Tumor Invasion: Smart healthcare system for brain tumor diseases diagnosis

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U-Net.
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A B S T R A C T

Brain tumors present a formidable challenge in medical practice, necessitating urgent and precise diagnoses due to their life-threatening nature and intricate characteristics. The complexity is heightened by varied tumor locations, invasive features, and inherent image distortions. Globally, there are over 700,000 new cases annually, underscoring the critical need for improved strategies. The five-year survival rate for malignant brain tumors at 36% highlights the urgency. With over 100 distinct types impacting patients physically, cognitively, and psychologically, brain cancer survival rates have shown minimal improvement despite extensive research. In the U.S., 1 million individuals live with a brain tumor, and 94,390 new cases are projected in 2023, with 18,990 expected fatalities. These statistics emphasize the imperative for continued research and innovative solutions. Our proposed solution leverages advanced technologies like federated learning and interpretable deep learning, ensuring privacy while enhancing models through collaborative, decentralized data training. Incorporating virtual reality for three-dimensional visualizations in brain tumor diagnostics, our approach facilitates precise tumor localization, risk assessment, and treatment planning. The anticipated outcome is a smart mobile application for brain tumor diagnosis, featuring a dice coefficient of 99.25% for 3D segmentation, 96.24% for 2D segmentation, and a CNN accuracy of 97.10%, offering reliable insights for informed decision-making in brain tumor diagnosis and treatment.

1. Introduction

1.1 introduction and Significance:

Brain tumors are a formidable medical challenge, with around 700,000 new cases diagnosed annually worldwide. The five-year survival rate for malignant brain tumors is approximately 36%, underscoring the critical need for accurate diagnosis and treatment. Existing brain tumor diagnosis applications often lack comprehensive solutions, focusing on singular aspects like classification or segmentation. This project aims to revolutionize brain tumor diagnosis by integrating classification, segmentation, and visualization, thereby addressing the limitations of current applications. The proposed solution employs advanced technologies like federated learning and interpretable deep learning to tackle life-threatening brain tumors, ensuring privacy and security by enabling collaborative model training across decentralized data sources, thereby enhancing models that learn from diverse cases. Additionally, the project leverages virtual reality for three-dimensional visualizations in brain diagnostics, providing medical practitioners with an immersive experience that aids in understanding tumor characteristics and treatment planning. This integration also enhances medical training by allowing practitioners to interact with complex cases in a simulated environment, thereby enhancing their understanding of complex cases. The project extends beyond conventional segmentation approaches; it distinguishes itself by accurately pinpointing the precise locations of brain tumors within medical images. Moreover, our application goes a step further by assessing the potential risk associated with each identified, providing a detailed evaluation of its tumor progression. This advanced analysis significantly augments the clinical utility of the application, delivering invaluable insights to medical professionals for more informed decision-making processes. Our project aims to overcome the inherent limitations in current brain tumor diagnosis applications, which often fall short in delivering a comprehensive solution. Existing applications typically focus on singular aspects such as classification or segmentation, lacking the personalized insights necessary for healthcare professionals. To address these shortcomings, our goal is to create an integrated platform with advanced 3D segmentation capabilities, offering a nuanced understanding of spatial characteristics related to brain tumors. The anticipated outcome is a user-friendly tool that seamlessly combines brain tumor classification, segmentation, and visualization. Unlike standalone applications, our integrated solution streamlines the diagnostic process for medical professionals, providing a holistic approach to brain tumor analysis. Utilizing federated learning, the model prioritizes privacy and security by conducting decentralized training on local datasets. This innovative approach enhances the accuracy of life-threatening brain tumor diagnoses without compromising the confidentiality of individual patient data. Moreover, the integration of virtual reality elevates the diagnostic experience, establishing a new benchmark for brain tumor diagnosis applications. The immersive nature of virtual reality enhances the visualization of tumors, facilitating a more detailed examination and understanding of their characteristics. This comprehensive and technologically advanced solution is poised to revolutionize the field, setting a higher standard for brain tumor diagnosis applications.

1.2 Gaps

Current brain tumor diagnosis applications often focus on singular aspects like classification or segmentation, lacking comprehensive solutions. There is a need for integrated platforms with advanced 3D segmentation capabilities to provide a nuanced understanding of spatial characteristics related to brain tumors.

1.3 Solution and Importance

The project's solution integrates classification, segmentation, and visualization, setting a new standard for brain tumor diagnosis applications. Utilizing advanced technologies like federated learning and interpretable deep learning, the solution enhances accuracy and privacy in diagnoses.

Virtual reality is employed for immersive three-dimensional visualizations, aiding in understanding tumor characteristics and enhancing medical training. The solution aims to overcome the limitations of current brain tumor diagnosis applications by providing a comprehensive and technologically advanced platform. The proposed solution aims to fill these gaps by providing a user-friendly tool that seamlessly combines classification, segmentation, and visualization. The team plans to develop a smart mobile application using artificial intelligence techniques to classify and diagnose brain tumor diseases.

1.4 Contribution to Scientific Discovery

The project's solution contributes to scientific discovery by providing a comprehensive and technologically advanced platform for brain tumor diagnosis. The solution integrates classification, segmentation, and visualization, setting a new standard for brain tumor diagnosis applications. Utilizing advanced technologies like federated learning and interpretable deep learning, the solution enhances accuracy and privacy in diagnoses. Virtual reality is employed for immersive three-dimensional visualizations, aiding in understanding tumor characteristics and enhancing medical training.

1.5 How does the user use the software?

- The user interacts with the software through a mobile app developed with Flutter, providing an easy-to-navigate platform.
- The app offers a "Choose Your Path" feature for healthcare professionals to select their preferred diagnostic journey.
- The solution employs advanced technologies like federated learning and interpretable deep learning to enhance accuracy and privacy in diagnoses.
- Virtual reality is utilized for three-dimensional visualizations, aiding in understanding tumor characteristics and enhancing medical training.

Overall, the solution aims to provide a user-friendly tool that integrates classification, segmentation, and visualization, setting a new standard for brain tumor diagnosis applications.

2. Related Work

This paper introduces a novel approach for automating brain tumor segmentation and classification leveraging a Deep Convolutional Neural Network (DCNN) with a multiscale framework. Unlike conventional methods, the model processes input images at three distinct spatial scales, inspired by the functionality of the Human Visual System. This multiscale strategy enables comprehensive analysis of MRI images containing meningioma, glioma, and pituitary tumor across sagittal, coronal, and axial views without the need for preprocessing to remove extraneous structures. We evaluate our proposed neural model using a publicly available MRI dataset comprising 3064 slices from 233 patients and compare its performance against classical machine learning and deep learning methodologies. The results demonstrate a remarkable tumor classification accuracy of 0.973, outperforming existing approaches on the same dataset.[1]

Medical image processing is crucial for clinical diagnosis, but traditional approaches have limitations in performance and efficiency. Misdiagnosis of brain tumors can impede proper treatment and patient survival. This study applies transfer learning and a novel model to classify augmented magnetic resonance images (n=12,256) into three tumor types: meningioma, glioma, and pituitary tumors. Using ADAM optimizers, accuracies of 83.30%-91.73% were achieved across various pre-trained models. Additionally, accuracies of 50.45%-84.82% were obtained with the SGDM optimizer. An Android and iOS mobile application, utilizing the novel model and flutter framework, achieved 82.5% accuracy on images from SRM hospital, surpassing existing models in execution speed and performance.[2]

Magnetic Resonance Imaging (MRI) plays a critical role in the early detection and treatment planning of brain tumors. Accurate segmentation of MR images is essential for rapid analysis and precise diagnosis. Various segmentation techniques, including support vector machines and random forest classifiers, have been employed in the past. However, existing methods utilizing Stationary Wavelet Transform (SWT) suffer from overlapping, reduced accuracy, and high noise levels. To address these limitations, we propose a system integrating Discrete Wavelet Transform (DWT) and Deep Belief Neural Network (DBN) for improved efficiency and accuracy. By adjusting structural data in the gray matter (GM) region and patching spectral data in the white matter (WM) region, our fusion approach yields superior results in terms of spectral discrepancy (SD) and average gradient (AG). Testing on three datasets normal axial, normal coronal, and Alzheimer's disease brain images—demonstrates the effectiveness of our method both visually and quantitatively.[3]

Brain tumors occur owing to uncontrolled and rapid growth of cells. If not treated at an initial phase, it may lead to death. Despite many significant efforts and promising outcomes in this domain, accurate segmentation and classification remain a challenging task. A major challenge for brain tumor detection arises from the variations in tumor location, shape, and size. The objective of this survey is to deliver comprehensive literature on brain tumor detection through magnetic resonance imaging to help the researchers. This survey is to deliver comprehensive literature on brain tumor detection through magnetic resonance imaging to help the researchers. This survey covered the anatomy of brain tumors, publicly available datasets, enhancement techniques, segmentation, feature extraction, classification, and deep learning, transfer learning and quantum machine learning for brain tumors analysis. Finally, this survey provides all important literature for the detection of brain tumors with their advantages, limitations, developments, and future trends. [4]

3. Software Description

Our innovative solution addresses the critical challenges in brain tumor diagnosis by introducing a smart mobile application that leverages cutting-edge technologies. Using federated learning and interpretable deep learning, our platform ensures accurate and secure diagnoses by collaboratively training models across decentralized data sources, safeguarding patient privacy. The application employs advanced 3D segmentation techniques, providing a nuanced spatial understanding of tumor characteristics and revolutionizing traditional segmentation approaches. Additionally, the integration of virtual reality not only enhances the diagnostic process by offering an immersive experience for medical practitioners but also sets a new standard in medical training. This user-friendly tool combines tumor classification, segmentation, and visualization, aiming to redefine the landscape of brain tumor diagnosis and contribute to improved patient outcomes.

3.1 Software architecture

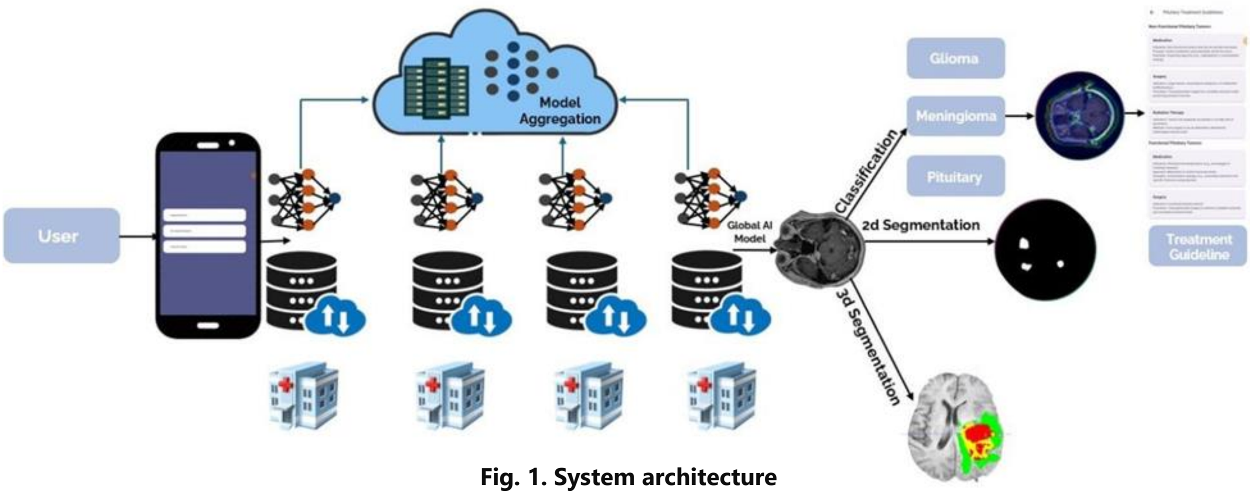

Fig. 1. System architecture

The software architecture is meticulously designed to offer a user-centric mobile application for brain tumor diagnostics. The system provides a choice between 2D segmentation, 3D segmentation, and classification, ensuring a personalized diagnostic approach. Users interact through an intuitive mobile interface, initiating their chosen pathway by uploading brain tumor images.

User Interaction: Upon user selection, the system dynamically engages advanced algorithms and models corresponding to the chosen diagnostic pathway.

Choice Processing: Based on the user's selection, the system initiates the chosen diagnostic pathway, utilizing advanced algorithms and models.

Federated Learning: Ensuring privacy and security, federated learning is incorporated to collaboratively train a global AI model from decentralized data sources.

Classification Output: In the case of classification, the system provides a detailed output categorizing tumors into glioma, meningioma, or pituitary types.

Treatment Guidelines: For classification, the application enriches the user experience by displaying treatment guidelines specific to the diagnosed brain tumor type, aiding medical practitioners.

Segmentation Output: Opting for segmentation generates either 2D or 3D segmentation outputs based on user preference.

Visualization Output: In 3D segmentation, the application offers a GIF illustrating spatial tumor characteristics, enhancing comprehensive visualization for medical professionals.

Tools and Technologies Used:

Flutter Framework: Core framework for mobile app development, ensuring a single codebase for both iOS and Android platforms.

Machine Learning Libraries: Specialized libraries compatible with Flutter, empowering model training and inference for enhanced diagnostic capabilities.

Image Processing Libraries: Flutter-compatible libraries for advanced image processing, facilitating seamless implementation of segmentation and visualization features.

Backend Technology (Flask): Flask serves as the backend, efficiently connecting the mobile application to the backend infrastructure for streamlined data processing and communication.

Virtual Reality Tools: In case of VR integration, tools like Unity or A-Frame complement Flask for VR development, providing an immersive experience.

3.2. Software functionalities

Diagnostic Pathway Selection: Allows users to tailor their diagnostic experience based on specific needs, providing flexibility and customization in the diagnostic process.

Image Upload and Processing: Enables users to seamlessly upload medical images, a fundamental step in obtaining accurate and detailed brain tumor diagnostics.

Federated Learning Integration: Enhances diagnostic accuracy by leveraging collaborative learning from diverse data sources while prioritizing patient data privacy.

Classification: Provides quick and accurate categorization of brain tumors, aiding medical practitioners in identifying the type and initiating appropriate treatment plans.

Treatment Guidelines Display: Offers valuable information on recommended treatment strategies

based on the diagnosed brain tumor type, guiding medical practitioners in providing optimal care.
Segmentation (2D and 3D): Delivers detailed visualizations of tumor boundaries, aiding medical professionals in understanding the spatial characteristics crucial for treatment planning.
Virtual Reality Integration: Elevates the user experience by providing an immersive virtual reality environment, enhancing understanding and interaction with complex cases during diagnosis and medical training.
User-Friendly Interface: Ensures a positive user experience with a modern, responsive design, making the application accessible and easy to navigate for medical practitioners and users.
These functionalities collectively create a robust platform that empowers users with a versatile, collaborative, and user-friendly solution for brain tumor diagnostics. The integration of cutting-edge technologies ensures accuracy, privacy, and an immersive user experience, making the application a valuable tool for medical practitioners and users alike.

3.3 Results and discussion

convolutional neural network (CNN) Model

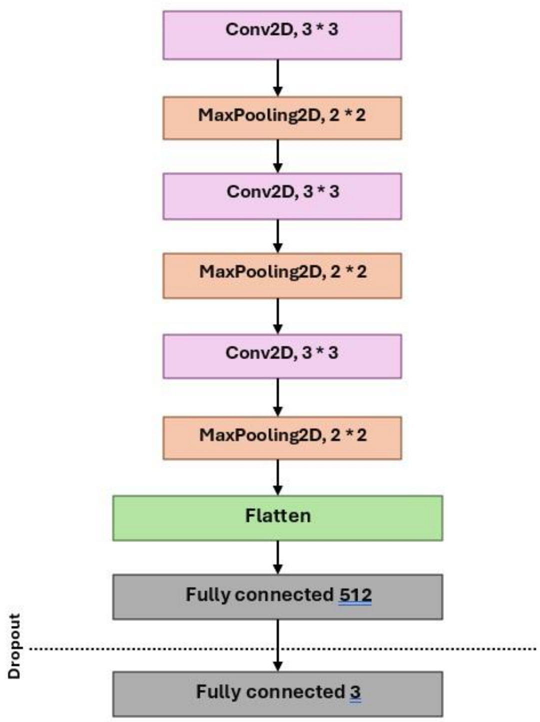

Fig. 2. CNN model architecture

Dataset Used [9]

The brain tumor dataset encompasses MRI images portraying Pituitary, Meningioma, and Glioma tumors. These images are initially grayscale and augmented into RGB format for training. Additionally, a separate set of test images is incorporated for evaluating the model's performance.

Algorithmic Components and Models Used

The classification model relies on a Convolutional Neural Network (CNN) architecture, comprising Conv2D and MaxPooling2D layers for feature extraction and Dense layers for classification. The model is tailored for brain tumor classification, demonstrating its adaptability to intricate image recognition tasks. The choice of CNN architecture ensures effective pattern recognition without relying on external pre-trained models.

Data Distribution

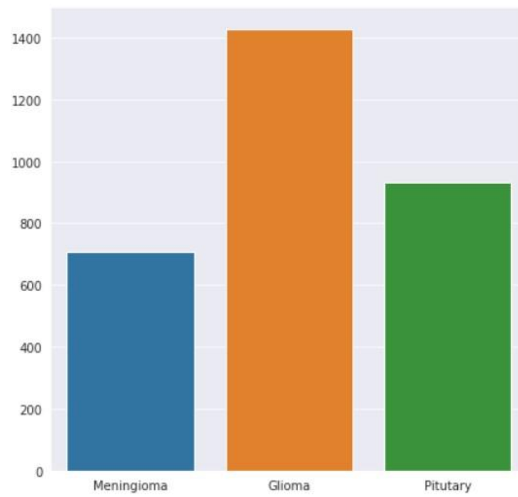

Fig. 3. the distribution of brain tumor scans across different categories

Meningioma: 708 scans
Glioma: 1426 scans
Pituitary: 930 scans

Model for Classification

The classification model harnesses the capabilities of a Convolutional Neural Network (CNN) architecture tailored for the intricate task of brain tumor classification. Specifically designed for its prowess in image recognition, this CNN model is adept at extracting relevant features from medical images. Its effectiveness lies in its ability to understand complex patterns inherent in brain tumor datasets.

Model Training, Testing, and Deployment

The dataset is split into training and testing sets, with images resized to 224x224 pixels for uniformity. The model is trained using Adam optimizer and categorical cross entropy loss over 10 epochs. Following successful training, the model is evaluated on the test set, achieving a commendable accuracy of 92.01%. The model is then ready for deployment in the brain tumor diagnostic application, showcasing its potential for real-time classification.

Results

Test Accuracy: The model achieves a test accuracy of 92.01%, indicating its proficiency in accurately classifying brain tumor types.

AUC (Area Under the Curve): The AUC score, a metric reflecting the model's ability to distinguish between classes, stands at 98.07%, affirming its strong discriminatory power.

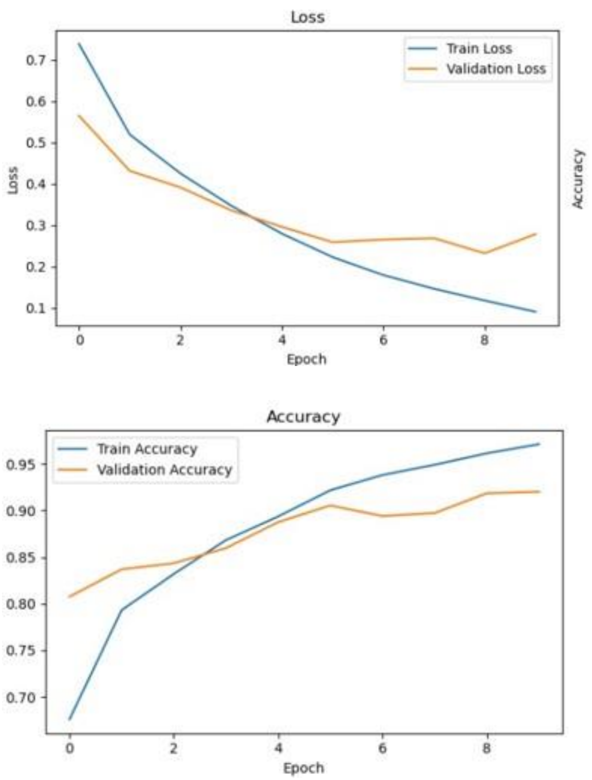

Fig. 4. Training history plots

Visual representations of training and validation loss, as well as accuracy over epochs, offer a comprehensive view of the model's learning trajectory. These plots demonstrate convergence and generalization capabilities, providing a valuable perspective on the model's performance.

Grad-CAM Visualization

Grad-CAM was strategically applied to unravel the intricate decisions made by the brain tumor classification model. This technique delves into the model's internal mechanisms, generating a heatmap that distinctly highlights regions in the input image pivotal to the model's predictions.

The resulting Grad-CAM heatmap served as a powerful tool, revealing the areas within the input image that wielded a substantial influence on the model's classification decisions. By visually contrasting these regions, the heatmap provided a transparent and interpretable representation of the model's decision-making process.

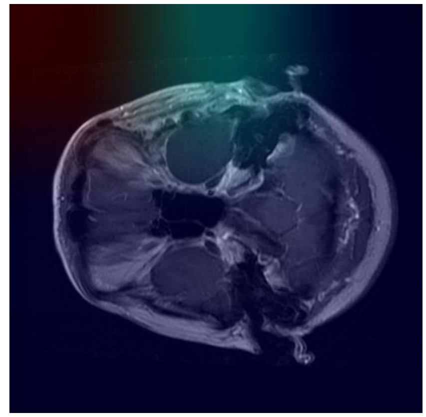

Fig. 5. Grad-Cam Heatmap

2D U-Net for Brain Tumor Segmentation

Datasets Used [10]

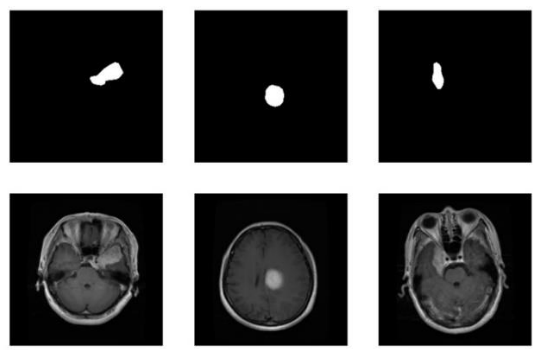

Fig. 6. Snippets of the 2d segmentation dataset

The model is trained, validated, and tested on a dataset comprising 3064 pairs of MRI brain images and their corresponding binary masks indicating tumor regions. The images are resized to 256x256 pixels and normalized for consistent model input.

Algorithmic Components and Model Architecture

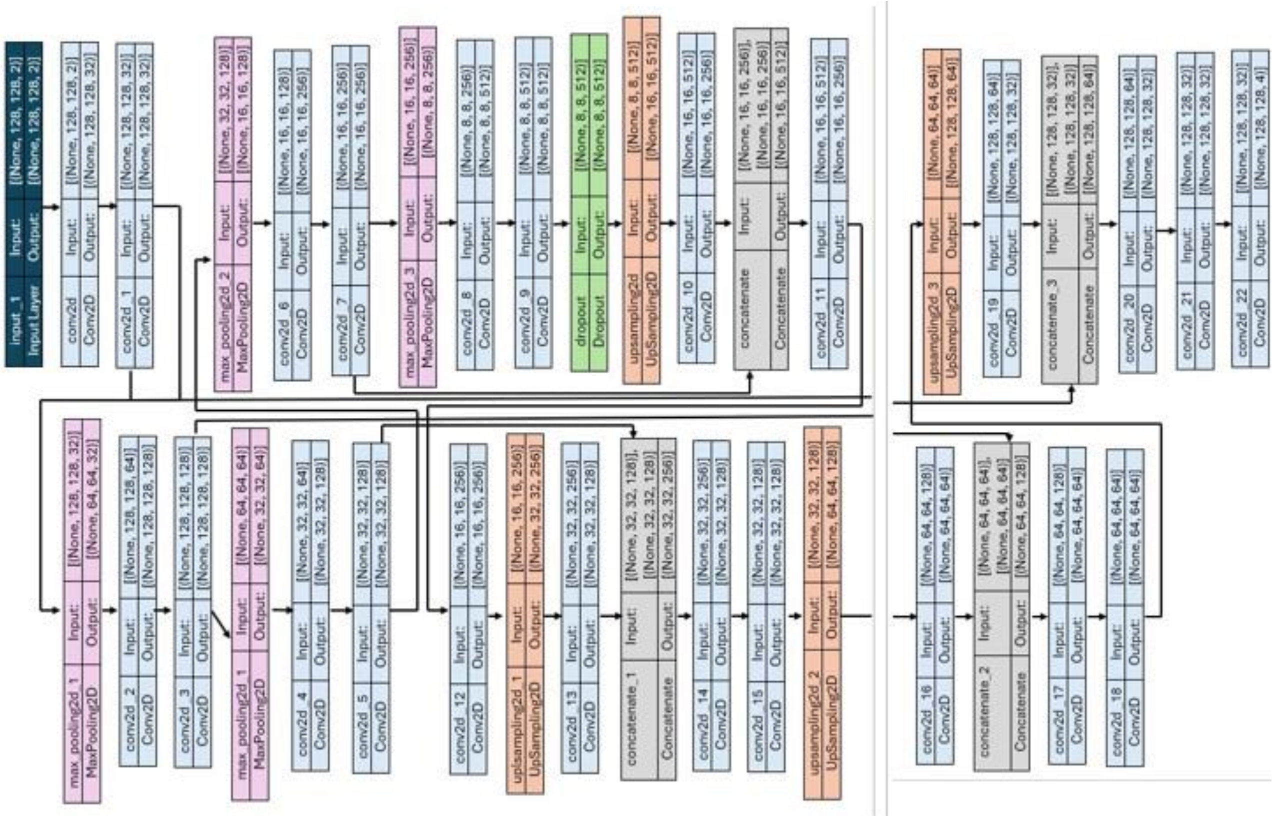

Fig. 7. 2D U-Net model architecture

The implemented 2D U-Net model is a convolutional neural network designed for semantic segmentation tasks, specifically for segmenting brain tumors in MRI images. The architecture consists of down sample blocks, each composed of two convolutional layers followed by max-pooling, and up sample blocks using transposed convolutional layers for upsampling. This architecture allows the model to capture intricate spatial features for accurate tumor segmentation.

Model Training

The dataset is split into training, validation, and test sets. The model is trained using binary crossentropy loss and Adam optimizer with a learning rate of 0.0001. Early stopping, model checkpointing, and learning rate reduction based on validation loss are implemented to ensure optimal training.

Model Testing

On the test set, the trained model is evaluated, and key metrics such as dice score and mean Intersection over Union (IoU) are computed to assess the model's performance in accurately segmenting brain tumors.

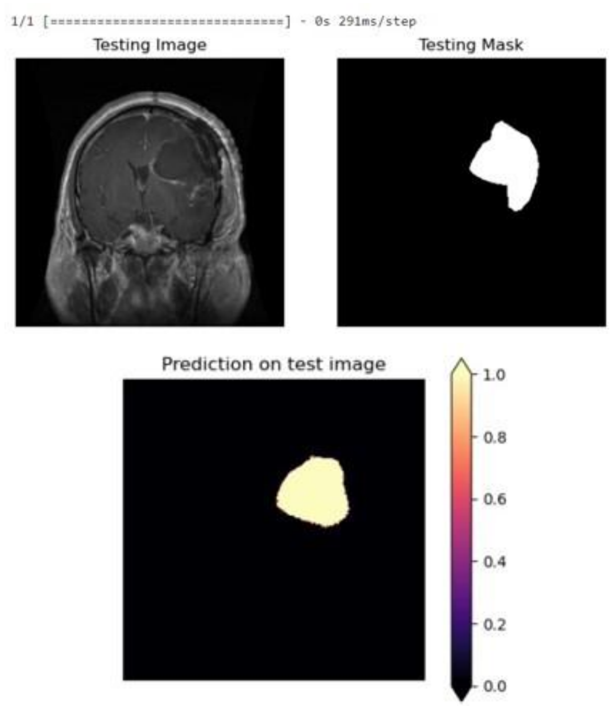

Fig. 8. Result Visualization

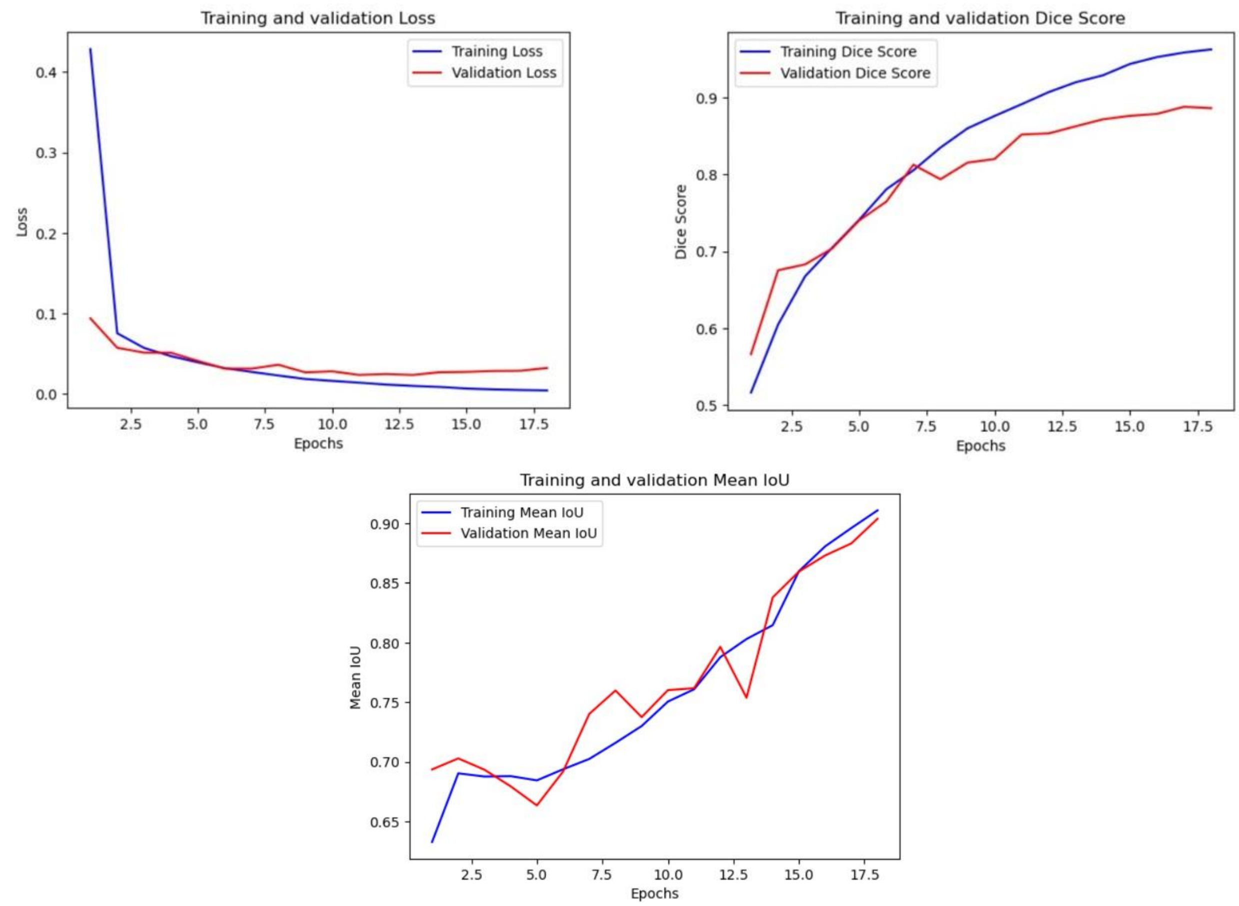

Fig. 9. Training history plots

Datasets Used [11]

The dataset employed for 3D brain tumor segmentation was the BraTS (Brain Tumor Segmentation) dataset. This dataset comprises multimodal MRI scans, including FLAIR, T1, T1-CE, and T2 modalities, along with corresponding segmentation masks indicating tumor sub-regions.

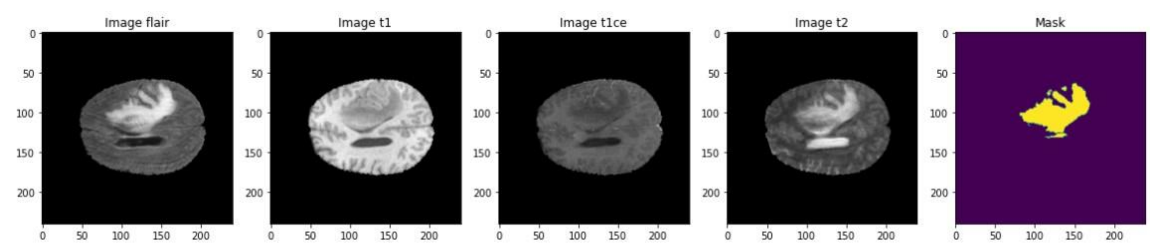

Fig. 10. slices from different modalities their corresponding segmentation mask

Training

Data was divided into training, validation, and test sets.
A custom data generator efficiently loaded and preprocessed 3D volumes in batches.
The 3D U-Net model was compiled with categorical cross-entropy loss and Adam optimizer.
Training involved multiple epochs with callbacks for early stopping, learning rate reduction, and model checkpointing.

Testing

The trained model was evaluated on a separate test set to assess its generalization to unseen data.
Evaluation metrics, including Dice Coefficient, were computed to quantify segmentation performance.

Deployment

The trained 3D U-Net model can be deployed for segmenting brain tumors in new MRI scans.

In a real-world scenario, the model could be integrated into a healthcare system for automated tumor segmentation.

Results

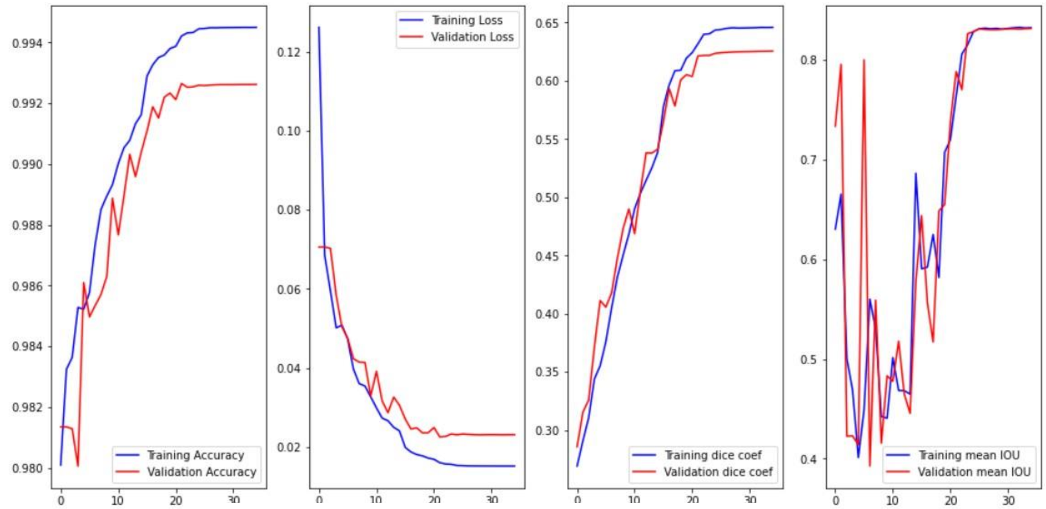

Fig. 11. Training history plots for 3d segmentation model

Model performance was assessed using quantitative metrics and visual inspection of segmented volumes.

Results demonstrated the effectiveness of the 3D U-Net architecture in accurately segmenting brain tumors.

Class-specific metrics provided insights into the model's ability to delineate different tumor sub-regions.

Algorithmic Components and Models Used

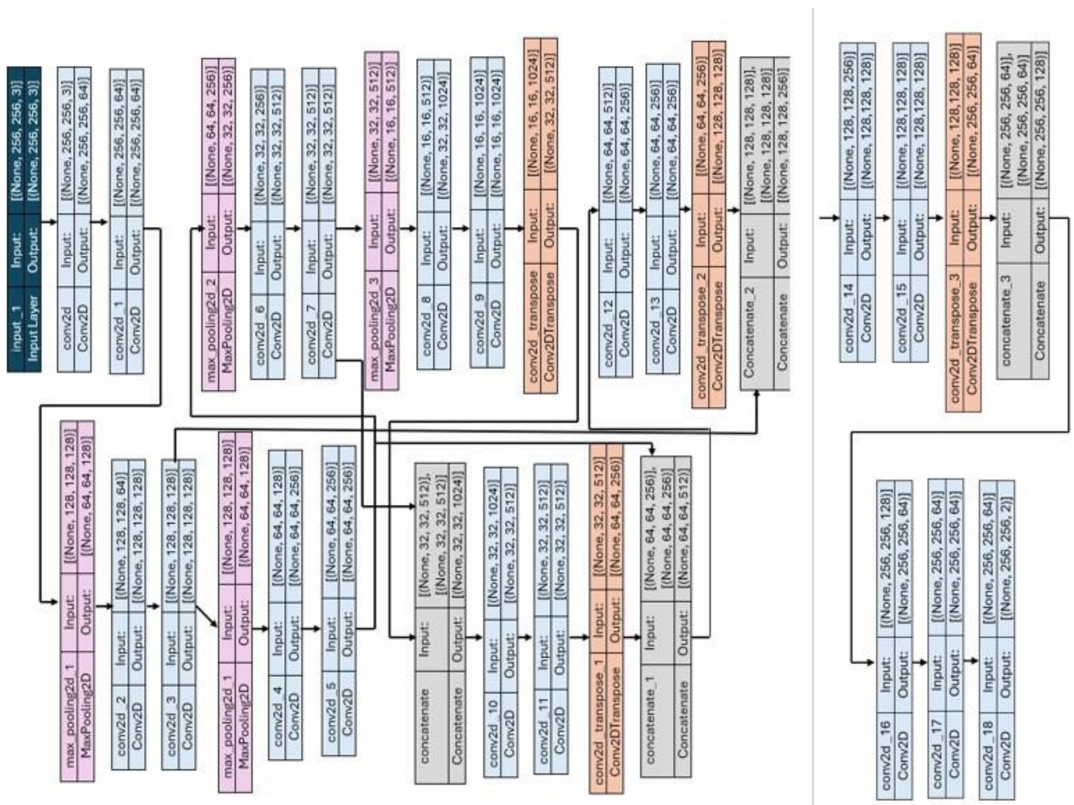

Fig. 12. 3D U-Net model architecture

The segmentation task was approached using a 3D U-Net architecture. The model architecture was designed to capture spatial dependencies across slices in all three dimensions. The key components of the algorithmic approach include:
3D U-Net Architecture: Utilized a 3D variant of the U-Net architecture. The model consists of encoder and decoder blocks to capture hierarchical features and enable precise localization.
Custom Evaluation Metrics: Defined custom metrics including 3D Dice Coefficient, Precision, Sensitivity, Specificity, and class-specific Dice Coefficients. These metrics provided a detailed assessment of segmentation performance.
Data Augmentation: Implemented data augmentation techniques, such as rotation and resizing, to enhance model generalization.

4. Illustrative examples

The proposed system is designed to be user-friendly and effective in a real-life healthcare environment, leveraging artificial intelligence for enhanced diagnostics.

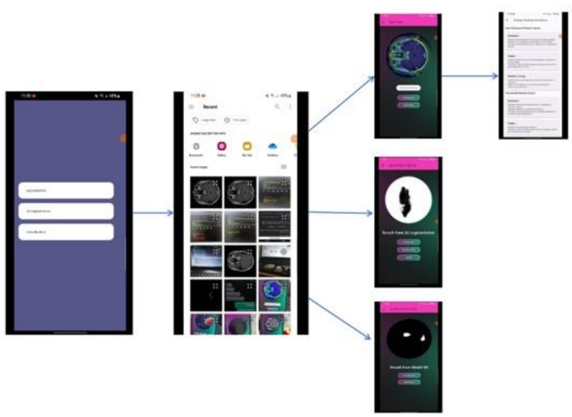

Fig. 13. APP Overview

Operational Steps in a Real-Life Environment:

Step 1: Choose Your Path
Upon launching the app, users, mainly healthcare professionals, are presented with two distinctive paths: "Classification" and "Segmentation," providing flexibility in the diagnostic approach.

Step 2: Uploading Tumor Scan
Users initiate the diagnostic process by securely uploading a brain tumor scan. This step ensures the confidential sharing of crucial medical imaging data, maintaining privacy and compliance with healthcare standards.

Step 3: Classification Journey
Opting for the "Classification" path streamlines the process. Users effortlessly upload a brain tumor scan, and the app processes the image promptly. It delivers an accurate classification of the tumor type, such as glioma, meningioma, or pituitary tumor. For a deeper understanding, a "Show More Details" button unveils a heatmap pinpointing the exact location of the tumor through the skull.

Step 4: Treatment Guidelines
Choosing "Show More Details" unlocks a wealth of information. Comprehensive and up-to-date treatment guidelines specific to the identified tumor type are provided. This facilitates well-informed decisions in the treatment planning process, empowering healthcare professionals with actionable insights.

Step 5: Segmentation Journey
Opting for the "Segmentation" path leads users to a distinct experience. The app instantly displays both 2D and 3D segmented images, offering crucial insights into the tumor's precise location and characteristics. This step enhances the understanding of the tumor's spatial distribution, aiding in personalized treatment strategies.

5. IMPACT

5.1 Target Audience

Our target audience can be summarized as follows:

1. **Neurologists:** fresh graduates with little to no experience, neurologists who need to develop their diagnostic abilities, and visually interpret brain tumors using the application capabilities.
2. **Laboratories:** Minimizing time and effort spent locating, identifying, and printing a full descriptive medical report with the help of the software.
3. **The Ministry of Health:** Our project stands as a beacon of progress in healthcare, directly contributing to Egypt's Vision 2030 by addressing critical challenges in medical diagnostics and education.

5.2 Innovative Aspects of the Design

3D U-Net Model and VR Integration: In the realm of advanced diagnostics, our system stands out through the incorporation of cutting-edge technologies, particularly the utilization of the state-of-the-art 3D U-Net model. This model is specifically designed for three-dimensional segmentation, enhancing our platform's capability to provide a comprehensive understanding of tumor spatial characteristics. By leveraging this advanced technology, we empower our system to contribute to more accurate localization and volumetric analysis of brain tumors.

Furthermore, our innovative approach extends beyond diagnostics into the realm of three-dimensional visualizations using Virtual Reality (VR). Integrating VR into our system enables us to create immersive and realistic three-dimensional representations of brain tumors. This functionality not only aids in enhancing the overall understanding of tumor structures but also opens avenues for creating lifelike surgical simulations.

Holistic Approach and Comprehensive Understanding:

The innovative aspects of our system design are rooted in its holistic approach, bringing together advanced diagnostics, user control, confidential data handling, and decision support. The integration of classification, segmentation, and treatment guidelines ensures a comprehensive understanding of brain tumors, providing healthcare professionals with actionable insights for informed decision-making.

Federated Learning for Enhanced Collaboration:

A key innovation lies in the incorporation of federated learning, a collaborative approach that allows our system to leverage diverse datasets for training. This enhances the model's generalization and effectiveness by fostering collaboration among multiple AI models. Through federated learning, our system adapts to the diversity present in brain tumor data, ensuring robust performance across various scenarios.

Emphasis on Interpretability and Data Protection

The emphasis on interpretable deep learning and the integration of a robust security and privacy layer adds layers of transparency and data protection. Interpretable deep learning frameworks ensure that the AI models' decision-making processes are understandable and trustworthy for healthcare professionals. Simultaneously, the security and privacy layer implement encryption protocols and access controls, prioritizing the safeguarding of patient data. This commitment to transparency and data protection enhances the overall reliability and trustworthiness of our system in a real-life healthcare environment.

In conclusion, the integration of the 3D U-Net model, VR technology, federated learning, and a strong focus on interpretability and data protection collectively contribute to the innovative and holistic aspects of our system design, positioning it at the forefront of advanced healthcare solutions for brain tumor diagnostics and treatment planning.

5.3 Accessibility of Software

Our software features a simple and intuitive user interface, allowing doctors to navigate through the application effortlessly. The interface is designed with accessibility in mind, incorporating clear navigation pathways, logical layout, and intuitive controls.

Visual Clarity: Visual clarity is paramount in our application design. We use high contrast colors, clear typography, and intuitive iconography to enhance readability and ensure that information is easily discernible for users with visual impairments or those working in low-light environments. By providing a user-friendly interface and intuitive navigation, our application streamlines the diagnostic process, allowing doctors to make quicker and more accurate diagnoses.

5.4 Reliability

We conducted pilot testing sessions with a select group of healthcare professionals representing our target audience. These pilot tests allowed us to gather feedback on usability, functionality, and reliability in a controlled environment.

We actively solicited feedback from healthcare professionals throughout the development process, incorporating their input to improve the reliability of the software. Feedback was collected through comprehensive conversations with a group of neurologists allowing us to identify areas for improvement and address any concerns or issues raised by users.

5.5 Future Research Directions

Advanced Imaging Techniques: Explore the integration of imaging technologies, such as functional MRI (fMRI) and (NIfTI), which is an open file format commonly used to store brain imaging data obtained using Magnetic Resonance Imaging methods. To provide additional insights into brain tumor characteristics. Investigate how these techniques can complement traditional MRI scans for more comprehensive diagnostics.

Multi-Modal Data Fusion: Explore how machine learning algorithms (Federated learning) can leverage diverse data sources for more personalized and precise patient care.

Integration of VR: Our software combines our AI models with VR technology to contribute to brain tumor diagnostics. By incorporating virtual reality into our technology, we can import our recently predicted 3D tumor and export it into realistic and engrossing three-dimensional brain tumor simulations using Unity. Here, medical professionals can comprehend thoroughly the size and location of the tumor.

5.6 Added Value

Patient Confidentiality: There are various ways that confidential data could be compromised, leaked, or get into the wrong hands [5]. A new technique could solve most of the issues, which is federated learning. The model ensures privacy, improving the accuracy of life-threatening brain tumor diagnoses without compromising individual patient data.

Advanced Diagnostic Capabilities: [6] Adding VR technology provides an immersive visualization experience, allowing healthcare professionals to interact with brain tumor data in a three-dimensional virtual environment.

Interpretable AI Module:[6] Clear visual explanations, encouraging continuous learning and skill growth.

Federated Learning: [7] By training our AI models on a distributed network of servers linked to medical facilities, we ensure robust performance across various data scenarios, enhancing diagnostic accuracy and reliability.

3D Integration:[8] offers a unique approach to brain tumor diagnosis that provides detailed spatial insights and enhances understanding for medical professionals.

5.7 Impact on target audience

The project revolutionizes brain tumor diagnosis by integrating classification, segmentation, and visualization into a unified tool. Leveraging federated learning and virtual reality, providing accurate and privacy-preserving diagnoses. The addition of 3D segmentation enhances spatial understanding, improving precision and aiding in treatment planning. Virtual reality immersion contributes to both diagnosis and medical training. Importantly, the project demonstrates improved performance over existing applications, setting new standards for brain tumor diagnosis. This advanced solution, tailored for medical practitioners, streamlines the diagnostic process based on insights gained from meetings with doctors. The commitment to accuracy, efficiency, and privacy underscores the potential for better patient outcomes. We found solutions that potentially depict obstacles project's stakeholders face, creating a better environment for them.

6. Conclusions

As a conclusion, the creation of the smart smartphone application marks a significant milestone in the field of brain tumor diagnosis and therapy. By seamlessly combining modern technologies like classification, segmentation, and interpretable AI, the program provides neurologists with unparalleled insights and possibilities. The application has been rigorously tested and refined, demonstrating its efficacy in reliably detecting and diagnosing brain tumors, assessing their danger level and progression, and offering actionable treatment planning advice. The successful launch of the application is a significant step forward in improving the efficiency, accuracy, and privacy of brain tumor diagnosis and treatment. The program raises the bar for diagnostic precision and medical training by utilizing federated learning and virtual reality, resulting in better patient outcomes and clinical practices.

7. Future Directions

Continuous improvement: involves refining algorithms and user interfaces to improve usability and accuracy.
Feature Expansion: Add additional functionalities to meet different clinical demands and developing issues.
Collaboration: Form alliances to spur innovation in brain tumor diagnosis and therapy.
Global Deployment: Broaden application reach by negotiating legal restrictions and cultural factors.
Patient Engagement: Empower patients with individualized resources and communication channels.
Ethical Considerations: Address privacy concerns and regulatory compliance to protect patient data.

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Brain Tumor Classification MRI Images: This dataset, with its diverse range of images, contributes to the development and evaluation of machine learning models. https://www.kaggle.com/datasets/jarvisgroot/brain-tumor-classification-mri-images

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Brain Tumor Segmentation on Kaggle (2D): The dataset is an asset for developing and evaluating 2D segmentation models. https://www.kaggle.com/datasets/nikhilroxtomar/brain-tumor-segmentation?select=images

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3D MRI Brain Tumor Segmentation on Kaggle: This dataset enhances the exploration of advanced segmentation techniques in three-dimensional medical imaging. https://www.kaggle.com/code/rastislav/3d-mri-brain-tumor-segmentation-u-net

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Project Codes

GitHub Repository:

https://github.com/nermeen426/Graduation_Project

Data Sources

Classification Data:

Brain Tumor Classification MRI Images. https://www.kaggle.com/datasets/jarvisgroot/brain-tumor-classification-mri-images

2D Segmentation Data:

Brain Tumor Segmentation Dataset.
https://www.kaggle.com/datasets/nikhilroxtomar/brain-tumor-segmentation?select=images

3D Segmentation Data:

3D MRI Brain Tumor Segmentation U-Net.
https://www.kaggle.com/code/rastislav/3d-mri-brain-tumor-segmentation-u-net

Project Video

Watch our project in action through the following video:
https://youtu.be/X7vtHSWfSEE?si=-9sUcmMgAaXe27eb