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Research Paper

Automated Brain Tumour Detection Using MRI Scans

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Abstract: Brain tumors are among the most critical neurological conditions, requiring timely diagnosis to improve treatment effectiveness and patient survival rates. Magnetic Resonance Imaging (MRI) is one of the most reliable imaging techniques for detecting brain abnormalities because of its superior image quality and detailed visualization of soft tissues. This research proposes an automated brain tumor detection framework that combines image processing and machine learning techniques to identify tumors from MRI scans with high precision.

The proposed system follows a structured workflow that includes image enhancement, preprocessing, segmentation, feature extraction, and classification. These stages help distinguish healthy brain tissues from tumor-affected regions efficiently. Deep learning models, particularly Convolutional Neural Networks (CNNs), are utilized to learn complex image patterns and improve diagnostic accuracy while minimizing manual intervention.

The model is trained and tested using publicly available MRI datasets to ensure reliability and robustness. Performance evaluation demonstrates strong results in terms of accuracy, sensitivity, specificity, and overall classification efficiency. Experimental findings indicate that the framework can successfully detect and localize brain tumors, providing valuable support to radiologists during the diagnostic process.

By enabling faster and more consistent tumor identification, the proposed system has the potential to enhance clinical decision-making, reduce diagnostic errors, and facilitate early treatment planning. This intelligent approach contributes to the advancement of computer-aided diagnosis systems and supports improved healthcare outcomes for patients affected by brain tumors.

Keywords: Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Image Processing, Machine Learning, Deep Learning, Convolutional Neural Network (CNN), Medical Image Analysis, Computer-Aided Diagnosis..

1.INTRODUCTION

Brain tumors represent a major health concern worldwide due to their potential to severely affect the normal functioning of the nervous system. These tumors develop when cells within the brain grow abnormally and uncontrollably, leading to the formation of masses that may interfere with essential neurological activities such as cognition, movement, speech, vision, and memory. Since brain tumors can be life-threatening, their early identification is vital for improving treatment success and enhancing patient survival rates.

Magnetic Resonance Imaging (MRI) is one of the most effective diagnostic tools used for detecting brain abnormalities. It provides high-resolution images of brain tissues, allowing medical experts to observe structural changes and identify suspicious regions with greater clarity. Despite its effectiveness, the interpretation of MRI scans often relies on the expertise of radiologists and neurologists. Analyzing large numbers of MRI images manually can be a time-intensive process and may sometimes result in inconsistencies or missed detections, particularly in complex cases.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have created new opportunities for improving medical image analysis. These technologies enable computer systems to learn patterns from imaging data and perform diagnostic tasks with high levels of accuracy. In particular, deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image recognition and classification applications, making them highly suitable for brain tumor detection.

The proposed automated brain tumor detection system utilizes MRI scans along with advanced image processing and deep learning techniques to identify tumor regions efficiently. The framework includes several stages such as image preprocessing, segmentation, feature extraction, and classification. Through these processes, the system can accurately distinguish between healthy and abnormal brain tissues while reducing the need for extensive manual intervention.

The primary objective of this research is to develop a reliable and efficient diagnostic support system that assists healthcare professionals in detecting brain tumors at an early stage. By providing fast and accurate results, the proposed approach can help reduce diagnostic workload, minimize human errors, and support timely clinical decision-making. Ultimately, the integration of intelligent detection systems into healthcare environments has the potential to improve patient care and contribute to better treatment outcomes.

2.LITERATURE SURVEY

1 Traditional Machine Learning Approaches

Early work in computer-aided brain tumor diagnosis relied on hand-crafted feature extraction combined with classical machine learning classifiers. Mohanaiah et al. (2013) explored texture feature extraction using Grey Level Co-occurrence Matrix (GLCM) combined with Support Vector Machines (SVM), achieving reasonable accuracy on small datasets. Similarly, Nandha and Karnan (2010) investigated fuzzy c-means clustering for MRI segmentation, demonstrating the potential of unsupervised methods.

Gumaei et al. (2019) proposed a hybrid feature extraction method using regularized extreme learning machines for brain tumor classification, combining traditional and neural approaches. Jothi and Inbarani (2016) applied hybrid tolerance rough set-firefly algorithms for supervised feature selection, achieving competitive results. However, these methods require extensive domain expertise for feature engineering, do not generalize well across diverse datasets, and struggle with the high dimensionality of MRI images.

2 Deep Learning and CNN-Based Approaches

The introduction of deep learning fundamentally changed the landscape of medical image classification. Havaei et al. (2017) demonstrated that deep neural networks could perform brain tumor segmentation with high accuracy, outperforming traditional methods. Kamnitsas et al. (2016) proposed an efficient multi-scale 3D CNN for brain lesion segmentation that achieved state-of-the-art performance on the BRATS benchmark dataset.

Pereira et al. (2016) applied CNNs to MRI tumor segmentation using small 3x3 convolution kernels, enabling the model to learn local features effectively while reducing overfitting. Their work highlighted the importance of data augmentation for small medical datasets. Sajjad et al. (2019) extended this by using extensive data augmentation combined with multi-grade tumor classification using deep CNNs, demonstrating the value of data diversity.

3 Transfer Learning Approaches

Transfer learning, leveraging models pre-trained on large image datasets such as ImageNet, has been widely explored. Gayathri et al. (2023) explored the VGG-16 architecture for brain tumor detection, demonstrating that pre-trained features could be effectively fine-tuned for medical image classification. Li et al. (2018) proposed H-DenseUNet, a hybrid densely connected UNet for liver and tumor segmentation from CT volumes, demonstrating the cross-domain applicability of such architectures.

Afshar et al. (2020) investigated capsule networks as an alternative to CNNs for brain tumor type classification, addressing the limitation of CNNs in preserving spatial relationships between features. While promising, capsule networks remain computationally expensive and have not yet achieved the widespread adoption of standard CNNs.

3.4 Gaps Identified and Justification for Proposed Approach

A consistent limitation across the reviewed literature is the reliance on small, homogeneous, or heavily augmented datasets. Many studies train on fewer than 3,000 images, limiting the model's generalizability. Furthermore, most research prototypes lack an accessible user interface, making clinical adoption difficult.

This project addresses these gaps by training on 10,153 real (non-augmented) MRI images, building a custom CNN optimized for the specific characteristics of grayscale MRI images, and deploying the model through a user-friendly Streamlit interface with downloadable report generation. The use of GELU activation as an alternative to ReLU provides improved learning for complex patterns.

3. METHODOLOGY

a) Proposed Work:

The proposed system is designed to bridge the gap between research-based AI models and practical diagnostic applications. It offers an automated, end-to-end brain tumor classification framework using CNNs. Unlike traditional CAD systems, this solution uses deep learning to automatically learn hierarchical patterns from MRI images, enabling classification with high accuracy and consistency.

At the core is a robust CNN model trained on 10,153 annotated MRI images across four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The architecture includes convolutional layers for spatial feature extraction, pooling layers for dimensionality reduction, batch normalization for training stability, dropout for regularization, and fully connected layers for class prediction. A softmax output layer provides probability scores for each class.

A user-friendly interface built with Streamlit allows medical professionals to upload MRI images, receive instant classification results with confidence metrics, and download a structured diagnostic report. The system is deployable locally or on cloud platforms, making it suitable for urban hospitals and rural clinics alike.

b) System Architecture:

- Presentation Layer: The Streamlit web interface serves as the front end. It handles user interaction, image display, result rendering, and report download functionality.

- Input Layer: The image upload module accepts MRI scan files in supported formats and validates file type and size before passing the image to the preprocessing layer.

- Preprocessing Layer: This module applies grayscale conversion, resizing to 200x200 pixels, pixel normalization to [0,1], and array reshaping to match the CNN input dimensions (1, 200, 200, 1).

- Model Inference Layer: The trained CNN model, loaded from the saved .keras file, receives the preprocessed image tensor and produces a probability vector across the four tumor classes via softmax activation.

- Output Layer: The class with the highest probability is selected as the prediction. The confidence score, tumor class label, and formatted diagnostic report are presented to the user. A download button enables report export..

c) Modules:

Module 1: Data Collection and Preparation

The dataset used in this project is the Brain Tumor MRI Dataset sourced from Kaggle. It contains 10,153 MRI images organized into four class folders: Glioma, Meningioma, Pituitary, and No Tumor. The following preprocessing steps are applied:

- Image Resizing: All images are resized to a fixed dimension of 200x200 pixels to ensure uniform input to the CNN.

- Grayscale Conversion: Images are converted to grayscale to reduce computational complexity while retaining diagnostic features.

- Normalization: Pixel values are scaled from [0, 255] to [0, 1] by dividing by 255.0 to improve training convergence.

- Data Splitting: The dataset is divided into 80% for training and 20% for testing using train_test_split with shuffle enabled.

- Directory Organization: Images are organized into structured subdirectories by class for seamless loading via ImageDataGenerator.

Module 2: Model Architecture and Training

A custom CNN architecture is designed and implemented using TensorFlow/Keras. The architecture consists of:

- Convolutional Layers: Multiple Conv2D layers with increasing filter depths (32, 64, 128) to extract progressively complex spatial features.

- Activation: GELU (Gaussian Error Linear Unit) activation, which provides smoother gradients than ReLU and improves learning on complex patterns.

- Pooling Layers: MaxPooling2D layers after each convolutional block to reduce spatial dimensions and computational load.

- Batch Normalization: Applied after convolutional layers to stabilize and accelerate training.

- Dropout & SpatialDropout2D: Applied at multiple layers to prevent overfitting by randomly deactivating neurons during training.

- Fully Connected Layers: Dense layers at the end of the network aggregate features for final classification.

- Output Layer: A Dense layer with 4 neurons and Softmax activation provides a probability distribution across the four tumor classes.

- Optimizer: SGD (Stochastic Gradient Descent) with tuned learning rate and momentum.

- Loss Function: Categorical Cross-Entropy, appropriate for multi-class classification.

Module 3: Model Evaluation

After training over 10 epochs, the model is evaluated on the held-out test set using:

- Accuracy: The percentage of correctly classified samples — overall accuracy of 99.5%.

- Precision: Glioma: 99.4%, Meningioma: 96.7%, Pituitary: 100%.

- Recall: Measures the proportion of actual positives correctly identified.

- F1-Score: Harmonic mean of precision and recall for balanced evaluation.

- Confusion Matrix: A 4x4 matrix visualizing class-wise prediction performance.

Module 4: Web Application Development

The Streamlit-based web interface provides an intuitive front end for end users:

- MRI Image Upload: A file uploader accepting JPG, PNG, and JPEG formats.

- Image Display: The uploaded image is displayed in the browser after grayscale conversion.

- Prediction Display: The predicted tumor class and model confidence percentage are shown prominently.

- Diagnostic Report: A formatted medical-style report is generated and displayed inline.

- Download Button: A Streamlit download_button allows users to save the report as a .txt file.

Module 5: Report Generation

The report generation module creates a structured diagnostic summary containing:

- Brain Tumor Detection Report header.

- Classification result (e.g., 'Meningioma').

- Model confidence score (e.g., '95.97%').

- A disclaimer note: 'This result is based on a deep learning model and should be confirmed by a qualified medical professional.'.

4. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

Precision = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$F1 - Score = 2 * \frac{(\text{Precision} \; * \; \text{Recall})}{((\text{Precision} \; + \; \text{Recall})\;)}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

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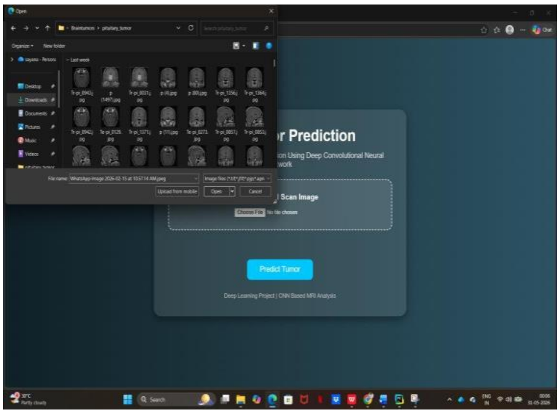

Fig 1:The folder contains four subfolders named glioma, meningioma, no_tumor, and pituitary, each representing a category of brain MRI images. This is likely part of a classification project where these folders contain sample images for training or testing a machine learning model

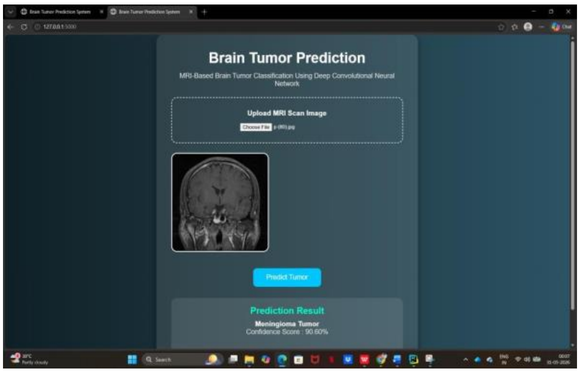

Fig 2: This shows a file selection window open to the "glioma" folder, part of a images folder used for brain tumor classification. The folder contains several MRI scan images labeled sequentially (e.g., gg (1), gg (2), etc.). These grayscale images display crosssectional views of the brain and are likely used to train or test a model in identifying glioma tumors. 36

5. CONCLUSION

The development of this AI-based brain tumor detection system represents a significant step toward enhancing the speed, accuracy, and accessibility of medical diagnostics. A deep Convolutional Neural Network was successfully designed, trained, and deployed to classify MRI images into four clinically meaningful categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The system achieved an overall accuracy of 99.5%, surpassing many existing deep learning architectures on comparable tasks.

The integration of image preprocessing, CNN-based inference, and a Streamlit web interface delivers a reliable, scalable, and accessible diagnostic aid. The system reduces diagnosis time, minimizes human error, and supports healthcare professionals in high-volume or resourcelimited settings. Comprehensive unit and integration testing validated the robustness and usability of all system components.

One of the greatest strengths of this project is its modular flexibility. The architecture supports continuous retraining, integration of additional tumor classes, and deployment across diverse environments including local hospital systems and cloud platforms. While the results are highly promising, certain limitations are acknowledged: model performance depends on dataset quality and diversity, the current version does not include tumor segmentation or explainability features, and formal clinical validation has not yet been conducted.

Nonetheless, this project demonstrates how AI can be responsibly applied to medical imaging, creating a practical and forward-thinking foundation for intelligent diagnostic tools that can evolve with advancing technology and changing healthcare needs

6.FUTURE SCOPE

Several meaningful enhancements are proposed for future development:

- Tumor Segmentation: Integration of segmentation models (e.g., U-Net) to precisely delineate tumor boundaries within MRI scans, providing spatial localization beyond classification.
- Explainable AI (XAI): Implementation of Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize the image regions influencing the model's decision, improving clinical transparency and trust.
- Expanded Tumor Classes: Extending the model to cover additional primary and metastatic brain tumor subtypes.
- 3D MRI Support: Incorporating volumetric analysis of 3D MRI data for more comprehensive tumor characterization.
- Cloud Deployment: Optimizing the system for deployment on AWS, GCP, or Azure with support for concurrent users and real-time diagnostics at scale.
- Mobile Application: Developing a mobile version for use on portable diagnostic devices, enabling deployment in remote and rural healthcare environments.
- EHR Integration: Connecting the system with hospital information and Electronic Health Record (EHR) systems to streamline clinical workflows.
- Treatment Recommendation: Coupling tumor classification with evidence-based treatment recommendation engines aligned with clinical guidelines.
- Multi-modal Imaging: Incorporating CT, PET, and functional MRI data to provide richer diagnostic context.

Federated Learning: Exploring privacy-preserving distributed training across hospital networks to improve model generalization without sharing raw patient data

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