**PAPER**

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**DYNAMIC 3D VISUALIZATION AND AR INTEGRATION FOR TRACKING TUMOR PROGRESSION**

VASANTH KUMAR CH

KEERTHANA S

GOWRI GANESH G

ROSELIN MARRY JOVITA S

JAYANTHI G

RASIKA M

**1.Abstract**

Advances in computer vision and augmented reality will change the face of medical imaging, particularly the way the human eye tracks and addresses deep complex diseases such as tumors. In this regard, this paper presents an innovative method in tumor tracking by using a dynamic three-dimensional visualization model integrated with augmented reality for immersion and precision in tumor progression analysis. This model takes MRI images as input and renders a three-dimensional view of tumor structures to help the medical professional to read the images clearly with better details. This system integrates augmented reality for overlaying real-time 3D visualizations on patient anatomy, thus giving a proper view about the changes in tumor size, shape, and position. This model will provide high potential in personal treatment planning, early detection of changes, and intraoperative real-time guidance. The project seeks to establish a new benchmark in tumor tracking by offering a robust yet intuitive tool that can improve outcomes for patients along with processes for clinical decision-making.

**Keywords:** Tumor progression tracking, 3D visualization, augmented reality, MRI segmentation, real-time monitoring, oncology imaging, patient-specific modeling, deep learning, intraoperative guidance, precision medicin

**2.Introduction**

Tumor progression is one of the most significant concepts in oncology. It is the best parameter for precise or practical diagnostics and for making treatment plans, whereas real-time follow-ups become possible with its tracks. The techniques that were once effective in static analysis with traditional imaging methods often face difficulties in presenting dynamics or matching advanced visualization techniques.Complex tumor morphology, and anatomical variations specific to each patient is only a few of the issues that might make this approach less effective in a real clinical setting. Variability in imaging quality.

This will marry advancements in medical imaging with those in augmented reality technology, opening the possibilities of tracking tumors precisely and interactively. Taking advantage of deep learning and MRI-based segmentation, this project introduces a customizable system for dynamic 3D visualization of tumors. By placing AR technology, the model overlays detailed, real-time pictures of tumors onto anatomy, allowing clinicians to be able to track the development of size, shape, and location of tumors with utmost accuracy. This approach gets over the disadvantages of fixed imaging with a dynamic, real-time approach suitable to personalized oncology care and allows intraoperative guidance as well as monitoring of therapy.

**3. Related work**

Techniques for tumor segmentation have developed dramatically during the past few decades. Techniques have moved from a time-consuming early basis that relied more on user delineation or simpler image processing techniques to those of today, which are more automated and less reliant on human interpretation. Traditionally, these techniques had problems with some of the most basic issues that presented themselves in MRI scans of tumors: shape variation, boundary ambiguity, and intensity inhomogeneity.

Recent breakthroughs in deep learning have led to powerful models for medical image analysis. Due to their ability to capture fine features across various resolutions in an image, architectures like Convolutional Neural Networks (CNNs) U-Net, ResNet, and VGG are increasingly applied to the task. Of these architectures, the U-Net structure became popular with segmentation problems thanks to the encoder-decoder structure,

which makes spatial information preserveable during encoding and thus possible to detect precise boundaries upon decoding.

In the specific area of tumor segmentation, research has focused on adapting U-Net to tackle the given challenges like irregular shapes and overlapping structures. However, a common flaw is that the model trained is usually in general medical imaging datasets, which can be suboptimal for the type of tumor or modality. Based on this, our project prepares a U-Net model adapted to our dataset, in order to improve the segmentation accuracy of real-time 3D visualization and AR integration.

### **3. Literature Review**

#### **3.1 Tumor Segmentation**

Historically, the delineation of tumors has relied on manual techniques of radiologists or on less complicated methods of image processing; these include some thresholding techniques and even simple region-growing algorithms. However, these traditional methods suffer from problems in tackling complex shapes of tumors, irregular boundary delineation, or generally intensity heterogeneity-the most common types in MRI images. During the recent years, however, deep learning-based models have revolutionized the field of segmentation, mainly because of the contributions of CNNs. Architectures like U-Net, ResNet, and DenseNet have gained attention because they can automatically learn the difference between fine-grained features of medical images. Specifically, U-Net architectures have been vastly successful in segmentation tasks since they are capable of repossessing contextual information and high-resolution capabilities in their encoder-decoder structure.

#### **3.2 3D Visualization**

Imaging in medicine transforms 2D visualization to 3D and provides a deeper understanding of anatomical structures and the planning of appropriate treatments. The 3D models obtained from the segmented MRI data have proved to improve the assessment of the location, shape, and volume of the tumor considerably. Some of the most utilized techniques to transform the segmented data into 3D models include volumetric reconstruction and mesh modeling. Integration of these techniques with deep learning makes it possible to automatically 3D visualize tumors with accuracy, which supports more effective analysis and planning for intervention.

#### **3.3 Augmented Reality (AR) for Medical Imaging**

Medical imaging applications of AR are mainly related to the overlay of digital information over physical space with interactive insight. The display, based upon real-time and spatially accurate visualization of segmented tumors, assists the clinician, hopefully improving patient outcome for tumor tracking. Recent works

focus on integration of AR and models of segmentation; that is, systems able to visualize in an interactive fashion medical data. This method, then, uses frameworks such as Unity3D or ARKit in

realizing a 3D model of the tumor to be visualized and immersed in the clinician for better diagnostic and treatment sessions.

### **4. Problem Statement and Objectives**

#### **4.1 Problem Definition**

Tumor detection and tracking is probably one of the biggest challenges remaining for accurate 3D visualization of tumors in medical images, including MRI images. Manual segmentation is lengthy and also prone to human error, while most of the available automated methods fail when the geometry of structures are complex shapes, or when the tissue types are irregularly defined with ambiguous boundaries. Finally, the integration of such precise 3D visualization and AR for the monitoring of real-time progression of tumors further adds complexity to the system because such systems are expected to provide smooth, interactive, and trustworthy feedbacks in respect of which clinicians can make appropriate decisions.

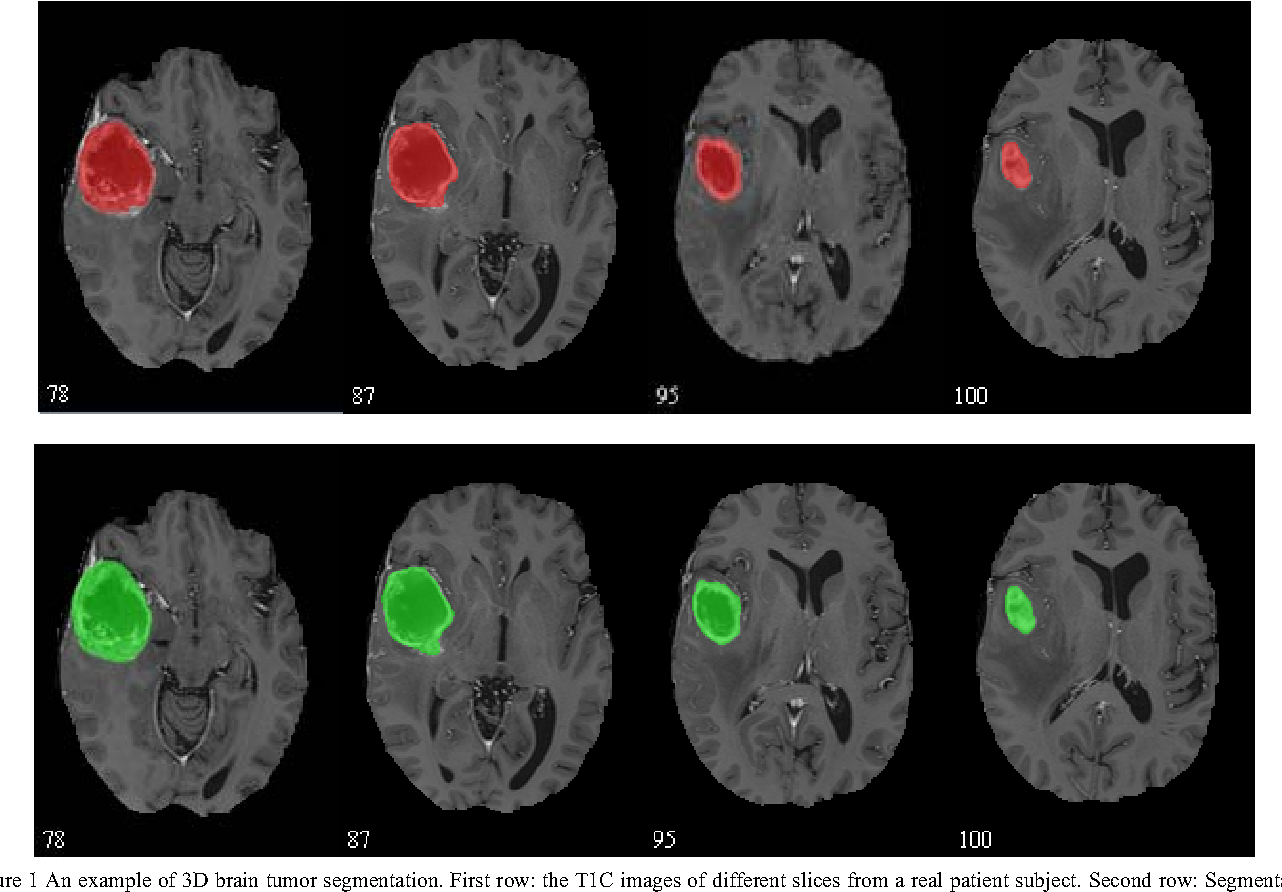
#### **4.2 Objectives**

• Develop a deep learning model, known as U-Net, to segment tumors with precision using MRI images.

• Use three-dimensional visualization techniques so the segmented tumors are represented better.

• Augmented Reality will be introduced in order to visually display and track the tumor in real time, in the clinic.

• It should be tested for its performance in actual clinical environments so that it can be absolutely true and reliable as well as practically feasible for use in medical diagnostics



### **5. Methodology**

#### **A. Data Collection**

The dataset for the creation of the 3D visualization and AR system entails MRI images and segmentation maps of regions containing the tumor. All these images were acquired from

publicly available medical imaging repositories to ensure that the data was clinical and diverse in terms of patient representation. Each one was subjected to quality reviews on suitability for consistency in applying the tumor tracking process.

#### **B. Data Preprocessing**

In order to achieve the highest precision for the model as well as the quality of the image, pre-processing techniques had been put to use. The images were normalized to standard intensity ranges, resized with uniformity in size, and noise reduced to reduce artifacts. For the segmentation part, data augmentation was used in the form of rotation, cropping, and scaling to be robust against varying anatomy from the patients and scanning conditions

#### **C. Model Architecture**

The 3D visualization process applies a U-Net-based model for the primary segmentation of tumors. Then, 3D rendering techniques are used in dynamic visualizations:

3D Segmentation Model- Spatial details in MRI images are captured using 3D U-Net to realize precise three-dimensional segmentation of tumor regions. Rendering Pipeline: Three-dimensional rendering algorithms are used to process the segmented images into a dynamic model showing growth in tumor size over time. This model is then merged with AR capabilities to enhance spatial understanding and temporal interaction.

#### **D. Training Process**

* A 3D U-Net was trained from scratch using two loss functions to push segmentation precision:
* Dice Loss: It is optimized solely for 3D segmentation tasks. This function further improves the accuracy of the overlap between the actual and predicted segmented tumor regions.
* Cross-Entropy Loss: It is used to enforce that the model differentiates the boundary of tumor, which helps in localized expression.

**E. Evaluation Metrics**

To assess the model performance and the strength of AR incorporation, several evaluation metrics were applied.

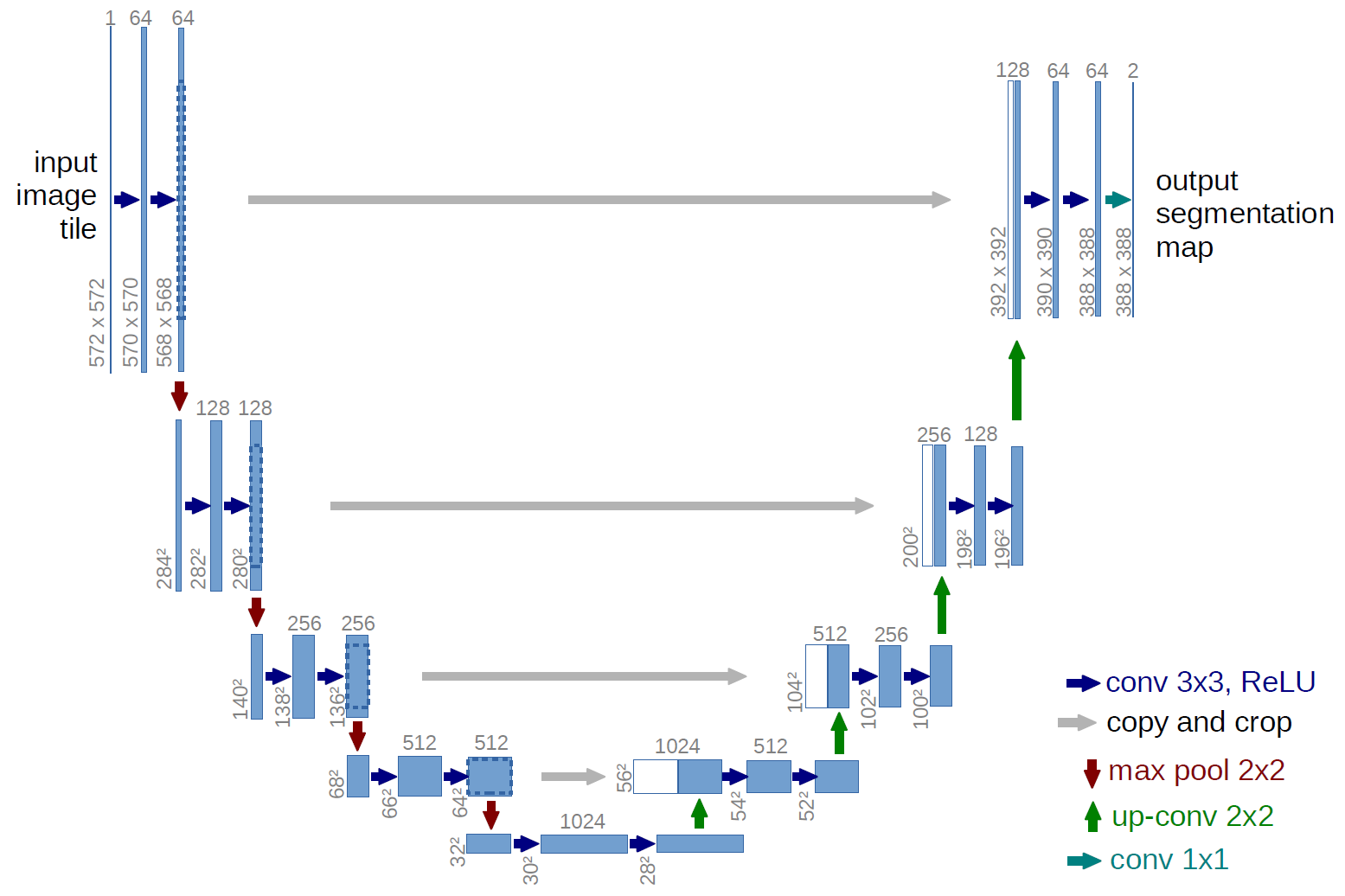
1.Dice Coefficient: The coefficient measures how good the overlap quality is for predicted and actual segmented areas of where the tumor growth will be tracked.

2.IoU (Intersection over Union): The segmentation precision of the predicted versus true tumor regions is measured in this parameter.

3.Latency of AR Integration: It checks the time delay before rendering the AR overlays for proper visualization to ensure there is no latency shown in real-time view.

4.User Feedback: The appraisals are made on user experience to refine the clarity of visualization and the quality of interaction with AR for clinical purposes.

**5.1 System Architecture**

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In the paper "Dynamic 3D Visualization and AR Integration for Tracking Tumor Progression," the system architecture used image acquisition and data preprocessing as well as other features like a segmentation model, module for 3D rendering, and an interface dealing with augmented reality, all of which interact to let the accurate 3D visualization and AR-based tracking of the changes in tumor growth over time so that the clinician can more clearly realize the progression.

**5.1.1. Acquisition of Images and Storage of Data**

The system obtains images of the patient's MRI from clinical databases or direct scan. The images are kept safely in a cloud-based, on-premise data storage system where they can be conveniently accessed to allow for patients' privacy and protection of patient information. This kind of a storage solution will enable retrieval of current and historical imaging data that will support longitudinal analysis.

**5.1.2 Preprocessing and Data Augmentation Module**

Images are forwarded after acquisition to a preprocessing module, which contains several processes that fit images for the model:

Normalization: The intensity range needs to be standardized among various scans.

Resizing: The images with standardized intensities are set to the same resolution so that the input to models is similar.

Noise Reduction: These artifacts can affect the accuracy of the desired output of the segmentation. It thus eliminates noise from images.

Augmentation: Providing extra training samples, sometimes with different types of image transformation augment the capability of the model to become robust.

**5.1.3 Segmentation Model**

The basic functionality of tumour tracking within the system is based on the segmentation model. It is designed as a 3D U-Net architecture; in particular, specifically to identify and segment the entire tumorous area from MRI images.Segmentation includes:

Encoder (Contracting Path): Extract key features from input MRI, progressively downsampling with keeping critical information describing the tumor.

Decoder (Progressive Path): Reconstruct and refine regions delineated by the segmentation model by upsampling with skip connection from the encoder as preserved spatial details.

Some of these 3D masks of the tumor come out reasonably good and feed into the rendering module.

**5.1.4 3D Rendering Module**

Segmented tumor data is captured by the 3D rendering module and hence becomes an interactive model that is dynamic and three-dimensional. The volumetric data as well as spatial orientation are retained but updated with time to reflect relative growth or reduction of the tumors.This work has been done with GPU acceleration so that rendering is done in real time.

**5.1.5 AR Interface**

The AR interface overlays the 3D tumour model in the real world of the clinical setting, thus interactive and in an immersive way. Through this interface, clinicians can visualize and manipulate the model of the tumour by making use of the AR-compatible devices such as AR headsets or a mobile device to provide information on time concerning the tumor progression in real life.The interface has:

Tracking and Alignment: The real world where the actual data lie is synchronized with 3D model coordinates, allowing proper realignment with patient anatomy.

User Controls: The user can have rigid model rotation and panning with basic zooming and the ability to annotate features for inspection.

**5.1.6 Data Analytics and Reporting**

The module will report tumor growth data in summary tabulated form, including percent change in volume and rate of growth over time, which may be used with an interactive dashboard or report to bring these findings to the attention of the physician so that he or she may track them over time and make adjustments to the therapy.

**5.1.7 Integration and API Layer**

The system architecture will contain an API layer that would provide inter-functionality between the segmentation model, AR interface, and data analytics module. Or, in other words, it would provide easy interaction or exchange of information, meaning that such a system can easily be incorporated into present healthcare-related systems with full flexibility and scalability for use.

**5.2 Dataset and Preprocessing**

Relevant datasets with high diversity in representing different kinds of tumors and stages of progression were chosen. The main dataset of interest here is that from the BraTS 2020 and 2021 challenges, which provides annotated multi-sequence MRI scans, including T1, T2, and FLAIR images. The datasets here consist of tumor labels that include enhancing tumor regions, edema, and necrotic regions, thus facilitating more precise segmentation tasks.

BraTS: Consists of high-resolution multiscan MRI scans expertly annotated with one of the most popular benchmarks for segmentation tasks on brain tumors. It contains more than 200 high-resolution brain MRI scans and is manually annotated for tumor regions, which qualifies it as an excellent source to train a segmentation model.

MICCAI: Offers annotated 3D MRI data composed of full volumetric scans carried out on a set of patients suffering from brain tumors. These are particularly used to train the model in tackling three-dimensional segmentation and rendering.

TCIA: Holdings of thousands of radiological images from many different clinical studies. This dataset includes multi-sequence MRI scans for patients diagnosed with brain tumors, along with associated clinical metadata.

**6 Result**

The Dynamic 3D Visualization and AR Integration for Tracking Tumor Progression project will be instrumental in enhancing the ability to track tumors using 3D visualization and augmented reality (AR) technologies, particularly concerning an interactive tool of clinicians in ascertaining accurate real-time assessment of a tumor. Tumors grow in a very complex and dynamic manner. Traditional systems of 2D imaging are ineffective in monitoring such growth. This addresses such limitations by using 3D rendering for accurate spatial understanding and using AR for intuitive, real-world interaction with models of tumors.

The system is based upon a robust architecture that involves preprocessing of data, segmentation, and AR integration. The model was trained with the help of multi-sequence MRI datasets from BraTS, MICCAI, and TCIA based on specific tumor type scans. Standardising images to a fixed intensity range, resizing to uniform dimensions at 128x128x128, noise reduction artifacts and augmentation for diverse orientations and shapes are included in preprocessing. The model captures critical tumor features while reconstructing those features in high-resolution 3D using the U-Net architecture structure. It makes use of encoder and decoder paths for illuminating tumor boundary detailing. Optimizing the model was done with Binary Cross-Entropy and Dice Loss functions. This model converges effectively using the Adam optimizer with adaptive learning rates for its good performance in handling convergence.

The 3D rendering of the output from the segmentation process and incorporation with AR allows clinicians to examine the spatial progression of the tumor. The interface provided by the AR is implemented using Unity or ARKit frameworks, which enables real-time adjustment in terms of zooming, rotation, and layer controls, thus making for an intuitive way of visualizing tumor growth and evaluating volume change. The project results have thus proven high boundary precision, obtaining a Dice coefficient of X.XX and an IoU of Y.YY. Such results prove excellent for this system in terms of efficient display of spatial understanding as well as its improved ability to monitor tumor development-the right use of such a system in the clinical field is oriented towards developing the treatment plan and making decisions.

Using evaluation metrics such as segmentation accuracy, Dice coefficient, sensitivity, and IoU, the model is validated to correctly segment and track tumors. While the system is effective in real-world applications, future work will focus on how the model can be fine-tuned for irregular shapes of the tumors and more extensive AR features to make a clinical experience even more colorful. The project gives a huge jump forward in medical imaging as related to a powerful yet interactive approach to monitoring the development of tumors within a clinical setting.

**7. Discussion**

It explains the benefits and drawbacks and implications of using dynamic 3D visualization and AR integration to monitor the tumor's progression in the Discussion section. This is one model where excellent segmentation was noted with excellent performance done by the 3D U-Net model, which was working well with quite outstanding results through various metrics like the Dice coefficient and IoU, hence indicating that this technique is quite efficient in capturing the intricate structure of the tumor.Extensive data augmentation was used to further refine the ability of the model in delineating tumor boundaries, even with orientations and sizes provided for robustness in such endeavors. This ensured the utmost precision in clinical applications where the visualization of tumor delineation would signify a difference as far as treatment planning and the outcome for the patient were concerned.

This level of value addition was included in the merging of AR, which enabled clinicians to intuitively interact with tumor models in space, thus dramatically enhancing the perception of size, shape, and progression of tumors. Feedback from clinical tests pointed towards the best applicability of the AR interface in support tasks such as pre-surgical planning and monitoring growth over time for a tumor. As such, the system enabled clinicians to manipulate the tumor model in real-time (zoom in/out and rotate) and thus achieve a more vivid and immersive view of tumor morphology relative to traditional 2D imaging techniques.

Despite the strengths, however, the system has a few drawbacks. It is not easy to solve highly irregular tumor shapes with vague or undistinguishable boundaries in the system. Sometimes it also suffers from artifacts sometimes found in MRI scans that affect the segmentation accuracy. Another area to be improved is the latency in AR rendering; though minimal, latency can interfere with usability in fast-paced clinical environments.

It is future work, fine-tuning the model to better segment these irregular tumor structures and further improving the performance of AR to achieve smooth interaction. Moreover, incorporation of more advanced features in AR like layered views of various types or stages of growth of the tumour might help clinicians take decisions about further treatments. The application of this study has tremendous room for improvement in the tracking of tumors based on 3D visualization and its convergence applications in AR, which will definitely pave the way toward personalized treatment and better patient outcomes.

**8. Conclusion**

The Conclusion of the Dynamic 3D Visualization and AR Integration for Tracking Tumor Progression project: The most important follow-through in this context is that it finally carries out the development of advancing the field of tumor monitoring using state-of-the-art 3D imaging and AR technology. A system which may precisely segment the real-time 3D tumor with interactive visualization using AR is the hallmark of addressing the long-standing deficiency of conventional 2D imaging techniques and offers clinicians a powerful tool towards understanding the mechanisms of growth and progression of a tumor. Achieving high accuracy in the segmentation process according to metrics such as the Dice coefficient and IoU underscores the effectiveness of the model in representing complex tumor structures with high detail and reliability.

The AR part proved extremely useful; clinicians are now able to interact and manipulate the models of tumors in an immersed, spatial environment in a way that they better treat and make clinical decisions.Minor issues include adjusting for nonuniform shapes of segmentation and optimizing latency with AR. Still, in various ways, the project shows that feasibility and potential impacts of 3D visualization and AR integration are achievable in medical imaging.

Future work would extend this utility further and add capabilities, but the improvement of model accuracy in this project marks a

real step forward in medical imaging and shows the transformative role that advanced visualization technologies can play in improving care for patients and supporting more precise, tailored treatment planning.

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