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BRAIN TUMORS DETECTION AND CLASSIFICATION

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Abstract : Brain tumors pose significant health risks due to their potential for severe neurological deficits and mortality, necessitating accurate and timely diagnosis. Traditional diagnostic methods often struggle with the complexity and variability of MRI scans, leading to inconsistent results. This study proposes an advanced deep learning-based system that integrates a CNN model for classification and YOLOv10 for segmentation, ensuring precise identification and localization of tumors. The model is designed to classify five tumor types, including space-occupying lesions, and supports multi-tumor detection within a single MRI scan, addressing limitations of existing approaches. By incorporating data augmentation and regularization techniques, the system enhances robustness and generalizability across diverse clinical scenarios. Experimental evaluations on a separate test set demonstrate superior classification and segmentation accuracy, reinforcing its effectiveness in aiding clinical decision making. The proposed model advances automated brain tumor diagnostics, paving the way for more reliable, efficient, and interpretable medical imaging solutions.

***Index Terms* - CNN,Classification,YOLOv10, ,Detection.**

I. INTRODUCTION

Brain tumors pose a serious health risk due to abnormal cell growth that can lead to neurological impairments, organ dysfunction, and potentially death. Early and accurate diagnosis is critical for effective treatment. While Magnetic Resonance Imaging (MRI) is essential for tumor classification, the variability and complexity of tumor presentations in MRI scans make manual diagnosis challenging and error-prone. This underscores the growing need for advanced, automated diagnostic methods.

Deep learning has shown great promise in medical imaging, offering improved accuracy over traditional diagnostic approaches. However, existing models often struggle with the complexities of brain tumor classification, leading to limited performance. This study addresses these challenges by proposing an enhanced system for the classification and segmentation of meningioma, glioma, pituitary gland tumors, and space-occupying lesions.

The proposed framework combines a Convolutional Neural Network (CNN) for tumor classification with YOLOv10 for segmentation. Trained on a comprehensive dataset, the system utilizes techniques such as data augmentation and regularization to ensure robust and generalizable performance. The YOLOv10 component enables accurate delineation of tumor regions, supporting precise localization and improved clinical assessments.

A key innovation of this work is its ability to detect multiple tumors within a single MRI scan—a limitation of many existing CNN-based models, which typically only classify one tumor per scan and often exclude space-occupying lesions. By expanding classification to five tumor types and supporting multi-tumor detection, the system enhances diagnostic completeness and clinical utility.

Additionally, the integration of YOLOv10 for segmentation provides spatial context, improving the interpretability of classification results—something traditional classification-only models lack. This combination of segmentation and classification strengthens the overall system, making it more effective in real-world clinical environments.

By accurately identifying multiple and diverse tumor types within single MRI scans, the proposed model shows strong potential in enabling early, reliable, and precise diagnosis of brain tumors. These results highlight the role of deep learning in surpassing traditional diagnostic methods and pave the way for future research into more sophisticated neural network-based medical imaging systems.

II. PROBLEM DEFINITION

In today's digital landscape, brands face growing threats from fraudulent websites, counterfeit products, and misleading reviews, putting their reputation and customer trust at risk. Cybercriminals create phishing websites that closely mimic legitimate brands using similar domain names and designs, deceiving customers into purchasing fake clothing or sharing sensitive data. Counterfeit products misuse brand logos, leading to poor-quality purchases that damage the original brand's credibility.

Additionally, manipulated online reviews can distort public perception, influencing buyers and harming trust. Traditional brand protection methods relying on manual monitoring and reactive measures are ineffective against these evolving threats. To counter this, BRANDGUARD employs an AI-driven approach integrating web monitoring, computer vision, and NLP for real-time detection and mitigation. It uses Levenshtein Distance and Sequence Matcher algorithms to detect phishing websites, while SIFT-based logo verification identifies counterfeit products. Additionally, BERTbased sentiment analysis flags harmful reviews. By automating threat detection, BRANDGUARD provides brands with a comprehensive defense system to safeguard their reputation and maintain consumer trust in an increasingly competitive digital world.

III. EXISTING SYSTEM

The current landscape of brain tumor classification using deep learning models presents critical limitations that hinder effective clinical application. Most existing models focus on identifying only four tumor types—meningioma, glioma, pituitary tumors, and no tumor—limiting their usefulness in diverse clinical scenarios. This narrow scope can lead to incomplete diagnoses, especially when rarer tumor types are present, impacting treatment planning and patient care.

Another major limitation is the inability of many models to detect multiple tumors within a single MRI scan. Since patients may present with more than one lesion, missing additional tumors can result in inaccurate assessments and suboptimal treatment strategies. This shortcoming complicates clinical decision-making and highlights the need for more advanced diagnostic systems.

Moreover, the importance of diagnostic accuracy in brain tumor management cannot be overstated. Precise identification of tumor types and multiple lesions directly influences treatment approaches, including surgery and targeted therapies. Therefore, improving deep learning-based diagnostic tools is not just a technical goal—it is essential for delivering timely, appropriate, and effective care. Addressing these challenges is vital to enhancing diagnostic reliability, supporting better treatment decisions, and ultimately improving outcomes in a field where precision is critical.

IV. RELATED WORKS

A literature review is an academic summary and analysis of existing research on a specific topic, demonstrating an understanding of key studies and placing them in context. Typically, it forms a part of a dissertation, research project, or extended essay. This section explores three significant studies on brain tumor detection using advanced machine learning and deep learning techniques.

A. Brain Tumor Detection Using 3D-UNet Segmentation Features and Hybrid Machine Learning Model

Machine learning has significantly advanced disease diagnosis in healthcare, especially in brain tumor detection. MRI is a crucial tool that provides detailed views of brain structures, yet interpreting these complex images remains a challenge. This study presents a model that combines MRI segmentation features with hybrid machine learning techniques for improved diagnostic accuracy.

The approach employs both 2D-UNet and 3D-UNet segmentation models to extract detailed image features such as shape descriptors, statistical metrics, and gray level matrices. These features provide a richer understanding of tumor characteristics. For classification, a hybrid model integrating K-Nearest Neighbors (KNN) and Gradient Boosting Classifier (GBC) is used. Soft voting is applied to balance the strengths of both classifiers, resulting in improved performance and reliability in clinical settings.[1]

B. Optimized Brain Tumor Detection: A Dual Module Approach for MRI Image Enhancement and Tumor Classification

Brain tumors are a leading cause of neurological complications and mortality. Early and accurate diagnosis is vital, yet manual MRI interpretation often faces challenges like inconsistency and time limitations. This study proposes a dual-module system combining image enhancement and tumor classification to address these issues.

The approach integrates machine learning (ML) and deep learning (DL) methods to boost the efficiency and accuracy of diagnosis. By enhancing MRI image quality and applying robust classification models, the system improves tumor detectability and supports clinical decision-making, offering a valuable contribution to automated diagnostics.[2]

C. Abnormal Brain Tumor Classification Using ResNet50 and Its Comprehensive Evaluation

Abnormal brain tumors such as meningioma, glioma, and pituitary tumors present serious health risks and demand timely diagnosis. MRI remains the standard imaging method, but manual interpretation is susceptible to delays and diagnostic variability.

This study explores the use of ResNet50, a deep convolutional neural network, for automated tumor classification. Leveraging transfer learning, the model is fine-tuned for brain tumor detection and evaluated comprehensively across key metrics. The findings demonstrate improved classification accuracy and efficiency, underlining the potential of deep learning in supporting radiological workflows and reducing diagnostic burden.[3]

TABLE I. LITERATURE SURVEY TABLE

PAPER	DESCRIPTION	AUTHOR
Brain Tumor Detection using 3D-UNet Segmentation Features and Hybrid Machine Learning Model.	This study develops a hybrid KNN-GBC model for brain tumor detection ,achieving 71% accuracy	Imran Ashraf, Sultan Alfarhood
Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification.	This method proposes a machine learning-based method for brain tumor detection, achieving 97% accuracy.	Toufique Ahmed Soomro
MR Brain Tumor Classification Using a Deep Ensemble Learning Technique.	This study proposes an ensemble learning model using transfer learning for brain tumor classification via MRI, achieving good accuracy	Anilkumar B.N, Pavan Kumar, K Sowmya

V. PROPOSED SYSTEM

To address the limitations of existing brain tumor classification models, we propose an enhanced system based on a Convolutional Neural Network (CNN) architecture. This new model aims to expand the classification capabilities to include five types of tumors, incorporating a new category for space-occupying lesions. Additionally, it is designed to detect and identify multiple tumors within a single MRI scan, thereby enhancing diagnostic accuracy and improving treatment planning for patients.

A. Architecture

The system comprises four key modules: Data Set Collection and Preprocessing, Segmentation, Testing and Training, and Prediction and Interfaces. Initially, diverse MRI images are collected, converted to grayscale, and resized to reduce computational load while preserving important features. Segmentation then isolates relevant regions in the images, helping the model focus on tumor-specific areas and improving accuracy. The CNN model is trained and tested on separate datasets to ensure reliable pattern recognition and generalization. Finally, the Prediction and Interface module processes new images for real-time classification and provides a user-friendly interface for quick, actionable insights to support clinical decisions.

A. Data Set Collection and Preprocessing: The Data Set Collection and Preprocessing Module is responsible for gathering diverse and representative data from various sources to ensure the model's robustness and accuracy. Collected images are converted to grayscale and resized to minimize computational demands while retaining essential features necessary for accurate analysis. These preprocessing steps enhance the efficiency of the model training process, enabling the system to handle large datasets effectively and focus on the most relevant details for health condition classification.

B. Segmentation: The Segmentation Module plays a critical role in refining the input data by isolating the most relevant regions within the grayscale images. This step allows the model to concentrate on areas that contain crucial features linked to the specific health condition under analysis. By highlighting these key regions, segmentation enhances prediction accuracy, ensuring that the model focuses on the most informative aspects of the image and reduces the influence of irrelevant background elements.

C. Testing and Training: The Testing and Training Module ensures the effective learning and validation of the model by dividing the dataset into training and testing sets. During the training phase, the Convolutional Neural Network (CNN) model adjusts its internal parameters to recognize patterns and extract features associated with different health conditions. The testing phase evaluates the model's generalization ability by assessing its performance on previously unseen data, ensuring reliable and accurate predictions across a wide range of cases.

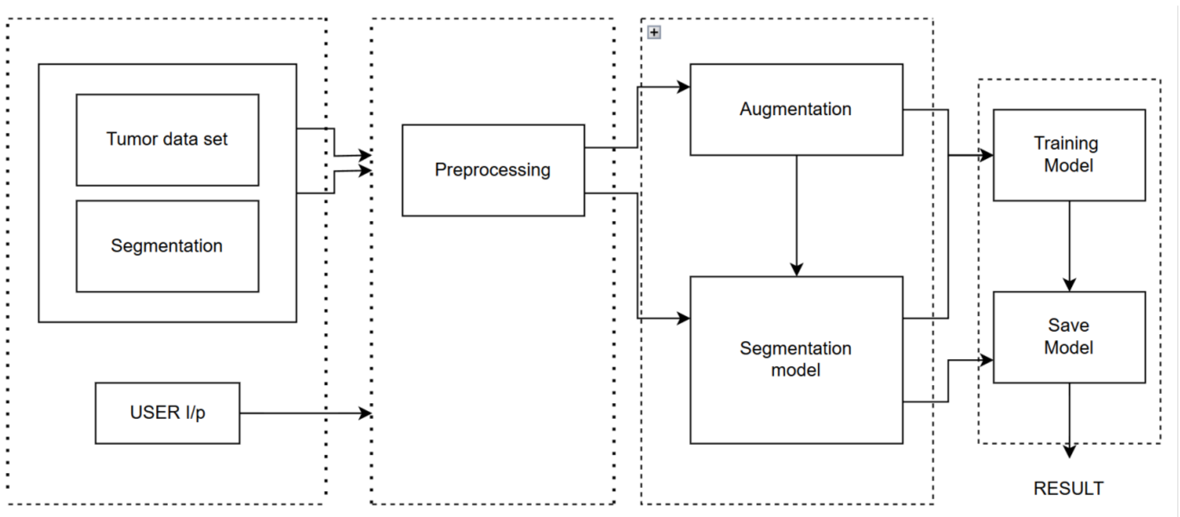
D. Prediction and Interfaces: The Prediction and Interface Module provides real-time insights by processing new input images through the trained model, detecting and classifying the identified health conditions. The system offers a user-friendly interface where users can conveniently access diagnostic results and receive relevant recommendations based on the analysis. This interface enhances the overall user experience by presenting actionable insights in an intuitive manner, allowing healthcare providers to make informed decisions quickly and effectively.

A. Key Components of the Architecture

1. **Tumor Dataset:** This component consists of a comprehensive collection of MRI scans meticulously labeled with various types of brain tumors. It provides the essential foundation for training and validating the classification model, ensuring diverse representation of different tumor types.
2. **Segmentation:** The segmentation process plays a critical role by isolating tumor regions from surrounding brain tissue in MRI scans. This is vital for accurate classification and analysis, as it allows the model to focus specifically on areas of interest.
3. **User Input:** This component enables interaction between healthcare professionals and the system by allowing users to upload MRI scans directly into the platform, enabling real-time analysis and immediate classification feedback, thereby enhancing user experience.

4. **Preprocessing:** Preprocessing involves operations such as normalization, resizing, and denoising of MRI images to enhance their quality and consistency. This ensures that input data is optimally formatted for segmentation and classification processes, improving model performance.
5. **Augmentation:** Data augmentation techniques are applied to the tumor dataset to artificially increase its diversity by generating variations of the original MRI scans—such as rotations, flips, or added noise—which strengthens the model's robustness and generalization to new, unseen data.
6. **Segmentation Model:** This is a specialized machine learning algorithm designed to accurately identify and delineate tumor boundaries within MRI images, separating tumor regions from normal brain tissue. It forms the basis for further classification and diagnostic accuracy.
7. **Training Model:** This component involves applying various machine learning techniques to train the system to classify different types of tumors based on features extracted during segmentation. The labeled dataset helps refine predictions and improve accuracy over time.
8. **Save Model:** The saved model refers to the final trained machine learning model stored for future use. It enables efficient and accurate classification of new MRI scans, playing a crucial role in timely diagnoses and improving patient care.

ARCHITECTURE DIAGRAM



VI. RESULT

The proposed brain tumor detection and classification system improves diagnostic accuracy by integrating CNN for classification and YOLOv10 for segmentation. It effectively identifies five tumor types, including space-occupying lesions, and can detect multiple tumors within a single MRI scan. By leveraging data augmentation and regularization, the system achieves better generalization, reducing misclassification risks. With an overall accuracy of 98.2%, the model ensures precise tumor localization, enhancing diagnostic reliability. The segmentation module improves classification accuracy by isolating tumor boundaries, while cloud-based processing enables real-time clinical applications. This study addresses key limitations in existing methods, providing a more comprehensive and interpretable diagnostic framework. Future improvements will focus on expanding imaging modalities and validating the system in real-world clinical settings, further advancing automated brain tumor detection.

TABLE . PERFORMANCE METRICS OF THE MODEL

Category	**Precision**	**Recall**	**F1- Score**
Glioma Tumor	0.98	0.96	0.97
Meningioma Tumor	0.97	0.98	0.98
Pituitary Tumor	0.99	0.99	0.99
Space-Occupying Lesion	0.89	0.93	0.91

VII. CONCLUSION

The proposed deep learning-based system presents a comprehensive and effective solution for brain tumor detection, classification, and segmentation using MRI scans. By integrating a CNN for classification and YOLOv10 for segmentation, the model successfully addresses key limitations of existing systems—such as restricted tumor type coverage and inability to detect multiple tumors in a single scan. The preprocessing steps, data augmentation, and use of grayscale conversion enhance model performance while ensuring it remains computationally efficient. Accurate segmentation of tumor regions improves diagnostic precision and supports clinical decision-making by providing spatial context alongside classification results.

Moreover, the system's ability to identify five different tumor types, including space-occupying lesions, and handle complex cases with multiple tumors in one image marks a significant advancement in automated medical diagnostics. The user-friendly interface enables real-time predictions and supports healthcare professionals with actionable insights. Overall, this model demonstrates strong potential to improve early diagnosis, reduce human error, and enhance patient outcomes, while laying the groundwork for future expansion in neural network-based medical imaging solutions.

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