NCU-Net: A Novel Retinal Vessel Segmentation technique based on U-Net Architecture

Submitted in partial fulfillment of the requirements for the degree of

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by

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May, 2023

DECLARATION

I hereby declare that the thesis entitled "NCU-Net: A Novel Retinal Vessel Segmentation technique based on U-Net Architecture" submitted by me, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of Prof. Aju D.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree ordiploma in this institute or any other institute or university.

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Bachelor of Technology in Computer Science and Engineering

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Executive Summary

Retinal vessel segmentation is an important task in understanding the geometry and structure of blood vessels in the optical system. Segmentation is important for the early diagnosis of ocular diseases such as diabetic retinopathy, glaucoma, and other ocular diseases which in the worst cases can lead to complete vision loss. Finding effective ways to segment retinal vessels for diagnosis or research purposes is crucial. There are several postulated and developed methods for retinal vessel segmentation using existing machine learning and deep learning techniques. However, a recurrent issue in these techniques is inability to properly segment the complex retinal vasculature and they also fall short while segmenting the low contrast retinal images and are plagued by inadequate feature representations. To overcome these drawbacks, a Normalized Convolutional U-Net (NCU-Net) is proposed. The proposed system utilizes an encoder-decoder framework with normalized convolutions and multiple layers to obtain the necessary feature representations for effective performance and is lightweight through the use of Batch Normalization operations. The proposed system is trained and tested using the DRIVE and CHASE_DB1 retinal image datasets and it outperforms several state-of-the-art retinal image segmentation models in metrics such as accuracy, precision, recall, f1-score, Jaccard score and specificity.

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List of Abbreviations

NCU-Net	Normalized Convolutional U-Net
BRVO	Branch Retinal Vein Occlusion
RISUM	Retinal Image Segmentation using Unsupervised Methods
RISSM	Retinal Image Segmentation using Supervised Methods
DCNN	Deep Convolutional Neural Network
GCN	Graph Convolutional Network
DRIVE	Digital Retinal Images for Vessel Extraction
CHASE	Child Heart and Health Study in England
ReLU	Rectified Linear Unit
CPU	Central Processing Unit
GPU	Graphics Processing Unit
OS	Operating System
TP	True Positive
TN	True Negative
FN	False Negative
FP	False Positive
AUC	Area Under Curve

Symbols and Notations

A_c	Accuracy
P	Precision
R	Recall
S_n	Sensitivity
F	F1 Score
J	Jaccard Score
S_p	Specificity
$\cap$	Intersection Operation
$\cup$	Union Operation

1. INTRODUCTION

1.1 THEORETICAL BACKGROUND

Vision is one of the most important senses for human beings. It enables us to perceive the surroundings around us. Vision is facilitated by the complex optical structure of the human visual system, involving the eyes, brain and associated nerves and blood vessels and this system enables us to understand most of the external information and all the visual stimuli[3]. In the visual system of human beings, retinal vessels play an important role in facilitating the blood flow and blood supply to the retinal neurons in the inner eye. The retina, which is responsible for transmitting incoming photons to the brain through neurons and allowing us to ‘see’, is supplied by these retinal vessels. Undoubtedly, the retinal vessels play a major role in the proper functioning of the human optical system. Therefore, any abnormalities in the parameter of the retinal vessels can be linked to onset of diseases which could have catastrophic consequences for vision. Some of the major diseases that can be associated with abnormalities in retinal vessels (often referred to as retinal vascular diseases) are Branch Retinal Vein Occlusion (BRVO), Juxta foveal Telangiectasia, Retinal Artery Microaneurysm, Glaucoma and Diabetic Retinopathy[4]. The early symptoms of these diseases involve blurred vision, dark regions in vision, and the final stage of all the mentioned diseases almost always is complete loss of vision[8]. Hence, proper study of retinal vessel structure and health is essential for early diagnosis of such diseases and could be imperative for the protection of human vision. Effective segmentation of retinal vessels provides both medical practitioners as well as scientists the opportunity to study the vessel structure and come to proper diagnosis and detection of disease or to check on signs that could possibly lead to such diseases that are mentioned above. It also allows for research to be conducted on these blood vessels that could possibly lead to more breakthroughs in cures.

Various old image segmentation techniques have been utilised for retinal vessel segmentation. These techniques include thresholding, clustering, and compression-based image segmentation techniques. Other techniques involve histogram methods and edge detection techniques[11]. Artificial intelligence and machine learning techniques have also been used for image segmentation purposes[9]. Recent advancements in artificial intelligence, machine learning, deep learning and image processing techniques have allowed for automated segmentation of retinal vessels with effective performance on established metrics[2]. Deep learning methods, particularly the use of convolution-based networks have gained significant popularity in the recent past, assuring a high degree of accuracy in segmentation tasks and reducing the burden on professionals who before used to have to rely on colour fundus images for inspection of health of the retinal vessels. Currently there are two major areas in retinal vessel segmentation. The first major area is retinal image segmentation using unsupervised techniques, abbreviated as RISUM and the second major area is retinal image segmentation based on supervised techniques abbreviated as RISSM[14]. The unsupervised methods, that are RISUMs have notably two disadvantages. They assume independence of pixels thereby reducing pixel correlation for vascular feature encoding purposes. The second drawback is that unsupervised methods generally contain pixel-level localization and thereby ignore useful broader scope context and semantic information[15]. These two disadvantages harm the overall performance of unsupervised methods and bring down their overall accuracy. Supervised methods (RISSM) on the other hand, are generally more reliable and are better for distinguishing features in blood vessels and separation of foreground from background. There are different types of RISSMs, which can be based on machine learning or deep learning. These RISSMs depend heavily on effective feature selection to be effective and have issues in adapting to multi-scale features as well as sometimes struggle to extract central reflex and thin vessel features as well morphological changes to vessel structure thereby causing ineffective segmentation of the smaller capillaries and vessels[8].

Recent advancements in deep learning techniques have helped overcome the issues mentioned above to a certain extent, all by varying degrees of effectiveness. The advent of deep convolution networks (DCNN) and the combination of DCNNs along with graph convolutional networks (GCNs) have allowed for better outcomes in retinal vessel segmentation[18]. Particularly, marked improvements have been made in the sensitivity and specificity of the models which have been proposed and developed. However, one of the most important breakthroughs in biomedical image segmentation came in 2015 when the first proposed the U-Net architecture based on a fully convolutional network was developed its efficiency was verified by segmentation of HeLa cell images[7]. Since then, various forms of U-Net architecture and modified U-Net models have been created for various biomedical image segmentation tasks. Even for retinal vessel segmentation, the use of U-Net based models are a source of exciting and active research with marked improvements being made in various metrics depending on the focus on the authors' focus on their proposed systems. Various retinal image segmentation techniques along with their results have been elucidated in the literature review section.

To overcome the issues mentioned above, in this project, a deep learning method is proposed that utilizes the U-Net architecture as a backbone for retinal vessel segmentation. The proposed model implements an encoder-decoder framework that is capable of effective propagation of context features of the target blood vessels to be segmented through optimized up-sampling and down-sampling via various convolution blocks. The general process is that of an encoder network which is based of convolution blocks that are generally arranged in a set structure followed by max pooling layers for efficient down-sampling for encoding of the retinal vessel images into feature representations using various layers. The second part of proposed system is a decoder network whose function is to reassemble the feature representations obtained from the encoder network and for semantic projections of important features. These discriminative features which are usually more rudimentary and low resolution are projected to obtain a dense classification, and thereby obtaining a higher resolution. The decoder section of the system is responsible for up-sampling, aggregation, concatenation, and this is followed by convolutions. The proposed system aims to overcome the issues faced by shallow convolutional networks or other machine learning and deep learning techniques such as discontinuous segmentation owing to insufficient feature representation. Other issues that the model aims to alleviate are the gradient errors in late training phase and irregular segmentation of complex retinal vessel structure. The proposed U-Net model also aims to improve segmentation accuracy by improving the feature extraction in the encoder phase and by enabling the model to properly distinguish between the retinal vessel foreground and the background which is complex due to the low contrast images. The proposed model will be verified using the DRIVE and CHASE_DB1 datasets which contain retinal vessel images, and the performance will be evaluated using metrics such as accuracy, F1 score and AUC.

1.2 MOTIVATION

There are several real-world benefits associated with the creation of a robust and efficient automatic retinal segmentation model.

Firstly, it can be utilised in medical diagnosis and monitoring of several eye related diseases such as Glaucoma, Diabetic Retinopathy and Retinal Artery Microaneurysm among others. By effectively and accurately segmenting the retinal vessel structure, professionals can find and monitor abnormalities in said structures, assess the existence or progression of disease and make the necessary informed treatment.

Another motivating factor for the development of the NCU-Net model is for disease screening. The proposed model can be deployed for large scale disease screening situations for the identification of individuals at particular risk of developing any associated retinal related diseases.

The automated model can assist in early detection and make early intervention possible which will ultimately allow for reduced costs and overall better outcomes. The automation of segmentation tasks will reduce the workload of ophthalmologists and scientific researchers quite significantly which will enable them to focus their time on more important areas of diagnosis and treatment.

Automated retinal segmentation models are one of the most interesting and valuable tools for scientific researchers for disseminating the complex structure and function of eye vessels. By carefully segmenting the vessels, researchers can examine characteristics such as vessel tortuosity, branching patterns, and vessel diameter. This analysis can shed light on both systemic and ocular illnesses.

For the benefit of those who have vision difficulties, assistive technology or applications can make use of automated retinal vessel segmentation models. By increasing their visual perception, these models can assist people with impaired vision in navigating and interacting with their environment more successfully. They accomplish this by emphasising and enhancing retinal vasculature in images and films.

Overall, the improvement of eye disease diagnosis, screening effectiveness, research capabilities, and assistive technologies is the goal of the development of retinal vessel segmentation models. This will result in better patient outcomes, reduced healthcare costs, and improved quality of life for people with visual impairments.

1.3 AIM OF THE PROPOSED WORK

The primary aims of the proposed NCU-Net model for retinal vessel segmentation are:

1. Segmentation accuracy and reliability. The proposed model should be able to accurately segment the complex retinal vessel structure and should be able to do so with a great degree of reliability. This is imperative for precise delineation as faculty segmentation could lead to potential wrong diagnoses.
2. The proposed model should be capable for effectively and efficiently segmenting the input retinal images thereby allowing it use in large diagnoses programs which will ultimately enable for overall reduction in medical costs.
3. The proposed model should be robust and generalizable, capable of handling various input retinal images from different sources and from a large input spectrum. This will ensure that the model shows good performance over a large variety of datasets and hence can be used in a wide range of scenarios.

4. The proposed model aims to improve the efficiency of clinicians and researchers by providing an automated retinal vessel segmentation model enabling them to focus on more crucial aspects of medical diagnosis.
5. The proposed model aims to perform well over various pre-existing and established metrics such as accuracy, precision, recall, f1-score and others.
6. The proposed model aims to improve upon the existing U-Net based models by the introduction of normalised convolutions which will enable for more accurate segmentation of the retinal structure.

1.4 OBJECTIVES OF THE PROPOSED WORK

The objectives of the proposed NCU-Net model for retinal vessel segmentation are as follows:

1. Implement a robust deep learning model based on U-Net architecture for retinal vessel segmentation.
2. Implement an encoder-decoder network that is capable of efficient down-sampling and up-sampling of input retinal vessel images.
3. Implement convolution blocks and max pooling layers for efficient down-sampling in the encoder network.
4. Implement up-sampling, aggregation and concatenation abilities and convolution blocks in the decoder network.
5. To overcome the issues faced by traditional machine learning techniques and shallow deep learning models in effectively segmenting retinal vessels in low contrast images.
6. Training and testing proposed model on publicly available datasets such as DRIVE and CHASE_DB1.
7. Ensuring effective and accurate segmentation of target retinal vessel images and verifying performance through metrics such as accuracy, precision. F1-score, recall (sensitivity), specificity and Jaccard score.

2. LITERATURE SURVEY

2.1 SURVEY OF EXISTING MODELS/WORK

Table 1: Literature Survey

Sr. No.	Title	Authors	Journal	Year	Overview/Summary	Results
1	A Fundus Retinal Vessels Segmentation Scheme Based on the Improved Deep Learning U-Net Model	Xiuqin Pan , Qinrui Zhang, Hong Zhang , and Sumin Li	IEEE Access	2019	The authors of this study use an enhanced deep learning U-Net Model to create a deep learning model for segmenting retinal vessels. The improved model combines U-net with a residual module and makes it possible to link the deconvolutional layer's and convolutional layer's outputs. This overcomes the issues with low-level information sharing and distribution and offers a fix for DCNN performance decline in residual networks at very deep levels. Using the DRIVE dataset, the authors	DRIVE dataset: 1. Accuracy: 0.9650 2. Sensitivity: 0.9310 3. Specificity : 0.9863 4. AUC: 0.9811

					have confirmed the model's effectiveness.	
2	A Three-Stage Deep Learning Model for Accurate Retinal Vessel Segmentation	Z. Yan, X. Yang, and K. T. Cheng	IEEE Journal of Biomedical and Health Informatics	2019	In this paper, the authors propose a retinal vessel segmentation deep-learning model that is of three stages for addressing the imbalance problem associated with the ratio of thick to thin vessels (majorly thick vessel pixels). The authors have divided vessel segmentation into three stages or tasks. The first stage involves thick vessel segmentation. This is followed by this vessel segmentation. The final stage is vessel fusion. The final stage enables further refinement of results by identifying the non-vessel regions and disregarding them from segmentation. The authors have used the DRIVE, CHASE_DB1 and	DRIVE dataset 1. Sensitivity: 0.7631 2. Specificity: 0.9820 3. Accuracy: 0.9538 4. AUC: 0.9750 STARE dataset 1. Sensitivity: 0.7735 2. Specificity: 0.9857 3. Accuracy: 0.9638 4. AUC: 0.9833 CHASE_DB1 dataset 1. Sensitivity: 0.7641 2. Specificity: 0.9806 3. Accuracy: 0.9607 4. AUC: 0.9776

					STARE datasets for their experiments.	
3	A Global and Local Enhanced Residual U-Net for Accurate Retinal Vessel Segmentation	S. Lian, L. Li, G. Lian, X. Xiao, Z. Luo, and S. Li	IEEE/ACM Transactions on Computational Biology and Bioinformatics	2021	In this paper, the authors develop an enhanced U-net based model that is both globally and locally enhanced for retinal vessel segmentation model. This model utilized local information and overcome the issue of overlooking the geometrical retinal constraints that is specific to a particular area of the image or considered patch. The developed model uses a weighted attention mechanism for determining the region of interest for segmentation purposes. The DRIVE and STARE datasets have been used by the authors for the experiments.	DRIVE dataset 1. Accuracy: 0.9692 2. Sensitivity: 0.8278 3. Specificity: 0.9861 4. Precision: 0.8637 STARE dataset 1. Accuracy: 0.9740 2. Sensitivity: 0.8342 3. Specificity: 0.9916 4. Precision: 0.8823
4	CRAUNet: A cascaded residual attention	F. Dong, D. Wu, C. Guo, S.	Computers in Biology and	2022	In this paper, the authors develop a deep learning U-net model that uses cascaded residual	DRIVE dataset: 1. Sensitivity: 0.7954 2. F1 Score: 0.8302

	U-Net for retinal vessel segmentation	Zhang, B. Yang, and X. Gong,	Medicine		attention (CRA) which abbreviates to CRAUNet. The model consists of sets of U-net models that enable representations ranging from coarse to fine levels. It also uses DropBlock regularisation to overcome overfitting and the authors have also developed an attention module that is robust in exploring and merging important features and information. The authors use the DRIVE and CHASE_DB1 datasets for their experiments.	3. Precision: 0.9212 4. Accuracy 0.9586 5. AUC: 0.9830 CHASE_DB1 dataset: 1. Sensitivity: 0.8259 2. F1 Score: 0.8156 3. Precision: 0.8996 4. Accuracy 0.9659 5. AUC: 0.9864
5	Biomedical Signal Processing and Control A retinal vessel segmentation method based improved	K. Sun, Y. Chen, Y. Chao, J. Geng, and Y. Chen	Biomedical Signal Processing and Control	2023	In this paper the authors develop an enhanced U-net model for retinal vessel segmentation. The developed model boosts feature transmissions, reduce explosive gradients, and improve overall feature extraction potential for various	DRIVE dataset: 1. Sensitivity: 0.8293 2. Specificity: 0.9807 3. Accuracy: 0.9675 4. AUC: 0.9832 STARE dataset:

	U-Net model				forms of retinal vessels. Series deformable convolutions are used alongside an attention mechanism, and, on this basis, the SDAU-Net is developed. Two attention mechanisms are employed, one lightweight and another dual attention, both of which are used in the decoder component and significantly boosts the extraction of complicated shapes and tiny retinal vessels. The DRIVE, STARE, CHASE_DB1 and IOSTAR datasets are used by the authors for their experiments.	1. Sensitivity: 0.8973 2. Specificity: 0.9903 3. Accuracy: 0.9833 4. AUC: 0.9963 CHASE_DB1 dataset: 1. Sensitivity: 0.8321 2. Specificity: 0.9825 3. Accuracy: 0.9732 4. AUC: 0.9858 IOSTAR dataset: 1. Sensitivity: 0.8842 2. Specificity: 0.9927 3. Accuracy: 0.9848 4. AUC: 0.9961
6	Deep Retinal Image Segmentat	V. Cheruk uri, V. K. Bg,	IEEE Transac tions on Image	2020	In this paper, the authors develop an enhanced deep neural network containing	DRIVE dataset: 1. F1 Score: 0.8220

	ion with Regularization under Geometric Priors	R. Bala, and V. Monga	Processing		two components. The first component is a representation network that enables the learning of geometric features from the input images. The second component is a novel residual task network that uses the geometric features obtained from the first component (representation network) for pixel-level segmentation. The authors also develop two novel constraint features. The first is an orientation constraint for curvilinear geometric feature diversity and the second is a noise regularization constraint that is adaptive to input data and enables proper penalty for false positives. The DRIVE, STARE and CHASE_DB1 datasets are used by	2. Accuracy: 0.9563 3. AUC: 0.9814 STARE dataset: 1. F1 Score: 0.8364 2. Accuracy: 0.9687 3. AUC: 0.9903 CHASE_DB1 dataset: 1. F1 Score: .8211 2. Accuracy: 0.972 3. AUC: 0.9833

					the authors for their experiments.	
7	ELEMENT: Multi-Modal Retinal Vessel Segmentation Based on a Coupled Region Growing and Machine Learning Approach	E. O. Rodrigues, A. Conci, and P. Liatsis	IEEE Journal of Biomedical and Health Informatics	2020	In this paper, the authors develop a novel multi-modal framework for retinal vessel segmentation called ELEMENT. Utilizing deep learning methods and region growing techniques, this framework comprises of feature extraction and pixel-based categorization which enables refined data collection based on vessel connection and grey level qualities. During the classification step, the information is smoothly sent across the pixels which allows for increased segmentation throughput is and decreased inconsistency. The DRIVE, STARE and CHASE-DB, VAMPIRE, IOSTAR and RC-SLO datasets are used by the	DRIVE dataset: 1. Accuracy: 0.9740 2. AUC: 0.9936 3. F1 Score: 0.8579 STARE dataset: 1. Accuracy: 0.9827 2. AUC: 0.9946 3. F1 Score: 0.8910 CHASE-DB dataset: 1. Accuracy: 0.9778 2. AUC: 0.9923 3. F1 Score: 0.8448 VAMPIRE dataset: 1. Accuracy: 0.9834 2. AUC: 0.9956 3. F1 Score: 0.8935

					authors for their experiments.	IOSTAR dataset: 1. Accuracy: 0.9804 2. AUC: 0.9959 3. F1 Score: 0.8635 RC-SLO dataset: 1. Accuracy: 0.9835 2. AUC: 0.9936 3. F1 Score: 0.9187
8	Hard Attention Net for Automatic Retinal Vessel Segmentation	D. Wang, A. Haytham, J. Pottenburgh, O. Saeedi, and Y. Tao	IEEE Journal of Biomedical and Health Informatics	2020	In this paper, the authors develop a hard attention net to overcome the issues incurred in the segmentation of thin retinal vessels and those regions which contain uncertain boundaries. The developed model is made up of three decoder networks, the first of which identifies and locates segmentation regions and assigns a difficulty (hard or easy) to it. The other	DRIVE dataset: 1. Sensitivity: 0.7991 2. Specificity: 0.9813 3. Accuracy: 0.9581 4. AUC: 0.9823 5. F1 Score: 0.8293 STARE dataset 1. Sensitivity: 0.8186 2. Specificity: 0.9844 3. Accuracy: 0.9673

					two networks segment the hard and easy regions. An attention mechanism is used to enable better segmentation of hard regions. The outputs from the three decoder networks are merged to form a final segmentation map. The DRIVE, STARE, CHASE_DB1, HRF and IOSTAR datasets are used by the authors for experimentation.	4. AUC: 0.9881 5. F1 Score: 0.8379 CHASE_DB1 dataset: 1. Sensitivity: 0.8239 2. Specificity: 0.9813 3. Accuracy: 0.9670 4. AUC: 0.9871 5. F1 Score: 0.8191 HRF dataset: 1. Sensitivity: 0.7803 2. Specificity: 0.9843 3. Accuracy: 0.9654 4. AUC: 0.9837 5. F1 Score: 0.8074 IOSTAR dataset 1. Sensitivity: 0.7538 2. Specificity: 0.9893

						3. Accuracy: 0.9652 4. AUC: 0.9859 5. F1 Score: 0.8161
9	Genetic U-Net: Automatically Designed Deep Networks for Retinal Vessel Segmentation Using a Genetic Algorithm	Wei, Jiahong Zhu, Guijie Fan, Zhun Liu, Jinchao Rong, Yibiao Mo, Jiajie Li, Wenji Chen, Xinjian	IEEE Transactions on Medical Imaging	2022	In this paper, the authors have developed a novel deep network based on U-net that uses a genetic algorithm for retinal vessel segmentation. The developed model is more automated compared to traditional deep learning methods and gives better performance with fewer architecture-oriented variables. A traditional U-net based backbone is used to ensure a flexible search space and an enhanced genetic algorithm is employed to identify those architectural parameters providing better performance in said search space. The DRIVE, STARE,	DRIVE dataset: 1. Accuracy: 0.9707 2. Sensitivity: 0.8300 3. Specificity: 0.9843 4. F1 Score: 0.8314 5. AUROC: 0.9885 STARE dataset: 1. Accuracy: 0.9792 2. Sensitivity: 0.8658 3. Specificity: 0.9886 4. F1 Score: 0.8630 5. AUROC: 0.9942 CHASE_DB1 dataset: 1. Accuracy: 0.9769

					CHASE_DB1 and HRF datasets are used by the authors for their experiments.	2. Sensitivity: 0.8463 3. Specificity: 0.9857 4. F1 Score: 0.8223 5. AUROC: 0.9914 HRF dataset: 1. Accuracy: 0.9715 2. Sensitivity: 0.8220 3. Specificity: 0.9839 4. F1 Score: 0.8179 5. AUROC: 0.9891
10	Graph-based convolution feature aggregation for retinal vessel segmentation	Shi, Cao Xu, Canhui He, Jianfei Chen, Yinong Cheng, Yuanzhi Yang, Qi Qiu, Haitao	Simulation Modelling Practice and Theory	2022	In this paper, the authors have developed a graph-based convolution feature aggregation network for retinal vessel segmentation. (GFCAN). The GFCAN focuses on the segmentation task as well as enhancement of non-vessel regions and uses graph methods for propagation and	Combined dataset: 1. Accuracy: 0.9679 2. Precision: 0.8189 3. Recall: 0.7521 4. Dice: 0.7825

					congregation of features from different layers. It consists of a feature extraction module, a low-level aggregation module and a high-level aggregation module. The first module extracts feature representations. The low-level module focuses on boundary data for vessel segmentation whereas the high-level module uses more semantic data for segmentation. The DRIVE, CHASE_DB1, IOSTAR and HRF datasets are processed and combined into a single dataset for experimentation.	
11	Joint segment-level and pixel-wise losses for deep learning based retinal vessel	Yan, Zengqiang Yang, Xin Cheng, Kwang Ting	IEEE Transactions on Biomedical Engineering	2018	In this paper the authors propose a novel segment-level loss for retinal vessel segmentation using deep learning methods. The proposed loss focuses on the consistency of the thickness of	DRIVE dataset: 1. Sensitivity: 0.7653 2. Specificity: 0.9818 3. Accuracy: 0.9542 4. AUC: 0.9752

	segmentation				particularly thin retinal vessels. The proposed loss is better at learning features and brings about performance enhancement for neural network architectures without increasing model complexity. The DRIVE, STARE and CHASE_DB1 datasets are used for experiments.	STARE dataset: 1. Sensitivity: 0.7581 2. Specificity: 0.9846 3. Accuracy: 0.9612 4. AUC: 0.9801 CHASE_DB1 dataset: 1. Sensitivity: 0.7633 2. Specificity: 0.9809 3. Accuracy: 0.9610 4. AUC: 0.9781
12	MFI-Net: Multiscale Feature Interaction Network for Retinal Vessel Segmentation	Y. Ye, C. Pan, Y. Wu, S. Wang, and Y. Xia	IEEE Journal of Biomedical and Health Informatics	2022	In this paper, the authors develop an MFI-Net which stands for multiscale feature interaction network. The MFI-Net is based on a U-Net backbone (effectively a U-CNN architecture). This network contains a pyramid excitation module, coarse to fine module and is capable of deep-level	DRIVE dataset: 1. AUC: 0.9884 2. Accuracy: 0.9699 3. Specificity: 0.9847 4. Sensitivity: 0.8166 5. F1 Score: 0.8249 STARE dataset: 1. AUC: 0.9919

					supervision and fusion of features. A multiscale and multichannel attention mechanism is employed to handle the varying retinal vessel thickness. The coarse to fine module is enhanced for residual feature map generation and re-processing with the objective of greater vessel preservation while decoding. The DRIVE, STARE, CHASE_DB1 and HRF datasets are used by the authors for their experiments.	2. Accuracy: 0.9753 3. Specificity: 0.9874 4. Sensitivity: 0.8237 5. F1 Score: 0.8280 CHASE_DB1 dataset: 1. AUC: 0.9897 2. Accuracy: 0.9693 3. Specificity: 0.9847 4. Sensitivity: 0.8317 5. F1 Score: 0.8424 HRF dataset: 1. AUC: 0.9880 2. Accuracy: 0.9713 3. Specificity: 0.9836 4. Sensitivity: 0.8236 5. F1 Score: 0.8159
13	ResDO-UNet: A	Y. Liu, J. Shen,	Biomedical	2022	In this paper, the authors develop a	DRIVE dataset:

	deep residual network for accurate retinal vessel segmentation from fundus images	L. Yang, G. Bian, and H. Yu	Signal Processing and Control		novel retinal vessel segmentation network based on U-net. The developed model overcomes the issue of information loss occurring due to multiple pooling and the issue of insufficient process for local feature context. The developed model uses an overparameterized convolution layer which changes depth-wise (DO-conv). The main backbone is formed of a residual network which is combined with the Do-conv to form the ResDO-conv network. Multiple max pool and avg. pooling layers are nonlinearly fused using a custom block (PFB). There also exists an attention fusion block for obtaining sufficient local feature context. The DRIVE, STARE and CHASE_DB1	1. Sensitivity: 0.7985 2. Specificity: 0.9791 3. Accuracy: 0.9561 4. F1 Score: 0.8229 STARE dataset: 1. Sensitivity: 0.7963 2. Specificity: 0.9792 3. Accuracy: 0.9567 4. F1 Score: 0.8172 CHASE_DB1 dataset: 1. Sensitivity: 0.8020 2. Specificity: 0.9794 3. Accuracy: 0.9672 4. F1 Score: 0.8236

					datasets are used for experiments.	
14	Retinal Vessel Segmentation with Skeletal Prior and Contrastive Loss	Tan, Yubo Yang, Kai-fu Zhao, Shi-xuan Li, Yong-jie	IEEE Transactions on Medical Imaging	2022	In this paper, the authors develop a network called SkelCon for retinal vessel segmentation. The developed system is focused on improving the discovery of features in retinal images and to improve the segmentation of thin vessels particularly. Thin vessel segmentation is boosted using a skeletal fitting module which improves thin vessel completeness. Both contrastive and prior loss are introduced to segregate vessel from background and a custom data augmentation technique is applied for better robustness of the model. The model is verified using DRIVE, STARE and IOSTAR datasets.	DRIVE dataset: 1. Sensitivity: 0.8323 2. Specificity: 0.9859 3. Accuracy: 0.9461 STARE dataset: 1. Sensitivity: 0.8610 2. Specificity: 0.9905 3. Accuracy: 0.9691 IOSTAR dataset: 1. Sensitivity: 0.8057 2. Specificity: 0.9703 3. Accuracy: 0.9548

15	SPNet: A novel deep neural network for retinal vessel segmentation based on shared decoder and pyramid-like loss	Xu, Geng-Xin Ren, Chuan-Xian	Neurocomputing	2022	In this paper, the authors develop a deep neural network for retinal vessel segmentation. This novel network is based on pyramid loss and utilizes a shared decoder which is used for multiscale semantic information capture. For more defined characterization of retinal vessels, particularly their edges, a residual pyramid structure is utilized whose function is to understand spatial information while decoding. The purpose of the pyramid loss function is for compensation for possible segmentation errors. The DRIVE, STARE and CHASE_DB1 datasets are used by the authors for their experiments.	DRIVE dataset: 1. Sensitivity: 0.8821 2. Specificity: 0.9716 3. Accuracy: 0.9601 4. AUC: 0.9787 STARE dataset: 1. Sensitivity: 0.8859 2. Specificity: 0.9842 3. Accuracy: 0.9739 4. AUC: 0.9909 CHASE_DB1 dataset: 1. Sensitivity: 0.8906 2. Specificity: 0.9817 3. Accuracy: 0.9725 4. AUC: 0.9857
16	A refined equilibrium	Y. Zhou, Z.	Neurocomputing	2021	In this paper, the authors develop a synthetic neural	DRIVE dataset: 1. Accuracy: 0.9563

	generative adversarial network for retinal vessel segmentation	Chen, H. Shen, X. Zheng, R. Zhao, and X. Duan			network which have the capacity for enhance thin vessel segmentation. The developed model consists of a symmetric equilibrium GAN (SEGAN) with multiple refine blocks which are multi-scale as well as contains an attention mechanism. The developed framework is optimized for local detail in images by maximizing feature representation and can maintain high-res image information. The refine blocks optimize the merging of features and the attention mechanism enhance feature discrimination. The DRIVE, STARE, CHASE_DB1 and HRF datasets are used by the authors for experimentation.	2. F1 Score: 0.8345 3. AUC: 0.9830 STARE dataset: 1. Accuracy: 0.9671 2. F1 Score: 0.8359 3. AUC: 0.9863 CHASE_DB1 dataset: 1. Accuracy: 0.9630 2. F1 Score: 0.8218 3. AUC: 0.9872 HRF dataset: 1. Accuracy: 0.9559 2. F1 Score: 0.8211 3. AUC: 0.9693
17	BSEResU-Net: An attention-based	D. Li and S. Rahardja	Computer Methods and	2021	In this paper, the authors develop a novel residual U-net that utilizes squeeze	DRIVE dataset: 1. AUC: 0.9820

	before-activation residual U-Net for retinal vessel segmentation		Programs in Biomedicine		and excitation technique before activation (BSEResu-Net) to overcome the imbalance problems in retinal vessel segmentation tasks such as ratio of thick to thin vessels or background to foreground problems. The BSE blocks use an attention module in conjunction to the regular skip connection to facilitate optimized performance of the model. Also implemented is a dropblock mechanism and a joint loss function for better and more balanced segmentation. The DRIVE, STARE and HRF datasets are used by the authors for their experiments.	2. Accuracy: 0.9574 3. Sensitivity: 0.8324 4. Specificity: 0.9757 STARE dataset: 1. AUC: 0.9912 2. Accuracy: 0.9759 3. Sensitivity: 0.8391 4. Specificity: 0.9887 HRF dataset: 1. AUC: 0.9637 2. Accuracy: 0.8067 3. Sensitivity: 0.9796 Specificity: 0.8044
18	Attention-inception-based U-Net for retinal vessel segmentati	Wang, Huadeng Xu, Guang Pan, Xipeng	Computers and Electrical Engineering	2022	In this paper, the authors develop a novel retinal vessel segmentation technique aimed at overcoming issues such as loss of	DRIVE dataset: 1. Accuracy: 0.9611 2. AUC: 0.9829 3. F1 Score: 0.8397

	on with advanced residual	Liu, Zhenbing Tang, Ningning Lan, Rushi Luo, Xiaonan			microvasculature information and interference of exudate. The authors have developed a AR-SA U-Net which uses residual modules alongside dilated convolutions. An attention mechanism and an inception module are also present. The DRIVE, STARE and CHASE_DB1 datasets have been used by the authors for experimentation.	STARE dataset: 1. Accuracy: 0.9796 2. AUC: 0.9902 3. F1 Score: 0.8394 CHASE_DB1 dataset: 1. Accuracy: 0.9662 2. AUC: 0.9873 3. F1 Score: 0.8340
19	Dual Encoder-Based Dynamic-Channel Graph Convolutional Network with Edge Enhancement for Retinal Vessel Segmentation	Y. Li, Y. Zhang, W. Cui, B. Lei, X. Kuang, and T. Zhang	IEEE Transactions on Medical Imaging	2022	In this paper, the authors develop a dynamic-channel GCN deep learning model that uses dual encoders along wide edge enhancement techniques for the purposes of retinal vessel segmentation. The proposed method takes into consideration dynamic topological correlations between the different feature representations which allows the system to	DRIVE dataset: 1. Accuracy: 0.9705 2. Sensitivity: 0.8359 3. Specificity: 0.9826 4. AUC: 0.9866 STARE dataset: 1. Accuracy: 0.9751 2. Sensitivity: 0.8405 3. Specificity: 0.9861

					produce better results through effective channel characterization. The develop model can preserve edge details even after image down sampling. The dynamic-channel GCN can create features from the channel characterizations in the topological space. The accuracy of thin vessel segmentation is improved by the dual encoder architecture. The DRIVE, STARE, CHASE_DB1, HRF and IOSTAR datasets are used for experiments.	4. AUC: 0.9899 CHASE_DB1 dataset: 1. Accuracy: 0.9762 2. Sensitivity: 0.8400 3. Specificity: 0.9856 4. AUC: 0.9898 HRF dataset: 1. Accuracy: 0.9695 2. Sensitivity: 0.8169 3. Specificity: 0.9825 4. AUC: 0.9845 IOSTAR dataset: 1. Accuracy: 0.9714 2. Sensitivity: 0.8372 3. Specificity: 0.9830 4. AUC: 0.9881
20	Edge-aware U-	Y. Zhang,	Biomedical	2022	In this paper, the authors develop an	DRIVE dataset:

	net with gated convolution for retinal vessel segmentation	J. Fang, Y. Chen, and L. Jia	Signal Processing and Control		edge-aware U-Net model which serves to increase the sensitivity of the model to fine capillary edges. The developed system also contains gated convolutions which serve to optimize edge presentation and places weight and emphasis on the edges of vessels. Features are extracted in the encoder path and the decoder process refines the segmentation outcomes. The DRIVE, STARE and CHASE_DB1 datasets have been used by the authors for experiments.	1. Sensitivity: 0.7719 2. Specificity: 0.9799 3. Accuracy: 0.9701 4. F1 Score: 0.8021 5. AUC: 0.8895 STARE dataset: 1. Sensitivity: 0.6912 2. Specificity: 0.9911 3. Accuracy: 0.9691 4. F1 Score: 0.7552 5. AUC: 0.8391 CHASE_DB1 dataset: 1. Sensitivity: 0.8506 2. Specificity: 0.9981 3. Accuracy: 0.9811 4. F1 Score: 0.7662 5. AUC: 0.9142

21	MSCNN-AM: A multi-scale convolutional neural network with attention mechanisms for retinal vessel segmentation	Fu, Qilong Li, Shuqiu Wang, Xin	IEEE Access	2020	In this paper, the authors develop a multi-scale CNN network with added attention modules, aimed specifically at improving segmentation accuracy and sensitivity. The developed method used varying dilation rates for effective capture of tiny vessel information and uses attention modules to decrease false positive rates and effectively segment retinal vessels instead of the background. The DRIVE, STARE and CHASE_DB1 datasets are used by the authors for their experiments.	DRIVE dataset: 1. Accuracy: 0.9555 2. AUC: 0.9795 3. F1 Score: 0.8267 STARE dataset: 1. Accuracy: 0.9658 2. AUC: 0.9863 3. F1 Score: 0.8401 CHASE_DB1 dataset: 1. Accuracy: 0.9644 2. AUC: 0.9839 3. F1 Score: 0.8237
22	MD-Net: A multi-scale dense network for retinal vessel segmentation	Shi, Zhengjin Wang, Tianyu Huang, Zheng Xie, Feng	Biomedical Signal Processing and Control	2021	In this paper the authors propose a deep learning technique using multiscale dense network for the purposes of retinal vessel segmentation. The developed model aims at improving	DRIVE dataset: 1. Accuracy: 0.9676 2. Sensitivity: 0.8065 3. Specificity: 0.9826 STARE dataset:

		Liu, Zihong Wang, Bolun Xu, Jing			segmentation accuracy particularly for the challenging morphology of tiny capillaries. The model uses a custom feature fusion mechanism and pyramid pooling for improving feature representation. The concatenation step is also boosted by the use of a squeeze and excite mechanism. The DRIVE, STARE and CHASE_DB1 datasets are used by the authors for their experiments.	1. Accuracy: 0.9732 2. Sensitivity: 0.8290 3. Specificity: 0.9866 CHASE_DB1 dataset: 1. Accuracy: 0.9731 2. Sensitivity: 0.7504 3. Specificity: 0.9889
23	Retinal blood vessel segmentation using pixel-based feature vector	Toptaş, Buket Hanbay, Davut	Biomedical Signal Processing and Control	2021	In this paper a pixel-based feature vector technique is employed by the authors to facilitate retinal vessel segmentation. The technique involves pixel-level feature extraction and group aggregation as well as edge detection and Hessian matrix features. The DRIVE and STARE datasets were used by the	DRIVE dataset: 1. Sensitivity: 08400 2. Specificity: 0.9716 3. Accuracy: 0.9618 4. Jaccard: 0.6148 5. Dice: 0.7609 STARE dataset: 1. Sensitivity: 06308 2. Specificity: 0.9824

					authors for experiments.	3. Accuracy: 0.9456 4. Jaccard: 0.5296 5. Dice: 0.6860
24	ILU-Net: Inception-Like U-Net for retinal vessel segmentation	Zhu, Zifan An, Qing Wang, Zhicheng Li, Qian Fang, Hao Huang, Zhenghua	Optik	2022	In this paper, the authors develop a novel retinal vessel segmentation technique based on U-Net that utilizes two different types of Inception blocks while encoding and decoding. One set of Inception blocks are used for up-sampling while the other is used for down-sampling. The authors have also developed a customs skip connection for better feature representation at a low-level and thereby producing better segmentation results. The DRIVE and STARE datasets are used by the authors for their experiments.	DRIVE dataset: 1. Accuracy: 0.9733 2. Sensitivity: 0.7919 3. Specificity: 0.9895 4. F1 Score: 0.8296 STARE dataset: 1. Accuracy: 0.9651 2. Sensitivity: 0.8353 3. Specificity: 0.9918 4. F1 Score: 0.8449
25	Prompt Deep Light-	Arsalan,	IEEE/ACM Transac	2022	In this paper, the authors have developed a light-	DRIVE dataset: 1. Sensitivity: 0.8250

	weight Vessel Segmentation Network (PLVS-Net)	Muhammad Khan, Tariq M. Naqvi, Syed S. Nawaz, Mehmood Razzak, Imran	tions on Computational Biology and Bioinformatics		weight segmentation network for retinal vessel segmentation. The proposed model uses prompt blocks to bridge semantic differences between the encoder and decoder networks. The developed systems also takes int account contextual features of the retinal vessel geometry. The prompt block contain a combination of asymmetric, separable, and ordinary convolutions for feature extraction. The DRIVE, STARE and CHASE_DB1 datasets are used by the authors for their experiments.	2. Specificity: 0.9837 3. Accuracy: 0.9678 4. AUC: 0.9815 STARE dataset: 1. Sensitivity: 0.8190 2. Specificity: 0.9874 3. Accuracy: 0.9727 4. AUC: 0.9706 CHASE_DB1 dataset: 1. Sensitivity: 0.8485 2. Specificity: 0.9887 3. Accuracy: 0.9749 4. AUC: 0.9841

2.2 SUMMARY/GAPS IDENTIFIED IN THE SURVEY

Recent advancement in deep learning have enable the creation of effective automated retinal segmentation models. Nowadays, there are broadly two different types of automated segmentation models, The first is unsupervised and the other is supervised. Unsupervised techniques often abbreviated as RISUM (Retinal Image Segmentation using Unsupervised Methods) primarily face two drawbacks. In order to reduce pixel correlation for vascular feature encoding, they assume that pixels are independent. The second problem is that unsupervised algorithms frequently use pixel-level localisation, which ignores useful context and semantic information with a wider application. Unsupervised algorithms suffer from these two drawbacks, which lower their overall performance and accuracy. The supervised models often abbreviated as RISSM (Retinal Image Segmentation using Supervised Methods) also come with their own set of drawbacks. The supervised methods surveyed above demonstrate a distinct lack of sufficient feature representation leading to the issue of discontinuous segmentation. Another issue currently plaguing supervised models are gradient errors occurring in the late training phase as well as irregular segmentation of the complex retinal vessel structure. Another important issue plaguing supervised models is the limited availability of annotated ground truths for basing the models upon.

Other general issues faced by developed models is the lack of adaptability of the developed models to a wide array of input data. The surveyed methods have also demonstrated a large degree of unwarranted sensitivity to input data originating from different sources. The existing models seem to struggle while segmenting low quality images often leading to inconsistencies in the final segmentation map. The proposed models also suffer from limited generalizability and hence cannot be readily applied to new datasets resulting in a setback to the large-scale adoption of automated retinal vessel segmentation models. The existing supervised models in particular are to very effective against pathological changes and are hence lacking when there are defects and diseases present in the input image. The recent models also suffer from being too heavy and having a large amount of computational complexity which limits their practicality. The proposed NCU-Net model aims to overcome some of the issues faced by the existing models by providing a relatively lightweight, robust, accurate and efficient model for retinal vessel segmentation.

3. OVERVIEW OF THE PROPOSED SYSTEM

3.1 INTRODUCTION AND RELATED CONCEPTS

The proposed NCU-Net architecture for Retinal Vessel Segmentation is based on the U-Net model proposed by Ronneberger et al [26] in 2015. The proposed architecture consists of a multi-level encoder-decoder framework (as shown in Fig 2.) with each layer consisting of a set of convolutional layers followed by associated activation functions and normalizations if required. The main purpose of the proposed architecture is to first down-sample the image into smaller sections and obtain more feature maps as we progress down the layers of the encoder network. This is followed by a decoder network seeking to up-sample the obtained feature maps into the required segmentation maps for the output.

The U-Net is so called because of its diagrammatic U shape which consists of an encoder part followed by a decoder section both of which are interconnected by means of a bottleneck. The encoder is responsible for feature extraction from input images and is also used for contextual understanding and the decoder network is generally used for up sampling for image generation. Both the encoder and decoder networks contain a variety of convolution based networks followed by pooling layers. The U-Net architecture also contains skip connection responsible for low-level and high-level feature fusion thereby facilitating a high quality segmentation.

The U-Net architecture is designed for both local and global feature extraction and retention due to which it is extremely popular for segmentation tasks both semantic and instance based segmentation. The U-Net architecture also facilitates exceptional and accurate boundary localization. The U-Net architecture is widely used for biomedical image segmentation but its also popular for other tasks as well. Variations of the U-Net are being worked upon by researchers by introducing methods such as residual connections, attention mechanisms and other methods. In our proposed NCU-Net architecture, normalised convolutional layers are used for efficient segmentation of the input retinal vessel images. The proposed architecture also consists of an encoder-decoder framework that differs from the original U-Net architecture by using Batch Normalization and ReLu to enable both robust and accurate retinal image segmentation.

3.2 FRAMEWORK, ARCHITECTURE OR MODULE FOR THE PROPOSED SYSTEM(WITH EXPLANATION)

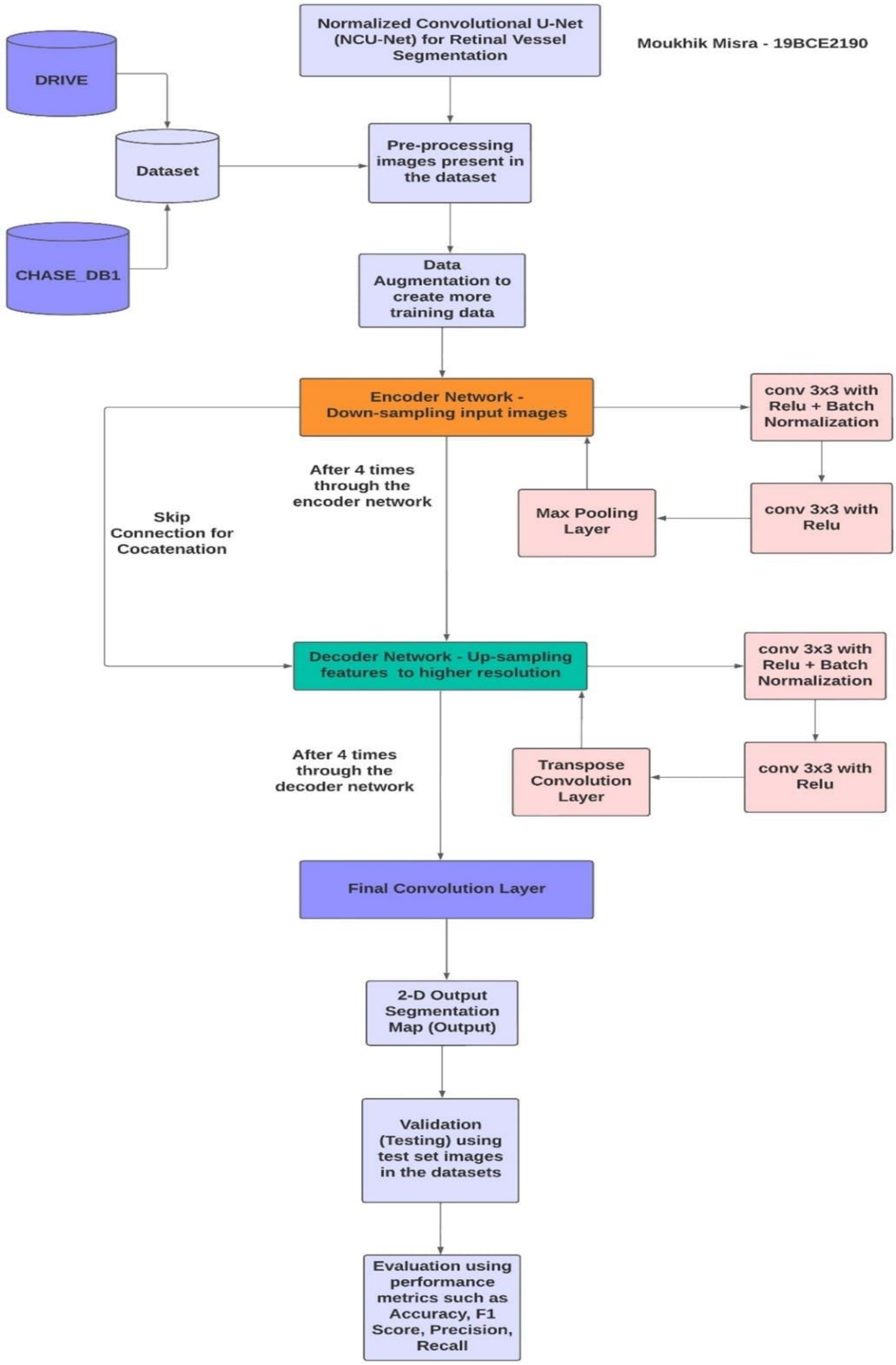

Fig. 1: Architecture Diagram for proposed NCU-Net for Retinal Vessel Segmentation

In the proposed NCU-Net, an encoder-decoder framework is used. First, the input images are pre-processed and augmented by vertical , horizontal flips and rotations, and these images are fed to the encoder phase of the architecture. The encoder phase which corresponds to the first half of the network is the contracting phase whose function is to reduce the size of fed image patch (down-sampling) and increase number of distinguishable feature maps as we move into deeper levels. The decoder phase, which corresponds to the second half of the network is the expanding phase and is responsible for up-scaling as well as concatenation of represented features and aggregation of obtained feature maps into high resolution output. The encoder-decoder network form of backbone of the proposed architecture. Each level in the encoder and decoder first consists of a 3x3 2-d convolutional layer with ReLU activation followed by batch normalization to prevent overfitting. This is followed by another 3x3 2-d convolution layer with ReLU activation. All levels of the encoder network, apart from the last level are then passed through a 2x2 max pooling layer for down-sampling which reduces the size of the images. In the decoder network, after passing through the two convolution layers, the obtained feature maps are up sampled by using 2x2 transposed convolutions to obtain higher resolution feature maps (aggregation of features). The encoder network layers are also concatenated to the decoder network layers by means of skip connections to overcome degradation problems. The final convolution provides the final 2-D Output Segmentation Map.

3.3 PROPOSED SYSTEM MODEL (MATHEMATICAL MODELLING AND METHODOLOGY)

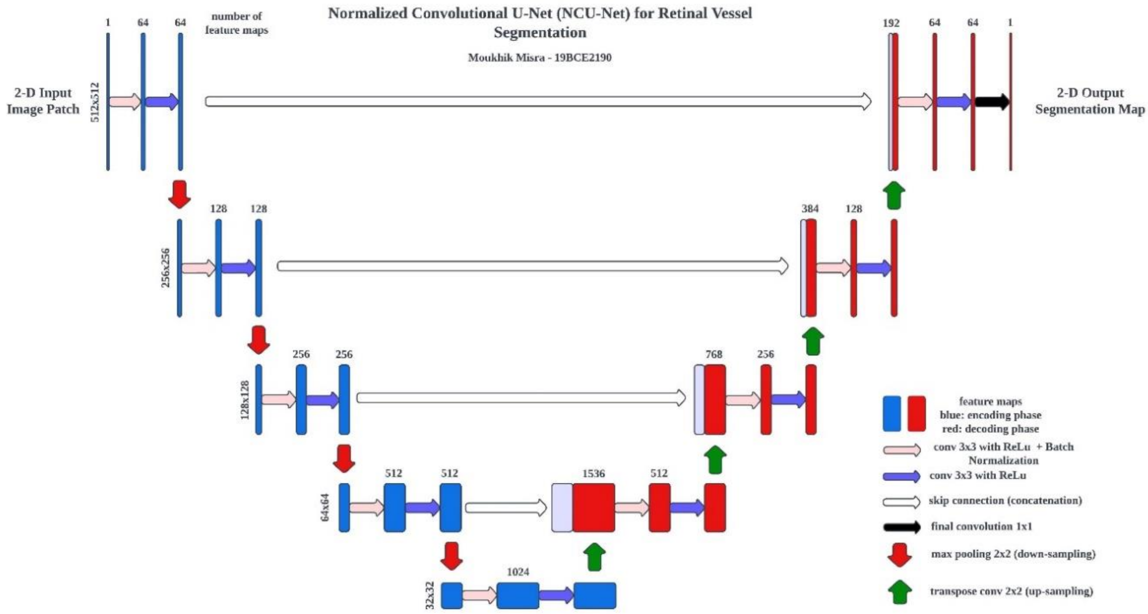

Fig. 2: Detailed mathematical model and process diagram for proposed NCU-Net model.

The figure presented above (Fig. 2) is a mathematical representation of the process flow of the proposed NCU-Net model. From the above figure, it can be observed that the sample input image is first passed through a normalised convolution block to generate 64 feature maps and is passed through another convolution block in the same encoder layer. Post this, it goes through max pooling layers and into a deeper encoder level. Following the encoder is the bottleneck layer to the decoder framework. The decoder up samples the image to produce the final segmentation map. The detailed methodology and procedure is provided below.

3.3.1 Pre-processing and Data Augmentation

Even before the model is created, the pre-processing of input data as well as data augmentation processes must be carried out. These processes are carried out on the DRIVE and CHASE_DB1 datasets (both publicly available). The dataset contains both actual retinal images as well as ground truth (mask) images. The retinal images consist of 3 channel image data of which each channel correspond to one of the RGB colour scheme. The mask images are only 1 channel as they are in greyscale. The pre-processing of both the retinal vessel and mask images consist of resizing the available image to a 512x512 pixel size so that it can be used as input for the model. The image processing operations are done using the opencv python library.

Following the standardising of the image sizes is the data augmentation stage. As the amount of base input data is quite low, data augmentation techniques need to be applied in order to provide more training data and ensuring optimal training and results. For data augmentation, the retinal vessel and mask images are flipped vertically, horizontally as well as rotated by 45 degreed to provide more training samples. The training images are also transposed (in matrix form) while reading the dataset to make then channel first which allows them to be compatible with deep neural network architectures created using the pytorch library.

3.3.2 Proposed U-Net based model for Retinal Vessel Segmentation

The proposed model is based on a multi-level encoder-decoder framework. Each level of the proposed model consists of two convolutional layers along with activation function and batch normalization. A detailed description of the encoder and decoder network is provided below.

3.3.2.1 Encoder Network

The encoder network is a 4-layer complex convolution-based architecture followed by a final layer that is necessary for the down-sampling of images for extensive feature map generation.

Each layer of the encoder network comprises of two sets of convolution functions and a skip connection. The first convolution function (or block) consists of a 3x3 2-d convolutional layer accompanied by ReLU activation and is followed by Batch Normalization to avoid overfitting. The Batch Normalization also serves to make the model faster and more stable during training and removes the need for using dropout layers. It also allows for the use of higher training rates. The second convolution block only consists of the 3x3 2-d convolution layer with ReLU activation.

In the first layer of the encoder network the input image, which has been pre-processed to 512x512 pixels, is fed to the model. This first layer (two convolution blocks) is used to generate 64 feature maps from the input which only contains 1 annotated map (mask or ground truth). Following this is a 2x2 max pooling layer which is used to down-sample the image into 256x256 pixels and the after the output of the max pooling is then fed to the second encoder layer.

In the second layer, the 256x256 input from the previous max pooling layer is passed through the two convolutional blocks to generate 128 feature maps. This is then passed through another max pooling layer to generate 128x128 input for the third encoder layer. In the third layer 256 feature maps are generated from the 128x128 input and post max pooling is a 64x64 output which is fed to the fourth layer. The fourth layer generates 512 feature maps and further decreases the size to 32x32 to the final encoder layer. The final encoder layer generates 1024 feature maps from the initial input image and the output of this layer is then fed to the decoder network.

3.3.2.2 Skip Connections

Each layer of the encoder network consists of two convolution blocks and a skip connection. The skip connection ensures that there exists no degradation and gradient flow (vanishing gradient) issues in the model. As the input image passes through the various layers of the encoder and decoder network there is a tendency for the network to ‘forget’ its purpose and lose factors of dimensionality and important spatial features while down-sampling and up-sampling. The skip connections tackle these issues and ensures that features with identical dimensionality can be re-used through the layers. Long skip connections (as between the 1^{st} encoding layer and last decoding layer in Fig. 2) are useful for retaining spatial features from the encoding network and passing them on to the decoding network through feature concatenation. The shorter skip connections enable the utilization of features again and have purposes for enhancing training stability.

3.3.2.3 Decoder Network

The decoder network is a 4-layer convolution-based network that is responsible for up-sampling the feature maps obtained from the encoder network and eventually providing the output segmentation maps. Each layer of the decoder network consist of two sets of convolution functions and a corresponding skip function. The convolution functions (or blocks) are identical to those found in the encoder network with the only difference being that the input channels and output channels are reversed (as the encoder network creates more feature maps and the decoder network combines feature maps).

The last layer of the encoder network contains 1024 feature maps. This is passed through a transpose convolutional layer (or up convolutional layer) for up-sampling the features to obtain the required output. The feature maps from the corresponding skip connection (512 features) are also concatenated to the up-sampled feature maps (to make a total 1536 feature maps). This is then passed through the two convolutional blocks to obtain 512 aggregated feature maps.

The 512 feature maps are passed through a transposed convolution layer and concatenated with the 256 features from the skip connection (768 features in total). This is passed through the two convolution blocks to get an aggregated 256 feature maps which is subsequently up-sampled and further concatenated with additional 128 feature maps from the skip connection to form 384 feature maps which are passed through the convolution blocks to obtain 128 aggregated feature maps.

In the final decoder layer, the 128 aggregated feature maps are passed through a transposed convolutional layer and concatenated with 64 features from the skip connection. The combined 192 features are passed through the two convolution blocks to obtain a final set of 64 feature maps. The 64 feature maps are passed through a final convolutional layer to obtain the final segmentation map.

Table 2: Number of feature maps per layer of the proposed model.

Layer No:	**Feature Maps generated in Encoder Network layer**	**Feature Maps in Decoder Network layer (with skip connection concatenation)**	**Feature Maps in Decoder Network layer (after passing through the two convolutional blocks)**
1	64	1536	512
2	128	768	256

3	256	384	128
4	512	192	64
5 (final layer)	1024	-	1 (output segmentation map)

Table 2 shows the number of feature maps present in each layer of the encoder and decoder network as well as total number of feature maps after including skip connections in the decoder network. Note that the final layers should be considered as such and are not entirely part of the encoder and decoder networks. The final layer in each case is two convolutional blocks as described earlier (see III. B 1. Encoder Network). The encoder network consists of 4 layers and the output of the final encoder layer is passed through two convolutional blocks to obtain the final encoder feature maps (1024 feature maps). Similarly in the decoder network the final layer isn't a layer as such but just a combination two convolutional blocks resulting in the final segmentation map.

3.3.3 Model Training

The model as defined above is trained on input retinal vessel images which are coloured, that is they consist of three channels, each corresponding to one of the RGB colours. The Adam optimizer is used for training the model. The training and test data is split 50-50. In the DRIVE dataset, there are 20 base images for training along with their ground truth masks and 20 for testing. The training data is then augmented to 80 samples as described previously which effectively creates a 75-25 division of train-test split. The model accepts images of 512x512 pixels dimensions. Other hyperparameters considered are batch size, which is set as 2, learning rate, which is set at 1e-04. The model is also trained for 50 epochs. Following model training, it is saved to a defined path as a .pth file (weights file) and hence it can be used for testing at any time without having to train the model repeatedly.

3.3.4 Testing and Evaluation

The sample test images from the DRIVE dataset along with their ground truth masks are passed into the model and the output segmentation map is obtained. The proposed model is also evaluated using popular metrics such as Accuracy, F1 Score, Precision, Recall and Jaccard Similarity Index.

The considered metrics are defined below:

1. Accuracy (A_c): $\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$ or $\frac{TP+TN}{TP+TN+FP+FN}$ [1]

2. Precision (P): $\frac{TP}{TP+FP}$ [3]

3. Recall (R) or Sensitivity (S_n): $\frac{TP}{TP+FN}$ [11]

4. Specificity (S_p): $\frac{TN}{TN+FP}$ [9]

5. F1 Score (F): $\frac{2xPxR}{P+R}$ [8]

Where TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

6. Jaccard Similarity Index J (A,B): $\frac{|A \cap B|}{|A \cup B|}$ [23]

Where A and B are two sets. In this case set A represents output segmentation map and set B represents ground truth map.

3.3.5 Dataset Details

The proposed U-Net based model is trained and tested on two publicly available datasets, namely DRIVE and CHASE_DB1.

1. DRIVE Dataset: The Digital Retinal Images for Vessel Extraction (DRIVE) dataset contains 40 colour fundus images of which 7 possess abnormalities. Each image is 584*565 pixels with three colour channels. The dataset comes pre-divided into 20 training images and 20 test images. The test set also contains ground truth values for evaluation purposes.

2. CHASE_DB1 Dataset: The CHASE_DB1 dataset contains 28 retinal images, each of whose dimensions are 999x960 pixels. The images are collected from both left and right eyes of 14 children. Each image in the dataset comes with manual annotation by experts.

4. PROPOSED SYSTEM ANALYSIS AND DESIGN

4.1 INTRODUCTION

The proposed NCU-Net system is based on the U-Net architecture and consist of an encoder-decoder framework. In the encoder part, each layer consists of 2 convolution blocks. The first convolution block consists of a convolution layer followed by a ReLU activation and a Batch Normalization layer. The first convolution layer is used to extract features from the input image into that layer. This is followed by a convolution block with just ReLU activation which is used for context understanding instead of feature extraction. This is followed by a max pooling layer which leads to the next layer of the encoder network. The max pooling layer is responsible for down sampling the image to a lower resolution, The next layer also consists of a similar structure as described above. The input image goes through the encoder layer and finally transitions through a bottleneck to arrive at the decoder layer. The decoder layer also consists of a similar structure to the encoder layer. However, instead of max pooling layers for down sampling, the decoder layer contains transposed convolutions which upscale the image to a higher resolution. As the image passes through the decoder network it is upscaled to finally generate the segmentation map. The system also contains skip connection between corresponding encoder-decoder layers which are primarily used to retain the dimensionality of the image through the layers. The detailed requirement analysis with function, non-functional, organizational, operational and system requirements of the proposed NCU-Net system are provided below.

4.2 REQUIREMENT ANALYSIS

4.2.1 Functional Requirements

4.2.1.1 Product Perspective

The proposed NCU-Net model for retinal vessel segmentation model should pay close attention to crucial factors such as robust and accurate segmentation of target input retinal images. The other factors that need oversight are data acquisition and pre-processing of the input images form a variety of sources to enable a standardised input to the model.

Model development should be a crucial focus for development and the model training and validation should be of core importance. This is followed by potential integration of the developed model to large scale public health databases and easy deploy ability of the model on various platforms. The product should also be fairly user friendly for clinicians and researchers to access. Another important area of focus is to ensure the performance and efficiency of said model by vigorous testing though various metrics. The developed model should be tested using metrics such as accuracy, precision, recall, f1 score, Jaccard score and specificity. A proper chain of documentation should also be kept for a future reference as well as for troubleshooting.

4.2.1.2 Product Features

The proposed NCU-Net model is designed to enable the robust and accurate segmentation of input retinal vessel images to assist clinicians and medical researchers. The proposed system is trained on the DRIVE and CHASE_DB1 datasets and can be fed target retinal vessel images. The system then generates a segmentation map for the input images and a mesh f images which consist of the original retinal vessel image, the annotated map and the generated segmentation map. The product also displays the performance metrics of the validation phase. The metrics which are being considered are accuracy, precision, recall, f1 score, Jaccard score and specificity.

4.2.1.3 User Characteristics

The developed model is aimed primarily towards ophthalmologists and other eye care professionals who have concrete understanding for the retinal structure and are of need for these segmentation maps for medical diagnosis.

The proposed system is also designed for medical researcher who intend to study ophthalmology and complex retinal structure. The developed model can also be used by technicians and assistants to handle the process the retinal vessel imaging. They may do the work of uploading target images to the model and submitting the output to the clinician.

The developed model can also be used by software engineers who can e responsible for maintenance and upgrades, as they have technical understanding of the underlying concepts. Finally, students can be a target audience as they seek knowledge of both retinal structure and deep learning methods.

4.2.1.4 Assumptions and Dependencies

The use of the proposed model is based on certain assumption and dependencies as listed below:

1. The quality of input images is good enough for accurate retinal vessel segmentation.
2. The input images for training and testing are pre-processed properly to meet the standards for the developed model.

3. The ground truth masks for the retinal images are available for the training of the model.
4. The training data is representative of the vast array of retinal vessel structures though a variety of public population and condition thereby ensuring the models applicability.
5. The developed model is generalizable and can be extended and scaled to accommodate new data.
6. The computational and algorithmic limitations and dependencies are well established.
7. Limitations and dependency on the hardware and computational resources available for model training.
8. The developed model is updated regularly and is well maintained by a dedicated team.
9. The proposed model can be extrapolated and integrated into existing large scale public health infrastructure.

4.2.1.5 Domain Requirements

The domain requirements for the proposed NCU-Net model for retinal vessel segmentation are elucidated below:

1. The proposed model should be able to accurately segment the target retinal images and produce high quality segmentation maps. It should be capable of segmenting the capillary structure precisely.
2. The developed model should be able to handle target images form a diverse array of inputs and populations and be able to segment them effectively.
3. The developed model should be robust and efficient in its segmentation tasks and be able to handle variations in target image quality. It should also have a good level of generalizability.
4. The computational complexity of the developed model should be such that it should be able to handle near real time segmentation of target retinal vessel images.
5. The proposed model should also be capable of horizontal and vertical scaling whilst maintaining similar levels of performance.
6. The proposed model should also be capable of integration with existing public health infrastructure.

4.2.1.6 User Requirements

The proposed model should be able to provide the user with an accurate segmentation map of complex retinal structure. For the target user which are medical professionals and researchers, it is imperative that the proposed model be effective so that they make the correct diagnosis, or the researchers make correct inferences for their study. The proposed model should also be fairly easy to use as complicating the automated segmentation tasks to a certain extent defeats its purpose. The proposed system should also be able to provide to the user, a low processing time for the generation of segmentation maps. It should also have wide generalizability for a variety of applications and be compatible with various hosting platforms and health records. Another requirement is for the model to handle various image types and formats. Finally, the user also expects the model to be well maintained and updated.

4.2.2. Non-Functional Requirements

4.2.2.1 Product Requirements

4.2.2.1.1. Efficiency (in terms of Time and Space)

The efficiency of the proposed model is of crucial importance to the proper functioning of the model. It is imperative for the model to be efficient in its segmentation tasks. The model should have low computational complexity to enable faster segmentation. For the proposed model a lightweight architecture using defined convolutional blocks are used followed by max pooling layers. The training of the model is also accelerated using the local machine's GPU. Other accelerators can also be used such as those available on cloud services such as AWS and Azure.

The proposed model also use Batch Normalization which optimizes the input data and hastens the training of our proposed model. It also allows for more stability in model training as it re-centres and scales the input layers and allows for batch processing to occur, thereby increasing the efficiency of the model. The proposed model is also memory efficient a sit provides computation in float data type thereby reducing the memory footprint.

The model is trained, and the weights are saved, thereby the model doesn't have to be trained multiple times. The model is also algorithmically efficient by use of convolution layers and ReLu activation along with Batch Normalization. The input data is also processed efficiently by standardising the size to 512x512 pixels. The local machine's GPU's parallel processing enables for faster processing time. The libraries and frameworks used for the model are meticulously chosen and redundancies are removed.

4.2.2.1.2. Reliability

The proposed model should be reliable and provide consistently accurate outputs. The developed model should be evaluated for its performance reliability by testing using metrics such as accuracy, precision, recall (sensitivity), f1 score, Jaccard score and specificity. The model should also be trained using reliable ground truths and its quality should be monitored and maintained. The model should also be robust and generalizable which adds to its reliability. The model should not be sensitive to input variations as well as to minute changes in parameters. Overall, to maintain the reliability of the model, it should be regularly maintained and updated. Another important step to maintain reliability is to acquire the feedback of potential user base.

4.2.2.1.3 Portability

For the proposed model to attain widespread availability and usage, it is essential for the system to be highly portable in nature. This portability is attained though enabling multi-platform compatibility as well through platform independence. The proposed system should be able to run with minimal setup on several operating systems and should be runnable on a variety of hardware architectures. The model is also developed using PyTorch which adds to its language independence as well non-framework dependence. This also enables it to integrate far easier into different programming environments. Another advantage is that the model is developed using Python which is a widely supported language. The developed model also can run across various hardware configurations of GPU, CPU etc. Having minimal external dependencies and running on python supported libraries, the developed model can be extremely portable. Another factor which adds to the portability of the model is the standardised inputs through pre-processing enabling the use of the model in a wide variety of areas.

4.2.2.1.4 Usability

The usability of the proposed model comes down to whether it can satisfy the requirement for generating accurate and precise segmentation maps of the input retinal vessel images. This will enable the target user base which primarily consist of medical professional sand scientific researchers to use the developed model effectively and hence it will be utilized to assist in their diagnoses. The proposed model should also be fairly simple to use without too many steps involved and without requiring too many manual inputs on the user side to generate the target output. The model should also be able to robustly generate the segmentation map with relatively small processing time i.e., the model should be efficient. The model should also perform well on a wide range of performance metrics such as accuracy, precision, f1 score among others. The proposed model should facilitate an intuitive design as well as enable user friendly interactions. The proposed model will also be able to gain widespread usability if it is compatible with existing public health infrastructure. The proposed model should also be able to integrate seamlessly into pre-existing images and formats by using standardised image formats and pre-processing to enable widespread usage. The usability of the model is also predicated on its responsiveness and performance while performing the complex retinal vessel segmentation tasks.

4.2.2.2 Organizational Requirements

4.2.2.2.1 Implementation Requirements (in terms of deployment)

The proposed automated retinal vessel segmentation model (NCU-Net) has very minimal implementation requirements from a technical stack standpoint. The entire model and system is designed using Python 3.9 as the language and the interpreter. The model also utilizes the popular PyTorch library for the NCU-Net model. Other popular libraries utilized by the system are os, time, numpy, time, sklearn, opencv and other popular python libraries. As mentioned, the model is developed using PyTorch. The database and arrays are handles using numpy and the image data is handled using opencv. For implementation of the designed system, it is required for a local machine to be capable of running Python 3.9 as well as have all the required libraries associated with the model. The model is designed to be operating system independent and can be accessed by means of Windows, MacOSX and Linux. The only requirement being a Python supporting local machine. The training and validation images are obtained from the DRIVE and CHASE_DB1 datasets both of which are publicly available. The pre-processing of the input images is done using developed code to standardise the inputs. The training data is also augmented by means of horizontal, vertical and 45-degree rotations of the input images. The model is also trained using a set of hyper parameters which is mentioned in the methodology section and its performance is evaluated using popular metrics.

4.2.2.2.2 Engineering Standard Requirements

Setting certain engineering standard requirements in as important section of the development of any application. In regard to the proposed NCU-Net model, the engineering standard requirements that are to be followed are provided below:

1. Extensive documentation that provides information of various aspects of the developed system ranging from data pre-processing to model evaluation.
2. Developing a modular system which consists of several defined section. In the proposed system, a pre-processing module is present as well as an encoder and then a decoder module.
3. Following the best coding practices to ensure ease of modification as well as easy maintenance and changes to the codebase.
4. Exhaustive testing of the system to ensure that all aspects of the model are performing their required actions and culminate in the required final output segmentation image.
5. Optimization of the model by improving training times, learning rate and reaching better performance metric scores.

4.2.2.3. Operational Requirements

4.2.2.3.1 Economic

The economic applicability of the proposed NCU-Net model lies in efficient diagnosis and treatment. The robust and precise retinal segmentation model will allow ophthalmologists to make better decisions and thereby detect possible diseases such as glaucoma. This will lead to overall reduction in medical costs as there is overall less manual labour involved in the process (no manual annotations are necessary). The proposed model could also bring benefits to remote healthcare applications thereby reducing travel costs. It can also have benefits in research where medical researchers can utilize the model to better study the retinal vessel structure. It will also assist in equipment development and can also be used in large scale public health programs thereby benefiting the general population.

4.2.2.3.2 Environmental

The environmental applicability of the proposed model lies in reduced paper usage in the digital retinal vessel segmentation method. This ultimately leads to less physical waste as well as assists in environment conservation. The automated retinal vessel segmentation process is also energy efficient by streamlining the healthcare workflow in general. Less use of physical infrastructure in remote medicine applications as well efficient resource usage by automation of early screening steps which minimizes the environmental impact. By accelerating digital medical research, a more sustainable approach to diagnosis and treatment can be obtained.

4.2.2.3.3 Social

The social applicability of the proposed model lies in providing access to healthcare facility to all aspects of the population by means of both large medical institutions as well as through remote medicine applications. It also enables a state of healthcare equity among the population by in general improving the quality and efficiency of obtained healthcare. The automated retinal vessel segmentation model can also assist in early disease detection and lead to overall reduced malaise progression and better quality of life. It can also narrow the gap between the haves and the have nots and the healthcare outcomes in various demographics. The automated model can be used for education and awareness purposes as well as for research and scientific development.

4.2.2.3.4 Political

The development of the proposed model can have political applicability in informing healthcare policies directly associated with eye diseases and health. The output can allow policymakers to understand the effect and severity of eye diseases and can address public health requirements. The model can also be used for large scale public health programs for the general public. The automation of medicine can enable a more effective distribution of resources in the healthcare sector as well as can lead to opportunities for international collaborations on eye health thereby addressing its challenges. It will also spread awareness among the public thereby driving the policymakers to take effective steps to address healthcare policies.

4.2.2.3.5 Ethical

The ethical applicability of the developed model lies in preserving the patient privacy and confidentiality of the retinal vessel images as they are private heath records. Robust security measures should be implemented to protect patient data. The concept of informed consent should also be applied, and patients should understand the risks and benefits of any advice provided. The proposed model would also provide a fair assessment without any applicable bias thereby not discriminating against any demographic group. Ethical guidelines should be created for the use and deployment of automated medical models. The models will also be built to promote overall well-being and prevent harm as well as provide healthcare equity and increased accessibility.

4.2.2.3.6 Health and Safety

The health and safety applicability of the developed model lies in its ability to make accurate and robust segmentation maps of the input retinal vessel images thereby enabling accurate diagnosis and improving treatment efficiency. The automates model will also allow for less errors made while diagnosing diseases as the medical professionals can use the output as a basis to make correct decisions. The developed model also can be applied in patient monitoring as well as in follow up appointments as the records being digital will still be available. The consistency of segmentation will allow professionals to stop misdiagnosis as well as aid in planning of necessary treatment methods and to see if surgical intervention is necessary. They will also improve safety by integrating seamlessly with the existing workflow thereby reducing manual labour and chances of errors.

4.2.2.3.7 Sustainability

The sustainability applicability of the proposed model also lies in reduced paper usage overall. As a result, there is less physical waste produced, and the digital method also helps with a sustainable approach to healthcare documentation. By improving the whole healthcare procedure, the automated retinal vascular segmentation technique is also energy efficient. Remote medical applications employ less physical infrastructure, and effective resource management through early screening phase automation reduces environmental impact and increases sustainability of the entire process. The use of cloud architecture will further enhance the sustainable approach by enabling storage optimization and data handling effectiveness. By accelerating digital medical research, a more sustainable approach to medical diagnosis can be found. Collaborations and sharing of data can also improve sustainability considerably.

4.2.2.3.8 Legality

The development of an automated model as proposed (NCU-Net) will most likely involve serious consideration about intellectual property rights as the underlying code is proprietary and needs to be protected. There also comes considerations for data protection and data privacy based on government policies. There are also existing regulation for medical devices as well as liability and malpractice problems that could arise. The concept of informed consent should also be taken seriously for legal applicability. The patient data should be protected, and the documentation should be maintained properly. There should also be compliance with international laws regarding medical laws and frameworks.

4.2.2.3.9 Inspectability

The outputs of the developed model should be interpretable and available to the relevant medical professionals. The process taken to arrive at the results should also be transparent. The internal working and the model processes should be explainable to address any potential issues of bias and unfairness. The model training and architecture in general should be available and transparent. The efficiency of the model as well as its performance in metrics such as accuracy, precision, f1 score and others should be available. The developed model should also be open to external audits. Accurate documentation of the process involve should also be maintained as well as the upholding of compliance and government policies.

4.2.3 System Requirements

4.2.3.1. Hardware Requirements (details about Application Specific Hardware)

1. **CPU:** Intel(R) Core(TM) i5-9300H CPU @ 2.40GHz
2. **RAM:** 8 GB
3. **GPU:** NVIDIA GeForce GTX 1650 (4096 MB GDDR5)
4. **Accelerator:** CPU, GPU (CUDA)

4.2.3.2. Software Requirements (details about Application Specific Software)

1. **OS:** Windows 11, MacOS 10.14, Linux
2. **Programming Language:** Python
3. **Interpreter:** Python 3.9

4. **IDE:** PyCharm
5. **Important Libraries:** opencv, pytorch, os, tqdm, imageio, albumenations, numpy, sklearn

5. RESULTS AND DISCUSSIONS

5.1 DRIVE DATASET RESULTS

5.1.1. Generated Segmentation Maps for DRIVE Dataset

The output of the designed NCU-Net model is a black and white segmentation map of the retinal vessel structure. The generated segmentation map will be created for each of the test images for the DRIVE dataset. The output images will be concatenated along with the original test image and test mask to highlight and accentuate the generated output further and to make visual comparisons easier. A few of the said outputs from the DRIVE dataset are given below.

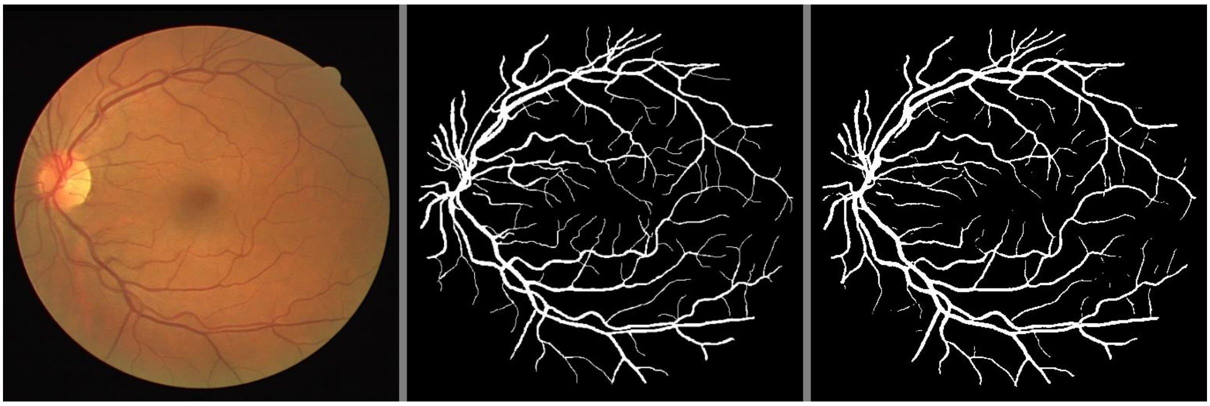

Fig. 3: First output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the DRIVE dataset.

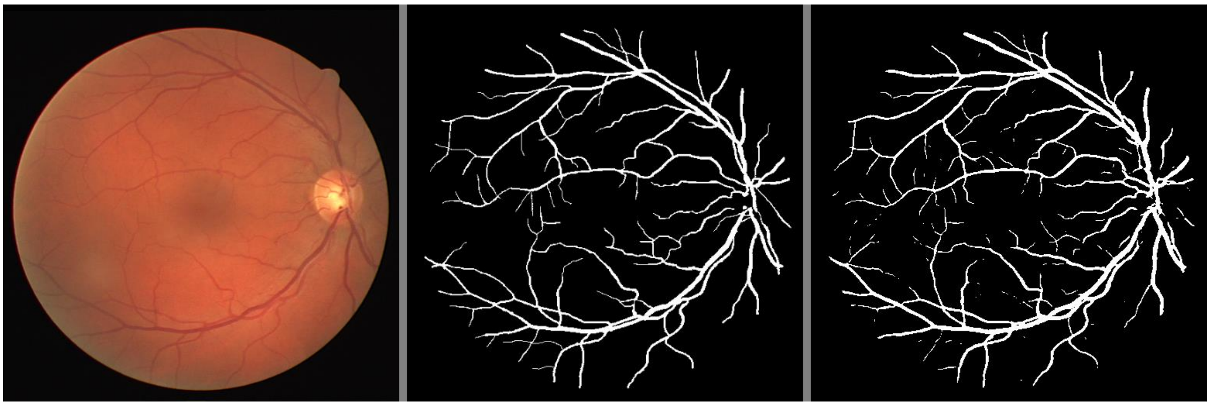

Fig. 4: Second output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the DRIVE dataset.

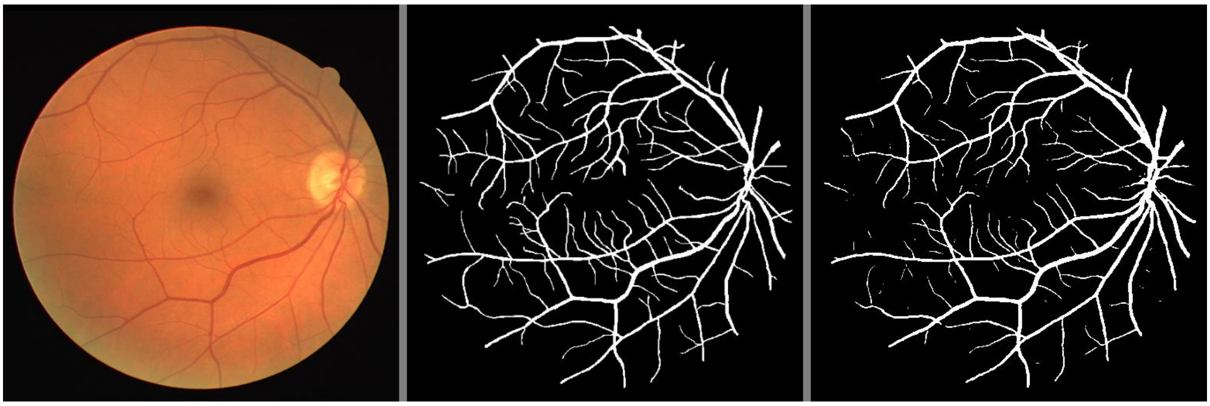

Fig. 5: Third output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the DRIVE dataset.

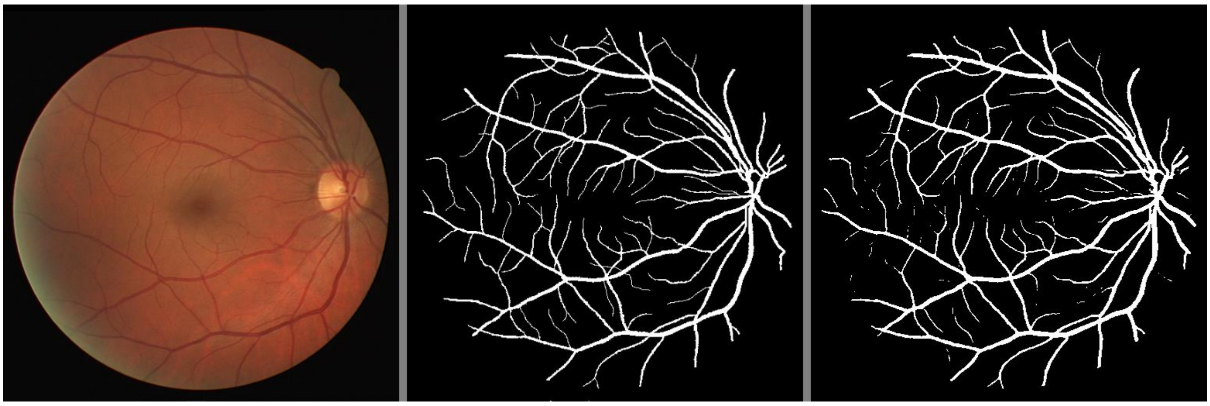

Fig. 6: Fourth output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the DRIVE dataset.

Fig. 3,4,5,6 show the result generated by the developed program and model on the DRIVE dataset. The developed program generates a collection of result images from each provided test image. Each such results consists of the test image which is seen as the coloured image on the left (3-channel RGB) and its black and white mask in the centre (1-channel). The rightmost image is that of the generated segmentation map from the proposed model. This layout enables easier distinction and macro visual comparison between the ground truth(mask) and the generated retinal vessel segmentation mask.

5.1.2. Performance Metrics and Comparisons for DRIVE Dataset

The proposed model is evaluated using standard evaluation metrics such as Accuracy, Precision, Recall, F1 Score, Jaccard Score and Specificity. The evaluation metrics considered are the mean evaluation metrics averaged over all the test images. Table with the performance metrics for the DRIVE dataset is provided below.

Table 3: Mean Performance Metrics for the DRIVE Dataset

Accuracy	Precision	Recall (Sensitivity)	F1-Score	Jaccard	Specificity
0.9657	0.8740	0.8271	0.8374	0.6641	0.9840

Table 3 contains the mean evaluation metrics for the DRIVE dataset. The accuracy obtained is 0.9657 which is extremely significant and proves the proposed models' effectiveness. The model scores 0.8740 for precision, 0.8271 for recall (sensitivity), 0.8374 for f1 score, 0.6641 for the Jaccard score and 0.9840 for specificity. The performance metrics are on par and surpass several cutting-edge retina vessel segmentation methods on the DRIVE dataset. The comparison of obtained metrics with existing models for retinal vessel segmentation on the DRIVE dataset is given in the table below (Table 4).

Table 4: Comparison of Performance Metrics with existing models (DRIVE)

Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Jaccard	Specificity
Xiuqin et al. [1]	0.9650	-	0.9310	-	-	0.9863
Yan et al [2]	0.9750	-	0.7631	-	-	0.9820
Lian et al. [3]	0.9692	0.8637	0.8278	-	-	0.9861
Dong et al. [4]	0.9586	0.9212	0.7954	0.8302	-	-
Sun et al. [5]	0.9675	-	0.8293	-	-	0.9807
Cherukuri et al. [6]	0.9563	-	-	0.8220	-	-
Rodrigues et al. [7]	0.9740	-	-	0.8579	-	-
Wang et al. [8]	0.9581	-	0.7991	0.8293	-	0.9813
Jiahong et al. [9]	0.9707		0.8300	0.8314		0.9843
Yan et al. [11]	0.9542	-	0.7653	-	-	0.9818

Ye et al. [12]	0.9699	-	0.8166	0.8249	-	0.9847
Liu et al. [13]	0.9561	-	0.7985	0.8229	-	0.9791
Tan et al. [14]	0.9461	-	0.8323	-	-	0.9859
Xu et al. [15]	0.9601	-	0.8821	-	-	0.9716
Zhou et al. [16]	0.9563	-	-	0.8345	-	-
Li et al. [17]	0.9574	-	0.8324	-	-	0.9757
Wang et al. [18]	0.9611	-	-	0.8397	-	-
Li et al. [19]	0.9705	-	0.8359	-	-	0.9826
Zhang et al. [20]	0.9701	-	0.7719	0.8021	-	0.9799
Fu et al. [21]	0.9555	-	-	0.8267	-	-
Shi et al. [22]	0.9676	-	0.8065	-	-	0.9826
Toptas et al. [23]	0.9618	-	0.8400	-	0.6148	0.9716
Zhu et al. [24]	0.9733	-	0.7919	0.8296	-	0.9895
Arsalan et al. [25]	0.9678	-	0.8250	-	-	0.9837
Proposed Model	**0.9657**	**0.8740**	**0.8271**	**0.8374**	**0.6641**	**0.9840**

From the table above (Table 4), it can be observed that the proposed model outperforms several existing models in a variety of metrics. A brief overview is that the existing model outperforms Fu et al.[21] and others (some are [23], [17], [16], [15], [14], [11], [6], [1], [4] and more). The full comparison can be viewed in Table 3. The proposed model performs marginally worse than Yan et al. [2] (0.9750 vs 0.9657) and a few others ([25], [24], [19] and others) in terms of accuracy. With regards to the precision metric, the proposed model performs better than Lian et al. [3] but falls short of Dong et. al [4]. With regards to the recall (sensitivity) metric, the proposed model outperforms several existing models such as Arsalan et al. [25], Zhu et al. [24] and others ([22], [20], [13], [12], [11], [8], [4], [2]. The proposed model significantly falls short of Xiuqin et al. [1] however in terms of recall (sensitivity). With regards to the Jaccard metric, the proposed model significantly outperforms Toptas et al. [23] (0.6641 vs 0.6148). Finally with respect to specificity, the proposed model again outperforms various existing model such as Xu et al. [15], Liu et al. [13], Yan et al. [2] among others ([5], [8], [11], [19], [22], [23] ad a few others. It however falls short of Zhu et al. [24] (0.9895 vs 0.9840). The bar charts corresponding to the performance obtained by all models by metric is provided below (Fig. 7, Fig. 8, Fig 9, Fig. 10, Fig. 11, and Fig. 12). From the figures provided, it can be observed that the proposed model performs effectively over a wide range of metrics.

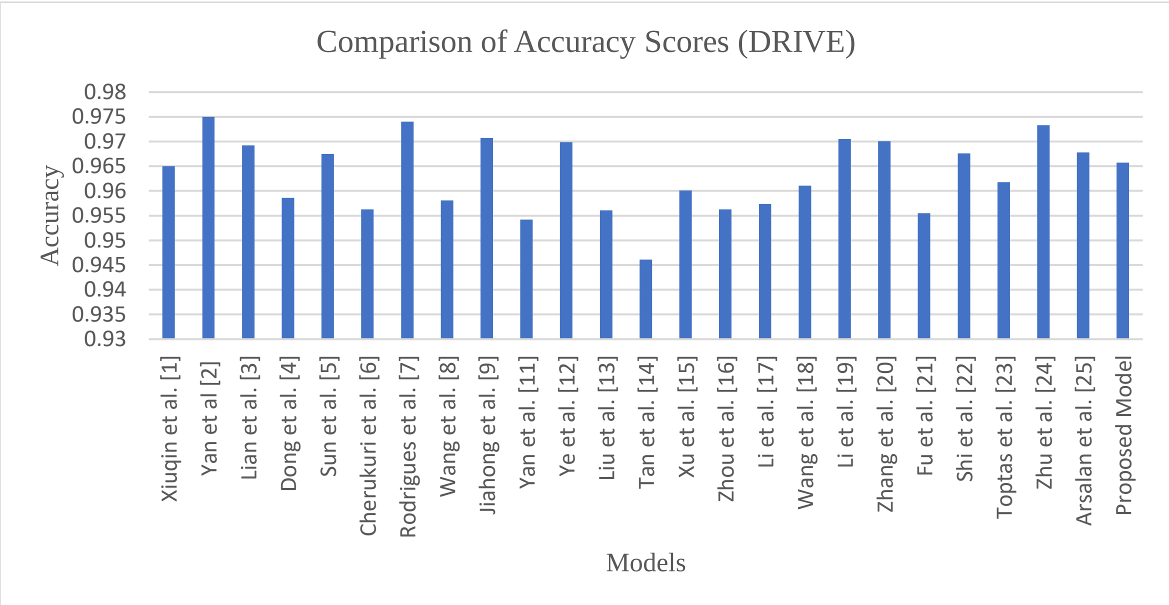

Fig. 7: Comparison of Accuracy Scores (DRIVE)

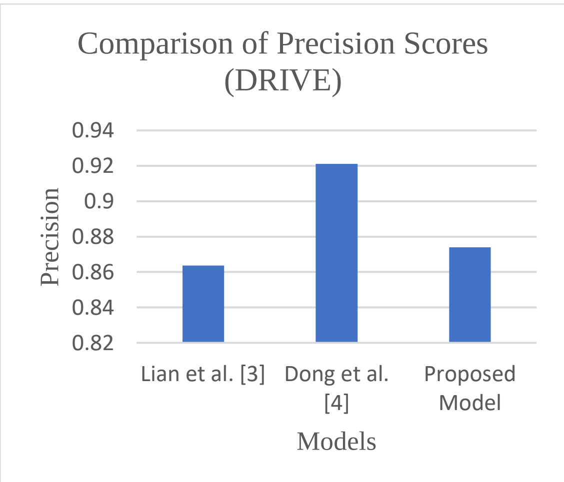

Fig. 8: Comparison of Precision Scores (DRIVE)

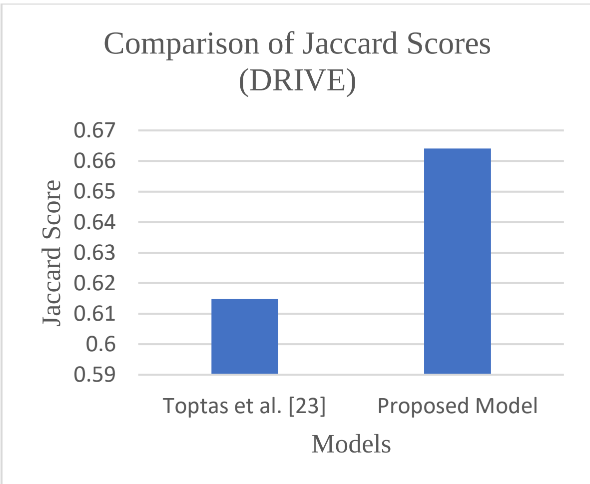

Fig. 9: Comparison of Jaccard Scores (DRIVE)

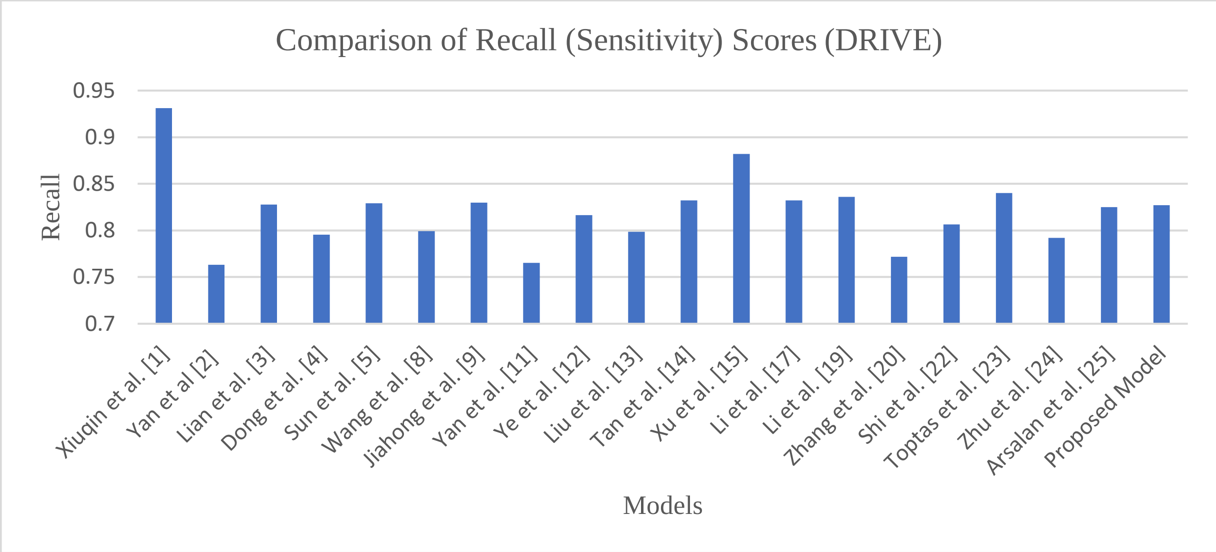

Fig. 10: Comparison of Recall (Sensitivity) Scores (DRIVE)

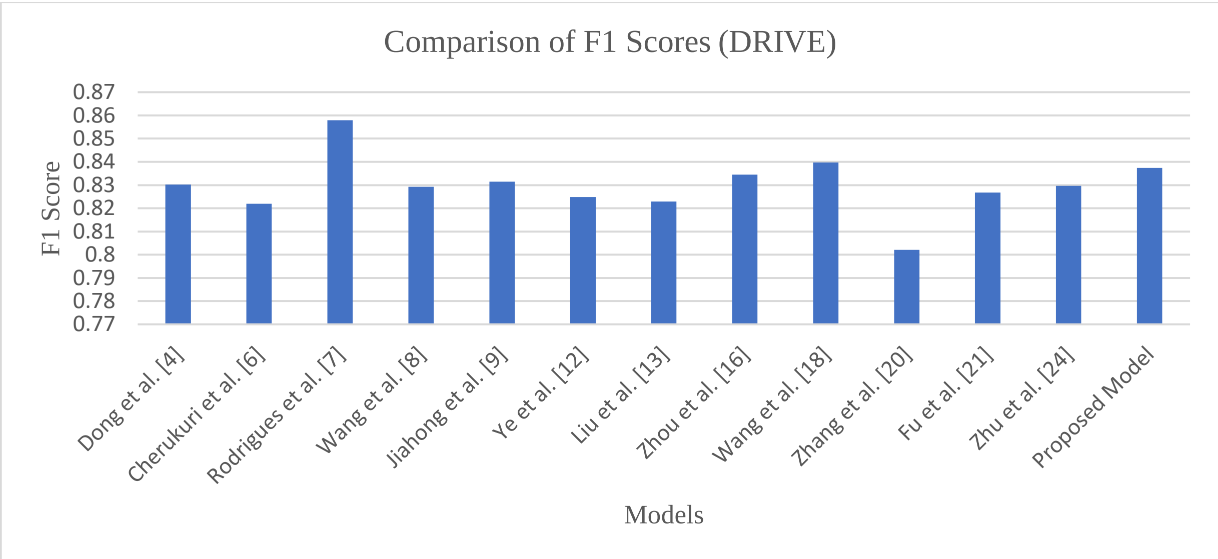

Fig. 11: Comparison of F1 Scores (DRIVE)

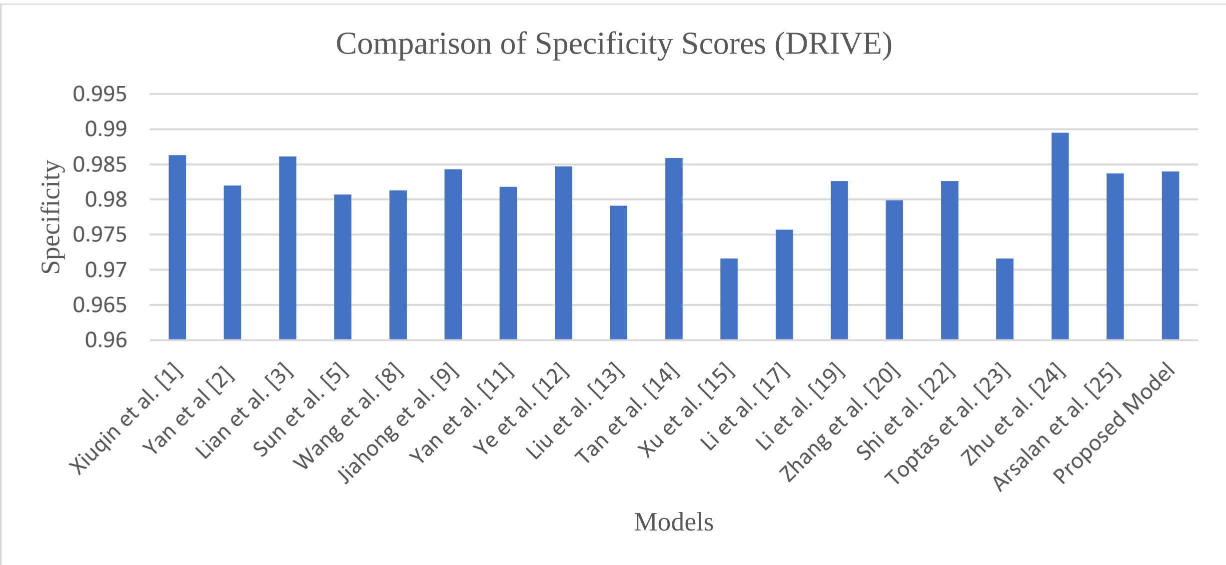

Fig. 12: Comparison of Specificity Scores (DRIVE)

The bar charts shown above provide a visualization of the performance of the proposed NCU-Net as compared to other state of the art automatic retinal vessel segmentation models across the performance metrics of accuracy, precision, recall (sensitivity), f1-score, Jaccard score and specificity. The comparison provided in the bar charts represent the performance of various model including the proposed model on the DRIVE Dataset. It is evident from the charts and the table that the proposed model is extremely efficient and performs extremely well on the DRIVE dataset.

5.2 CHASE_DB1 DATASET RESULTS

5.2.1 Generated Segmentation Maps for CHASE_DB1 Dataset

The output of the designed NC-UNet model is a black and white segmentation map of the retinal vessel structure. The generated segmentation map will be created for each of the 14 test images for the CHASE_DB1 dataset. Similar to the outputs obtained in the previous section, a collage of original image with original mask and the final segmentation map is provided. A few of the said outputs from the CHASE_DB1 dataset are given below.

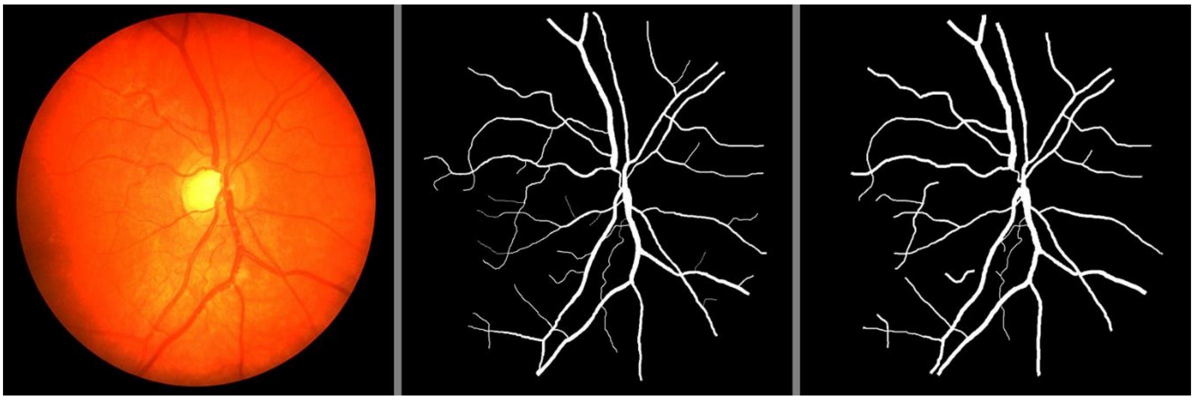

Fig. 13: First output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the CHASE_DB1 dataset.

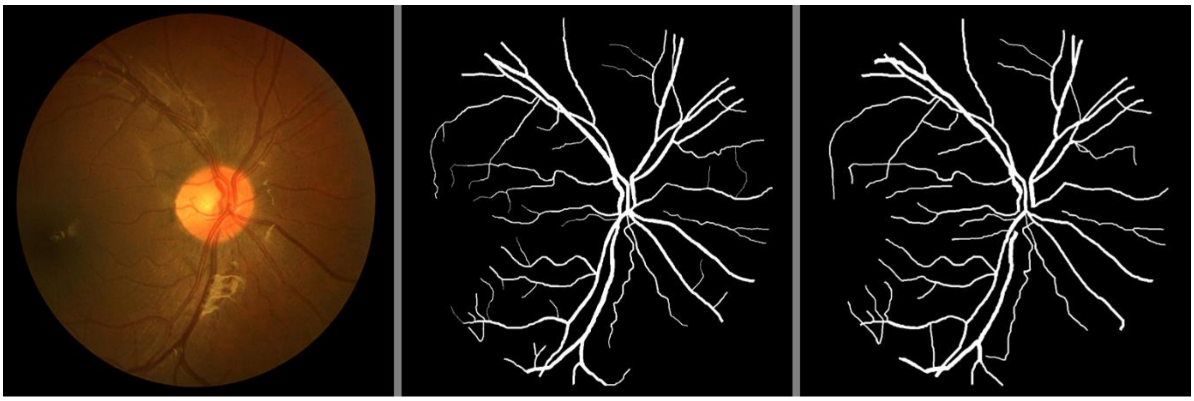

Fig. 14: Second output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the CHASE_DB1 dataset.

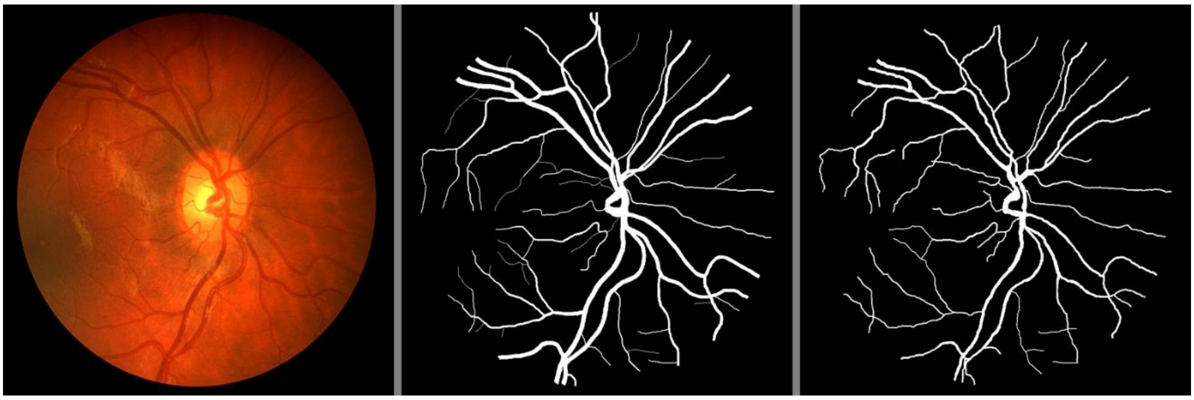

Fig. 15: Third output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the CHASE_DB1 dataset.

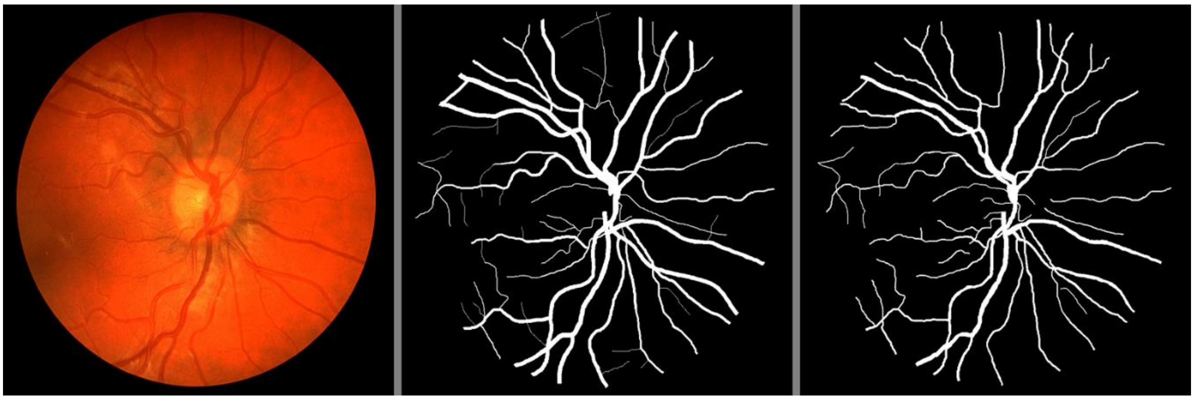

Fig. 16: Fourth output which contains the generated segmentation map (right most) along with one of the original test 3-channel coloured image (left) and the test mask (centre) from the CHASE_DB1 dataset.

Fig. 13,14,15,16 show the result generated by the proposed NCU-Net model on the CHASE_DB1 dataset. The developed model generates a collection of result images from each provided test image. The layout of the results includes a coloured test image on the left (RGB), a black and white mask in the centre (1-channel), and the generated segmentation map on the right. This arrangement allows for clear differentiation and a broad visual comparison between the ground truth mask and the retinal vessel segmentation generated by the model. The layout facilitates easy interpretation and analysis of the results by presenting the components side by side.

5.2.2. Performance Metrics and Comparisons for CHASE_DB1 Dataset

The proposed NCU-Net model is evaluated for the CHASE_DB1 dataset using evaluation metrics such as Accuracy, Precision, Recall, F1 Score, Jaccard Similarity Index and Specificity. The evaluation metrics considered are the mean evaluation metrics averaged over all the test images. Table with the performance metrics for the CHASE_DB1 dataset is provided below.

Table 5: Mean Performance Metrics for the CHASE_DB1 Dataset

Accuracy	Precision	Recall (Sensitivity)	F1-Score	Jaccard	Specificity
0.9742	0.8825	0.8367	0.8352	0.7026	0.9853

Table 5 contains the mean evaluation metrics for the CHASE_DB1 dataset. The accuracy obtained is 0.9742 which denotes the designed model's efficiency and performance. The precision, recall (sensitivity) and F1 scores are also provided in the table above along with the Jaccard Similarity and specificity metrics. The model scores 0.8825 for precision, 0.8367 for recall (sensitivity), 0.8352 for f1 score, 0.7026 for the Jaccard score and 0.9853 for specificity. The performance metrics are on par and surpass several cutting-edge retina vessel segmentation methods on the CHASE_DB1 dataset. The comparison of obtained metrics with existing models for retinal vessel segmentation on the CHASE_DB1 dataset is given in the table below (Table 6).

Table 6: Comparison of Performance Metrics with existing models (CHASE_DB1)

Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Jaccard	Specificity
Yan et al [2]	0.9607	-	0.7641	-	-	0.9806
Dong et al. [4]	0.9659	0.8996	0.8259	0.8156	-	-
Sun et al. [5]	0.9732	-	0.8321	-	-	0.9825
Cherukuri et al. [6]	0.9720	-	-	0.8211	-	-
Rodrigues et al. [7]	0.9778	-	-	0.8448	-	-
Wang et al. [8]	0.9670	-	0.8239	0.8191	-	0.9813
Jiahong et al. [9]	0.9769		0.8463	0.8223		0.9857
Yan et al. [11]	0.9610	-	0.7633	-	-	0.9809
Ye et al. [12]	0.9693	-	0.8317	0.8424	-	0.9847

Liu et al. [13]	0.9672	-	0.8020	0.8236	-	0.9794
Xu et al. [15]	0.9725	-	0.8906	-	-	0.9817
Zhou et al. [16]	0.9630	-	-	0.8218	-	-
Wang et al. [18]	0.9662	-	-	0.8340	-	-
Li et al. [19]	0.9762	-	0.8400	-	-	0.9856
Zhang et al. [20]	0.9811	-	0.8506	0.7662	-	0.9981
Fu et al. [21]	0.9644	-	-	0.8237	-	-
Shi et al. [22]	0.9731	-	0.7504	-	-	0.9889
Arsalan et al. [25]	0.9749	-	0.8485	-	-	0.9887
Proposed Model	**0.9742**	**0.8825**	**0.8367**	**0.8352**	**0.7026**	**0.9853**

From the table above, it is evident that the proposed NCU-Net model outperforms several state-of-the-art retinal vessel segmentation models over a wide range of performance metrics. In terms of accuracy, the proposed model outperforms the likes of Fu et al. [21], Wang et al. [18], Zhou et al [16] and others ([6], [8], [5] and more). The proposed model does fall slightly short of Arsalan et al. [25] and is most significantly beaten by Zhang et al [20] in terms of accuracy (0.9811 vs 0.9742) In term of precision the model performs slightly worse than Dong et al. [4] (0.8996 vs 0.8825). In terms of recall (sensitivity), the model beats the likes of Ye et al. [12], Yan et. al [11] and others ([13] and more). However, it most significantly falls short against Xu et al. [15] (0.8906 vs 0.8367). In terms of F1 score, the model outperforms the likes of Fu et al. [21] and Zhang et al. [20] among others ([13], [8] and more). It is most heavily beaten by Rodrigues et al. [7] (0.8448 vs 0.8352). The model score a 0.7026 Jaccard score with no available comparison measures. Finally, in terms of specificity, the model outperforms Xu et al [15] and Liu et al [13] and others. It is most significantly beaten by Zhang et al. [20] (0.9981 vs 0.9853) The bar charts which show a visual representation of the comparisons for the CHASE_DB1 dataset are provided below.

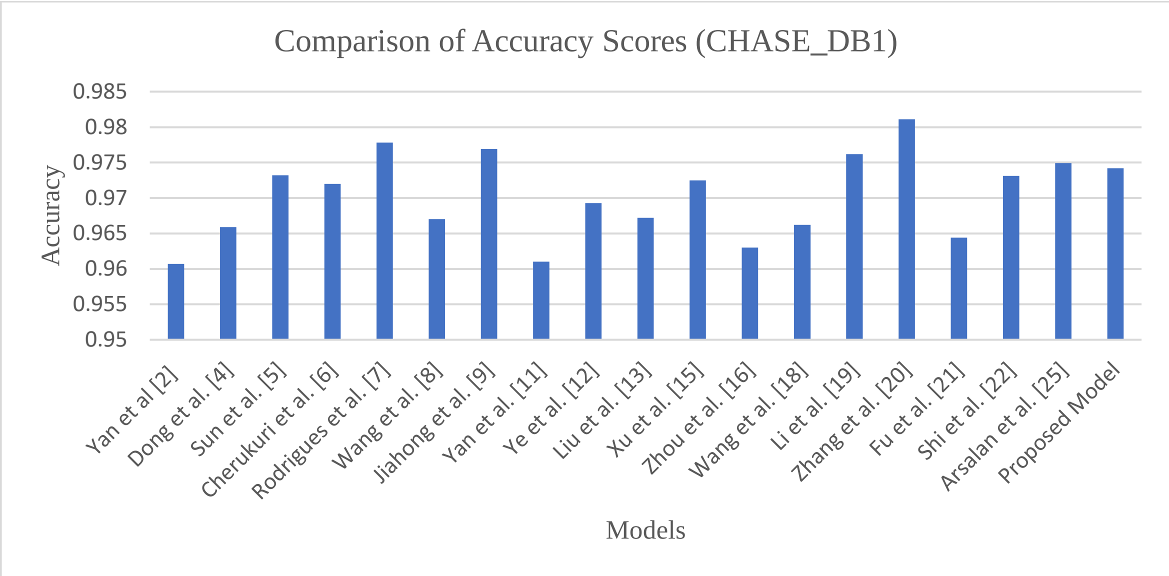

Fig. 17: Comparison of Accuracy Scores (CHASE_DB1)

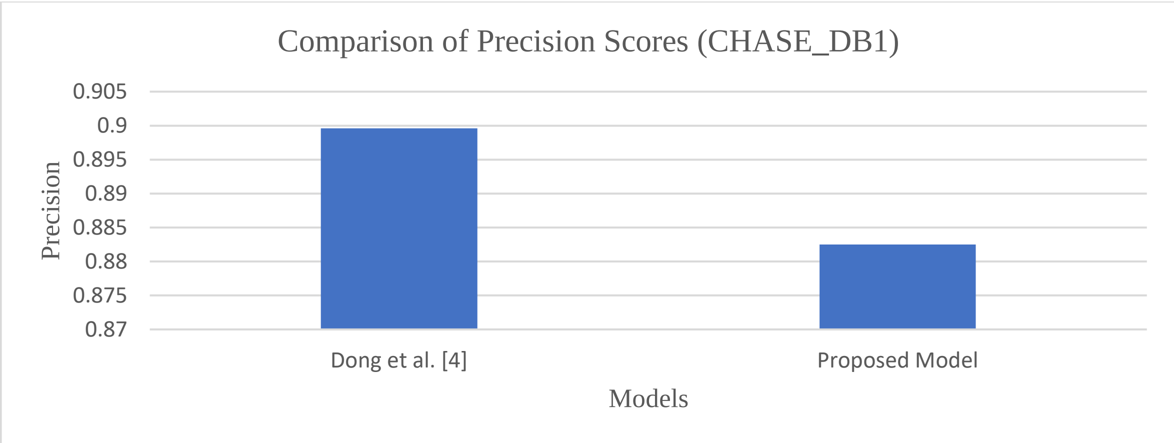

Fig. 18: Comparison of Precision Scores (CHASE_DB1)

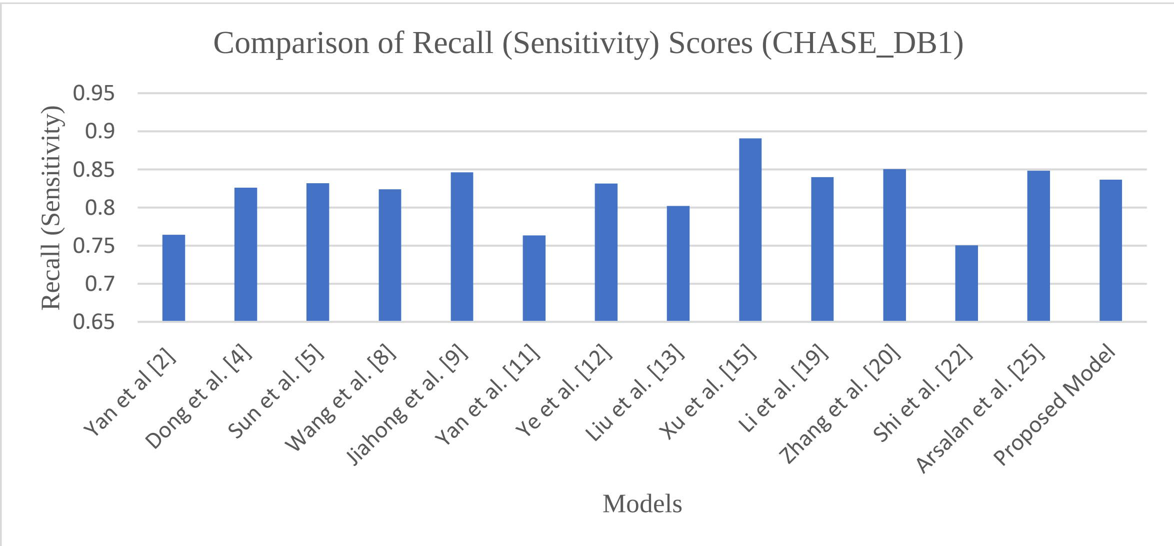

Fig. 19: Comparison of Recall (Sensitivity) Scores (CHASE_DB1)

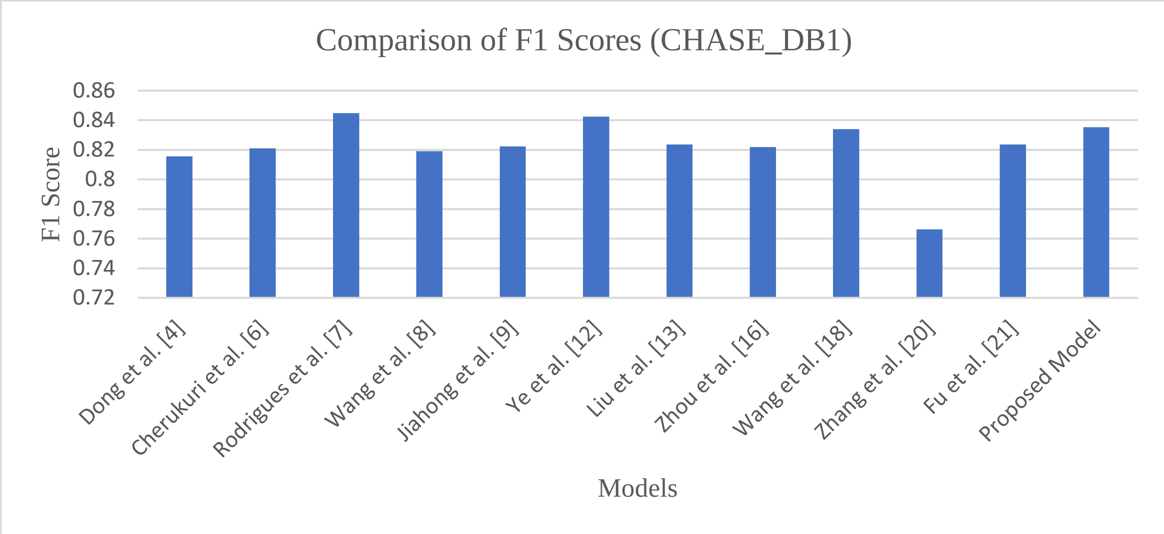

Fig. 20: Comparison of F1 Scores (CHASE_DB1)

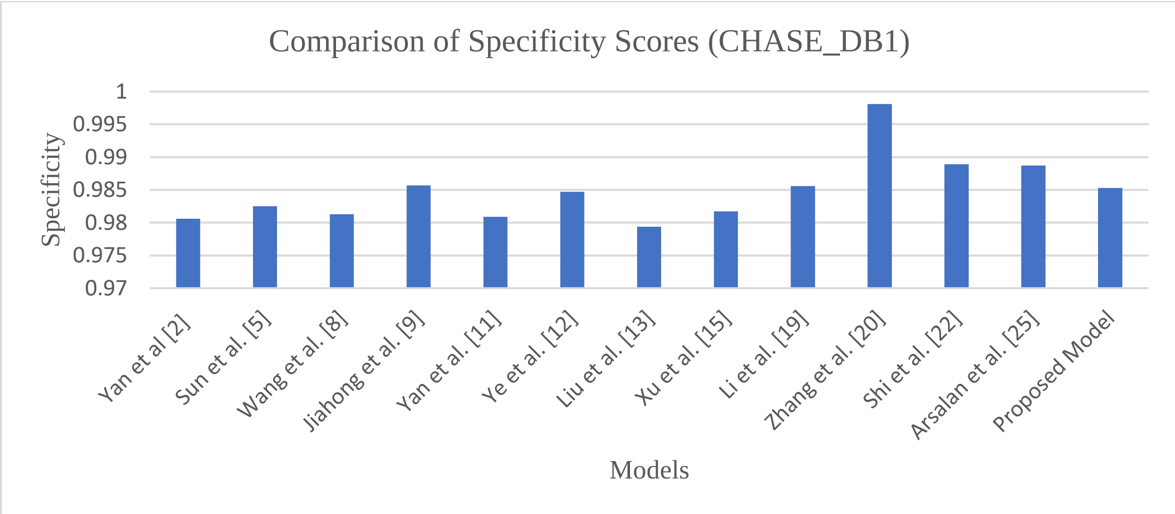

Fig. 21: Comparison of Specificity Scores (CHASE_DB1)

The bar charts shown above (Fig. 17, Fig. 18, Fig. 19, Fig. 20, and Fig. 21) provide a visualization of the performance of the proposed NCU-Net as compared to other state of the art automatic retinal vessel segmentation models across the performance metrics of accuracy, precision, recall (sensitivity), f1-score, Jaccard score and specificity. The comparison provided in the bar charts represent the performance of various model including the proposed model on the CHASE_DB1 Dataset. It is evident from the charts and the table that the proposed model is extremely efficient and performs extremely well on the CHASE_DB1 dataset.

6. CONCLUSION

The developed NC-UNet model displays effective performance over a wide range of metrics such as accuracy, precision, recall, f1 score, specificity and Jaccard score on two publicly available datasets namely DRIVE and CHASE_DB1. The proposed model can compete with and exceed the performance of several recently developed state of the art models for retinal vessel segmentation. By utilising the power of the encoder decoder framework provided by the UNet architecture, along with normalised convolution operations, the proposed model can perform highly accurate and robust segmentation of retinal vessel images. The proposed method has the ability for enhanced feature extraction whilst overcoming the various obstacles faced by other proposed models for extracting feature from retinal images. The use of normalised convolution operations as a basis for the model enables it to improve overall segmentation performance and enhance the model's ability to capture the fine details in the retinal vessel structure as well as improving the efficiency of the model by making the model more lightweight through the use of Batch Normalization operation. The effectiveness of the model is furthermore demonstrated by its ability to segment retinal vessels in low contrast images. The obtained results for the DRIVE dataset of accuracy: 0.9657, precision: 0.8740, recall (sensitivity): 0.8271, f1 score: 0.8374 Jaccard score: 0.6641 and specificity: 0.9840 give quantitative evidence of the effectiveness and robustness of the model. Similarly, the performance metrics of the NCU-Net model for the CHASE_DB1 dataset which are accuracy: 0.9742, precision: 0.8825, recall (sensitivity): 0.8367, f1 score: 0.8352, Jaccard score: 0.7026 and specificity: 0.9853, also prove the effectiveness of the model and showcase its adaptability to variation in input. In conclusion, the Normalised Convolutional UNet (NC-UNet) holds significant promise to improve retinal disease detection and treatment, which will eventually be advantageous to both patients and medical professionals. Future work can involve optimizing the training parameters to potentially obtain better results and the incorporation of the proposed model into computer-aided diagnosis systems to determine how well it performs on larger and custom datasets and in real-world scenarios.

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