

Development of a Medical Image Segmentation Model for Tumor Localization in CT Scans Using U-NET Architecture and Transfer Learning

M.Sampoorna, X Jesurun, S Jaffar, U Sai Sathvika, E Hemavathi

Asst. Professor, Department of CSE (AI&ML), Kuppam Engineering College, AP, India

Student, Department of CSE(AI&ML), Kuppam Engineering College, AP, India

Student, Department of CSE(AI&ML), Kuppam Engineering College, AP, India

Student, Department of CSE(AI&ML), Kuppam Engineering College, AP, India

Student, Department of CSE(AI&ML), Kuppam Engineering College, AP, India

ABSTRACT: Medical image segmentation plays a crucial role in accurate tumor detection and diagnosis. Precise localization of tumors in CT scan images helps radiologists in early diagnosis and treatment planning. This paper proposes a deep learning-based tumor segmentation model using the U-Net architecture. The proposed system utilizes an encoder-decoder framework with skip connections to capture both contextual and spatial features efficiently. The model is trained on preprocessed CT scan images with data augmentation techniques to improve performance on limited datasets. Evaluation metrics such as Accuracy, Intersection over Union (IoU), and Dice Coefficient are used to assess performance. The experimental results demonstrate that the proposed U-Net-based model achieves high segmentation accuracy and precise tumor boundary detection, making it suitable for medical imaging applications.

KEYWORDS: Medical Image Segmentation, Tumor Localization, U-Net, Deep Learning, CT Scan Analysis, Encoder-Decoder Architecture, Dice Coefficient, IoU, Transfer Learning.

I. INTRODUCTION

Medical imaging technologies such as CT scans are widely used for detecting tumors and abnormal growths in human organs. Accurate segmentation of tumor regions is essential for diagnosis, treatment planning, and monitoring disease progression.

Traditional image processing techniques struggle with complex tumor shapes, unclear boundaries, and variations in image intensity. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have significantly improved segmentation performance.

The U-Net architecture, introduced by Olaf Ronneberger and his team, is specifically designed for biomedical image segmentation. It consists of a contracting path to capture context and an expansive path for precise localization. Skip connections help preserve spatial information, enabling accurate pixel-level segmentation even with limited training data. This research focuses on developing an efficient U-Net-based tumor segmentation model that can accurately localize tumors in CT scan images.

In recent years, the rapid advancement of deep learning techniques has transformed the field of medical image analysis. Automated tumor segmentation systems reduce human error, minimize diagnosis time, and provide consistent results compared to manual annotation. However, developing a reliable segmentation model requires careful handling of limited medical datasets, class imbalance, and boundary precision challenges. Therefore, leveraging a specialized architecture such as U-Net, which is designed specifically for biomedical image segmentation, provides a robust and efficient solution for accurate tumor localization in CT scan images.

II. LITERATURE SURVEY

Ronneberger et al. (2015) introduced the U-Net architecture for biomedical image segmentation. Their model demonstrated excellent performance in medical datasets with limited training samples.

Ciresan et al. used sliding-window CNN approaches for biomedical segmentation but faced computational inefficiency and redundancy issues.

Long et al. proposed Fully Convolutional Networks (FCN), enabling end-to-end pixel-wise segmentation, but localization precision was limited compared to U-Net.

Recent studies integrate transfer learning and data augmentation to improve tumor segmentation accuracy while reducing the need for large datasets.

From the literature review, it is evident that U-Net provides a strong balance between localization accuracy and contextual understanding, making it suitable for tumor detection tasks.

Fully Convolutional Networks (FCNs) introduced end-to-end pixel-wise segmentation and improved automation in medical imaging. However, repeated pooling operations reduced spatial resolution, leading to less precise tumor boundary detection compared to U-Net-based architectures.

Multi-scale feature extraction techniques were later proposed to improve segmentation performance. These approaches combine low-level spatial details with high-level contextual features, helping in better identification of tumors with varying sizes and shapes in CT images.

Transfer learning has been widely applied in medical image segmentation to address limited dataset availability. By fine-tuning pre-trained models, researchers achieved faster convergence and improved accuracy, especially in tumor localization tasks.

Attention-based U-Net variants further enhanced segmentation accuracy by focusing on relevant tumor regions while suppressing background noise. These models demonstrated improved Dice and IoU scores compared to traditional CNN-based approaches.

III. PROBLEM STATEMENT

Accurate tumor segmentation in CT scan images remains a challenging task in medical image analysis. Tumors often exhibit irregular shapes, varying sizes, and unclear boundaries that blend with surrounding tissues. Differences in image contrast, noise levels, and scanning conditions further complicate precise localization. These factors make manual segmentation time-consuming and prone to human error, creating a need for reliable automated solutions.

Traditional image processing and rule-based segmentation techniques are limited in handling complex medical images. Methods based on thresholding, edge detection, or region growing often fail when tumor intensity closely resembles healthy tissue. Moreover, these approaches lack adaptability and struggle to generalize across different datasets and imaging conditions.

Another major challenge is the limited availability of annotated medical datasets. Creating ground truth segmentation masks requires expert radiologists, making the annotation process expensive and time-intensive. As a result, deep learning models trained on small datasets may suffer from overfitting and reduced generalization performance, affecting the reliability of tumor detection systems.

Therefore, there is a critical need for an efficient deep learning-based segmentation model that can accurately localize tumors at the pixel level while working effectively with limited training data. The proposed system aims to address these challenges by utilizing a U-Net architecture that preserves spatial information, improves boundary detection, and enhances segmentation accuracy for clinical applications.

IV. PROPOSED SYSTEM

A. System Overview:

The proposed system is a deep learning-based medical image segmentation framework designed to accurately localize tumors in CT scan images. It utilizes the U-Net architecture, which follows an encoder-decoder structure to perform pixel-level classification. The system aims to automate tumor detection and assist medical professionals in faster and more reliable diagnosis.

The overall architecture consists of multiple stages, beginning with image input and preprocessing. CT scan images are first resized, normalized, and enhanced to ensure consistent quality and compatibility with the deep learning model. Data augmentation techniques such as rotation, flipping, and elastic deformation are applied to improve model generalization and handle limited training data effectively.

Academic diagram of U-Net architecture showing encoder and decoder paths with skip connections, convolution blocks, max pooling, upsampling layers is illustrated in Fig 1.

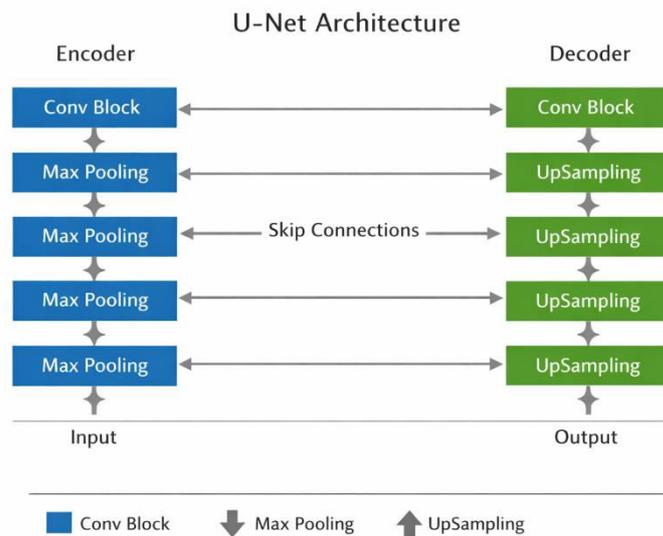


Fig. 1. Academic diagram of U-Net architecture showing encoder and decoder paths with skip connections, convolution blocks, max pooling, upsampling layers.

The core component of the system is the U-Net model, which contains a contracting path (encoder) and an expanding path (decoder). The encoder extracts high-level contextual features through convolution and pooling operations, while the decoder reconstructs the spatial resolution of the image using upsampling layers. Skip connections are incorporated to combine low-level spatial details with high-level semantic information, ensuring accurate tumor boundary detection.

During the training phase, the model learns from labeled CT scan images by minimizing segmentation loss functions such as Dice Loss and Binary Cross-Entropy Loss. Optimization techniques like the Adam optimizer are used to update model weights efficiently. This training process enables the model to identify complex tumor patterns and variations in medical images.

Finally, the trained model generates a binary segmentation mask highlighting tumor regions in the CT scan image. The output can be visualized alongside the original image for better interpretation by radiologists. The system is designed to be scalable and can be deployed as a web-based or standalone application, making it suitable for integration into real-world clinical environments.

B. Use Case Diagram

The Use Case Diagram represents the interaction between the user and the tumor segmentation system. The primary actor in the system is the radiologist or medical practitioner who utilizes the application for tumor analysis and diagnosis.

The user initiates the process by uploading CT scan images into the system. Once the image is provided, the system performs preprocessing operations such as normalization and resizing to prepare the image for segmentation.

After preprocessing, the U-Net model is executed to perform tumor segmentation. The system analyzes the CT scan image and generates a segmented output highlighting the tumor region with high precision.

A UML use case diagram for tumor segmentation system with actor Radiologist and system functions, as shown in Fig 2.

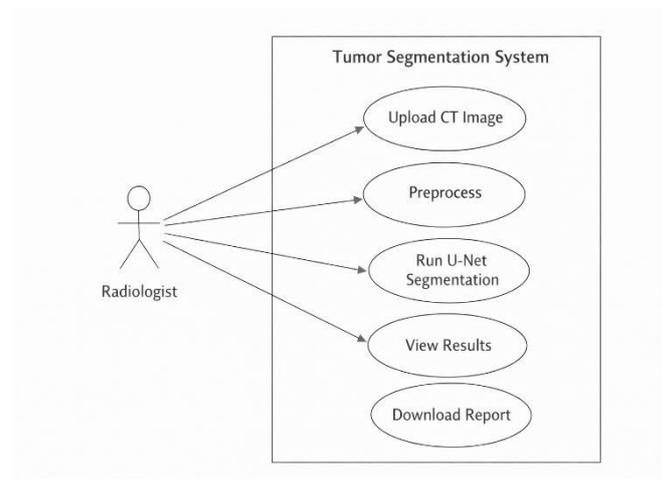


Fig. 2. UML use case diagram for tumor segmentation system with actor Radiologist and system functions

V. METHODOLOGY

A. Data Collection

The dataset used in this research consists of CT scan images collected from publicly available medical imaging repositories and hospital sources. These images include both normal and tumor-affected scans, along with corresponding ground truth segmentation masks annotated by medical experts. The availability of labeled data enables supervised learning for accurate tumor localization.

The dataset captures variations in tumor size, shape, and intensity, making it suitable for training a robust segmentation model. By including diverse samples, the system is able to learn complex patterns and improve its ability to generalize across different CT scan conditions and patient cases.

B. Data Preprocessing

Raw CT scan images often contain noise, intensity variations, and inconsistencies that can affect model performance. Therefore, preprocessing is performed to enhance image quality and ensure uniformity. Images are resized to a fixed resolution, normalized to standard intensity ranges, and filtered to reduce noise.

To overcome the limitation of small datasets, data augmentation techniques such as rotation, flipping, scaling, and elastic deformation are applied. These techniques increase dataset diversity, prevent overfitting, and help the model learn invariant features, leading to improved segmentation accuracy.

C. Model Training

The proposed system employs the U-Net architecture, which consists of an encoder–decoder structure with skip connections. The encoder extracts hierarchical features through convolutional and pooling layers, while the decoder restores spatial resolution using upsampling operations. Skip connections enable the model to retain fine-grained spatial details essential for accurate tumor boundary detection.

The model is trained using labeled CT scan images and corresponding segmentation masks. Loss functions such as Dice Loss and Binary Cross-Entropy are used to optimize segmentation performance. The Adam optimizer is employed for efficient weight updates, ensuring faster convergence and stable training.

D. Model Evaluation

The performance of the trained model is evaluated using standard segmentation metrics. These include Accuracy, Dice Coefficient, Intersection over Union (IoU), Precision, and Recall. These metrics provide a comprehensive assessment of the model’s ability to correctly identify tumor regions and minimize false predictions.

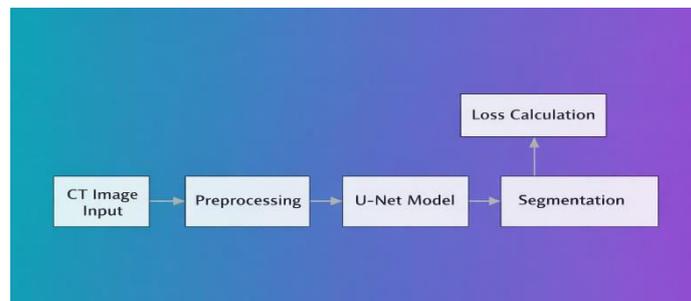


Fig. 3. Deep learning workflow diagram

Evaluation is performed on a separate test dataset that was not used during training. The results demonstrate that the U-Net–based model achieves high accuracy and precise tumor localization, confirming its effectiveness in handling complex medical images with limited training data.

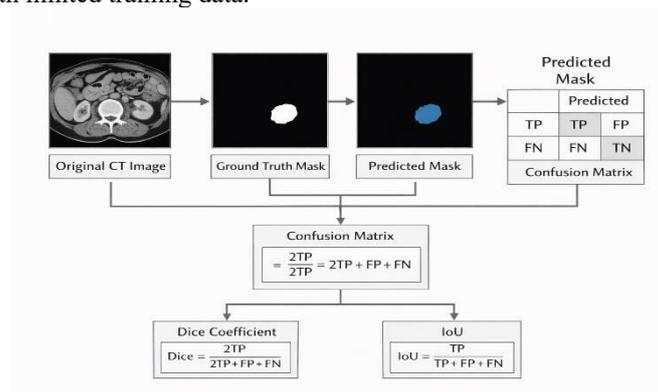


Fig. 4. Professional academic diagram showing medical image segmentation evaluation process

In addition to quantitative metrics, a confusion matrix is used to analyze the classification performance of the segmentation model. The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives. This analysis helps in understanding how accurately the model distinguishes tumor pixels from non-tumor regions. A lower number of false positives and false negatives indicates better boundary precision and improved reliability of the segmentation system.

Furthermore, visual evaluation of the segmented output is performed by comparing predicted masks with ground truth annotations. Overlaying the predicted tumor mask on the original CT scan image allows for qualitative assessment of boundary accuracy and region consistency. The model demonstrates strong alignment with expert-labeled masks, confirming its ability to accurately localize tumors and minimize segmentation errors. These results validate the robustness and clinical applicability of the proposed U-Net-based model.

E. Deployment

After successful training and evaluation, the model is deployed to enable practical usage. The trained U-Net model is saved and integrated into a user-friendly application using a lightweight web framework such as Flask. This allows users to interact with the system through a simple interface.

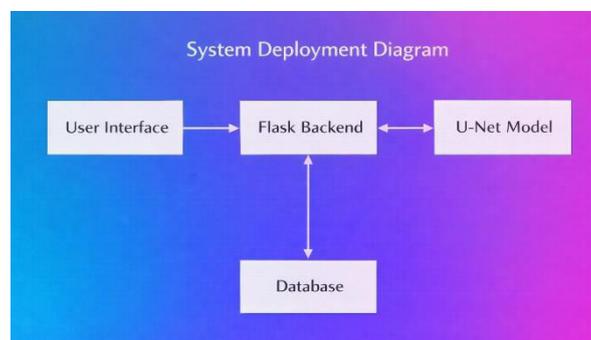


Fig. 5. System deployment diagram showing user interface

During deployment, users can upload CT scan images, and the system performs preprocessing and segmentation in real time. The segmented tumor output is then displayed to the user, making the system suitable for clinical support and medical research applications.

VI. EXPECTED OUTCOMES

The proposed U-Net-based tumor segmentation system is expected to achieve high accuracy in identifying and localizing tumor regions in CT scan images. By leveraging the encoder-decoder architecture with skip connections, the model can precisely capture both contextual and spatial features, resulting in accurate pixel-level segmentation. This helps in clearly distinguishing tumor tissue from surrounding healthy regions.

Another expected outcome is improved robustness and generalization of the model when working with limited annotated medical datasets. The use of data preprocessing and augmentation techniques enhances the model's ability to handle variations in tumor size, shape, and intensity. As a result, the system is capable of maintaining consistent performance across different CT scan conditions and patient cases.

Additionally, the system is expected to reduce manual effort and support medical professionals in faster decision-making. Automated tumor segmentation minimizes dependency on time-consuming manual annotation and reduces human error. The deployed system can serve as a reliable clinical support tool, contributing to improved diagnostic accuracy, treatment planning, and overall healthcare efficiency.

VII. CONCLUSION

This paper presented a deep learning-based medical image segmentation model for tumor localization in CT scan images using the U-Net architecture. The encoder-decoder framework with skip connections enables precise pixel-level segmentation by effectively combining contextual and spatial information. The proposed approach addresses the limitations of traditional image processing methods and provides an efficient automated solution for tumor detection.

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The methodology incorporated structured stages including data collection, preprocessing, model training, evaluation, and deployment. Performance metrics such as Dice Coefficient, IoU, Accuracy, Precision, and Recall demonstrate that the model achieves reliable segmentation results. The experimental analysis confirms that the system accurately identifies tumor regions while minimizing false predictions, making it suitable for practical medical applications.

Overall, the proposed system contributes to the advancement of intelligent medical imaging solutions by supporting radiologists in accurate and timely diagnosis. The integration of deep learning techniques enhances segmentation precision and reduces manual workload. With further improvements and real-world deployment, the model has strong potential to assist in clinical decision-making and improve patient care outcomes.

VIII. FUTURE ENHANCEMENTS

The proposed system can be extended by implementing a 3D U-Net architecture to process volumetric CT scan data. This would allow the model to analyze tumor structures across multiple slices, improving segmentation accuracy and providing better clinical insights.

Future work can also include integrating attention mechanisms and hybrid deep learning models to further enhance boundary detection and reduce false positives. These advanced techniques can help the model focus more effectively on relevant tumor regions.

Additionally, the system can be deployed on cloud platforms and integrated with hospital information systems for real-time clinical usage. Developing a mobile or web-based interface with multilingual support would improve accessibility and make the solution more practical for healthcare environments.

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