Using Image Segmentation to Model Kidney Vasculature

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I. Abstract

At present image segmentation is already widely used in the medical field. However traditional segmentation methods like manual segmentation and current automated algorithms have posed various challenges that have made them unreliable. Manual segmentation required experts and is a time consuming and expensive task. Current segmentation algorithms are dependent on older training data and outdated neural networks producing highly inaccurate results. This lack of medical images reduced our understanding of diseases, delayed diagnosis and hindered early treatment that could be life saving. In order to overcome this difficulty, this paper proposes employing a specialised algorithm designed specifically for biomedical image segmentation which can process multiple image slices at once. The segmentation of kidney scans allows us to model the intricate vascular networks which is significant because they function as the body's filtration system. Medical fields including urology and oncology use these models to diagnose diseases, identify tumours and monitor the conditions to produce a surgical plan suited for their patient. Machine learning algorithms can also help improve the performance and efficiency of analysing these medical images. Our project uses 2.5D kidney CT images from a Hip-CT database of kidney CT scans, and U-Net, a Convolutional Neural Network specialised in medial image processing, to produce cutting edge and high resolution models. Our experiments demonstrate that our approach matches and sometimes outperforms existing state-of-the-art models.

A. Index terms

segmentation, augmentation, CNN, deep learning, U-Net

II. Introduction

Cancer tumours are steadily on the rise and there is a constant race to find new treatments and develop alternative strategies to cure cancer. Kidney tumours are consistently in the top occurring tumours and affect millions of people every year with 430,000 new cases in 2020 alone. [1] [2] The urinary system is most at risk because most kidney tumours become hostile and inflict damage to other cells which commonly leads to bladder cancer. Unfortunately the cause of kidney cancer is still unclear but it has been narrowed down to environmental factors and genetic factors. [3] This is where medical imaging is extremely useful because doctors can use it to visualise and detect the tumours.

Computer Assisted Diagnosis (CAD) is an important part of the diagnosis and treatment of disease, and in recent years the use of deep learning for medical image segmentation has become a powerful new tool for the diagnosis, treatment and prevention of various diseases. [4] This has not just been limited to the medical field as deep learning has proven effective in other industries like building supercomputers, fully autonomous driving and gaming. For medical image processing accurate results can be created using image segmentation for the classification and identification of tumours. [5] Compared to traditional segmentation methods our deep learning algorithm utilises multiple processing layers to extract detailed scans from the training data.

The volume research into CNNs has allowed us to fine tune them for our medical needs and image segmentation has benefited greatly. They are now capable of completing an entire segmentation without the need of human intervention. However this still relies on having a large quantity of high resolution, labelled medical images which can be difficult and time consuming to produce. To address the issue of limited data, our project uses a variety of augmentations to increase the variability of our data and prevent over-fitting. This strategy explores transforming certain elements like size, rotation, brightness and contrast in order to create new training data completely unique from the original image. It allows the dataset to be more adaptable to real world clinical scenarios where anything can happen and unexpected features often show up. This augmentation greatly improves the availability of training data for our model.

In this paper we introduce an image segmentation algorithm that accurately create a segment map of the kidneys vasculature, allowing us to assemble a 3D model of the blood vessels within the kidney which can be used by physicians to aid in the diagnosis and treatment of disease. An example of the type of segmentation mask produce by our algorithm can be seen in figure 1.

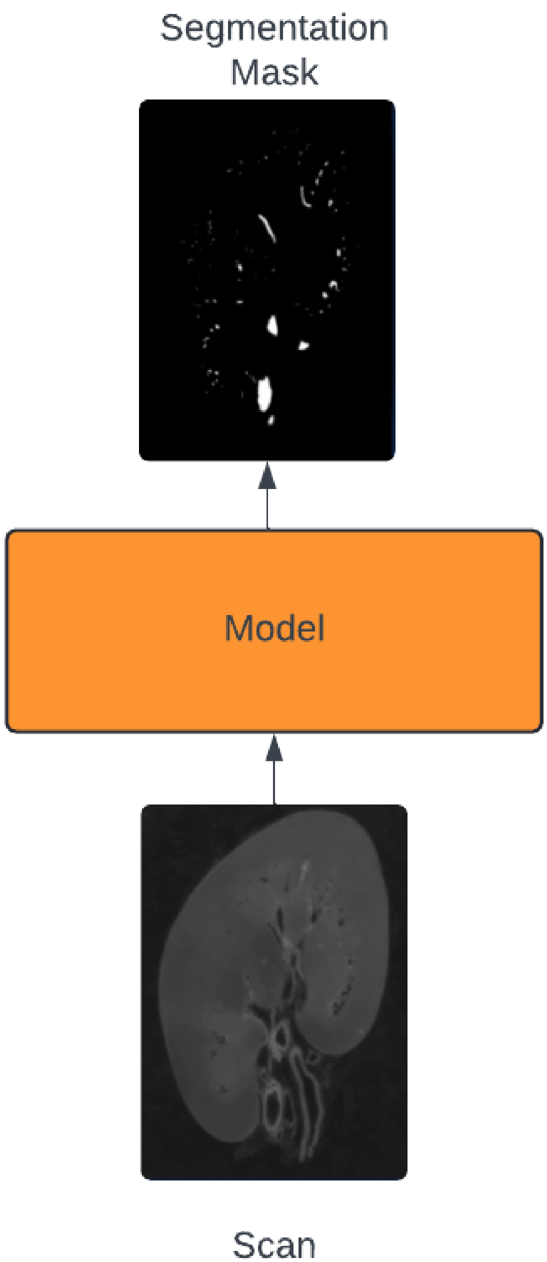

Fig. 1. Creating a segmentation mask from a kidney CT

III. Related Works

In recent years, the segmentation of kidneys and kidney tumors has gained significant attention due to the necessity for accurate diagnostic tools. Several innovative methodologies have been proposed to enhance the performance of segmentation algorithms.

One such method is the 2.5D MFFAU-Net proposed by Sun et al., which utilizes a convolutional neural network specifically designed for kidney segmentation [1]. This approach is complemented by Tang et al.'s augmentation strategy that employs statistical shape models and 3D thin plate splines to improve the data quality for deep learning applications [2].

Khalifa et al. introduced a hybrid framework that integrates geometric deformable models and nonnegative matrix factorization (NMF) for 3D kidney segmentation from CT images [3]. Sadeghi et al. further advanced the field by proposing a weakly-supervised approach for kidney tumor segmentation using image-level labels [4].

Campadelli et al. focused on the automatic segmentation of abdominal organs from CT scans, providing a robust system evaluated on multiple patient datasets [5]. Liu and Xiang proposed a method for kidney blood vessel segmentation from computed tomography images, which has shown promising results in accuracy and efficiency [6]. Similarly, Dai et al. proposed a 3D fast GrowCut algorithm for kidney segmentation, which demonstrated significant accuracy and speed improvements [7].

Avesta et al. compared 3D, 2.5D, and 2D approaches to brain image segmentation, revealing the benefits of each method in terms of accuracy and computational efficiency [8]. Sun et al.'s MM-GAN leveraged generative adversarial networks for 3D MRI data augmentation, which has shown promising results in enhancing segmentation accuracy [9].

In their survey, Abdelrahman and Viriri provided a comprehensive overview of deep learning techniques for kidney tumor segmentation, highlighting state-of-the-art methods and their efficacy [10]. The H-DenseUNet proposed by Li et al. combines 2D and 3D convolutional networks to achieve superior segmentation results for liver and tumors from CT volumes [11].

Recent advancements also include the development of the nnU-Net, a self-configuring method for deep learning-based biomedical image segmentation by Isensee et al. [12]. Hussain et al. proposed DilUNet, a U-Net based architecture specifically designed for blood vessels segmentation, demonstrating significant improvements in accuracy [13].

Zhao et al. introduced the Boundary Attention U-Net, which enhances kidney and kidney tumor segmentation by incorporating boundary attention mechanisms [14]. Wang et al. provided an evaluation of the U-Net model specifically for renal structure segmentation, highlighting its strengths and areas for improvement [15].

Xu et al. proposed an automatic data augmentation method for 3D medical image segmentation, which optimizes augmentation strategies to improve model performance [16]. Ronneberger et al.'s U-Net architecture remains a foundational model in biomedical image segmentation, known for its efficiency and effectiveness [17].

Additional noteworthy contributions include the work by Kittipongdaja and Siriborvornratanakul, who explored 2.5D ResUNet and DenseUNet for kidney segmentation and malignant potential analysis in renal cysts [18]. Shorten and Khoshgoftaar's survey on image data augmentation techniques for deep learning provides valuable insights into enhancing training datasets [19].

Suji et al. presented a comprehensive survey and taxonomy of 2.5D approaches for lung segmentation and nodule detection, highlighting the importance of intermediate dimensional techniques in medical imaging [20]. Xu et al.'s review of image augmentation techniques for deep learning further emphasizes the significance of data augmentation in improving model generalization [21].

Chen and Zhang's ensemble of 2.5D ResUNet models for kidney and mass segmentation demonstrated the effectiveness of combining multiple models to enhance segmentation performance [22]. Moccia et al. reviewed blood vessel segmentation algorithms, providing a thorough analysis of methods, datasets, and evaluation metrics [23].

Kaur and Juneja surveyed kidney segmentation techniques in CT images, summarizing various methods and their applications [24]. Lastly, da Cruz et al. proposed a 2.5D DeepLabV3+ model for kidney tumor segmentation from CT images, showcasing its ability to balance model complexity and segmentation accuracy [25].

Kirillov et al. introduced a novel segmentation framework capable of segmenting any object in an image, providing a versatile tool for medical image analysis [26]. Tan and Le proposed the EfficientNet model, which scales convolutional neural networks to achieve better performance with fewer parameters, a method that can be adapted for medical image segmentation tasks [27].

Hu et al. developed a 2.5D segmentation approach for cancer detection in MRI images using a U-Net architecture, which can be extended to kidney and tumor segmentation [28]. Han et al. introduced a 2.5D perpendicular UNet for liver segmentation, demonstrating the effectiveness of intermediate dimensional approaches in medical imaging [29].

IV. Medical Image Segmentation Model

A. U-Net in Medical Image Segmentation

U-Net, introduced by Ronneberger et al. [17], is a prominent architecture in medical image segmentation. Its distinctive U-shaped structure features a contracting path that captures context and an expanding path that enables precise localization. This dual-path approach is particularly effective for tasks requiring detailed segmentation, such as those in biomedical imaging. U-Net's design has proven highly capable in handling the often limited datasets available in medical imaging, making it a cornerstone model for various segmentation challenges.

B. V-Net in Medical Image Segmentation

V-Net, developed by Milletari et al., extends the principles of U-Net to 3D image segmentation [7]. Specifically designed for volumetric data, V-Net utilizes volumetric convolutions to efficiently process 3D medical images, such as CT and MRI scans. This model excels in segmenting complex anatomical structures, demonstrating significant effectiveness in the field of medical imaging. Its ability to manage and segment 3D data robustly highlights its importance in advanced medical diagnostics.

C. Vision Transformer in Medical Image Segmentation

The Vision Transformer (ViT), introduced by Dosovitskiy et al., represents a major advancement in image segmentation by applying the transformer architecture originally used in natural language processing [8]. ViT processes images as sequences of patches and employs self-attention mechanisms to capture global dependencies within the image. This approach is particularly useful for complex segmentation tasks, such as kidney blood vessel segmentation, where understanding and interpreting intricate structures are crucial. ViT's innovative methodology enhances the accuracy and efficiency of segmenting detailed vascular structures, contributing significantly to renal healthcare diagnostics and treatment planning.

D. U-Net with Attention Gates in Medical Image Segmentation

Enhancing the traditional U-Net architecture with attention mechanisms, U-Net with Attention Gates [11] focuses on relevant regions of an image to improve segmentation accuracy. This modification is particularly beneficial for tasks requiring high precision, such as kidney blood vessel segmentation. The attention gates selectively highlight important features, thus refining the model's ability to distinguish intricate vascular structures. This advanced version of U-Net offers significant improvements in accuracy and detail, vital for effective diagnosis and treatment planning in medical imaging.

E. UniverSeg in Medical Image Segmentation

UniverSeg, introduced by Butoi et al., is designed for universal medical image segmentation tasks without needing additional training for new tasks [10]. This approach uses a Cross-Block mechanism to facilitate accurate segmentation across diverse medical imaging modalities and anatomies. UniverSeg's adaptability makes it particularly valuable for dynamic medical environments, where different imaging challenges are encountered frequently. This model underscores the importance of flexibility and efficiency in medical image segmentation, aligning well with the diverse demands of kidney blood vessel segmentation.

F. UNETR in Medical Image Segmentation

UNETR, introduced by Hatamizadeh et al., builds upon the U-Net architecture by integrating transformer-based attention mechanisms specifically for 3D volumetric data [1]. This model's ability to capture long-range dependencies within 3D data makes it particularly effective for complex structures like kidney blood vessels. Unlike traditional convolutional approaches, UNETR's attention-based strategy enhances the model's focus on relevant spatial features across different slices of 3D scans, significantly improving segmentation accuracy and efficiency in medical imaging tasks.

G. *TransUNet in Medical Image Segmentation*

TransUNet, developed by Chen et al., combines the strengths of Transformer and U-Net architectures [16]. This hybrid model leverages the global context captured by Transformers with the robust local feature extraction capabilities of U-Net. TransUNet excels at capturing detailed textural and structural information from medical scans, crucial for accurate kidney blood vessel segmentation. By integrating self-attention mechanisms, TransUNet effectively addresses the challenge of segmenting fine-grained structures in medical images, offering significant improvements over traditional CNN-based models.

V. Data Preprocessing

A. *Dataset*

We utilized a comprehensive dataset tailored for our kidney segmentation project. The dataset comprises high-resolution 3D images of kidneys and corresponding 3D segmentation masks of their vasculature. The images were captured using advanced imaging techniques, which provide extremely high-resolution 3D scans. The dataset includes both densely and sparsely segmented kidney images as well as scans captured at varying resolutions. This diversity is intended to help our model perform well under real-world imaging conditions. The dataset is substantial, containing over 14,000 files and totaling 43 GB in size.

B. *Data Preprocessing*

Data preprocessing is a crucial step in our methodology. The preprocessing pipeline involves cleaning the data to remove any artifacts or noise, standardizing pixel values to ensure consistency across images, and resizing the images to a uniform size of 512x512 pixels. This preprocessing ensures that the data is in a suitable format for the model to process effectively.

C. *Data Augmentation*

Given the limited size of our dataset compared to typical deep learning tasks, data augmentation is essential to enhance the model's ability to generalize. We employed various augmentation techniques, including rotations (up to 45 degrees), random scaling (between 0.8 and 1.25), cropping, gamma correction, brightness/contrast adjustments, and blurring (Gaussian and motion blur).These transformations help simulate a wide range of imaging conditions, thereby preventing the model from overfitting and improving its robustness to diverse input data. This approach aligns with the augmentation strategies discussed in the literature, such as the use of statistical shape models and 3D thin plate splines for deep learning applications [2], [19], [21].

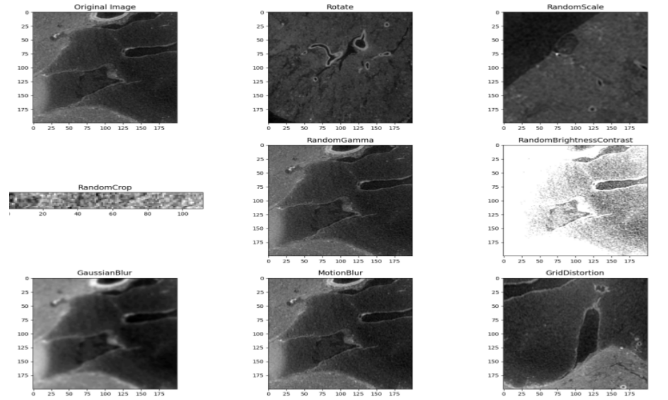

Fig. 2. Augmentation on the Dataset

VI. Methodology

A. *U-Net Architecture*

In our study, we employed the U-Net architecture, a specialized Convolutional Neural Network (CNN) designed for biomedical image segmentation. The U-Net model is particularly well-suited for tasks requiring precise localization, such as medical image analysis. It features a symmetrical structure consisting of an encoder (contracting path) and a decoder (expanding path), with skip connections that link corresponding layers in the encoder and decoder. This design allows the model to capture both context and fine details, making it ideal for segmenting intricate structures like blood vessels in kidney images [30].

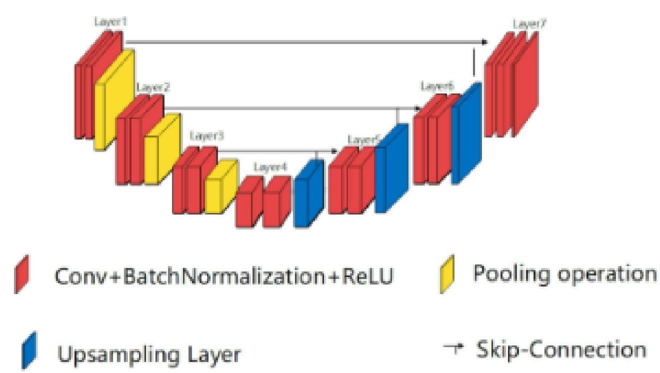

Fig. 3. U-Net Model Structure [31]

1) Encoder Path: The encoder path of the U-Net model captures the context of the input image through a series of convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation function and batch normalization. The spatial dimensions of the input image are progressively downsampled using max-pooling layers, which reduce the resolution while increasing the depth of the feature maps. This hierarchical feature extraction enables the model to learn multiple levels of abstraction, crucial for understanding complex medical images.

2) Decoder Path: The decoder path reconstructs the high-resolution segmentation map from the encoded features. It consists of upsampling layers followed by convolutional layers, batch normalization, and ReLU activation functions. The upsampling layers increase the spatial resolution of the feature maps, while skip connections concatenate the corresponding encoder feature maps to the upsampled feature maps. This combination helps the model retain fine details and spatial information that might be lost during downsampling.

3) Bottleneck: The bottleneck layer serves as the bridge between the encoder and decoder paths, processing the deepest feature maps and preparing them for upsampling in the decoder. This layer is composed of convolutional layers, batch normalization, and ReLU activation functions, ensuring that the learned features are effectively transformed for reconstruction.

4) Final Convolution: The final convolutional layer maps the feature maps to the output channels, corresponding to the segmentation classes. Using a 1x1 convolution reduces the depth of the feature maps to the number of desired output classes, enabling precise delineation of structures.

5) Model Architecture: The U-Net model integrates the described blocks into an encoder-decoder structure. The encoder consists of successive convolutional modules with max pooling, while the decoder utilizes upsampling and convolutional modules. The bottleneck connects the encoder and decoder paths. At each level of the decoder, skip connections concatenate the upsampled features with the corresponding encoder features, ensuring that both high-level context and fine-grained details are preserved. The final convolutional layer generates the segmentation map, which corresponds to the target classes.

B. Training Process

Our training process involves several key steps to ensure optimal performance of the U-Net model including using a 2.5d imaging technique to improve accuracy as it does not increase model size considerably.:

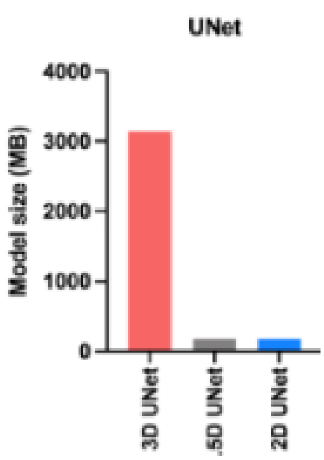

Fig. 4. Model Size Comparsion [32]

1) Model Configuration: We defined a configuration class to manage crucial parameters such as model type, backbone architecture, image size, batch sizes, learning rate, and other hyperparameters. For this project, we used the U-Net model with an SE-ResNeXt50 backbone, a popular choice for segmentation tasks due to its balance of performance and computational efficiency [11].

2) Data Handling and Normalization: Custom data handling functions were implemented to load images and labels, convert them to tensors, and perform normalization. We employed min-max normalization to standardize pixel values across the dataset, ensuring consistent input for the model. Additionally, controlled noise was added to the dataset to enhance the model's robustness by simulating real-world variations [2].

3) Training Loop: The training loop iteratively feeds the original and augmented datasets into the model. The model is trained for 20 epochs, balancing thorough learning and computational efficiency. The Dice Loss function was used to measure the overlap between the predicted and true masks, particularly suitable for segmentation tasks. The AdamW optimizer was chosen for its effectiveness in dealing with sparse gradients, and the OneCycleLR scheduler was used to dynamically adjust the learning rate, promoting better convergence. The autocast feature for mixed precision training was utilized to speed up computation and reduce memory usage, allowing for larger batch sizes [33].

4) Validation and Model Saving: After each training epoch, the model was validated on a separate validation set to evaluate its performance. The Dice coefficient measured the accuracy of the model's predictions. This validation step ensures that the model generalizes well to new data and is not overfitting. We periodically saved the model's state to preserve the best-performing versions, ensuring progress is not lost and allowing training to resume from the best checkpoints. This process is critical for refining the model and achieving optimal performance.

5) Importance of Key Components:

- **Encoder Path**: Captures multiple levels of abstraction, which is crucial for understanding the complex structures in medical images.
- **Decoder Path**: Ensures that high-resolution details are retained, enabling precise segmentation.
- **Skip Connections**: Combine high-resolution features from the encoder with upsampled features, enhancing the model's ability to produce accurate segmentation maps.
- **Batch Normalization and ReLU Activation**: Improve the stability and convergence of the model, ensuring that the network learns effectively.
- **Controlled Noise Addition**: Enhances the robustness of the model, making it more resilient to variations in real-world data.

VII. Results

A. Model Performance

The U-Net model demonstrated significant improvements in segmentation accuracy, particularly when compared to traditional methods. The use of 2.5D U-Net provided a balance between computational efficiency and the ability to capture 3D spatial information. The application of advanced data augmentation techniques further enhanced the model's robustness and generalization capabilities.

B. Evaluation Metrics

The model's performance was evaluated using the Dice coefficient, a metric that quantifies the similarity between the predicted and true segmentation masks. This coefficient is especially useful for segmentation tasks as it measures the overlap between the two masks, providing a clear indication of accuracy.

The Dice coefficient is calculated as follows:

$$\text{Dice coefficient} = \frac{2 \times |A \cap B|}{|A| + |B|}$$

where A represents the set of pixels in the predicted segmentation, and B represents the set of pixels in the ground truth segmentation. The numerator, $2 \times |A \cap B|$, is the count of pixels correctly identified in both the prediction and the ground truth. The denominator, $|A| + |B|$, is the total number of pixels in both the predicted and true segmentations.

This formula effectively measures the overlap between the predicted segmentation and the actual segmentation, making it a valuable metric for assessing the performance of segmentation models.

VIII. Results

Our Model was a success and performed very highly as indicated with a Dice coefficient of 0.81, demonstrating accurate segmentation of kidney vascular structures. This performance is being compared to other segmentation models, as summarized in Table I. Our model, labeled 'Customised U-Net', outperformed several established models, showcasing its effectiveness in medical image segmentation tasks being 13 perfect more successful than the any other model used.

TABLE I
Comparison of Dice Scores for Different Models

Model	**Dice Score**
Customised U-Net	0.81
U-Net	0.621
V-Net	0.586
SegNet	0.522
DeepLab	0.593
AttenU-net	0.642
UNETR	0.651
AttenTripleU-Net	0.679

A. Visual Representations of Results

IX. Visualization of Results

The visual results presented in Figures 5, 7, and 8 highlight the performance and effectiveness of our customized 2.5D U-Net model across various stages of the training and evaluation process.

Fig. 5. Visual representation of model training score.

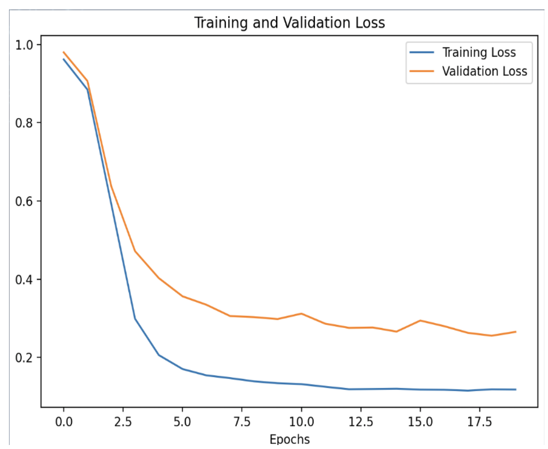

Fig. 6. Visual representation of model training loss.

Figure 5 and 6 shows us the training and validation loss curves, illustrating the model's convergence over the training epochs. The steady decline in loss indicates effective learning and adaptation to the data.

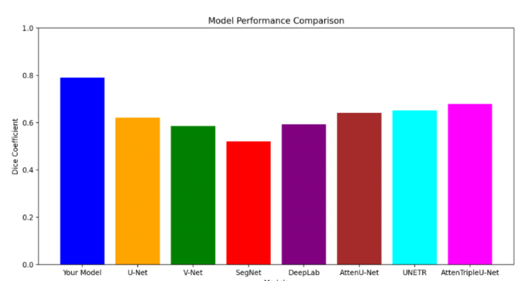

Fig. 7. Visual representation of model performance compared to other models.

Figure 7 compares the Dice coefficients of our model with other established segmentation models. Our customized U-Net achieved the highest Dice score, demonstrating superior performance in segmenting kidney structures on the same dataset. This represents the high accuracy and high 3D model capabilities further cementing its ability to alter Medical Image Segmentation in the Medical Industry.

Fig. 8. 3D representation of the model's segmentation results.

Figure 8 provides a 3D visualization of the kidney segmentation results. This representation highlights the model's capability to accurately segment the complex vascular of the kidney from high-resolution CT scans. It showcases the complexity of the project and its ability to produce high definition, high detail imagery

The comprehensive visualization of these results underscores the effectiveness of our model, from training through to performance evaluation and the practical application in generating detailed 3D segmentation's which can be used within clinical, diagnostic, training and educational settings.

A. *Explain Results*

Our customised 2.5D U-Net model demonstrated superior performance in accurately segmenting kidney vasculature from high-resolution CT scans. The model's Dice coefficient of 0.81 indicates a high degree of overlap between the predicted segmentation masks and the ground truth masks, surpassing the performance of several established segmentation models (Table I).

The training process, visualized in Figure 5, shows a steady decrease in training loss over epochs, indicating that the model effectively learned to produce increasingly accurate segmentations. The use of advanced data augmentation techniques played a crucial role in enhancing the model's robustness and generalization capabilities, enabling it to handle variations in real-world data more effectively.

The 3D representation of the model's segmentation output (Figure 8) allows for the visualization of the intricate vascular structures within the kidney, covering the internal vascular structure thus demonstrating the model's ability to delineate these complex structures successfully.
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Clinical Applications

1. **Pre-Surgical Planning**: Accurate segmentation of kidney vasculature can aid surgeons in planning procedures by providing detailed maps of vascular structures, reducing the risk of intraoperative complications.

2. **Diagnosis and Monitoring**: Enhanced segmentation accuracy helps in identifying and monitoring vascular abnormalities, such as aneurysms or blockages, contributing to early diagnosis and effective treatment.

3. **Radiology Assistance**: Radiologists can utilize the model to automate the analysis of CT scans, speeding up the workflow and improving diagnostic accuracy.

4. **Educational Tool**: The 3D visualizations generated by the model can serve as educational tools for medical students and professionals, helping them to better understand kidney anatomy and pathologies.

5. **Research and Development**: The model can be used in research to study kidney diseases and develop new treatment protocols, leveraging its ability to accurately model and visualize the vascular network.

The strong quantitative and qualitative results obtained by the customized 2.5D U-Net model demonstrate its potential for enhancing medical image analysis in the domain of kidney vasculature segmentation.

X. Conclusion

In conclusion, our study highlights the potential for developing specialised deep learning algorithms for biomedical applications, particularly in the field of renal imaging. The ability of our model to accurately model and visualise the intricate vascular networks within the kidney has significant implications for medical fields related to the renal system with the potential to aid in diagnosis, treatment, and monitoring. The superior performance of our customised 2.5D U-Net model highlights the importance of continuing research and development in this area so that we can further refine and optimise these algorithms and unlock new possibilities for non-invasive diagnostic techniques. Ultimately, this paper has proved that advanced deep learning methods do have the capability to revolutionise the field of medical imaging with the ability to do what was previously thought impossible.

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