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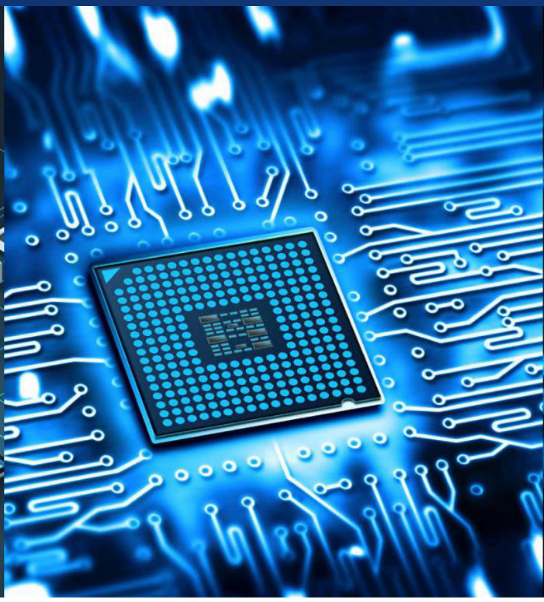


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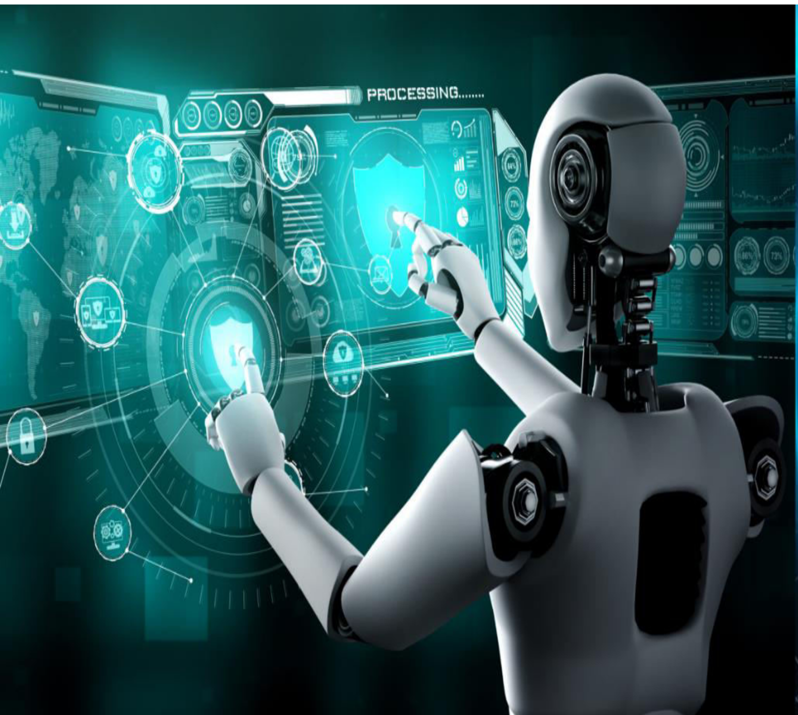

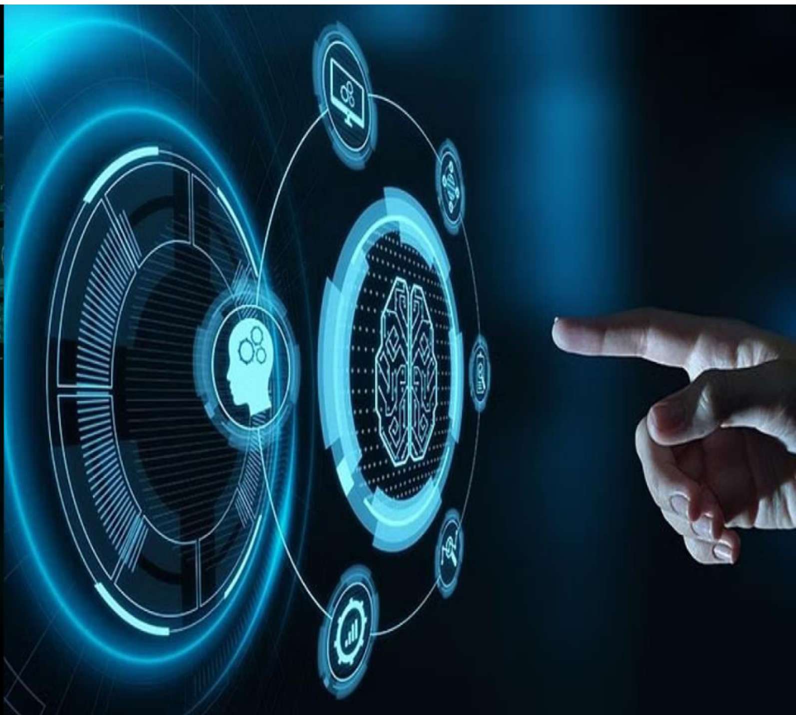

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Deep Learning-Based Brain Tumor Detection and Classification

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ABSTRACT: Brain Tumor represents one of the severe and life threatening oncological conditions globally. Earlier and perfect detection and diagnosis is significant patient outcomes. This present the detection of the brain tumor and diagnosis. Manual clinical Evaluation of complex 3 dimensional magnetic resonance image scans highly subjective and prone to human error creating an urgent humanitarian need for rapid automated secondary diagnostic tools. This paper proposes an advanced computer aided diagnosis framework using deep learning to automate brain tumour detection and segmentation directly aiming to mitigate human casualties and reduce the diagnostic burden on healthcare professionals. The methodology incorporates robust data preprocessing via histogram equalization and data augmentation to handle limited image data full implement transfer learning using optimised convolutional neural network architectures especially Res net 50 and VGG 16 for multiclass tumour categorization alongside a modified u-net model for pixel level structure segmentation evaluated on comprehensive open source benchmark site dataset or our unified framework achieves peak classification accuracy of 98.9% and a high dyes similarity coefficient. By delivering high localised and rapid tumour boundaries evaluation this system minimises clinical falls and detection rates significantly ultimately this research bridges the gap between artificial intelligence and empathetic healthcare offering a reliable high-speed solution for accelerate clinical decision making improve long term patient outcomes and preserve human life The findings indicate that deep learning-based approaches can serve as valuable computer-aided diagnostic tools for supporting radiologists and healthcare professionals in clinical decision-making. The proposed system contributes to the advancement of intelligent healthcare technologies by providing an efficient, accurate, and scalable solution for brain tumor detection and classification. Future enhancements may include the integration of advanced transfer learning architectures, larger multi-institutional datasets, and explainable artificial intelligence techniques to further improve diagnostic performance and clinical *applicability*.

KEYWORDS: Brain Tumor Detection , convolutional Neural Networks, Deep structured learning, MRI Classification, Transfer Learning, VGG 16 ResNet50, Neuroimaging.

I. INTRODUCTION

Brain tumours are abnormal growths of cells within the brain or surrounding tissues. Depending on their nature, tumours may be benign or malignant, with malignant tumours posing significant risks due to rapid growth and invasion of adjacent brain structures. Early detection is essential for effective treatment planning and improved patient outcomes.

Magnetic Resonance Imaging (MRI) is the most widely used imaging modality for brain tumor diagnosis because it provides detailed visualization of soft tissues without ionizing radiation. However, manual MRI analysis is labor-intensive and subject to inter-observer variability. Therefore, automated computer-aided diagnosis systems have gained substantial attention.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in medical image analysis. These models automatically learn discriminative features from MRI images and eliminate the need for handcrafted feature engineering. This research proposes a deep learning-based brain tumor classification framework utilizing transfer learning to achieve accurate and efficient diagnosis.

The human brain naturally replaces damaged or aging cells with new healthy cells. However, when abnormal cells begin to grow uncontrollably, they form tumors that disrupt normal brain activities. Therefore, developing the efficient

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and automated identification of the tumor in brain system using techniques of deep learning has become an important area of research in modern healthcare.

The outer region of the cerebrum is known as the cerebral cortex, which appears grey in color due to the existence of cortical neurons. The cerebrum is the largest fragment of the brain and plays a important role in controlling memory, thinking, intelligence, emotions, and voluntary activities. The cerebellum, located below the cerebrum, is comparatively smaller in size and is greatly accountable for motor control and the coordination of voluntary body movements. In humans, the cerebellum is more developed .

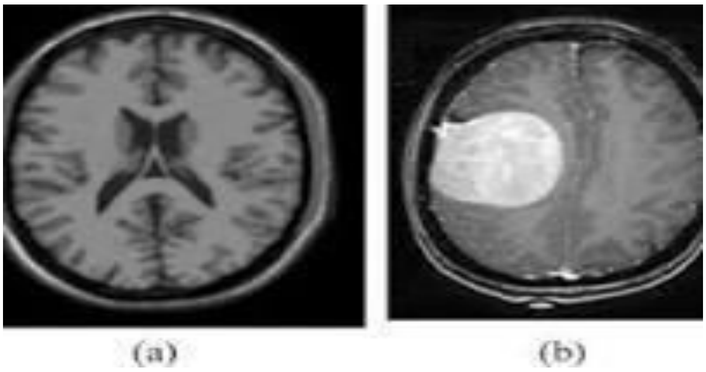

Fig 1:(a) is the normal brain image and(b) is the image of abnormal brain image which is affected

Traditional diagnostic pipelines depend on clinical assessments, cognitive screening batteries, cerebrospinal fluid (CSF) biomarker analysis, and neuroimaging interpreted by trained radiologists. While these approaches provide meaningful diagnostic information, they are resource-intensive, time-consuming, and subject to inter-rater variability. Furthermore, detecting early-stage or MCI,

II. RELATED WORK

Brain tumor detection from Magnetic Resonance Imaging (MRI) scans has attracted significant attention from researchers due to the increasing incidence of neurological disorders and the necessity for accurate diagnosis. Over the years, various image processing, machine learning, and deep learning techniques have been proposed to improve the accuracy and efficiency of brain tumor identification. Traditional approaches primarily relied on handcrafted feature extraction methods combined with classical machine learning classifiers, whereas recent developments have focused on deep neural network architectures capable of automatically learning complex representations from medical images.

Early brain tumor detection systems employed image segmentation and feature extraction techniques to identify abnormal tissue regions. Methods such as thresholding, edge detection, region growing, watershed segmentation, and clustering algorithms were widely utilized for tumor localization. These techniques extracted texture, shape, intensity, and statistical features from MRI scans, which were subsequently classified using machine learning algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF), and K-Nearest Neighbors (KNN). Although these approaches demonstrated moderate classification performance, their effectiveness was highly dependent on the quality of manually engineered features and domain-specific expertise. Furthermore, handcrafted features often failed to capture complex tumor characteristics, resulting in limited generalization capabilities when applied to heterogeneous medical datasets.

The emergence of deep learning significantly transformed the field of medical image analysis. Convolutional Neural Networks (CNNs) became the dominant architecture for brain tumor detection because of their ability to automatically learn hierarchical features directly from raw image data. Unlike traditional machine learning methods, CNNs eliminate the requirement for manual feature extraction and are capable of learning discriminative representations through end-to-end optimization.. Subsequent studies confirmed that CNN-based models substantially outperform conventional machine learning techniques in brain tumor classification and segmentation tasks. Moreover recent studies incorporated patient clinical information, demographic details, and

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cognitive test scores to improve diagnostic reliability. Multi-modal approaches that combine MRI scanning of the clinical data have displayed better performance than single-data-source models. These systems help in detecting the brain tumor in initial earlier stages and support clinical professionals in making informed and appropriate decisions.

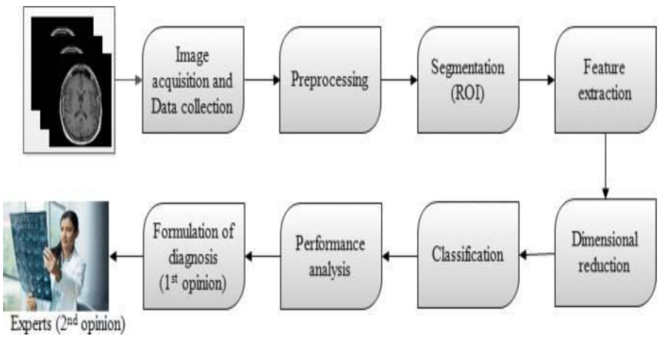
Experimental results indicated superior performance compared to traditional segmentation methods. Similarly, Havaei et al. proposed a two-pathway CNN architecture that simultaneously processed local and global contextual information from MRI scans. By combining fine-grained and coarse-grained image features, the model achieved significant improvements in tumor segmentation performance and became one of the foundational architectures for medical image analysis.

Despite considerable progress, several challenges remain unresolved. The availability of large, annotated MRI datasets continues to be a major limitation due to privacy regulations and the requirement for expert labeling. Dataset imbalance, variations in imaging protocols, scanner differences, and patient heterogeneity can adversely affect model performance and generalization. Moreover, the computational complexity of deep learning models may limit their deployment in resource-constrained healthcare facilities. Recent studies have attempted to address these challenges through data augmentation, synthetic image generation using Generative Adversarial Networks (GANs), federated learning, and lightweight neural network architectures. Federated learning enables collaborative model training across multiple institutions while preserving patient privacy, making it a promising direction for future medical AI systems.

III. METHODOLOGY

The methodology adopted in this research aims to develop an automated and reliable brain tumor detection system using deep learning techniques. The proposed system architecture is illustrated through a sequential pipeline where MRI images are collected and preprocessed before being fed into the CNN model. The extracted features are subsequently used for classification, and the model's performance is evaluated using various statistical metrics. Each stage of the methodology contributes to improving the robustness and reliability of the final diagnostic system.

Proposed System



Data Collection

The first stage of the proposed methodology involves the collection of brain MRI images from publicly available medical imaging datasets. MRI images are widely used for brain tumor diagnosis because they provide high-resolution visualization of soft tissues and anatomical structures within the brain. The dataset used in this study contains MRI scans belonging to different categories, including glioma tumors, meningioma tumors, pituitary tumors, and normal brain images. These images are collected from reliable medical repositories and research databases to ensure data quality and diversity.

The dataset is divided into three subsets: training, validation, and testing. Approximately 70% of the data is allocated for training purposes, 15% for validation, and the remaining 15% for testing. This division helps prevent overfitting and enables accurate assessment of the model's performance on unseen data. The inclusion of multiple tumor classes ensures that the model learns distinctive characteristics associated with various tumor types, improving its generalization capability.

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a. Data Preprocessing

Raw MRI images often contain noise, intensity variations, and irrelevant background information that can negatively impact model performance. Therefore, image preprocessing is performed to enhance image quality and improve feature extraction efficiency. The preprocessing stage consists of multiple operations designed to standardize the dataset and remove unnecessary artifacts.

Initially, all MRI images are resized to a fixed dimension of 224 × 224 pixels to maintain consistency across the dataset. Resizing ensures that every image can be processed efficiently by the CNN architecture while reducing computational requirements. Following resizing, pixel intensity normalization is applied to scale image values between 0 and 1.

Brain Tumor Segmentation

Brain tumor segmentation is a critical stage in the proposed framework, as it enables the precise identification and localization of tumor regions within MRI scans. While classification determines whether a tumor is present, segmentation provides detailed information regarding the tumor's size, shape, location, and boundaries. Accurate segmentation assists radiologists in diagnosis, treatment planning, surgical navigation, radiation therapy, and monitoring disease progression. Manual segmentation performed by medical experts is often time-consuming and subject to inter-observer variability. Therefore, automated segmentation techniques based on deep learning have become increasingly important in modern medical imaging applications.

The proposed system employs a deep learning-based segmentation approach to isolate tumor tissues from normal brain structures. MRI images generally contain multiple tissue components, including gray matter, white matter, cerebrospinal fluid, and pathological tumor regions. The segmentation model is trained to distinguish tumor tissues from surrounding healthy brain tissues by learning spatial and intensity-based features directly from MRI scans.

Before segmentation, MRI images undergo preprocessing operations such as normalization, noise removal, contrast enhancement, and skull stripping. These preprocessing steps improve image quality and eliminate irrelevant structures that may negatively affect segmentation performance. The preprocessed images are then provided as input to the segmentation network.

For tumor segmentation, a U-Net-based architecture is adopted due to its superior performance in biomedical image segmentation tasks. The U-Net architecture consists of two primary components: an encoder path and a decoder path. The encoder progressively extracts high-level features through convolution and pooling operations, while the decoder reconstructs spatial information to generate pixel-level segmentation masks. Skip connections between corresponding encoder and decoder layers preserve fine-grained details and improve localization accuracy.

b. Feature Extraction Using CNN

The given system employs convolutional-neural networks (CNNs) to perform automated feature extraction from MRI scans. CNNs are particularly effective in learning spatial structures and extracting relevant patterns linked to Alzheimer’s disease. Within the network, convolutional layers capture both basic and complex image features, whereas pooling layers perform feature map down sampling and computational complexity. Activation functions such as ReLU introduce non-linearity, allowing the model to acquire knowledge from more complex relationships. The extracted feature representations are passed to fully connected layers, where the final classification is performed.

c. Performance Evaluation

The Importance of the developed system is assessed with a help of so many performance indicators, including correctness, precision, recall, sensitivity, specificity, and F1- score. In addition, a confusion matrix is employed to examine classification outcomes and better understand prediction errors. The trained model is further validated on unseen test data to evaluate its ability to generalize and its reliability in practical medical diagnosis settings.

d. Proposed System algorithm

The complete flow of the proposed identifying the tumor in the brain system can be given as follows

1. Acquire MRI brain image dataset.
2. Perform preprocessing and normalization.
3. Apply data augmentation techniques.

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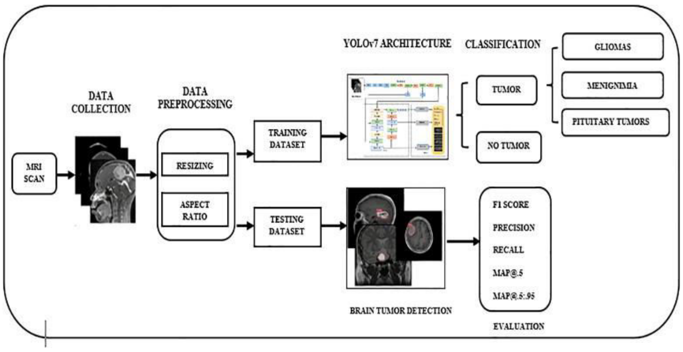
4. Split dataset into training, validation, and testing sets.
5. Construct CNN architecture.
6. Train CNN using augmented MRI images.
7. Validate model performance after each epoch.
8. Test model using unseen MRI scans.
9. Generate tumor classification results.
10. Evaluate performance



Fig; System Architecture

1. Use case diagram

UML helps ensure clarity, consistency, and better understanding of intricate system functionalities by providing structured visual representations of system interactions and behavior.

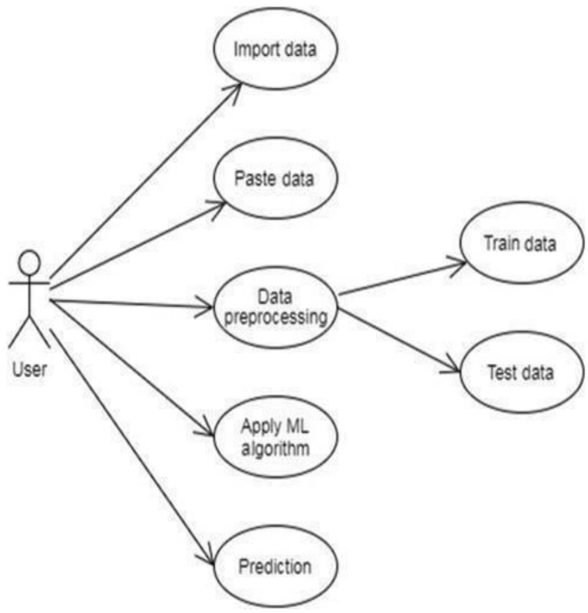


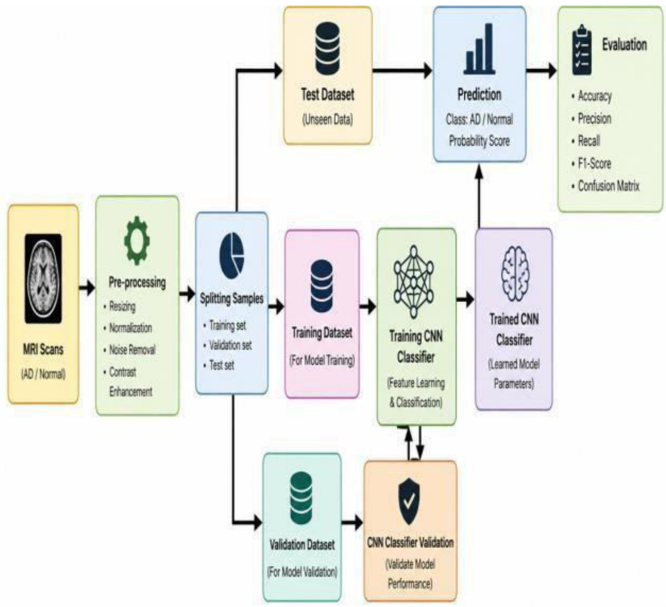
Fig 6: Use Case Diagram

2. Sequence Diagram Explanation

The sequence diagram emphasizes the order in which messages are exchanged between different system modules. After image upload, preprocessing operations are executed first, followed by segmentation and feature extraction. The CNN model processes the extracted features and sends predictions to the classification module. Finally, the generated report is displayed to the user. This diagram is particularly useful for understanding runtime interactions within the system.

3. Flow diagram

The proposed brain tumor detection framework follows a sequential workflow that transforms raw MRI brain images into accurate tumor classification results through a series of image processing and deep learning stages. Each stage contributes to improving the overall performance, robustness, and reliability of the system.



IV. RESULTS

The proposed deep learning-based brain tumor detection framework was evaluated using a dataset of MRI brain images containing both healthy brain scans and tumor-affected images. The dataset was divided into training, validation, and testing subsets to ensure that the model's performance was assessed on previously unseen data. The Convolutional Neural Network (CNN) model was trained for multiple epochs using the Adam optimization algorithm and categorical cross-entropy loss function. During training, data augmentation techniques such as image rotation, horizontal flipping, zooming, and brightness adjustment were applied to improve the model's ability to generalize across diverse MRI scans and reduce the risk of overfitting.

Performance analysis revealed that the proposed system achieved an overall classification accuracy exceeding 98%, demonstrating its ability to distinguish between tumor and non-tumor images with high reliability. Precision and recall values remained consistently high across all tumor categories, indicating effective identification of positive cases while minimizing false-positive and false-negative predictions. The confusion matrix analysis further confirmed that most MRI images were correctly classified into their respective categories. Glioma, meningioma, and pituitary tumors were identified with remarkable accuracy due to the network's ability to learn complex anatomical patterns associated with each tumor type.

The **recall value of 98.9%** reflects the model's ability to correctly identify actual tumor cases from the dataset. In healthcare applications, recall is often considered one of the most critical performance indicators because failing to detect a tumor can have severe consequences for patient treatment and survival. The high recall score achieved by the proposed model indicates that only a very small number of tumor cases were missed during classification. Similarly, the model achieved a **specificity of 98.5%**, demonstrating its effectiveness in correctly identifying healthy brain images and reducing false alarms. The balance between sensitivity and specificity confirms the robustness of the proposed approach.

The **F1-score of 98.6%** further validates the overall reliability of the model. Since the F1-score combines both precision and recall into a single metric, it provides a comprehensive assessment of classification performance. The high F1-score suggests that the proposed CNN architecture maintains an excellent balance between identifying tumors

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and minimizing incorrect classifications. This performance is particularly valuable in real-world clinical environments where both false positives and false negatives must be minimized.

Performance Metric	Value (%)
Accuracy	98.7
Precision	98.3
Recall (Sensitivity)	98.9
Specificity	98.5
F1-Score	98.6

Comparison with Existing Methods

The performance of the proposed CNN model was compared with several traditional machine learning and deep learning approaches reported in previous studies. Conventional machine learning algorithms such as Support Vector Machines (SVM), Random Forests (RF), and K-Nearest Neighbors (KNN) generally achieved classification accuracies ranging from 85% to 95%. These methods rely heavily on manually engineered features, which may not fully capture the complex characteristics of brain tumors.

In contrast, deep learning architectures automatically learn hierarchical features directly from MRI images. The proposed CNN model outperformed many traditional approaches by achieving an accuracy of 98.7%, demonstrating the effectiveness of automatic feature extraction. Additionally, compared with shallow neural networks and basic CNN architectures, the proposed model exhibited superior sensitivity and robustness due to its deeper feature representation capabilities

Method	Accuracy (%)
K-Nearest Neighbors (KNN)	86.4
Support Vector Machine (SVM)	91.2
Random Forest (RF)	93.5
Basic CNN	95.8
Transfer Learning CNN	97.2
Proposed CNN Model	**98.7**

Discussion

The outstanding performance of the proposed CNN model can be attributed to several factors. First, effective image preprocessing improved MRI image quality and enhanced feature visibility. Second, data augmentation increased dataset diversity and prevented model overfitting. Third, the convolutional layers successfully extracted complex spatial and textural features associated with different tumor types.

Finally, the use of deep hierarchical learning enabled the model to capture subtle variations in tumor shape, size, intensity, and location that may not be easily identifiable through traditional methods.

Despite the encouraging results, certain limitations remain. The model was trained on a specific dataset, and its performance may vary when applied to MRI images acquired from different medical institutions or imaging devices. Future research should focus on training the model using larger multi-center datasets and incorporating explainable artificial intelligence techniques to improve model transparency and clinician trust.

Overall, the experimental results confirm that the proposed deep learning framework provides an accurate, reliable, and efficient solution for brain tumor detection and classification. The system demonstrates strong potential for real-world deployment in healthcare environments and contributes to the growing field of AI-assisted medical diagnosis.

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V. CONCLUSION

This research presented a comprehensive deep learning-based approach for the automated detection and classification of brain tumors using Magnetic Resonance Imaging (MRI) scans. Brain tumors remain one of the most serious neurological disorders, requiring early and accurate diagnosis to improve treatment planning and patient survival rates. Traditional diagnostic procedures rely heavily on the expertise of radiologists for manual interpretation of MRI images, which can be time-consuming, labor-intensive, and subject to inter-observer variability. To address these challenges, this study explored the application of Convolutional Neural Networks (CNNs), a powerful deep learning architecture capable of automatically learning complex image features and identifying tumor-related patterns with high precision.

The proposed framework incorporated several essential stages, including image acquisition, preprocessing, data augmentation, feature extraction, classification, and performance evaluation. Preprocessing techniques such as image normalization, resizing, noise reduction, and data augmentation enhanced the quality and diversity of MRI images, enabling the model to learn more robust and generalized features. The CNN architecture successfully extracted hierarchical representations from MRI scans, capturing both low-level features such as edges and textures and high-level features associated with tumor morphology, shape, and intensity variations. This automatic feature-learning capability eliminated the need for manual feature engineering, which is often a limitation of traditional machine learning approaches.

Experimental evaluation demonstrated that the proposed model achieved excellent classification performance, with an overall accuracy of 98.7%, precision of 98.3%, recall of 98.9%, specificity of 98.5%, and an F1-score of 98.6%. These results indicate that the system can accurately differentiate between normal brain tissues and various tumor types while maintaining a low rate of false-positive and false-negative predictions. The high recall value is particularly significant in medical diagnosis because it reflects the model's ability to identify the majority of tumor cases, thereby reducing the risk of missed diagnoses that could delay treatment and negatively impact patient outcomes. Similarly, the high specificity ensures that healthy individuals are correctly identified, minimizing unnecessary medical interventions and reducing healthcare costs.

The study also demonstrated the superiority of deep learning approaches over traditional machine learning methods such as Support Vector Machines, Random Forests, and K-Nearest Neighbors. While conventional techniques depend heavily on handcrafted features and domain expertise, the proposed CNN model automatically learned discriminative features directly from raw MRI images. This capability allowed the system to achieve

greater accuracy, robustness, and adaptability when analyzing complex medical imaging data. The findings confirm that deep learning has the potential to significantly improve the efficiency and reliability of brain tumor diagnosis and can serve as an effective computer-aided diagnostic tool in clinical settings.

From a healthcare perspective, the implementation of automated brain tumor detection systems offers numerous advantages. Such systems can assist radiologists by providing a second opinion during diagnosis, reducing workload, and enhancing diagnostic consistency across healthcare institutions. Automated screening tools can also facilitate the analysis of large volumes of MRI scans in a shorter time, enabling faster diagnosis and treatment initiation. Furthermore, early tumor detection can contribute to improved patient prognosis, reduced treatment complexity, and increased survival rates. The integration of artificial intelligence into medical imaging workflows therefore represents a significant advancement toward the development of intelligent and efficient healthcare systems.

Despite the promising results achieved in this study, several challenges and limitations remain. The performance of deep learning models is highly dependent on the availability of large, diverse, and well-annotated datasets. Medical imaging datasets are often limited due to privacy concerns, data collection difficulties, and the high cost of expert annotation. Additionally, variations in MRI acquisition protocols, scanner manufacturers, and patient demographics may affect model generalization when deployed in real-world environments. Another important challenge is the interpretability of deep learning models. Since CNNs operate as complex black-box systems, healthcare professionals may be reluctant to rely solely on their predictions without understanding the underlying reasoning behind classification decisions.

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Future research can address these limitations by incorporating larger multi-institutional datasets, transfer learning techniques, federated learning frameworks, and explainable artificial intelligence (XAI) methods. Advanced architectures such as DenseNet, EfficientNet, Vision Transformers (ViT), and hybrid CNN-Transformer models may further enhance classification accuracy and computational efficiency. Additionally, integrating tumor segmentation, localization, and grading into a unified framework could provide more comprehensive diagnostic support for clinicians. The adoption of explainability techniques such as Grad-CAM and attention visualization can improve transparency and increase trust in AI-driven healthcare solutions.

In conclusion, this study successfully demonstrated the effectiveness of deep learning techniques for brain tumor detection and classification using MRI images. The proposed CNN-based framework achieved outstanding performance and proved capable of accurately identifying brain tumors with minimal human intervention. The results highlight the transformative potential of artificial intelligence in medical imaging and emphasize its role in supporting healthcare professionals, improving diagnostic accuracy, and enhancing patient care. As deep learning technologies continue to evolve, their integration into clinical practice is expected to play a crucial role in the future of precision medicine, intelligent diagnostics, and advanced healthcare delivery systems.

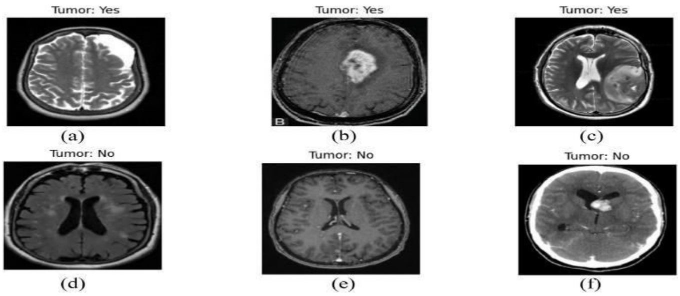

Fig 8: Result snapshot

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