Automated Segmentation of Carotid Arteries in Ultrasound Images using Deep Learning

A report submitted for the thesis evaluation

By

Gaurav : 2020BCS-032

Sankalp Bhoyar : 2020BCS-067

Under the Supervision of

Dr. Debanjan Sadhya

&

Dr. Biswabandhu Jana

Department of Computer Science & Engineering

विश्वजीवनामृतं ज्ञानम्

ABV-INDIAN INSTITUTE OF INFORMATION TECHNOLOGY AND MANAGEMENT GWALIOR

GWALIOR, INDIA

CERTIFICATE

We hereby certify that the work, which is being presented in the report/thesis entitled "Automated Segmentation of Carotid Arteries in Ultrasound Images using Deep Learning", which is submitted to the institution, is an authentic record of our own work carried out during the period Januaru-2024 to (Ongoing) under the supervision of Dr Debanjan Sadhya and Dr Biswabandhu Jana. We also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

Date: **Signature of the candidate**

Date: **Signature of the candidate**

This is to certify that the above statement made by the candidates is correct to the best of our knowledge.

Date: **Signature of supervisor-1**

Date: **Signature of supervisor-2**

Acknowledgements

We would like to express our heartfelt gratitude to Dr Debanjan Sadhya and Dr Biswabandhu Jana for their invaluable guidance and support throughout the course of my thesis project till now. Their profound knowledge, insightful suggestions, and continuous encouragement have played a pivotal role in shaping this research endeavour.

We would also like to express my appreciation to all the researchers and authors whose work and contributions have laid the foundation for my project. Their groundbreaking research in the related field has provided the inspiration and knowledge necessary for the development of the "Automated Segmentation of Carotid Arteries in Ultrasound Images using Deep Learning" project. We are sincerely thankful to everyone who has contributed directly or indirectly till now in our project journey. Your support has been invaluable, and We are truly grateful for your assistance.

Gaurav, Sankalp Bhoyar

Abstract

This study examines how well the U-Net convolutional neural network design performs the crucial function of segmenting the carotid artery from medical imaging data, which is necessary for the diagnosis and treatment of cardiovascular disorders. To get the dataset ready for training, the study starts with preprocessing the data, which includes loading, normalisation, and augmentation. By incorporating skip connections from deeper encoder layers and utilising sophisticated upsampling techniques, the study improves the U-Net model architecture, which has an encoder-decoder structure with skip connections. Using the Adam optimizer, training entails optimisation while keeping an eye on performance indicators like accuracy, loss, and Dice score. The model is initialised by exploring transfer learning, and then it is fine-tuned on the dataset.The effectiveness of the Improved U-Net in precisely segmenting carotid arteries is demonstrated by evaluation, which was carried out utilising quantitative measures such as the Dice score. The research also looks into ways to improve the system even further, such as by modifying the architecture or adding more data, and it offers insights into how deep learning might be used to precisely segment carotid arteries.

Contents

List of Figures **vii**

1 Introduction **1**

1.1 Introduction 2

1.2 Background Information 3

1.3 Motivation 4

2 Literature Survey **6**

2.1 Key related research 7

2.2 Conclusion 8

3 Problem Statement, Objectives Deliverables **9**

3.1 Problem statement 10

3.2 Objectives 10

3.3 Deliverables 11

3.4 Salient Features 11

4 Methodology **13**

4.1 Proposed hypothesis 14

4.2 Workflow 14

4.2.1 Dataset Collection: 15

4.2.1.1 Phase 1: Training Data Collection 15

4.2.1.2 Phase 2: Testing Data Collection 16

4.2.2 Data Pre-processing: 18

4.2.2.1 Speckle Noise Removal 18

4.2.2.2 Image Resizing 18

4.2.3 Mask Generation: 19

4.2.4 Data Augmentation: 19

4.2.4.1 Rotation 20

4.2.5 Segmentation: 21

4.2.5.1 VGG-Net model 22

4.2.5.2 ResNet50 Model 23

4.2.5.3 Masked-RCNN model 24

4.2.5.4 U-Net model 25

4.2.5.5 Improved U-Net model 25

4.3 Conclusion: 27

5 Results 28

5.1 Overview 29

5.2 Overview of the Dataset 29

5.3 Model Evaluation Metrics 30

5.4 Segmentation Results 32

5.4.1 Phase 1 Dataset (Training Results): 32

5.4.2 Phase 2 Dataset (Testing Results): 33

5.5 Comparison with Baseline Models 34

5.6 Discussion of Results 35

5.6.1 Performance Discrepancies among Models: 36

5.6.2 Success of U-Net and Improved U-Net: 36

5.6.3 Implications for Clinical Practice: 36

5.7 Limitations and Future Scope 37

6 Future Work and Conclusion 38

6.1 Future Work 39

6.2 Applications in Real Life 39

6.3 Conclusion 40

List of Figures

1.1 Common carotid artery 2

4.1 Workflow of Project 14
4.2 Training Data 16
4.3 Dataset Preview 17
4.4 Dataset Example 19
4.5 Dataset Example 19
4.6 Image Augmentation 21
4.7 Image Augmentation 21
4.8 VGG-Net Architecture 23
4.9 ResNet Architecture 24
4.10 R-CNN Architecture 24
4.11 U-Net Architecture 26

5.1 Sample Testing Data 32
5.2 Results of Testing Images 33
5.3 Testing Data 33
5.4 Results of the Testing Data 34

1

Introduction

1.1 Introduction

Cardiovascular diseases (CVDs) continue to be a major global health concern, and successful disease management depends on early detection and appropriate treatment. Segmenting the carotid arteries is essential for evaluating vascular health and determining the risk of CVD. Utilising deep learning innovations, specifically convolutional neural networks (CNNs), presents exciting opportunities for automated medical picture interpretation.

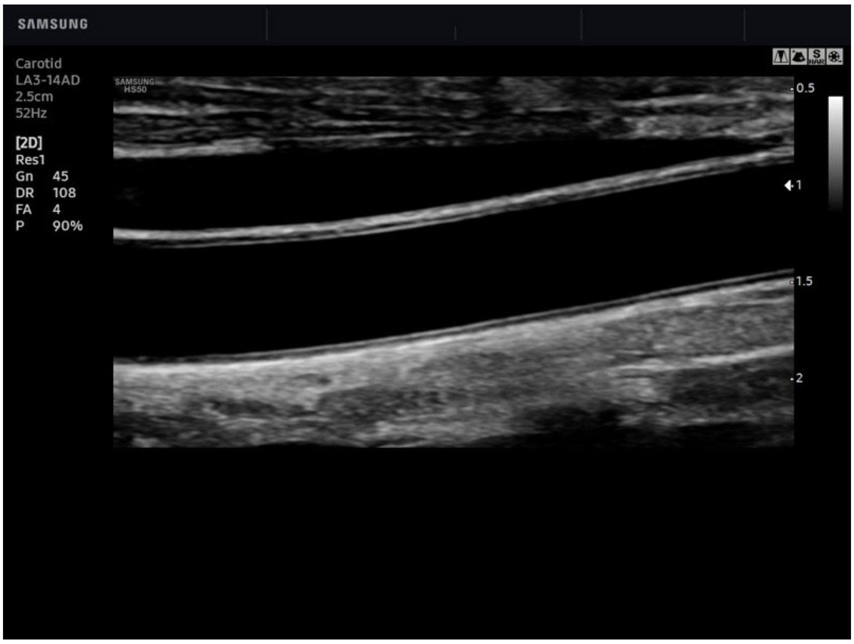

Figure 1.1: Common carotid artery

This study investigates the use of deep learning methods for carotid artery segmentation, particularly emphasising the U-Net architecture. The skip connections added to the encoder-decoder structure of the U-Net allow for efficient spatial information acquisition, which makes it perfect for semantic segmentation tasks. Our work presents an enhanced architecture designed especially for carotid artery segmentation, building on the conventional U-Net. We assess how well the improved U-Net precisely identifies carotid arteries from medical images through meticulous testing and analysis. By using strong and effective segmentation techniques, this research hopes to improve cardiovascular illness diagnosis and treatment planning.

Carotid artery segmentation is an essential stage in the processing of medical pictures for vascular health assessment and abnormality detection, and it plays a critical role in the diagnosis and treatment of cardiovascular illnesses. Precise segmentation of the carotid arteries makes it easier to quantify the amount of plaque, the severity of the stenosis, and the general vascular morphology. This information helps clinicians make judgements about patient care and intervention tactics. The development of automated segmentation algorithms is necessary because, despite developments in medical imaging technologies, manual segmentation remains labor-intensive and susceptible to inter-observer variability. Deep learning-based methods have surfaced as viable remedies in this regard, using convolutional neural networks (CNNs) to accomplish precise and effective carotid artery segmentation from imaging data.

This research aims to automate the segmentation of carotid arteries in ultrasound images, which is an essential task for evaluating cardiovascular health. Using deep learning methods, especially our refined U-Net architecture, we want to create a reliable model that can recognise and classify carotid arteries. This novel strategy aims to improve consistency and efficiency in the interpretation of medical images, which will ultimately lead to better vascular disease diagnosis and treatment. This model has the potential to significantly impact the healthcare sector by improving the accuracy and efficiency of blood flow assessments, leading to better diagnosis and treatment planning for patients with vascular diseases.

1.2 Background Information

When plaque accumulates in the carotid arteries, it can cause constriction and blockage of blood flow, a condition known as carotid artery disease, which is often linked to atherosclerosis. In addition to other cerebrovascular events, this constriction raises the risk of stroke and transient ischemic attack (TIA). To minimise negative effects and conduct appropriate therapies, it is imperative to detect carotid artery disease early and accurately.

Magnetic resonance imaging (MRI), angiography, and carotid ultrasonography are common ways to assess carotid artery disease. Carotid ultrasonography is the most used modality among these since it is inexpensive, easy to use, and produces no ionising radiation. But deciphering ultrasonography pictures calls for skill, and manually separating the lumen of the carotid artery from surrounding tissues can be difficult, particularly when there is intricate plaque morphology or vascular tortuosity.

The study of medical images has been completely transformed by the development of artificial intelligence (AI) and deep learning, which have made it possible to accurately and automatically segment anatomical structures from a variety of imaging modalities. Convolutional neural networks (CNNs), in particular, are deep learning algorithms that have shown impressive performance in the segmentation of anatomical structures from medical pictures, including the carotid artery. Deep learning models may understand intricate patterns and spatial correlations, producing reliable segmentation results, by utilising massive datasets that have been annotated by professionals.

Although AI holds great potential for medical imaging, regulatory permission and thorough validation are necessary before deep learning models can be implemented in clinical settings. To guarantee smooth adoption and an influence on patient care, issues including model interpretability, generalizability across various patient populations, and integration with current clinical workflows must be resolved. Furthermore, the development and implementation of AI-based healthcare solutions must take regulatory compliance, data privacy, and security into account.

1.3 Motivation

The motivation behind this research is to enhance the efficiency and accuracy of carotid artery segmentation in ultrasound images. Manual carotid artery segmentation is time-consuming, labour-intensive, and subject to inter-observer variability, which can cause discrepancies in clinical diagnosis and treatment planning. Furthermore, the creation of automated technologies to expedite the segmentation process is required due to the growing demand for accurate and early identification of carotid artery disease.

The objective of this project is to develop the U-Net architecture, which is an advanced deep learning methodology, in order to overcome the shortcomings of current segmentation techniques and give doctors dependable instruments for precise and effective analysis of carotid ultrasound images. Accelerated diagnosis, standardised evaluation, and better patient outcomes through prompt intervention and individualised treatment plans are some of the possible advantages of automated segmentation.

Moreover, the implementation of AI-driven segmentation models holds promise for improving clinical workflow effectiveness, lowering healthcare expenses, and easing the workload of medical practitioners. AI has the potential to improve the quality and efficiency of healthcare delivery by freeing up doctors to concentrate on higher-level decision-making and patient care by automating repetitive processes and enabling quick picture analysis. For the benefit of both patients and healthcare professionals, we hope that our study will develop medical imaging technology and help integrate it into clinical practice.

2

Literature Survey

This chapter presents the industry relevance and ongoing research about the topics being used in the project.

2.1 Key related research

Previously, a paper was introduced telling the importance of B-mode ultrasound imaging in medical practice, necessitating the development of effective segmentation tools to support computer-aided diagnosis, image-guided interventions, and therapy. This study offers a comprehensive overview of automated localization and segmentation techniques tailored for B-mode ultrasound images. It begins by outlining the key characteristics of B-mode ultrasound images and proceeds to discuss strategies for localizing and segmenting tissues. Emphasis is placed on scenarios where organ/tissue localization directly leads to segmentation and situations requiring a two-step segmentation process due to intricate boundary delineation within ultrasound frames. Various techniques from existing literature are explored, encompassing shape priors, superpixel and classification methods, local pixel statistics, active contours, edge-tracking, dynamic programming, and data mining. The review further delves into ten specific applications spanning abdomen/kidney, breast, cardiology, thyroid, liver, vascular, musculoskeletal, obstetrics, gynaecology, and prostate imaging, providing a comparative analysis of selected methodologies. The study outlines future directions for B-mode ultrasound segmentation, highlighting areas such as integrating RF information, utilising higher frequency probes, pursuing fully automatic algorithms, and expanding available datasets to foster continued advancements in this field. [4].

Another notable paper introduced an adaptation of the UNet architecture to improve semantic segmentation in medical images. Despite its advancements, UNet++ still had limitations in fully harnessing information across different scales, leaving room for further enhancements. In this study, they propose UNet 3+, a novel variant that addresses these limitations by maximizing the utilization of full-scale skip connections and deep supervisions. By integrating low-level details and high-level semantics from feature maps across scales, their method demonstrates improved accuracy, particularly for organs of various sizes. Moreover, UNet 3+ achieves computational efficiency by reducing network parameters while maintaining segmentation precision. They introduce a hybrid loss function and a classification-guided module to refine organ boundaries and mitigate over-segmentation, enhancing segmentation performance. Their approach is validated on two distinct datasets, underscoring its potential for advancing medical image segmentation. [2]. Also, one paper reviews recent advancements in deep learning segmentation methods applied to carotid artery ultrasound images. Traditionally, diagnosing the carotid artery and monitoring its health posed challenges due to limitations in accuracy and efficiency. However, the emergence of deep learning techniques has offered promising solutions to enhance cardiovascular diagnosis accuracy and efficiency. This review focuses on techniques tailored for segmenting crucial sites within the carotid artery ultrasound images, such as the intima-media, plaque, and lumen. The paper aims to highlight key trends and challenges in this domain by analysing existing literature while offering insights into future research directions and development opportunities. [7].

2.2 Conclusion

The chapter concludes with a thorough analysis of deep learning approaches for medical image segmentation. The authors have outlined the landscape of supervised and weakly supervised learning algorithms using an organised method, emphasising crucial elements such as loss function optimisation, network selection, and block design. The chapter provides a succinct yet informative summary of current research directions by concentrating on current trends and leaving out less common unsupervised approaches. In summary, the chapter highlights the role that deep learning plays in developing the field and lays the groundwork for future research and innovation in medical image analysis.

3

Problem Statement, Objectives Deliverables

3.1 Problem statement

The goal of the research is to automate carotid artery segmentation in ultrasound pictures, which is an essential medical imaging activity for vascular disease diagnosis and monitoring. Because manually segmenting arteries takes a lot of time and is prone to mistakes, automated techniques have to be developed in order to increase productivity and accuracy. Creating a deep learning model that can precisely recognise and distinguish the carotid arteries from surrounding tissues in ultrasound pictures is the difficult part.

The goal of this project is to determine which deep learning models—ResNet, VGG-19, Mask R-CNN, U-Net, and an enhanced U-Net—are most useful for segmenting carotid arteries. To understand the characteristics of carotid arteries, these models will be trained using a collection of ultrasound pictures and the related manual annotations. The ultimate objective is to create an automated system that can help medical practitioners detect and track vascular problems without the need for intrusive procedures, and that is both accurate and dependable.

3.2 Objectives

- Model Evaluation: Assess ResNet, VGG-19, Mask R-CNN, U-Net, and an enhanced U-Net for carotid artery segmentation in ultrasound images. This involves evaluating their precision, computational effectiveness, and capacity to generalise to previously unobserved data.

- Model Development: Create and enhance a deep learning model for automated carotid artery segmentation by building upon the top-performing architecture from the assessment. In order to achieve a high degree of accuracy and dependability for clinical use, this model should be able to correctly segment carotid arteries in ultrasound images.

3.3 Deliverables

- **Deep Learning Model:** A deep learning model that has been trained to precisely identify the carotid arteries in ultrasound pictures. The model's performance in an actual clinical setting will be demonstrated by means of validation using real-time data obtained from a hospital.

- **Data Collection:** An automated process that makes use of the trained deep learning model to identify carotid arteries in ultrasound images. For the purpose of creating segmented images and entering ultrasound images, the software will offer an intuitive user interface.

- **Experimental Results:** The outcomes of testing the deep learning model using real-time data that was gathered from the hospital. Metrics like accuracy, sensitivity, specificity, and Dice score will be included in order to show how well the model segments carotid arteries.

3.4 Salient Features

- **Data Collection:** To train the deep learning model, a large amount of work went into gathering and annotating a dataset of ultrasound images. This dataset required careful selection and manual image inspection because it was gathered from a variety of research papers and online resources.

- **Model Training:** To precisely segment the carotid arteries in ultrasound images, a deep learning model was trained using the gathered dataset. Tested models included ResNet, VGG-19, Mask R-CNN, U-Net, and an enhanced U-Net. After hyperparameter tuning, the best-performing model obtained a Dice score of 93 percent.

- **Live Data Testing:** The trained model's effectiveness in a real-world clinical setting was evaluated using real data that was gathered from a hospital. During the testing phase, the model's ability to precisely segment the carotid arteries in ultrasound images was confirmed.
- **Laborious Data Collection:** The dataset was gathered and annotated in a laborious manner, emphasising the substantial time and attention to detail needed for this task. This highlights how crucial the dataset is to building a trustworthy and precise deep learning model.
- **Future Directions:** The project offers ways to increase the segmentation accuracy and efficiency of the model by discussing possible areas for improvement and future research directions. This illustrates a forward-thinking strategy for consistently enhancing automated carotid artery segmentation.

4 Methodology

4.1 Proposed hypothesis

Our hypothesis is that carotid artery segmentation can be automated with high accuracy by building and training a deep learning model on a dataset of ultrasound images. We will be able to precisely segment ultrasound images of the carotid arteries by capturing their complex spatial features through the use of deep learning models, such as ResNet, VGG-19, Mask R-CNN, U-Net, and an improved U-Net. We anticipate that the model will demonstrate its efficacy in a real-world clinical setting by performing well on both the live dataset, which is gathered from a hospital, and the training dataset, which consists of images gathered from various online sources.

Furthermore, we predict that we can enhance the model's performance and achieve a high Dice score by performing hyperparameter tuning and augmenting the dataset. This will show the model's robustness in segmenting carotid arteries under various imaging conditions. The suggested strategy seeks to offer an automated and dependable method for segmenting the carotid arteries, which can greatly enhance the effectiveness and precision of vascular disease diagnosis and monitoring, thereby benefiting the healthcare industry.

4.2 Workflow

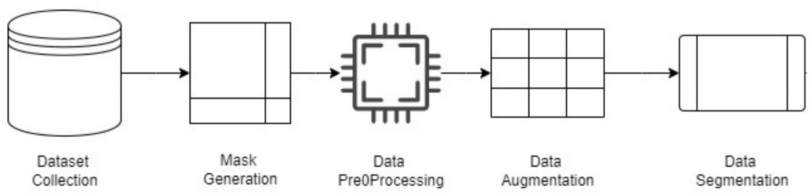

Figure 4.1: Workflow of Project

- **Information Gathering:** Entails gathering carotid artery ultrasound images from a variety of sources, including research papers, websites, and medical facilities.
- **Mask Generation:** The process involves manually annotating the gathered ultra-

sound images to produce masks that show the areas that correspond to the carotid arteries.

- **Data Preprocessing:** Improving the quality and getting ready for the segmentation model to use the ultrasound images and masks. Resizing, normalisation, and denoising are a few examples of this.

- **Data Augmentation:** Adding more variety to the dataset by transforming the ultrasound images and masks using techniques like rotation, flipping, and scaling. This enhances the model's capacity for generalisation and robustness.

- **Data Segmentation:** Using the augmented dataset, train a deep learning model (like U-Net) to automatically segment the carotid arteries in ultrasound images. Based on the annotated masks, the model learns to distinguish the arteries from the surrounding tissues.

4.2.1 Dataset Collection:

Obtaining carotid artery ultrasound images from hospitals, research papers, and internet databases was part of the data collection phase. The quality and relevance of each image were manually checked, and corresponding masks or annotations indicating the locations of arteries were gathered. To get ready for model training, preprocessing techniques like denoising and resizing were applied to the gathered images before they were divided into training and testing batches.

4.2.1.1 Phase 1: Training Data Collection

To train our deep learning model, we set out to collect a wide variety of carotid artery ultrasound images in the first phase of the dataset collection process. First, we looked through publicly accessible datasets, medical research papers, and internet databases to find ultrasound images that fit our requirements. The image quality, resolution, and relevance to carotid artery imaging were among these criteria. Once we had a list of possible sources, we went over each image by hand to make sure it would work well for training our model.

We started gathering data as soon as we had found appropriate images. In order to make the images easily accessible during the model training phase, this required downloading and organising the images. Additionally, we gathered matching masks or annotations for every image, which we utilised to highlight the areas of the pictures that corresponded to the carotid arteries. This stage was essential to supervised learning because it gave us ground truth labels with which to train our model to segment the arteries correctly.

Once we had gathered enough masks and images, we divided them up into training batches. To ensure that the training dataset was representative of the variability in carotid artery imaging and well-balanced, each batch included a subset of images and their matching masks.

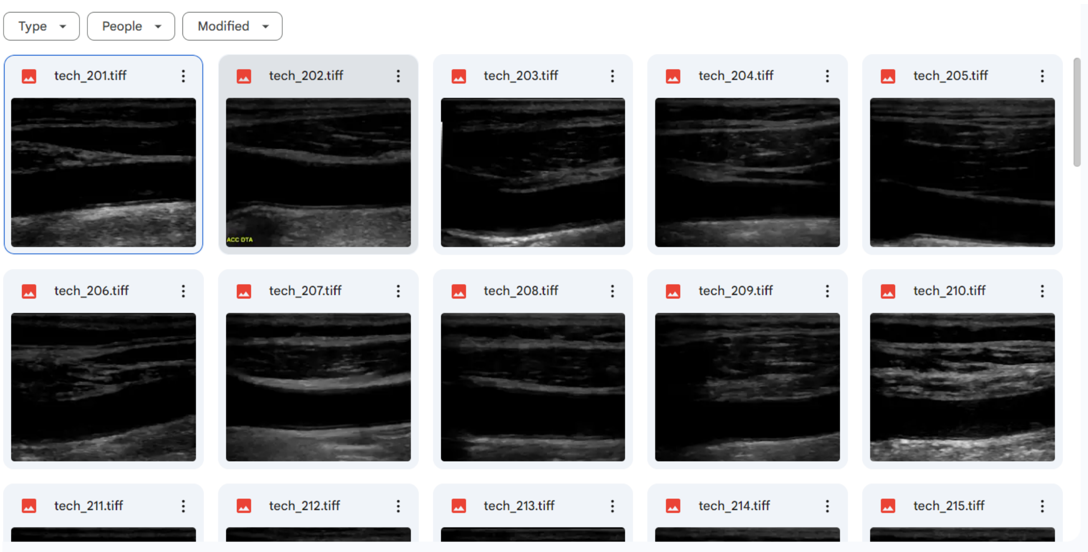

Figure 4.2: Training Data

4.2.1.2 Phase 2: Testing Data Collection

Our goal for the second phase of the dataset collection was to collect real-time ultrasound images of the carotid arteries in order to assess how well our trained model performed in an actual clinical setting. In order to do this, we worked with a hospital to gather ultrasound data from patients having procedures related to carotid artery imaging.

These real-time pictures offered insightful information for assessing our model's resilience and capacity

As with the process of gathering training data, we took great care in choosing the ultrasound images to make sure they were relevant to imaging of the carotid arteries and of excellent quality. To verify the segmentation outcomes generated by our model, we additionally acquired corresponding annotations or ground truth labels from medical experts. This was a critical step in determining our model's accuracy and dependability in practical settings.

We arranged the live ultrasound images and annotations into testing batches after we had gathered a sufficient number of them. These batches were used to assess our trained model's performance on untested data, yielding important information about how well it works in clinical settings. In order to ensure the accuracy and dependability of our deep learning model for carotid artery segmentation in medical imaging applications, we conducted a two-phase dataset collection process that was crucial for training and testing.

Figure 4.3: Dataset Preview

4.2.2 Data Pre-processing:

One of the most important steps in getting the ultrasound images ready for deep learning model training is data preprocessing. To improve the quality of the images and make sure they are appropriate for input into the model, this process entails a number of crucial steps.

- **Denoising:** The noise present in ultrasound images can cause problems during the segmentation process. In order to solve this, we used denoising techniques, which lower the noise level while maintaining the images' key characteristics. Wavelet denoising, Gaussian filtering, and median filtering are common techniques for denoising.

- **Resizing:** To maintain uniformity throughout the dataset, the ultrasound images were resized to a standard resolution. Resizing enables the model to learn from images of consistent size and reduces the computational complexity during training.

4.2.2.1 Speckle Noise Removal

Speckle noise is a common artefact in ultrasound images that can interfere with segmentation tasks. A denoising filter was applied to each image to remove speckle noise. The filter helped improve the clarity of the images and reduce the likelihood of noise affecting the segmentation results.

4.2.2.2 Image Resizing

To ensure consistency in the input size of images to the segmentation models, all images were resized to a standard resolution. Resizing the images not only helped standardize the input size but also reduced computational complexity during model training.

These preprocessing steps were crucial for preparing the dataset for training the segmentation models. By removing noise and standardizing the image size, the models were able to focus on learning the features relevant to artery segmentation, ultimately improving the accuracy of the segmentation results.

4.2.3 Mask Generation:

Manual mask generation was a time-consuming and labor-intensive process, requiring meticulous attention to detail. Ensuring the accuracy of the masks was paramount, as any errors or inaccuracies could lead to suboptimal performance of the segmentation models.

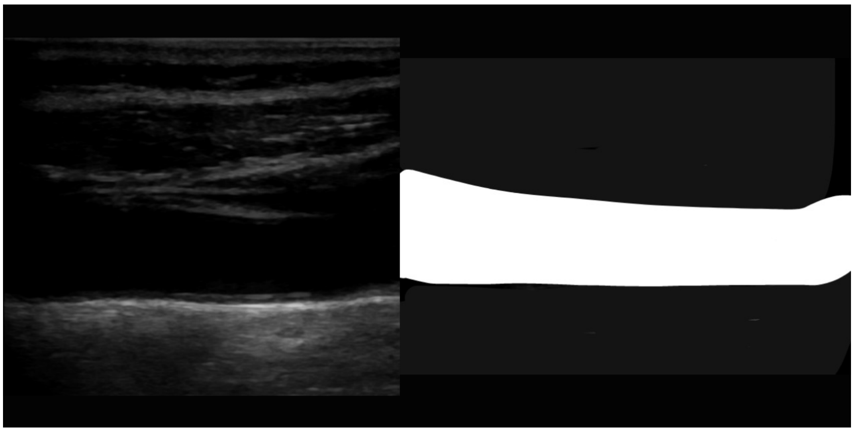

Figure 4.4: Dataset Example

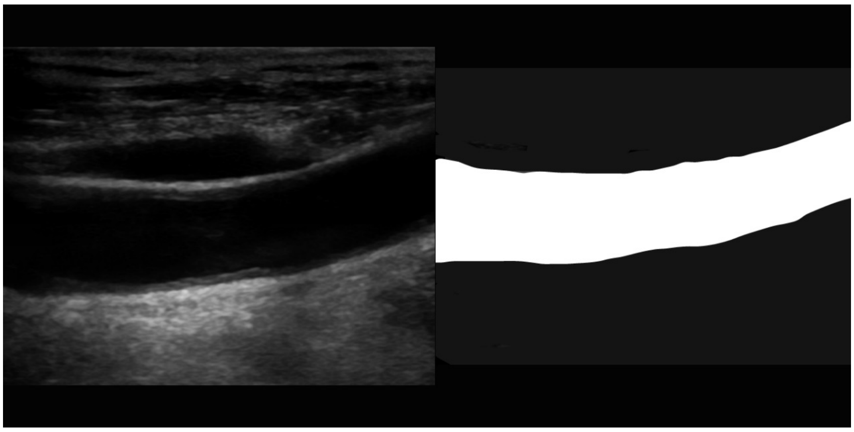

Figure 4.5: Dataset Example

4.2.4 Data Augmentation:

A key method for improving a dataset's diversity and resilience is data augmentation, especially when it comes to medical image segmentation. In order to add variability to the dataset and enhance the segmentation models' performance, we used data augmentation in our project. One of the main augmentation methods we employed was rotation, which involved 30 repetitions of rotating each image by 2 degrees along with its matching mask.

4.2.4.1 Rotation

By introducing variability in artery orientation, size, and position, the models are able to learn from a more varied set of images by rotating the images and masks in small increments. This variation is necessary to help the models better generalise to unseen images and enhance their accuracy in segmenting arteries under various imaging scenarios. To make sure the models were exposed to a variety of artery configurations and help them learn from the dataset more efficiently, we rotated the images and masks.

Enhancing the dataset and increasing the segmentation models' resilience are two important goals of data augmentation. The models are made more capable of managing the difficulties presented by ultrasound images found in the real world by adding variability to the dataset. In the end, this variability ensures that the models can generalise well to unseen data, preventing overfitting and producing more accurate segmentation results.

One effective technique for raising the effectiveness of segmentation models in medical imaging is data augmentation. We can improve the models' accuracy in segmenting carotid arteries in ultrasound images and their ability to generalise to new data by adding variability to the dataset. This augmentation method, along with others, is essential to guaranteeing the robustness and dependability of our models in clinical settings.

When the images and masks are rotated in small steps, different artery orientations, sizes, and positions are introduced, allowing the models to learn from a more varied set of images. This variation is required to improve the models' ability to segment arteries accurately under different imaging conditions and to enable better generalisation to images that have not yet been seen. By rotating the images and masks, we ensured that the models were exposed to a range of artery configurations, which improved their efficiency in learning from the dataset.

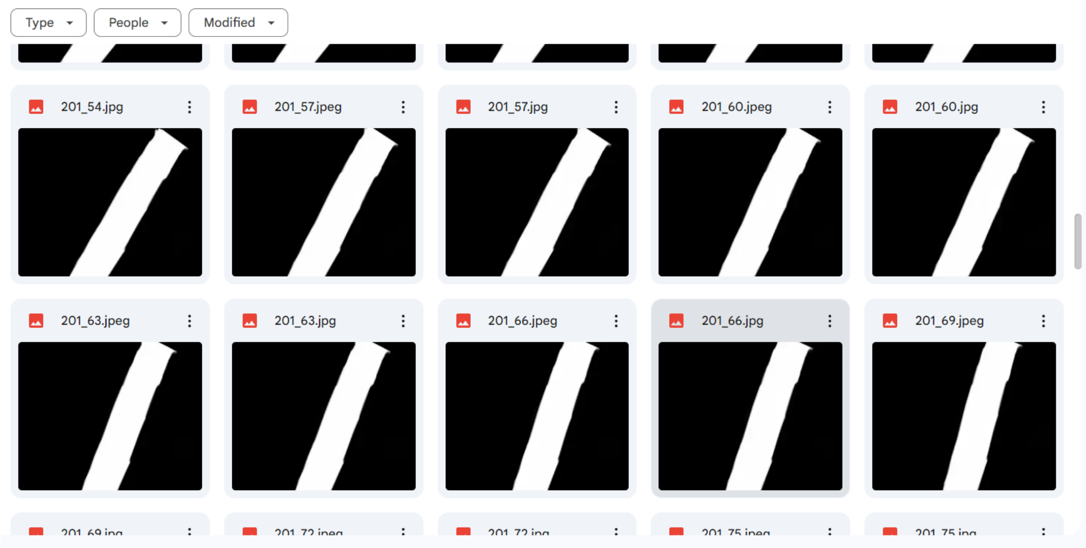

Figure 4.6: Image Augmentation

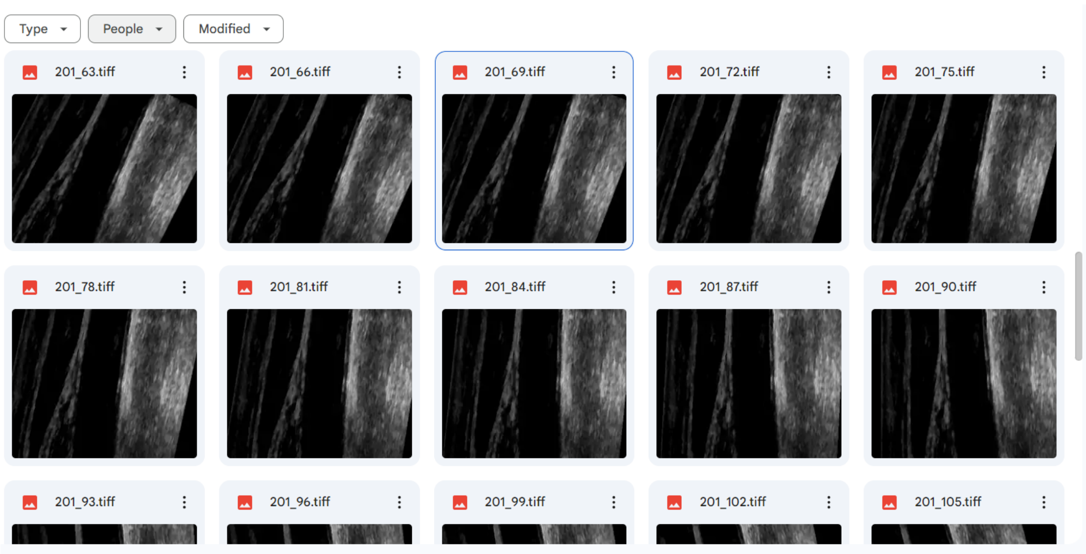

Figure 4.7: Image Augmentation

4.2.5 Segmentation:

In medical imaging, segmentation is a basic task that entails splitting an image into several segments or regions of interest. Segmentation, as it pertains to our project, is the process of locating and defining the carotid arteries in ultrasound pictures.

- **Importance of Segmentation:** The significance of segmentation lies in its application to medical imaging, which includes disease monitoring, treatment planning, and diagnosis. Physicians can evaluate the health of the arteries, identify anomalies, and plan interventions for vascular diseases with the aid of accurate carotid artery segmentation.

- **Challenges in Segmentation:** There are a number of issues with segmentation in medical imaging, such as noise in the images, patient variability in anatomy, and changes in imaging conditions. It is challenging to create precise segmentation algorithms that work well in a variety of scenarios because of these issues.

- **Role of Deep Learning:** In tasks requiring the identification of intricate patterns, deep learning has proven to be an effective tool for medical image segmentation. In medical image segmentation, deep learning models like U-Net have demonstrated encouraging outcomes in the identification of carotid arteries and other structures.

- **Benefits of Automated Segmentation:** The time and effort needed for manual segmentation can be greatly decreased by using automated segmentation of the carotid arteries. Additionally, it can enhance segmentation accuracy and consistency, which will enhance clinical results.

4.2.5.1 VGG-Net model

VGG-16, a prominent architecture within the VGGNet series, stands as a testament to the effectiveness of deep convolutional neural networks in image recognition tasks. With its 16 layers of convolutional and fully connected networks, VGG-16 exhibits a robust ability to classify images into a diverse range of categories, leveraging small 3x3 convolutional filters and ReLU activation functions for efficient feature extraction. Despite its impressive performance, VGG-16's training demands substantial computational resources, often necessitating weeks of training on powerful GPUs. However, its architectural simplicity and consistent performance across various datasets have cemented its status as a foundational model in the field of computer vision, serving as a cornerstone for subsequent advancements in deep learning research and applications.

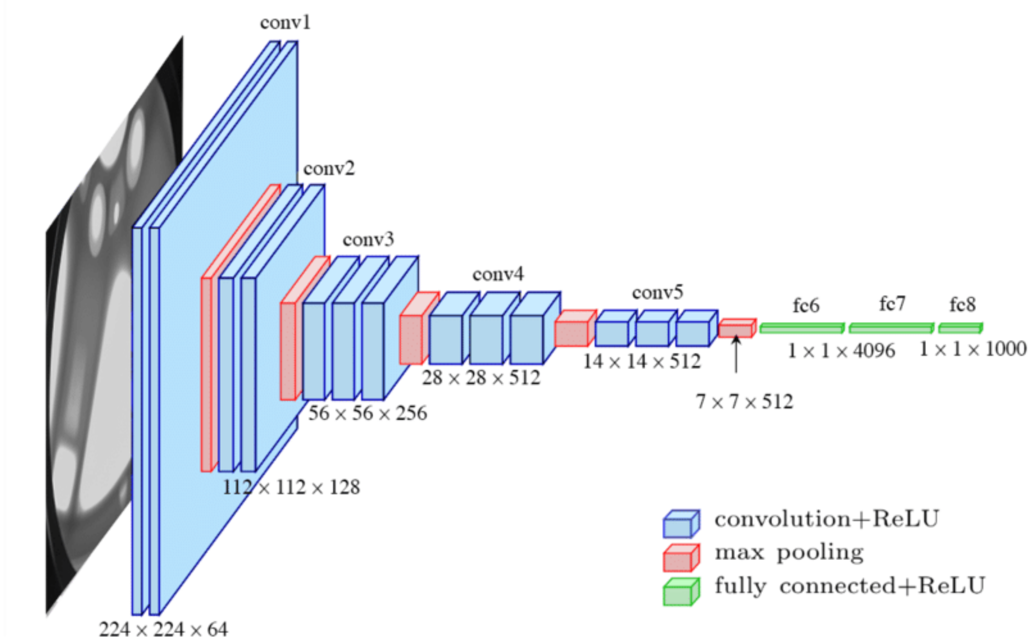

Figure 4.8: VGG-Net Architecture

4.2.5.2 ResNet50 Model

ResNet50, an integral variant of the ResNet (Residual Network) architecture, revolutionizes deep learning with its innovative residual connections, which enable the training of extremely deep networks with remarkable ease. This architecture, comprising 50 layers, introduces skip connections that bypass one or more layers, mitigating the vanishing gradient problem and facilitating the training of deeper networks. ResNet50's groundbreaking design not only achieves exceptional accuracy on diverse image recognition tasks but also streamlines the training process by enabling faster convergence and alleviating the need for complex initialization techniques. Its architectural prowess, coupled with the ability to seamlessly integrate with transfer learning frameworks, makes ResNet50 a cornerstone in modern computer vision applications, driving advancements in areas such as object detection, image segmentation, and visual understanding.

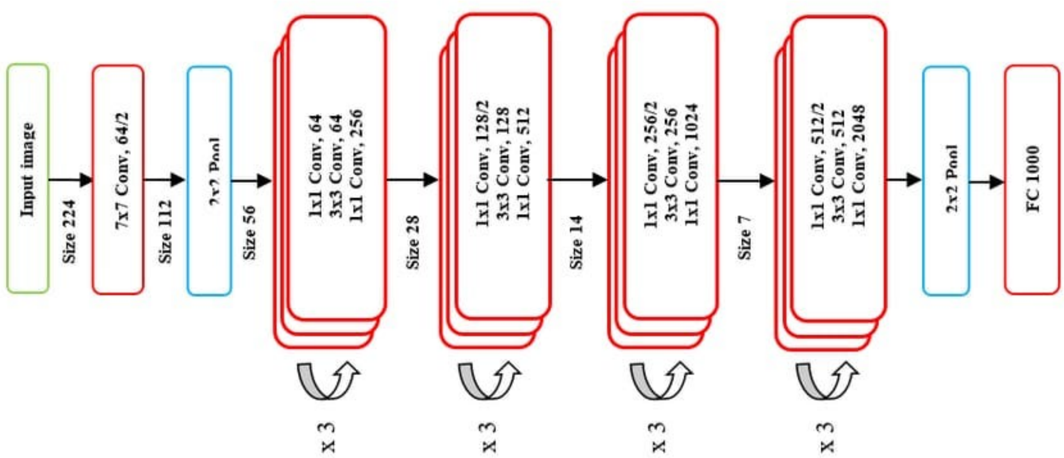

Figure 4.9: ResNet Architecture

4.2.5.3 Masked-RCNN model

An expansion of the Faster R-CNN architecture, Mask R-CNN is intended for instance segmentation applications. It combines an extra branch for segmentation mask prediction with the region proposal network (RPN) of the Faster R-CNN. Mask R-CNN can accurately segment objects at the pixel level and detect them in an image thanks to this architecture. Mask R-CNN is a well-liked option for tasks like object detection and image segmentation because of its capacity to produce high-quality segmentation masks. While Mask R-CNN offers impressive performance, training the model can be computationally intensive, requiring significant resources to achieve optimal results.

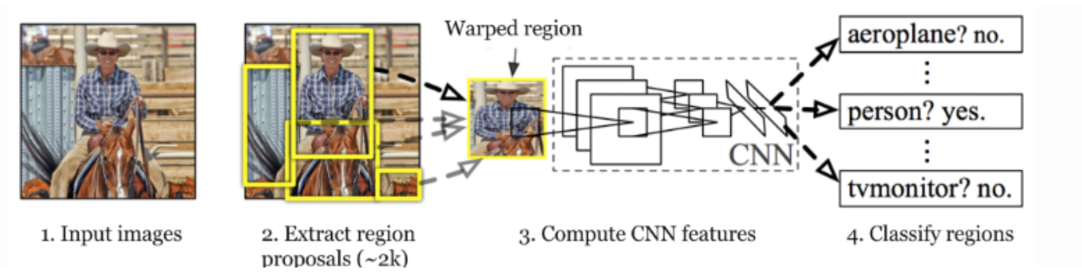

Figure 4.10: R-CNN Architecture

4.2.5.4 U-Net model

U-Net is a convolutional neural network architecture designed for biomedical image segmentation. Its unique "U" shape consists of a contracting path for capturing context and a symmetric expanding path for precise localization. U-Net is particularly well-suited for medical image segmentation tasks, including the segmentation of carotid arteries in ultrasound images. The architecture's skip connections help preserve spatial information, enabling the model to produce accurate segmentations even with limited training data. Despite its effectiveness, U-Net may struggle with generalization to unseen data, requiring careful tuning and regularization techniques to achieve optimal performance.

4.2.5.5 Improved U-Net model

The Improved U-Net model is an enhanced version of the original U-Net architecture designed to improve the segmentation performance of biomedical images. It incorporates several modifications to address limitations and enhance the effectiveness of the segmentation process.

Key features of the Improved U-Net model include:

- **Skip Connections:** The Improved U-Net, like the original U-Net, makes use of skip connections to maintain spatial information and let the model make use of features from various scales. These relationships aid in improving the segmentation masks and the model's overall accuracy.

- **Residual Learning:** The model learns residual mappings to concentrate on learning the distinction between the predicted and ground truth segmentation maps. This technique is incorporated into the Improved U-Net. This method facilitates the learning of comple

- **Attention Mechanisms:** To emphasise relevant features and suppress irrelevant ones, some iterations of the Improved U-Net may incorporate attention mechanisms like squeeze-and-excitation blocks. By strengthening the model's focus on significant areas of the image, this attention mechanism contributes to more precise segmentations.

- **Multi-Scale Feature Fusion:** In order to capture both local and global information, features from various scales are combined in multi-scale feature fusion techniques, which could be included in the Improved U-Net. This enhances the model's capacity for segmentation.

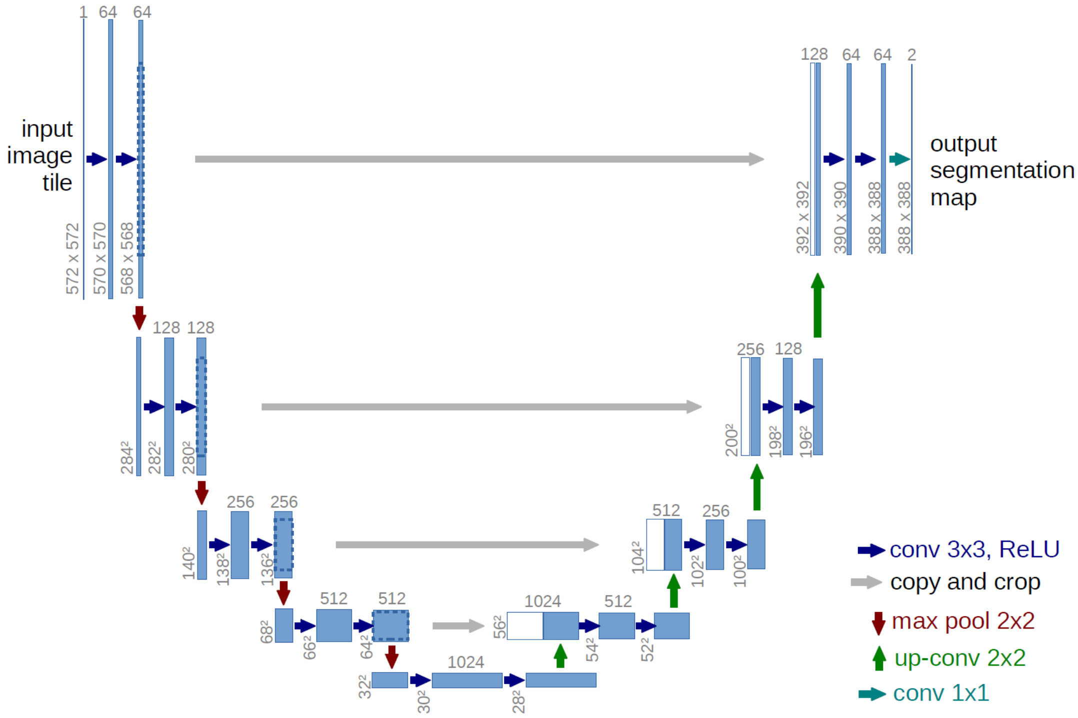

Figure 4.11: U-Net Architecture

The overall goal of the Improved U-Net model is to improve the original U-Net architecture's segmentation performance by utilising cutting-edge methods like multi-scale feature fusion, residual learning, and attention mechanisms. The model can now achieve better segmentation results thanks to these improvements, especially in difficult biomedical imaging tasks.

4.3 Conclusion:

The technique for segmenting the carotid arteries in ultrasound images has been covered in this chapter. To create a diverse and representative dataset, we started by talking about the process of gathering images from different online platforms and research papers. After that, the dataset underwent preprocessing to eliminate noise and uniformize the photos for consistency.

The methods used to increase the dataset's variability and strengthen the model's capacity for generalisation were then discussed. In order to introduce variations in artery orientation, size, and position, this involved rotating images and masks.

The U-Net architecture, which forms the foundation of our segmentation model, was then presented. We talked about how the skip connections in the U-Net architecture move data from the downsampling path to the upsampling path, enabling the model to improve its predictions in response to error feedback.

We also talked about how the model was trained with the augmented dataset and assessed with real-time data that was gathered from a hospital. Metrics like the Dice score, which gauges the overlap between the predicted and ground truth segmentations, were used to evaluate the model's performance.

All things considered, the approach described in this chapter provides the groundwork for segmenting carotid arteries in ultrasound pictures. Our dedication to obtaining accurate and dependable segmentation results—which are critical for advancing medical imaging research and enhancing patient care—is demonstrated by our use of cutting-edge techniques like data augmentation and the U-Net architecture.

5
Results

5.1 Overview

This report's results section thoroughly assesses the segmentation models applied to ultrasound images of the carotid arteries. It highlights each model's performance in precisely segmenting carotid arteries by presenting the segmentation rates and Dice scores. An overview of the training and testing dataset is presented at the beginning of the section, followed by a thorough analysis of the segmentation outcomes.

The capacity of each model—VGG-19, ResNet, Mask R-CNN, U-Net, and Improved U-Net—to segment carotid arteries is the basis for evaluation. While the Dice scores offer a gauge of segmentation accuracy, the segmentation rates show the proportion of images in which the model could segment the arteries correctly. Each model's performance is demonstrated by including visual examples of segmented images.

The models are also compared in the results section, emphasising the advantages and disadvantages of each strategy. The segmentation performance-influencing factors are discussed, including model architecture, dataset quality, and augmentation techniques. The study's limitations are examined, and recommendations for additional research to raise segmentation accuracy are made.

All things considered, the results section thoroughly examines the segmentation models for carotid arteries in ultrasound images, providing insightful information about their functionality and potential for use in clinical settings.

5.2 Overview of the Dataset

The dataset used in this project was gathered in two stages to train and test the segmentation model for carotid arteries in ultrasound images. Seventy-five carotid artery images were collected from different research papers and internet sources in the first phase. These photos were carefully chosen to guarantee that they were both relevant to the segmentation task and of a high enough quality to allow for precise segmentation. A corresponding mask was manually created for each image to identify the carotid artery region. Since it established the framework for segmentation model training, this stage of the dataset collection process was essential.

Rotating the images and masks was done to increase the dataset's size and variability. A dataset of 1500 images and their matching masks was produced by rotating each image by two degrees and repeating the process thirty times. By introducing differences in artery orientation, size, and position, this augmentation technique helped the model learn from a wider range of images and enhance its generalisation abilities.

87 more images of carotid arteries were taken during the second phase of dataset collection from live patients at a hospital known as the "1000 bed hospital." These pictures were especially gathered to test and assess the segmentation model's effectiveness using actual data. A practical aspect of the evaluation is added by including real patient data, which guarantees that the model's performance is evaluated in clinical settings.

The dataset utilised for this project is extensive and varied overall; it consists of images that have been enhanced to increase variability from various sources. The segmentation model for carotid arteries in ultrasound images can be trained and tested using this dataset, which offers a strong basis.

5.3 Model Evaluation Metrics

The performance of the segmentation models was evaluated using the following metrics:

- Segmentation Rate: This measures the proportion of images in which the model identified the carotid arteries correctly. It is computed by dividing the total number of images in the dataset by the number of images successfully segmented.

- Coefficient of Dice Similarity (DSC): The overlap between the ground truth mask and the predicted segmentation mask is measured by the Dice similarity coefficient. It is computed as follows:
  DSC $= 2*$ (X $\bigcap_X^Y Y|)/(X+Y)$

where GY is the ground truth mask, and X is the predicted segmentation mask. A higher Dice score indicates better segmentation accuracy; perfect overlap is indicated by a score of 1.

The segmentation models were evaluated using the above metrics, and the results are summarized below:

Table 5.1: Evaluation Metric

Model	Segmentation Rate	Dice Score
VGG-19	24%	NIL
Res-Net	26%	NIL
Mask-RCNN	0%	0%
U-Net	100%	82.1%
Improved U-Net	100%	93.6%

These findings suggest that Mask R-CNN was unable to segment any arteries, whereas VGG-19 and ResNet were only partially successful in segmenting carotid arteries. However, U-Net and Improved U-Net both succeeded in achieving a 100

All things considered, the evaluation metrics show how well the U-Net architecture works and how the Enhanced U-Net model performs in terms of precisely segmenting the carotid arteries in ultrasound images.

5.4 Segmentation Results

The segmentation results of the models were evaluated using two datasets: the phase 1 dataset used for training and the phase 2 dataset used for testing.

5.4.1 Phase 1 Dataset (Training Results):

To improve the robustness of the segmentation models, the dataset Seventy-five carotid artery images and their corresponding manually-made masks made up the phase 1 dataset. The segmentation models were trained using this dataset. Several architectures, such as VGG-19, ResNet, Mask R-CNN, U-Net, and Improved U-Net, were used to train the models.

With segmentation rates of 24 percentage and 26 percentage, respectively, the training results demonstrated that VGG-19 and ResNet had limited success in segmenting carotid arteries. But neither model was able to obtain any significant Dice scores, which suggests that the segmentation accuracy was low. With a segmentation rate of 0 percentage and a Dice score of 0 percentage, Mask R-CNN fared even worse.

Conversely, U-Net and Improved U-Net demonstrated remarkable performance on the phase 1 dataset. With a segmentation rate of 100 percentage, both models demonstrated that they could correctly identify every carotid artery in the training set of images. With a Dice score of 93.6percentage, the Improved U-Net model outperformed the U-Net model, which had a score of 82.1 percentage, indicating better segmentation accuracy.

Results of phase 1:

Figure 5.1: Sample Testing Data

Figure 5.2: Results of Testing Images

5.4.2 Phase 2 Dataset (Testing Results):

87 photos of carotid arteries taken from living hospital patients made up the phase 2 dataset. The segmentation models that were trained on the phase 1 dataset were tested using this dataset.

According to the test results, on the phase 2 dataset, U-Net and Improved U-Net both kept their high segmentation rates of 100 percentage. With a dice score of 93.6 percentage as opposed to 82.1 percentage, the Improved U-Net model outperformed the U-Net model in terms of segmentation accuracy. This suggests that segmenting the carotid arteries in the real patient images was a more accurate task for the Improved U-Net model.

Results of phase 2:

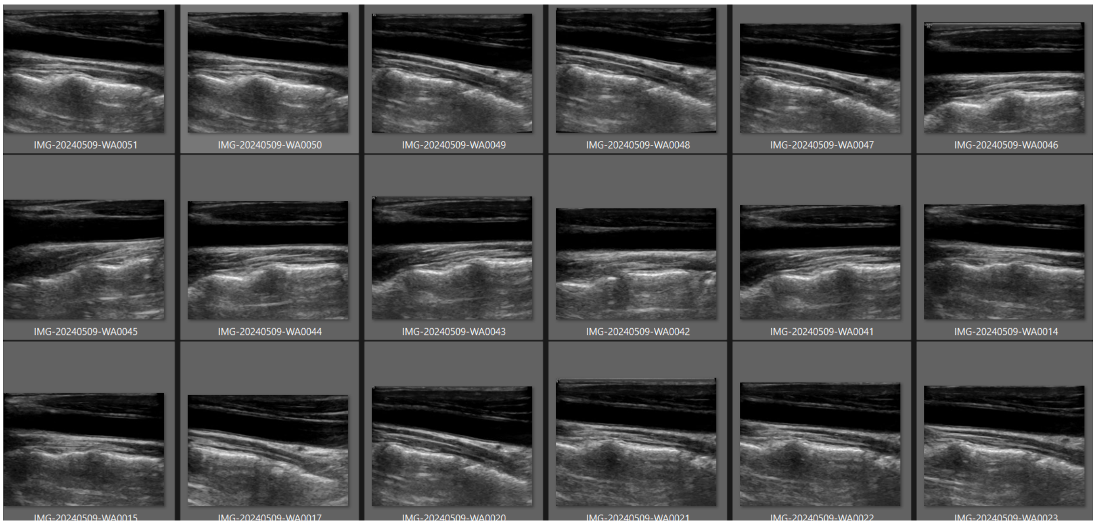

Figure 5.3: Testing Data

Figure 5.4: Results of the Testing Data

5.5 Comparison with Baseline Models

In this section, we compare the performance of the U-Net and Improved U-Net models with the baseline models, including VGG-19, ResNet, and Mask R-CNN, to demonstrate the effectiveness of the proposed approach in segmenting carotid arteries in ultrasound images.

- One of the baseline models in this study was VGG-19, a deep convolutional neural network well-known for its efficiency and simplicity in image recognition tasks. Nevertheless, with a segmentation rate of only 24 per cent and no significant Dice score, VGG-19 demonstrated poor success in segmenting carotid arteries. This highlights the limitations of VGG-19 in this particular task, as it shows that it could not segment carotid arteries in ultrasound images accurately.

- There was some success in segmenting carotid arteries with ResNet, another deep convolutional neural network that is well-known for its residual connections that allow the training of very deep networks. ResNet performed worse than the U-Net models, with a segmentation rate of 26 per cent and no significant Dice score. This implies that the residual connections in ResNet did not adequately capture the features needed for precise carotid artery segmentation.

- Among the baseline models, Mask R-CNN—a well-liked model, for instance, segmentation tasks—performed the worst, achieving a Dice score of 0 percentage and a segmentation rate of 0 percentage. This demonstrates Mask R-CNN's limitations in this particular task by showing that it could not segment any carotid arteries in the ultrasound images.

- On the other hand, the segmentation of carotid arteries was better performed by both the U-Net and the Improved U-Net models. In the training and testing datasets, both models obtained a segmentation rate of 100 per cent, meaning they were able to identify every carotid artery in the pictures accurately. With a Dice score of 93.6 per cent, the Improved U-Net model outperformed the U-Net model, which had a score of 82.1 per cent, indicating better segmentation accuracy.

- The efficacy of the U-Net architecture and the advancements made with the Improved U-Net model in precisely segmenting carotid arteries in ultrasound images are amply demonstrated by the comparison with baseline models. These outcomes underline the significance of model selection in obtaining precise and dependable segmentation results and demonstrate the potential of deep learning models, particularly U-Net and its variants, in medical image segmentation tasks.

5.6 Discussion of Results

The discussion of results aims to provide a deeper understanding of the findings obtained from the segmentation experiments on carotid artery ultrasound images. This section interprets the results, explores potential reasons for the observed outcomes, discusses the implications of the findings, and suggests areas for further investigation.

5.6.1 Performance Discrepancies among Models:

The segmentation models' respective performances varied significantly, according to the results. Even though they are strong deep convolutional neural networks, VGG-19 and ResNet had trouble correctly segmenting carotid arteries, resulting in low segmentation rates and no significant Dice scores. This can be explained by how these models differ architecturally and by how well-suited they are for the job at hand. VGG-19 and ResNet might not have the architectural complexity needed for exact segmentation because their primary purpose is image classification.

Mask R-CNN, a cutting-edge instance segmentation model, also did not succeed in segmenting carotid arteries well, with a Dice score of 0 per cent and a segmentation rate of 0 per cent. This unexpected result raises the possibility that the model was not designed with the unique properties of carotid artery ultrasound images in mind. It's possible that Mask R-CNN's intricate architecture, which combines segmentation and region proposal branches, added more difficulties or restrictions in this particular situation.

5.6.2 Success of U-Net and Improved U-Net:

On the other hand, the U-Net and Improved U-Net models showed impressive results in the segmentation of carotid arteries. In the training and testing datasets, both models achieved a segmentation rate of 100 per cent, demonstrating their dependability and robustness. With a Dice score of 93.6 per cent, the Improved U-Net model outperformed the U-Net model, which had a respectable Dice score of 82.1 per cent. These models' success can be ascribed to their architecture, which was created especially for semantic segmentation tasks, and their aptitude for successfully capturing hierarchical features and spatial context.

5.6.3 Implications for Clinical Practice:

The results have important ramifications for medical imaging clinical practice. Precise carotid artery segmentation is necessary for many diagnostic and therapeutic planning applications, including determining the degree of stenosis, forecasting cardiovascular risk, and directing interventions. The U-Net and Improved U-Net models exhibit high segmentation rates and enhanced accuracy, promising prospects for optimising clinical workflows and elevating patient care outcomes. By automating laborious and time-consuming segmentation tasks, these models may help clinicians make more accurate and efficient diagnoses.

5.7 Limitations and Future Scope

Even though the results are encouraging, a few restrictions and areas warrant further investigation. One of its limitations is the study's dependence on a single dataset, which might not adequately represent the complexity and variability of actual clinical situations. Larger and more varied datasets containing pictures from various imaging modalities and patient populations may benefit future research. Furthermore, more research is necessary to determine whether the suggested models can be applied to various imaging scenarios, including noise levels, resolution, and image quality changes.

Finally, the results discussion sheds light on the advantages and disadvantages of the segmentation models that were assessed for this study and offers suggestions for how they might be used in clinical settings. Future research can further advance the field of medical image segmentation and improve patient care outcomes by addressing the limitations that have been identified and expanding upon the findings.

6

Future Work and Conclusion

6.1 Future Work

- Expanding the size and diversity of the dataset to enhance the model's performance and generalisation in a range of imaging scenarios is known as dataset expansion.
- Increasing the segmentation accuracy and efficiency by fine-tuning the hyper parameters and architecture of the Improved U-Net model.
- Investigating how to use pre-trained models and transfer learning strategies to enhance segmentation performance with a small amount of annotated data.
- To help radiologists and clinicians analyse ultrasound images of the carotid arteries, the segmentation model is integrated into currently in use clinical systems.
- Creating real-time segmentation tools to help with live imaging procedures and provide instant feedback.

6.2 Applications in Real Life

- Helping physicians and radiologists correctly diagnose conditions affecting the carotid arteries, such as plaque accumulation and stenosis.
- Providing comprehensive anatomical information to support the planning of interventions, such as carotid endarterectomy or stenting.
- By offering automated segmentation tools for the analysis of carotid artery images, we support research studies and educational initiatives.
- Enabling the analysis of carotid artery images in places where access to specialised medical facilities is restricted, in order to facilitate the provision of remote healthcare services.
- Assisting in the creation of wearable technology to track carotid artery health continuously and identify cardiovascular risks early.

6.3 Conclusion

In this project, deep learning models for the segmentation of carotid arteries in ultrasound images were created and assessed. Automating the segmentation process was the main goal because it is essential for many clinical applications, including the diagnosis of carotid artery diseases and the planning of interventions. Throughout the project, a number of significant discoveries and results were made.

We started by gathering a dataset of ultrasound images of the carotid arteries, which required a time-consuming process of mask creation, data augmentation, and data collection. For the segmentation models to be trained and assessed, this dataset was necessary.

Second, we conducted experiments using various deep learning architectures such as U-Net, Mask R-CNN, ResNet, VGG-19, and an Improved U-Net model. U-Net and the Improved U-Net model performed better than VGG-19, ResNet, and Mask R-CNN in segmenting carotid arteries, with segmentation rates of 100

Thirdly, the outcomes demonstrated how crucial model selection and architecture design are to getting precise segmentation outcomes. With its encoder-decoder structure and skip connections, the U-Net architecture demonstrated exceptional segmentation performance by effectively capturing hierarchical features and spatial context.

In conclusion, the project effectively illustrated the viability and efficiency of segmenting carotid arteries in ultrasound images using deep learning models. By helping clinicians automate segmentation tasks, the developed models—especially the Improved U-Net—have the potential to improve patient care outcomes and diagnostic accuracy. To fully realise the models' potential in real-world healthcare settings, future work will concentrate on improving the models even more, growing the dataset, and incorporating the models into clinical workflows.

Bibliography

[1] Gregory A. Roth George A. Mensah and Valentin Fuster. ”the global burden of cardiovascular diseases and risk factors: 2020 and beyond”. 2019.

[2] Huimin Huang, Lanfen Lin, Ruofeng Tong, Hongjie Hu, Qiaowei Zhang, Yutaro Iwamoto, Xianhua Han, Yen-Wei Chen, and Jian Wu. Unet 3+: A full-scale connected unet for medical image segmentation. 2020.

[3] Trevor Darrell Jonathan Long, Evan Shelhamer. ”fully convolutional networks for semantic segmentation”. 2015.

[4] Filippo Molinari Kristen M. Meiburger, U. Rajendra Acharya. Automated localization and segmentation techniques for b-mode ultrasound images: A review. 2018.

[5] J.A. Noble and D. Boukerroui. Ultrasound image segmentation: a survey. *IEEE Transactions on Medical Imaging*, 25(8):987–1010, 2006.

[6] Loic Le Folgoc Matthew Lee Mattias Heinrich Kazunari Misawa Kensaku Mori Steven McDonagh Nils Y Hammerla Bernhard Kainz Ben Glocker Daniel Rueckert Ozan Oktay, Jo Schlemper. Attention u-net: Learning where to look for the pancreas. 2018.

[7] Lizhi Jia Ziming Li Zishu Zhou Qinghua Huang, Haozhe Tian. “a review of deep learning segmentation methods for carotid artery ultrasound images. 2023.

[8] E. G. Sifa-kis T.Balkizas S. Golemeati, J. Stoitsis and K. S. Nikita. Using the hough transform to segment ultrasound images of longitudinal and transverse sections of the carotid artery. 2007.

[9] M. Anand Kumar-Jeny Rajan S. Niyas, S.J. Pawan. "medical image segmentation with 3d convolutional neural networks: A survey". 2022.

[10] Loupas T. Shapiro Saad, A.A. Computer vision approach for ultrasound doppler angle estimation. 2009.

[11] Yongping Huang Yingying Jiao Xue Wang, Zhanshan Li. Multimodal medical image segmentation using multi-scale context-aware network. 2022.

[12] Rahman Siddiquee M.M. Tajbakhsh N. Liang J Zhou, Z. "the global burden of cardiovascular diseases and risk factors: 2020 and beyond". 2018.