. The confusion matrix shows high values along the diagonal, indicating correct classifications across multiple tumor classes such as glioma, meningioma, pituitary, and no tumor. However, some off-diagonal values reveal minor misclassifications, particularly between visually similar tumor types, highlighting areas for improvement. the CNN-based model achieves high classification accuracy and demonstrates robust performance in multi-class tumor detection tasks. It outperforms traditional machine learning approaches by effectively capturing complex image features. However, challenges such as over fitting, requirement of large, annotated datasets, and model interpretability remain. Future work can focus on improving specificity to reduce false positives and enhancing model generalization for diverse datasets.

7. CONCLUSION

Machine learning-based brain tumor detection and analysis, particularly leveraging deep learning architectures like DCNNs, LSTMs, and ResNet-50, has demonstrated significant potential in improving diagnostic accuracy and patient outcomes. These techniques enable the extraction of complex features from medical images, facilitate contextual analysis, and offer enhanced sensitivity to early-stage tumors. The integration of pre-trained models and dimensionality reduction techniques further strengthens the robustness and generalization of these systems. Ultimately, these advancements pave the way for more efficient and precise brain tumor screening and diagnosis, potentially leading to earlier interventions and improved survival rates.

Future Scope:

The model's ability to learn detailed spatial hierarchies from the images enables it to detect subtle abnormalities that may be overlooked by human radiologists. In the future, further improvements could be made by fine-tuning VGG 16 with more advanced techniques like transfer learning and integrating it with AI-powered diagnostic systems for faster and more accurate decision-making.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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