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BRAIN TUMOUR DETECTION AND CLASSIFICATION USING MODIFIED YOLOV8 ON MRI AND X-RAY IMAGES

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Abstract - *Brain tumor detection plays a vital role in medical diagnosis, as early and accurate identification directly impacts patient treatment and survival. Traditional manual analysis of MRI images is time-consuming and depends heavily on expert radiologists, which may result in inconsistent diagnoses. To overcome these limitations, this paper presents an automated brain tumor detection system based on deep learning techniques. The proposed system uses a convolutional neural network–based model to detect and localize tumor regions in MRI images. Image preprocessing methods such as resizing and normalization are applied to improve detection accuracy. The system provides real-time predictions through a user-friendly interface, enabling faster and more reliable analysis. Experimental results show that the proposed approach effectively reduces diagnostic time while maintaining accurate tumor detection.*

Keywords: **Brain Tumor Detection, Medical Image Processing, Deep Learning, MRI Analysis, Convolutional Neural Network, Computer-Aided Diagnosis, Artificial Intelligence in Healthcare.**

1. INTRODUCTION

Brain tumors are among the most serious neurological disorders, often leading to severe health complications and, in critical cases, death if not detected at an early stage. A brain tumor occurs due to abnormal and uncontrolled growth of cells within the brain, which can disrupt normal brain functions such as memory, vision, and motor coordination. Finding problems early and getting the right diagnosis quickly is very important for making good treatment plans and helping patients live longer.

Magnetic Resonance Imaging, or MRI, is one of the most common ways to see inside the brain and find tumors because it shows soft tissues in great detail.. However, manual interpretation of MRI scans requires extensive expertise and careful observation by radiologists. This process is time-consuming and may be affected by human fatigue, subjectivity, and the complexity of tumor structures. In many healthcare facilities, especially in rural or under-resourced regions, the shortage of skilled medical professionals further increases the risk of delayed or inaccurate diagnosis.

Recent advancements in artificial intelligence (AI) and deep learning have shown significant potential in addressing these challenges. Deep learning models, especially convolutional neural networks (CNNs), can automatically learn complex patterns from medical images and do accurate classification and detection tasks. These models lessen the need for manual analysis and provide consistent results, making them suitable for medical image processing applications.

This paper proposes an automated brain tumor detection system using deep learning techniques to analyze MRI images efficiently. The system aims to detect and localize tumor regions with high accuracy while minimizing diagnostic time. By integrating intelligent image processing with a user-friendly interface, the proposed approach assists medical professionals in decision-making and supports early diagnosis. The implementation highlights the effectiveness of AI-based solutions in enhancing medical imaging analysis and improving healthcare outcomes.

II. SYSTEM ARCHITECTURE

The proposed brain tumor detection system is designed with a modular architecture to ensure accuracy, efficiency, and ease of use. It integrates MRI image acquisition, preprocessing, deep learning–based analysis, and result visualization to achieve automated and reliable tumour detection.

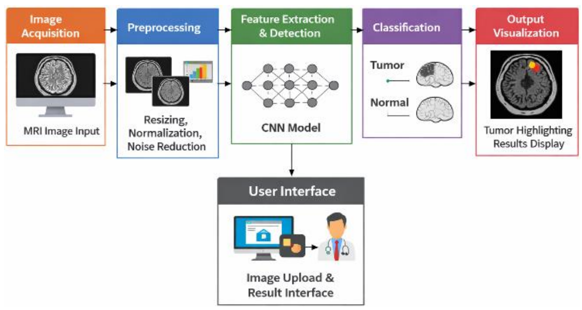

Fig. 2. System Architecture For Brain Tumor Detection

Image Acquisition Module

MRI brain images are collected from standard medical datasets or uploaded by users through the system interface. This module ensures compatibility with commonly used MRI image formats.

Preprocessing Module

The acquired images are pre-processed to enhance quality and consistency. Operations such as resizing, normalization, and noise reduction are applied to improve model performance and detection accuracy

Feature Extraction and Detection Module

A convolutional neural network is used to find important features from the images that have already been processed. This module detects and localizes tumor regions by learning discriminative patterns between normal and abnormal brain tissues.

Classification Module

Detected tumor regions are classified based on learned features. This classification provides meaningful diagnostic information that assists in preliminary medical assessment.

Output Visualization Module

The detection results are displayed by highlighting tumor regions on MRI images. Real-time visualization enables faster and clearer interpretation of results.

User Interface Layer

simple and user-friendly interface allows users to upload images and view results easily, ensuring smooth interaction with the system.

Overall, the system architecture enables efficient integration of deep learning with medical image analysis, providing fast, accurate, and practical brain tumour detection for healthcare applications.

III. RELATED WORK

Several studies have explored machine learning and deep learning techniques for brain tumor detection using medical images. Early methods used traditional image processing techniques like thresholding and segmentation,which provided basic tumor identification but were highly sensitive to noise and image variations. These approaches lacked robustness and were unsuitable for complex clinical environments. With the advancement of machine learning, classifiers like SVM, KNN, and decision trees were used for brain tumor classification. Even though these methods improved accuracy, they needed manual feature extraction and showed limited generalization across diverse MRI datasets. Deep learning models, particularly convolutional neural networks, later achieved better performance by automatically learning features from MRI images.

To overcome this limitation, object detection frameworks like Faster R-CNN, SSD, and YOLO were introduced in medical imaging. These models enabled simultaneous detection and classification with faster inference. Recent advancements in deep learning–based detection methods have further improved accuracy and processing speed. However, there is still a need for efficient and user-friendly systems suitable for real-world healthcare use. The proposed work addresses this gap by developing an automated brain tumor detection system that enhances accuracy and reduces diagnostic time.

IV. METHODOLOGY

The proposed brain tumor detection system follows a systematic methodology designed to ensure accurate analysis, efficient processing, and practical usability. The implementation is divided into multiple stages, starting from data acquisition to final result generation. Each stage contributes to the overall performance and reliability of the system.

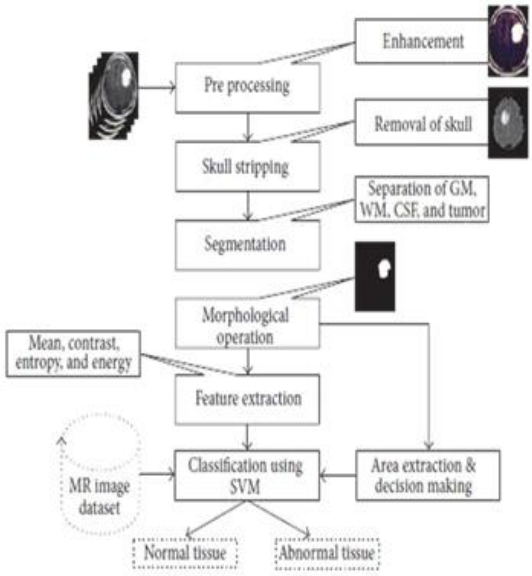

Fig. 3. blog diagram of brain tumor detection

Dataset Collection

The first step involves collecting MRI brain images from publicly available and authenticated medical datasets. The dataset includes both tumor-affected and normal brain scans, allowing the model to learn meaningful distinctions between healthy and abnormal tissues. The diversity of images in terms of resolution, contrast, and tumor appearance improves the generalization capability of the system.

Data Preprocessing

To enhance the quality of input data, preprocessing techniques are applied before model training. All MRI images are resized to a fixed resolution to maintain consistency. Pixel intensity normalization is performed to standardize image values, reducing the impact of illumination variations. In addition, noise reduction techniques are applied to eliminate irrelevant artifacts, enabling the model to focus on important tumor-related features.

Model Design and Training

A convolutional neural network–based deep learning model is employed for tumor detection and localization. The network automatically extracts hierarchical features from the preprocessed MRI images. During training, the model learns to identify discriminative patterns that differentiate tumor regions from normal brain tissues. Training is performed using optimized hyperparameters such as learning rate, batch size, and number of epochs to achieve stable convergence and improved accuracy.

Tumor Detection and Classification

Once trained, the model processes unseen MRI images to detect tumor regions. The detection module identifies the presence of abnormal regions, while the classification component categorizes the detected output as tumor or non-tumor. This combined approach provides both localization and classification, supporting effective preliminary diagnosis.

System Integration and User Interface

The trained model is integrated into a user-friendly application interface that allows users to upload MRI images and view results. The system generates real-time predictions and visually highlights detected tumor regions. This design ensures ease of use for medical professionals and reduces the time required for manual analysis.

Performance Evaluation

The system performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Testing is conducted on unseen MRI images to assess the generalization capability of the model. The evaluation results demonstrate the effectiveness of the proposed methodology in achieving reliable and efficient brain tumor detection.

V. RESULTS AND DISCUSSION

The proposed brain tumor detection system was evaluated using a separate test dataset to assess its performance on unseen MRI images. This evaluation ensured reliable measurement of the model's generalization capability. The system demonstrated effective tumor detection across different image samples.

Performance Evaluation

The model achieved strong performance in distinguishing tumor-affected images from normal scans. Evaluation metrics such as accuracy, precision, recall, and F1-score indicate reliable detection results. High recall values show the system's ability to identify tumor cases accurately, which is essential for medical diagnosis.

Detection and Localization

The system successfully localized tumor regions within MRI images by highlighting affected areas. This capability improves clinical relevance by providing clear visualization of tumor position and size. The model remained robust across variations in tumor shape and appearance.

Discussion

Compared to traditional manual analysis and classical machine learning methods, the proposed system reduces diagnostic time while maintaining consistent accuracy. By automatically learning features, it minimizes human dependency and supports radiologists in decision-making. Overall, the results demonstrate that the system is effective and suitable for practical healthcare applications, particularly in resource-limited environments.

Comparison with Traditional Methods

Compared to traditional manual analysis and classical machine learning techniques, the proposed system significantly reduces diagnostic time while maintaining reliable accuracy. Unlike conventional methods that rely on handcrafted features, the deep learning model automatically learns relevant features, resulting in improved consistency and reduced human dependency. This makes the system suitable for assisting radiologists in routine diagnostic workflows.

VI. CONCLUSION AND FUTURE WORK

Conclusion

This paper presented an automated brain tumor detection system based on deep learning techniques for efficient analysis of MRI images. The proposed approach successfully detects and localizes tumor regions while reducing reliance on manual interpretation. By integrating image preprocessing and a convolutional neural network–based model, the system provides accurate and consistent diagnostic support. Experimental results demonstrate that the system effectively reduces diagnostic time and supports early identification of brain tumors. The user-friendly implementation makes the proposed solution suitable for assisting medical professionals, especially in healthcare environments with limited access to specialized expertise.

Future Work

Although the proposed system shows promising results, several enhancements can be explored in future work. The performance of the model can be further improved by training on larger and more diverse MRI datasets to enhance generalization. Future extensions may include multi-class tumor classification, segmentation of tumor boundaries, and integration with clinical decision support systems. Additionally, deploying the system on cloud or mobile platforms can increase accessibility and real-time usage. Incorporating explainable AI techniques may also help improve transparency and trust in automated medical diagnosis.

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