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USE OF DEEP LEARNING TO INVESTIGATE THE RELATIONSHIP BETWEEN TORTUOSITY OF THE VASCULATURE OF THE RETINA AND THE BULBAR CONJUNCTIVA

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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The supervisors should certify the Thesis with the following declaration.

The above candidate has carried out research for the Master of Science (Major Component Research) Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

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ABSTRACT

Accurate segmentation of conjunctival vessels is critical for the non-invasive assessment of systemic microvascular disease. While diabetes is commonly evaluated using retinal imaging, alternative accessible biomarkers remain underexplored. Conjunctival vessels are directly visible and may reflect systemic vascular changes; however, reliable quantification is challenging, as conventional deep learning models prioritise pixel-wise accuracy without preserving vascular topology or diameter-specific structure.

In this thesis, we propose a transformer-augmented U-Net architecture designed for topology-preserving, diameter-sensitive segmentation of conjunctival vasculature from standard DSLR-captured images. The model integrates dilated convolutions, attention mechanisms, and transformer-based contextual modelling to balance local feature representation with global structural awareness, enabling improved detection of small-caliber vessels while maintaining vascular continuity.

A curated dataset of conjunctival images with diameter-specific annotations was developed for training and evaluation. Through systematic ablation studies, we demonstrate that no single architectural component is sufficient in isolation; rather, the full hybrid design provides the most consistent preservation of vessel geometry. Compared with multiple state-of-the-art segmentation methods (U-Net, Attention U-Net, TransUNet, IterNet, and U^2-Net, Swin-UNet), the proposed approach achieves comparable pixel-wise performance while significantly reducing tortuosity error and centreline deviation, highlighting the importance of topology-aware segmentation for downstream analysis.

Clinically, the proposed framework enables robust estimation of vessel tortuosity, revealing significantly elevated conjunctival tortuosity in individuals with diabetes compared to healthy controls, consistent with established retinal findings. These re-

sults support conjunctival imaging as a low-cost, non-invasive modality for microvascular phenotyping and suggest its potential for scalable screening and longitudinal monitoring.

Despite limitations related to dataset size, patch-based training, and cross-domain generalisation, this work establishes that topology-preserving, diameter-aware segmentation is essential for clinically meaningful vascular analysis. Future work will focus on expanding multi-institutional datasets, improving spatial calibration, and validating the framework across diverse populations and vascular pathologies.

Keywords: Diabetes, Vascular Tortuosity, Conjunctival Imaging, Topology-Preserving Segmentation, Diameter-Aware Segmentation, Deep Learning, Transformers, Attention Mechanisms

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LIST OF ABBREVIATIONS

ANCOVA	Analysis of Covariance
B-COSFIRE	Bar-selective Combination Of Shifted Filter Responses
BMI	Body Mass Index
CNN	Convolutional Neural Network
CRF	Conditional
DR	Diabetic Retinopathy
DRC	Diabetes-Related-Complications
DRIVE	Digital Retinal Images for Vessel Extraction
DSLR	Digital Single-Lens Reflex
ERC	Ethics Review Committee
GPU	Graphics Processing Unit
IoU	Intersection over Union
LDR	Length-to-Diameter Ratio
MCC	Matthews Correlation Coefficient
MHCA	Multi-Head Cross Attention
MHSA	Multi-Head Self Attention
NHSL	National Hospital of Sri Lanka
OLS	Ordinary Least Squares
RNN	Recurrent Neural Network
SBVPI	Sclera Blood Vessels Periocular and Iris

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