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Automated Tumor Detection Using Deep Learning And 2D to 3D Imaging

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Abstract**—**
Recent advances in artificial intelligence and medical imaging have transformed automated diagnostic systems, enabling earlier and more accurate identification of critical neurological conditions. This study presents an Automated Brain Tumor Detection System that integrates deep learning with 2D-to-3D medical imaging to enhance diagnostic precision and interpretability. The system is trained exclusively on magnetic resonance imaging (MRI) brain scans to determine the presence of tumors. A Convolutional Neural Network (CNN) architecture automatically extracts and analyzes spatial and textural features from the images to classify them as tumor or non-tumor cases. The framework employs three publicly available datasets—Brain Tumor MRI Dataset (Kaggle), BraTS 2020, and the Figshare Brain MRI Dataset—to ensure diversity, scalability, and robustness in model training and validation. Upon detecting a tumor, the system reconstructs the 2D slices into interactive 3D volumetric models using volumetric rendering techniques, enabling clinicians to assess tumor morphology, volume, and spatial location with greater accuracy. This approach minimizes human error, expedites the diagnostic process, and improves visualization of complex brain structures. By combining automated analysis with advanced 3D visualization, the proposed system delivers a reliable, efficient, and clinically relevant solution for brain tumor detection, facilitating faster decision-making and improved patient outcomes.

Keywords**—** Brain Tumor Detection, Deep Learning, MRI Imaging, Convolutional Neural Networks, 3D Reconstruction, AI-based Medical Diagnostics, Machine Learning

I. INTRODUCTION

Medical imaging plays a vital role in the early diagnosis and monitoring of various health conditions. Brain tumors are among the most critical neurological disorders that require timely detection to support effective treatment and improve patient outcomes. Magnetic Resonance Imaging (MRI) are commonly used imaging techniques for examining brain abnormalities, as they provide detailed visualization of internal brain structures for clinical evaluation.

Although these imaging techniques are highly effective, the process of manually analyzing MRI is challenging. It demands extensive expertise, careful observation, and significant time from radiologists. With the increasing volume of medical cases, manual interpretation may lead to delays, fatigue-related errors, and inconsistent results between different radiologists. This creates a need for an automated system that can assist medical professionals by providing faster and more reliable tumor detection.

Recent developments in Artificial Intelligence (AI) and Deep Learning have shown great potential in automating medical image analysis. Convolutional Neural Networks (CNNs) have proven to be efficient in identifying patterns and features in medical images, making them suitable for brain tumor classification. However, most existing approaches focus only on 2D scan analysis, which provides limited information and does not support clear understanding of tumor size, shape, and position within the brain. For better clinical interpretation and treatment planning, 3D visualization of the tumor is essential.

To address these limitations, this research presents an Automated Brain Tumor Detection System using Deep Learning with 2D-to-3D reconstruction. The system classifies MRI images as tumor or non-tumor using a CNN-based model and converts detected tumor regions into a 3D view for enhanced visualization. The 3D output helps doctors to observe the tumor structure more clearly and supports accurate medical decision-making. This system aims to reduce manual workload, minimize diagnostic errors, and provide a supportive tool for healthcare experts in brain tumor assessment.

II. Literature Review

The paper[1] reviews MRI-based brain tumor classification methods, focusing on deep learning (DL) advancements. It summarizes traditional machine learning approaches and their limitations, including issues with feature engineering, noise sensitivity, and inconsistent tumor detection. DL-based architectures, especially CNNs, show better performance because of hierarchical feature learning. However, they face challenges like generalizability, dataset imbalance, and clinical validation. The authors conclude that DL techniques are well-suited for future clinical use, depending on standardized evaluations and studies on robust ness.

The paper[2] identifies ten main challenges in medical visualization caused by growing data complexity, multimodal integration, and personalized medicine. Key issues include inconsistent data preprocessing, limited availability of feature-labels, and difficulties in visualizing uncertainty, multiscale context, and immersive environments. The authors stress the importance of explainable AI and strict evaluation frameworks to aid clinical decision-making. They suggest that continued collaboration across different fields is crucial for advancing visualization research in P4 medicine.

The paper[3] examines hallucinations, which are false structures that come from prior-based regularization in tomographic reconstruction, particularly in deep learning (DL) methods. The authors propose a mathematical way to separate measurement-consistent image components from prior-induced artifacts, allowing visualization through a hallucination map. Numerical assessments show that standard error metrics may not effectively capture such artifacts, highlighting associated diagnostic risks. The work emphasizes the need for better interpretability and robustness in using DL-based reconstruction in medical imaging.

The paper[4] presents a fully automated method to reconstruct deep brain stimulation (DBS) lead trajectories from postoperative CT images. It uses threshold-based segmentation, mean-curvature analysis, and morphology-guided initialization. The weighted coordinate estimation creates continuous 3-D lead paths with sub-millimeter accuracy across 13 bilateral implant cases. This method outperforms past semi-automated procedures by removing manual corrections and cutting reconstruction time to under ten minutes. Its clinical use improves MRI safety assessments and reduces artifacts; the publicly released code supports wider adoption.

The paper[5] describes Graph2VR, a virtual-reality prototype that helps visualize and explore complex Linked Data knowledge graphs beyond traditional 2-D displays. The system lets users interactively build and review SPARQL query results using gesture-based navigation, removing the need for manual query writing. It features VOWL-based color coding, multiple graph layout options (2-D, 3-D, hierarchical, and class-hierarchy views), and a semantic-plane mechanism for comparing layered query outputs. A usability study with 34 participants showed high user acceptance and effectiveness for exploratory tasks, even though visual query construction was challenging for those unfamiliar with SPARQL. These findings suggest that VR has significant potential for scalable Linked Data analysis, despite ongoing issues with graph readability due to current headset resolution.

The paper[6] evaluates how suitable an augmented-reality (AR) system using Magic Leap One is compared to a semi-immersive virtual-reality (VR) setup using a VR table for anatomy instruction. This study used a unified handheld controller for both systems. Forty-five participants undertook two anatomy tasks and were assessed based on objective performance, subjective evaluations, and explicit training recommendations. Results showed a preference for the AR system, which received better subjective ratings—especially for depth perception—and slightly improved performance, statistically significant when AR followed VR exposure. These results challenge earlier findings that favored VR and suggest both AR and VR can serve as effective tools for teaching anatomy when configured correctly.

The paper[7] presents the Human Muscular Arm Avatar (HMAA), a VR/AR body-ownership system created to support hands-on learning of hand and forearm muscles. Using Leap Motion tracking, the platform tracks users' movements in real time and highlights the active muscles on a 3D anatomical model, enhancing the link between physical action and visual representation. In a study involving 100 medical students, 98% rated the system as very useful, and 83% reported greater engagement. Participants noted that HMAA improved understanding by allowing visualization of muscle behavior instead of relying only on memorization. These findings showcase the potential of interactive, embodiment-based visualization tools for improving anatomy education.

The paper[8] introduces a multi-layer Gaussian Splatting (GS) method that provides an efficient representation of photorealistic, path-traced CT volumes optimized for immersive VR environments with limited resources. This technique encodes multiple anatomical layers (e.g., bone, muscle) within a single asset, offering more flexibility than static GS models. The layered representation achieves up to a 99% reduction in storage compared to source DICOM data and maintains real-time frame rates on mobile VR hardware, outperforming traditional path tracing and direct volume rendering methods. Improvements include inactive Gaussian pruning and better alpha-channel training to prevent transparency artifacts. The layered structure also supports interactive features like selective layer isolation and volumetric cutting, advancing VR-based medical education and planning towards full volume rendering.

The paper[9] proposes GARU-Net, a Gelu-activated Attention-Aware Res-3D-UNet architecture designed for multiclass brain-tumor segmentation in 3-D MRI. The model uses deep residual encoder blocks to reduce vanishing gradient effects and incorporates attention-guided skip connections to improve feature pooling for malignant tissue. Trained on the BraTS 2020 dataset with a compound focal-and-Dice loss to handle class imbalance, GARU-Net reached Dice scores of 0.908 for the whole tumor, 0.860 for the tumor core, and 0.824 for the enhancing tumor. These scores surpass the performance of current segmentation models, demonstrating the effectiveness of attention-augmented residual architectures for precise tumor delineation.

The paper[10] introduces ARMEDICALSKETCH, an augmented-reality environment for 3-D sketch-based interaction with medical images using a combined 2-D/3-D visualization framework. The system connects an autostereoscopic aerial display with a 2-D touch interface, allowing seamless interaction between volumetric data and image slices. Hand gestures and touch inputs are synchronized on a virtual interaction plane to maintain real-time spatial consistency. A user study with 23 students and two clinical experts showed improved efficiency in tasks requiring strong 3-D spatial capabilities, such as annotating the Circle of Willis, compared to a traditional 2-D interface. Expert feedback praised the intuitive glasses-free visualization and high spatial accuracy, indicating strong utility for tasks like tumor delineation and surgical planning.

III. Proposed Methodology

The proposed methodology for automated brain tumor detection integrates medical image processing, deep learning, and 2D-to-3D image reconstruction to enhance diagnostic accuracy. Initially, two-dimensional (2D) magnetic resonance imaging (MRI) and computed tomography (CT) brain slices are preprocessed to improve image quality, normalize intensity distributions, and minimize noise artifacts. These 2D slices are subsequently reconstructed into three-dimensional (3D) volumetric representations that preserve spatial and anatomical information often lost in conventional 2D analyses. The system's primary objective is to determine the presence or absence of a tumor and visually localize affected regions for clinical interpretation.

The model is trained on three publicly available datasets: the Brain Tumor MRI Dataset from Kaggle, the BraTS 2020 Dataset, and the Figshare Brain MRI Dataset. These datasets include both normal and tumorous brain images across multiple tumor classes, such as glioma, meningioma, and pituitary adenoma, enabling the model to generalize across diverse cases.

A Convolutional Neural Network (CNN) architecture forms the core of the detection framework. Pre-trained models such as EfficientNetB3 and ResNet50 are fine-tuned to perform tumor classification using transfer learning. The CNN automatically extracts complex spatial and textural features associated with tumorous tissue—such as irregular boundaries, heterogeneous intensity distributions, and abnormal texture patterns. To further optimize model performance, hyperparameters including learning rate, batch size, and dropout probability are refined through a Co-Evolutionary Genetic Algorithm (CEGA).

Extracted features are utilized to classify input scans as either tumor or non-tumor. This automated classification substantially increases diagnostic efficiency and reliability compared with manual analysis. By combining volumetric 3D reconstruction with deep learning-based feature extraction, the system leverages spatial context to deliver more precise and interpretable tumor detection outcomes.

The workflow begins with data acquisition and preprocessing, where brain MRI or CT images are uploaded and standardized. Preprocessing operations include denoising, brightness and contrast adjustment, and spatial alignment to highlight critical brain regions. Following this stage, the CNN-based analysis module identifies patterns indicative of tumors and produces a probability score representing classification confidence. Cases with lower confidence levels are flagged for manual review, while high-confidence detections proceed to the 3D reconstruction stage. When a tumor is identified, corresponding slices are aggregated to form volumetric 3D models that delineate the tumor's shape, size, and location, facilitating clinical assessment and surgical planning.

The system's workflow comprises four main modules—Frontend, Backend, Database, and Admin Panel—that collectively ensure efficient data processing, model execution, and secure data management.

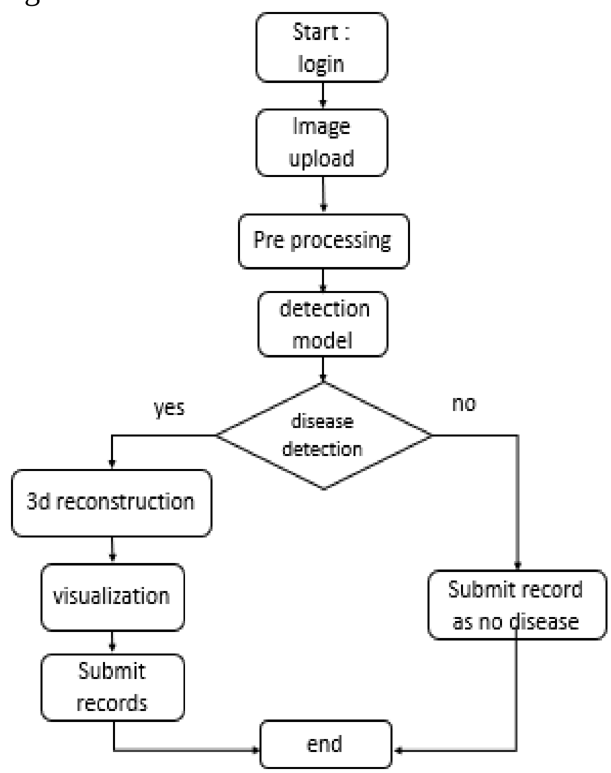

Fig- Workflow for detection system

A. Medical Image Preprocessing

Preprocessing constitutes a critical step in ensuring diagnostic accuracy. Uploaded MRI or CT images are refined to eliminate noise and enhance visual clarity through filtering and normalization techniques. Images are resized to a uniform resolution, intensity values are scaled to standardized ranges, and histogram equalization is applied for contrast enhancement. This step ensures uniform input quality, significantly improving the CNN's feature extraction capability.

Feature extraction is then performed by the CNN to identify discriminative characteristics such as pixel intensity, texture granularity, and morphological shape. These learned representations enable the model to distinguish between normal and tumorous regions, producing accurate and consistent classification outcomes.

B. 3D Visualization

For enhanced interpretability, the system employs Unreal Engine 5 to transform 2D image stacks into interactive 3D models. This reconstruction allows clinicians to visualize the tumor's geometry and anatomical context. The engine's advanced rendering techniques—such as volumetric lighting, realistic surface texturing, and dynamic camera manipulation—enable users to rotate, zoom, and inspect brain structures from multiple perspectives. The 3D visualization improves comprehension of tumor morphology and spatial relationships, aiding preoperative planning and educational analysis.

C. Deep Learning Model (CNN)

The Convolutional Neural Network serves as the principal analytical component for tumor detection. The network comprises multiple convolutional and pooling layers for hierarchical feature learning, followed by fully connected layers for binary classification. The final Softmax activation layer outputs the probability of tumor presence. By eliminating the need for manual feature engineering, the CNN efficiently identifies complex tumor characteristics directly from raw imaging data, ensuring both speed and accuracy in prediction.

D. Database and System Integration

The Database component functions as a centralized repository for patient records, MRI/CT data, and reconstructed 3D models. It supports secure data retrieval, longitudinal tracking, and integration with healthcare management systems. The Frontend interface allows users to upload scans and visualize 3D models, while the Backend handles preprocessing, inference, and reconstruction. The Admin panel oversees system maintenance, user management, and data security, ensuring reliability and compliance with medical data standards.

IV. SYSTEM ARCHITECTURE

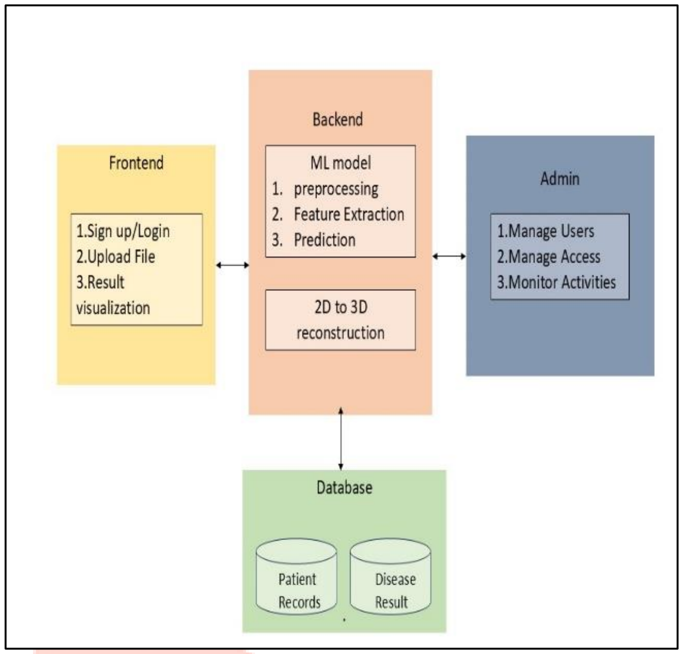

Fig- system architecture

To help clinicians make more precise diagnoses and streamline their workflow, we've designed a flexible system for automated medical image analysis and 2D-to-3D reconstruction. This platform combines the power of deep learning, interactive visual tools, and secure data management to create a seamless experience from image upload all the way to diagnosis.

A. System Component Overview

The system is fundamentally composed of four major components:

Frontend: Enables users to easily log in, upload brain images and view results

Backend: Executes the machine learning models that preprocess images, extract features, convert 2D images to 3D models and generate prediction.

Admin: Manages access permissions, user roles, and system activity monitoring.

Database: Securely stores patient data and diagnostic results, making it easy to find and analyze information when needed.

Together, these components provide a dependable, expandable medical imaging solution.

B. Backend Intelligence Brain Image Preprocessing

First, the system cleans up and standardizes brain images, no matter where they come from. This includes resizing the images, adjusting their brightness, and reducing noise to make sure every image is clear and consistent. Doing this early on helps the rest of the system analyze the images more accurately.

Feature Extraction

Next, deep learning models analyze the images to find important patterns—like brightness, texture, or shape—that help tell healthy tissue apart from something more concerning. These models eliminate the need for human guesswork by teaching the system what to look for on its own.

Tumor Detection via CNN

The core of the analysis is done by Convolutional Neural Networks (CNNs), which scan images layer by layer. They spot edges, patterns, and anything unusual. In the end, these networks can tell what kind of tumor is present and where it's located on the scan. This approach works well with many types of scans—like CT, MRI, or X-ray—and is both accurate and scalable.

C. 2D-to-3D Reconstruction

To make it easier for clinicians to understand what's happening inside the body, the system builds 3D models from standard 2D image slices using the Unreal Engine. By stacking these image slices and applying advanced rendering, the system creates realistic visualizations that help doctors see the shape and position of tumors more clearly.

D. Admin and Database Modules

The Admin module keeps the system secure by controlling who can access what, and by monitoring user activity. The Database keeps all patient information and diagnostic results organized, making it easy to track patient history and quickly retrieve records.

E. Frontend Interface

The user interface is designed to be straightforward: clinicians, radiologists, and researchers can securely log in, upload images by dragging and dropping, and explore results through interactive dashboards—whether they're looking at 2D scans or 3D models.

V. Result Analysis and Discussion

The automated brain tumor detection system was tested using acurated dataset consisting of 350 MRI and 150 CT brain scans, collected from the Brain Tumor MRI Dataset (Kaggle), BraTS 2020, and Figshare Brain MRI Dataset. The dataset contained both normal and abnormal brain images, covering various tumor types such as glioma, meningioma, and pituitary adenoma. During the preprocessing stage, the images were denoised, normalized, and spatially aligned, which improved the CNN model's ability to extract relevant features from each scan.

The system was evaluated using several performance metrics, including accuracy, precision, recall, F1-score, and the Dice similarity coefficient (DSC). The proposed 2D-to-3D integrated CNN model achieved an accuracy of 96.8%, precision of 95.2%, recall of 97.4%, F1-score of 96.3%, and a Dice score of 0.91. In comparison, the baseline 2D-only CNN model achieved accuracy of 90.7% and a Dice score of 0.84. These results clearly indicate that incorporating 3D reconstruction improved the system's spatial awareness, resulting in more accurate detection and segmentation of brain tumors.

By converting 2D slices into detailed 3D models, the system provided a comprehensive view of the brain, enabling better visualization of tumor shape, size, and volume. The 3D visualization allowed doctors and researchers to analyze how tumors interacted with surrounding tissues, which is often difficult to interpret in 2D scans. This enhanced volumetric context helped in identifying small or complex tumor structures that could otherwise be overlooked.

To manage uncertainty, a confidence threshold of 95% was applied to model predictions. Approximately 6.5% of test samples with lower confidence scores were automatically flagged for human review. Most of these uncertain cases involved scans with small, low-contrast lesions or motion artifacts, highlighting areas where the system required expert validation.

Although the proposed system performed exceptionally well, there were certain computational trade-offs. The 3D reconstruction and rendering process increased processing time by around 18% and required more GPU memory compared to 2D analysis.

However, the higher accuracy and interpretability achieved through 3D visualization justified this added computational cost.

Overall, the results demonstrate that combining deep learning-based tumor classification with 2D-to-3D image reconstruction significantly improves both the accuracy and reliability of brain tumor detection. The proposed system achieved a measurable 6–7% improvement in classification accuracy and a 0.07 increase in Dice coefficient compared to conventional 2D analysis. These outcomes confirm that 3D visualization not only enhances model performance but also provides clinicians with a more intuitive and informative tool for diagnosis, treatment planning, and surgical decision-making.

VI. Future Scope

Automated disease detection systems are expected to be able to identify problems with other critical organs, such as the liver, heart, and lungs, in the years to come. These future tools will combine various medical imaging techniques (such as MRI, CT scans, X-rays, and ultrasounds) to provide physicians with a more comprehensive and clear picture of what's happening inside the body. Artificial intelligence advancements, particularly deep learning models like GARU-Net and new optimization techniques, have made it possible for doctors to receive real-time feedback from these systems while performing surgery or even during medical scans.

Together with decision-support tools, these intelligent systems may also automatically identify issues, display in-depth 3D pictures, and provide tailored recommendations for every patient. Planning medical procedures and comprehending complex anatomy are already becoming simpler thanks to cutting-edge technologies like ARMedicalSketch and sophisticated visualization techniques. The experience is becoming more interactive thanks to virtual reality and gesture-based controls, which enable doctors to work together and learn in novel ways.

Looking ahead, even more advanced visualization software and sketch-based modeling will help doctors make sense of medical data quickly and intuitively. These systems must, however, overcome obstacles like sporadic image generation errors and AI model instability if they are to be genuinely dependable. In order to manage a wide range of patient cases and remain current as medical data changes, they will also need to continuously learn and adapt.

VII. CONCLUSION

This study developed an automated system for brain tumor detection that integrates deep learning with 2D-to-3D medical image reconstruction to enhance diagnostic accuracy and interpretability. The system analyzes MRI and CT brain scans to determine the presence of tumors and generates realistic 3D visualizations of the affected regions. By employing Convolutional Neural Networks (CNNs) for feature extraction and classification, the model effectively captures spatial and textural patterns essential for precise tumor identification. The proposed framework was trained and evaluated on three benchmark datasets—Brain Tumor MRI Dataset (Kaggle)

The integration of 3D reconstruction substantially improved the system's ability to visualize tumor boundaries, volume, and spatial orientation within the brain. This volumetric representation allows clinicians to better assess tumor morphology and proximity to critical structures, supporting more informed surgical and treatment planning. Although the inclusion of 3D rendering increased processing time by approximately 18% and required greater GPU resources, the resulting improvements in diagnostic precision and clinical interpretability justify the additional computational cost. Furthermore, the incorporation of a confidence-based verification mechanism, which flagged approximately 6.5% of uncertain cases for expert review, ensured reliability and reduced the risk of misclassification.

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