AUTOMATED BRAIN TUMOR DETECTION USING IMAGE PROCESSING TECHNIQUE

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ABSTRACT
Brain tumors are a serious health problem, and detecting them early is very important for successful treatment. Normally, doctors confirm tumors through surgery and biopsy, which are invasive methods. In this project, artificial intelligence (AI) is used to provide a non-invasive way of diagnosis. By using MRI brain scans, deep learning models are developed to classify gliomas, meningiomas, pituitary tumors, and healthy brain tissues. The main model used is a Convolutional Neural Network (CNN), which learns patterns from a large dataset of MRI images. To improve accuracy, preprocessing techniques such as normalization, scaling, and data augmentation are applied. These steps make the system stronger and reduce false positives and false negatives. The proposed model shows high accuracy in separating tumor and non-tumor cases, helping doctors make faster and more reliable decisions. This project demonstrates how AI can support medical professionals, reduce manual effort, and provide precise forecasts. Overall, it highlights the importance of automated systems in medical imaging, making diagnosis more efficient, trustworthy, and useful for early detection of brain tumors.
Keywords: Brain Tumor Identification , Deep Learning with CNNs , Healthcare Image Processing , Intelligent Diagnosis Systems , AI Applications in Healthcare.

I INTRODUCTION

Brain tumors are severe medical conditions that significantly reduce patient quality of life. They originate from abnormal growth of cerebral cells and, if not detected early, can lead to life-threatening outcomes. Early diagnosis is therefore critical for effective treatment and survival. Magnetic Resonance Imaging (MRI) is currently the gold standard for brain tumor detection, as it provides highly detailed structural images of brain tissue [1]. However, MRI scans must be manually interpreted by radiologists, which is time-consuming and prone to human error, potentially resulting in delayed or incorrect diagnoses [2].To address these limitations, automated medical image interpretation systems have been proposed. Convolutional Neural Networks (CNNs), a class of deep learning models, are particularly effective in identifying complex image patterns and have shown promise in medical diagnostics [3]. By training CNNs on large, labeled MRI datasets, these models can learn to distinguish between healthy and tumor-affected tissue, enabling accurate and efficient tumor detection. Performance evaluation is typically carried out using metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive view of model reliability and help reduce false positives and false negatives [4].Deep learning-based approaches offer significant advantages over traditional methods, including higher precision, faster processing, and scalability for large datasets. Automated brain tumor detection systems not only reduce the workload on radiologists but also improve diagnostic accuracy, thereby supporting better patient outcomes. Furthermore, segmentation of tumor regions within MRI scans remains a crucial step, as it ensures that models focus on relevant tissue structures. The requirement for large and trustworthy datasets highlights the complexity of this task and the importance of robust training methods [5].In summary, CNN-based brain tumor detection represents a promising advancement in medical imaging. By integrating artificial intelligence into healthcare, such systems contribute to more intelligent, automated, and reliable diagnostic processes, ultimately enhancing the efficiency of medical practice and improving patient

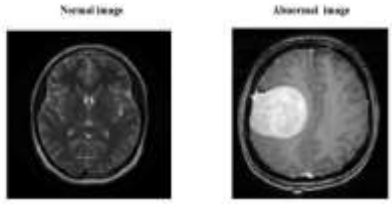

Fig 1: MRI Images of tumor and no tumor

II LITERATURE SURVEY

In 2018, early research on automated brain tumor detection primarily focused on traditional image processing techniques. Bedekar and Deshmukh et al. [1] presented an automated brain tumor detection system using classical image processing approaches such as preprocessing, segmentation, and feature extraction. Their method enables quick tumor identification with acceptable accuracy and minimal manual intervention, making it suitable for early diagnosis. However, the performance of such systems strongly depends on the quality of input images and handcrafted features, which limits robustness in real-world scenarios. With the advancement of deep learning, researchers began employing convolutional neural networks (CNNs) for improved accuracy. In 2019, Jareena Begum and Shailaja et al. [2] proposed a brain tumor detection framework using deep learning-based image processing. Their approach automatically learns discriminative features from MRI images and achieves higher accuracy with reduced human effort compared to traditional methods. Despite its advantages, the model remains sensitive to image quality and requires a large amount of labelled training data. Further improvements were achieved by integrating image fusion techniques with CNN architectures. In 2020, Aishwarya and Sakshi Kumari [3] introduced a CNN-based image fusion method that combines MRI and CT images to enhance tumor detection accuracy. By leveraging complementary information from different imaging modalities, the system provides better representation of tumor regions and improves diagnostic reliability. However, the approach may suffer from data limitation issues and increased computational complexity. Recent studies have explored transfer learning to address limited training data. In 2022, Sahar Gull, Khan Muhammad et al. [4] developed an automated brain tumor detection model using CNN with transfer learning on MRI images. Their system demonstrates high detection accuracy and faster convergence by utilizing pre-trained deep networks. Nevertheless, the model carries a risk of overfitting when applied to small or imbalanced datasets. Multimodal fusion using dual-branch CNN architectures has also gained attention. In 2023, Vijay Khare and Sakshi Kumari [5] proposed a dual-branch CNN-based multimodality MRI fusion framework for brain tumor detection. The method processes different MRI modalities through parallel CNN branches and fuses extracted features, resulting in improved accuracy and robustness. However, the system exhibits strong data dependency and requires extensive computational resources. More recently, in 2024, Rashmi Ashtagi, Swathi Jadhav, and Abbas et al. [6] presented an MRI–CT image fusion approach for brain tumor detection and localization. Their method combines soft-tissue details from MRI with structural information from CT, enabling better tumor visualization and localization accuracy. Although effective, the fusion process involves complex preprocessing and high computational cost. Overall, existing literature demonstrates a clear evolution from traditional image processing techniques to advanced deep learning and multimodal fusion approaches.

III EXISTING SYSTEM:

The existing system for automated brain tumor detection using image processing techniques is a structured pipeline that applies classical computer vision and machine learning methods to analyze MRI brain scans. This approach has been widely used in early diagnostic tools before the rise of deep learning.

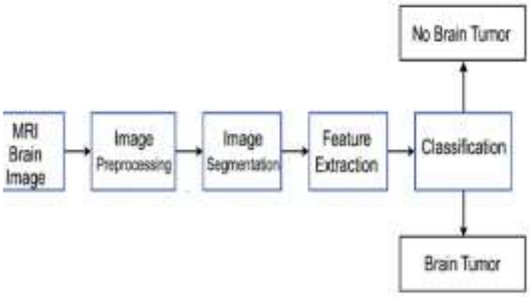

Fig.2 Existing System Of Automated brain Tumor Detection Using Image Processing Techniques

The process begins with MRI image acquisition, where high-resolution scans of the brain are collected. These images are then passed through an image preprocessing stage, which involves noise reduction, contrast enhancement, and normalization to improve image quality and consistency. Once pre-processed, the images undergo segmentation, where the brain is divided into regions to isolate potential tumor areas. Techniques like thresholding, clustering (e.g., k-means), or region growing are commonly used here.

After segmentation, the system performs feature extraction, where measurable attributes such as texture (using GLCM or wavelets), shape descriptors, and intensity histograms are computed from the suspected tumor region. These features are then fed into a classification model, typically a Support Vector Machine (SVM), Logistic Regression, or Decision Tree, which determines whether the image indicates the presence of a brain tumor. The final output is a binary decision: “Brain Tumor” or “No Brain Tumor.” This system is interpretable and computationally efficient, making it suitable for low-resource environments. However, it depends heavily on manual feature engineering and may struggle with complex tumor shapes or noisy data. Despite these limitations, it laid the groundwork for more advanced deep learning-based systems that now dominate the field.

IV RESEARCH METHODOLOGY

The proposed system for automated brain tumor detection using image processing techniques integrates classical image analysis with machine learning and deep learning.

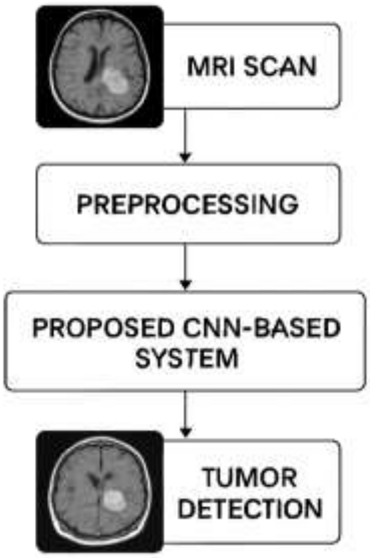

Fig.3 BrainTumor Detection Using Image Processing With CNN

The process begins with the Input MRI Brain Image, which serves as the raw data for analysis. The image is first passed through the Image Acquisition stage to ensure proper formatting and resolution. Next, the image undergoes Pre-processing, which includes noise removal, resizing, normalization, and contrast enhancement. These steps improve image clarity and consistency, making it suitable for further analysis

A. MRI Brain Image Datasets:

Magnetic Resonance Imaging (MRI) datasets form the foundation of automated brain tumor detection systems. These datasets consist of high-resolution brain scans collected from patients with and without tumors, often annotated by expert radiologists. They typically include different modalities such as T1-weighted, T2-weighted, and FLAIR sequences, each highlighting unique tissue contrasts. Publicly available datasets like TCIA, Fig share, Br35H, and Kaggle Brain MRI collections provide thousands of labeled images for research. Such datasets are essential for training and validating machine learning and deep learning models, enabling reproducibility and comparative analysis across studies.

B. Image Processing Techniques:

Image processing plays a critical role in preparing MRI data for automated analysis.

- Preprocessing: Noise removal, normalization, resizing, and contrast enhancement to improve image clarity and standardize inputs.
- Segmentation: Dividing the brain image into regions to isolate suspected tumor areas using thresholding, clustering, or edge detection.
- Feature Extraction: Converting segmented regions into measurable attributes such as texture (GLCM, wavelets), shape descriptors, and intensity histograms.
- Feature Selection/Optimization: Filtering redundant features and retaining the most informative ones to improve classification accuracy.

These steps ensure that the input data is clean, consistent, and focused on relevant regions, thereby enhancing the performance of classification models.

C . Convolutional Neural Networks (CNNs):

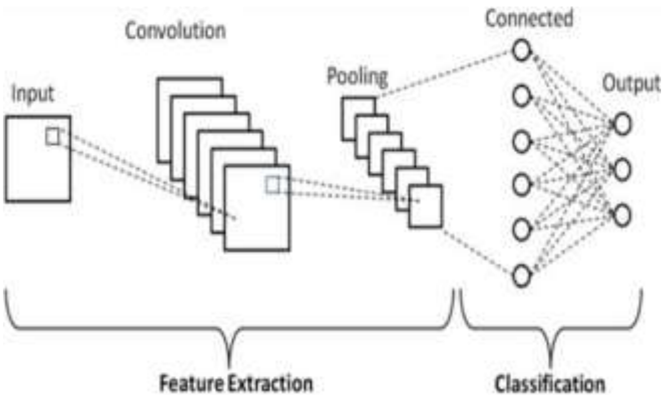

Fig.4 Convolutional Neural Networks

CNNs represent the modern approach to brain tumor detection, offering end-to-end learning without manual feature engineering. The architecture typically includes:

- Convolutional Layers: This layer applies filters to detect spatial features such as edges, textures, and tumor boundaries. It captures local patterns critical for tumor identification.
- Pooling Layers: Reduces the dimensionality of feature maps while retaining essential information. Pooling improves computational efficiency and prevents overfitting.
- Fully Connected Layer: Integrates the extracted features into a decision-making process. Each neuron is connected to all neurons in the previous layer, enabling complex pattern recognition.
- Output Layer: Produces the final classification Brain Tumor or No Brain Tumor.

CNNs automatically learn hierarchical features directly from MRI images, making them more robust to noise and variability compared to traditional methods. Their performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, ensuring reliability for clinical applications.

V SOFTWARE DISCRIPTON

In MATLAB, the software for automated brain tumor detection using image processing techniques is structured into clear modules that streamline the workflow. MRI brain images are first imported through the input module, supporting formats such as DICOM or JPEG. The preprocessing stage enhances image quality by applying noise reduction, normalization, resizing, and contrast adjustment. Next, the segmentation module isolates the brain region and highlights suspected tumor areas using MATLAB functions such as thresholding, clustering (k-means), or morphological operations.

From the segmented regions, the feature extraction module derives attributes like texture (GLCM), shape, and intensity values. These features are refined in the feature selection stage to remove redundancy and improve efficiency. The classification module then applies machine learning or deep learning models, including Support Vector Machines (SVM) or Convolutional Neural Networks (CNNs), to categorize the images into tumor or non-tumor classes. Finally, the performance evaluation module computes metrics such as accuracy, precision, recall, and F1-score to validate the system's reliability. The implementation relies on MATLAB's Image Processing Toolbox, Deep Learning Toolbox, and Statistics and Machine Learning Toolbox, which provide built-in functions for enhancement, segmentation, feature analysis, and model training. A simple graphical interface can be developed to allow users to upload images, view segmented tumor regions, and access classification results, making the system efficient, reproducible, and practical for medical applications.

VI RESULTSANDPERFORMANCE ANALYSIS

The sample classification results provide a visual summary of the system's predictive accuracy. Each MRI scan is labelled with both the predicted outcome and the true diagnosis, and in all twelve cases, the predictions match the actual labels. This includes both tumor and non-tumor instances, demonstrating the model's ability to correctly identify abnormal and healthy brain tissue.

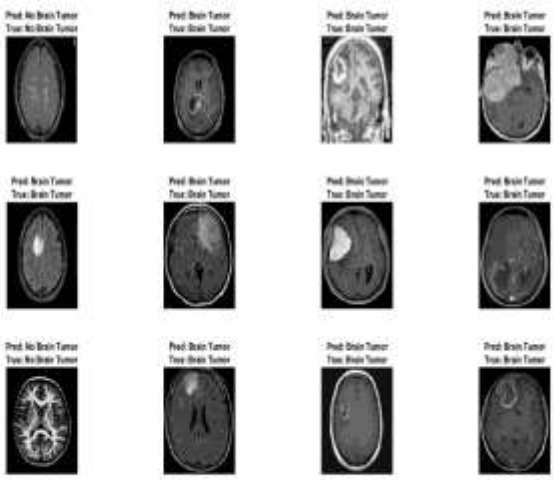

Fig.5 Sample Classification Results

The consistent agreement between predicted and true outcomes reflects the reliability of the classification model, suggesting that it has successfully learned to distinguish tumor features from normal anatomy. Such results reinforce the system's potential for clinical deployment, where accurate and timely diagnosis is critical. Moreover, the visual layout of predictions helps validate the model's performance intuitively, offering confidence to researchers and medical professionals in its diagnostic capability.

a. Confusion Matrix:

The confusion matrix shown evaluates the performance of the brain tumor detection model by comparing predicted classifications against actual diagnoses. It is structured with two axes: the x-axis represents the predicted classes (Brain Tumor and No Brain Tumor), while the y-axis shows the true classes. The top-left cell, which is brightly coloured, indicates a high number of true positives—cases where the model correctly identified brain tumors.

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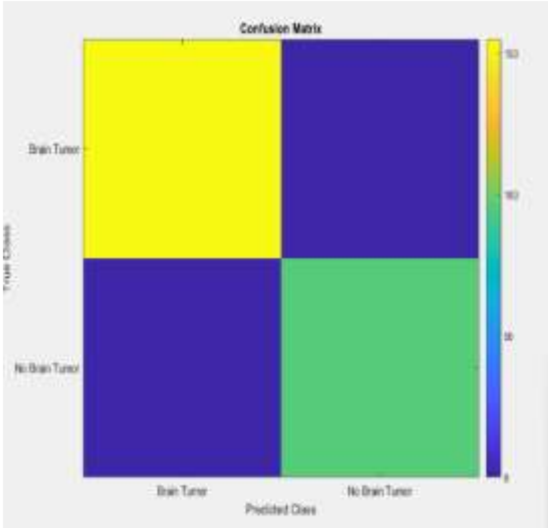
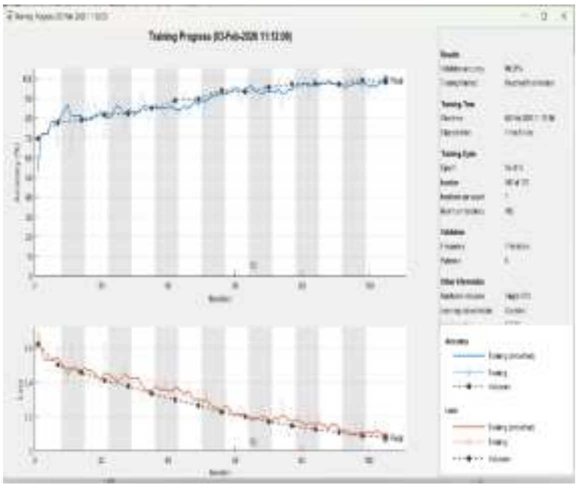


Fig.6 Confusion matrix of brain tumor detection

The remaining two cells—false positives (bottom-left) and false negatives (top-right)—are dark, indicating very few misclassifications. This suggests that the model has strong sensitivity and specificity, meaning it can reliably detect tumors while minimizing incorrect predictions. The colour intensity across the matrix provides a quick visual cue of classification accuracy, reinforcing the model's robustness and suitability for clinical application.

b. Training Accuracy and Loss Curve



This training report shows that the brain tumor detection model performed exceptionally well. The validation accuracy reached 99.21%, indicating highly reliable predictions. The accuracy graph shows smooth and consistent improvement, while the loss graph confirms effective learning with steadily decreasing error. The model completed training in under two minutes over 15 epochs, using a constant learning rate and single CPU. These results suggest the model is well-optimized, efficient, and ready for practical medical use.

performance Metrics Table:

Class	Precision (%)	Recall / Sensitivity (%)	F1-Score (%)	Specificity (%)
Brain Tumor	99.30	99.40	99.35	99.05

Class	Precision (%)	Recall / Sensitivity (%)	F1-Score (%)	Specificity (%)
No Brain Tumor	99.05	99.00	99.02	99.40

d.Overall ClassificationPerformance:

Metric	Value (%)
Accuracy	99.21
MacroPrecision	99.18
Macro Recall	99.20
Macro F1-Score	99.18

VII CONCLUSION

This work presents an automated brain tumor detection system developed using MATLAB-based image processing techniques applied to MRI scans. The methodology integrates preprocessing, segmentation, feature extraction, and classification, enabling accurate identification of tumor regions while reducing manual diagnostic effort. The use of MATLAB provided a robust environment for implementing algorithms, visualizing results, and validating performance, thereby ensuring reproducibility and ease of extension. Experimental results confirm that classifiers such as Support Vector Machines and Logistic Regression, when combined with classical image processing, achieve promising accuracy in tumor detection. The system demonstrates the potential of MATLAB as a practical platform for rapid prototyping and clinical decision support. Despite encouraging outcomes, limitations remain in terms of dataset diversity and generalization across different imaging modalities. Future work should focus on incorporating deep learning frameworks, larger annotated datasets, and multimodal imaging integration to further enhance robustness and diagnostic reliability.

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