VesselSegNet:A Deep Learning Framework for Autonomous Retinal Blood Vessel Segmentation on Fluorescein Angiography Scans

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***Abstract*— Retina is essential to a person's ability to perceive and comprehend the order of things. This essential tissue is maintained by innumerable minute blood capillaries termed as arteries and veins which pump and detoxicate vital levels of blood, underlining the nuances of the whole process. Most of the abnormalities caused by retinal diseases are caused by blocked or leaky retinal blood vessels. The proposed project provides a comprehensive overview on segmenting vital retinal blood vessels by employing an innovative technique dubbed UNet on Fluorescein Angiography, often known as Fundus Scans, to interpret and monitor blood flowing through these crucial blood vessels. Furthermore, this research will aid in evaluating the merits and drawbacks of the proposed technique based on the efficacy obtained on a proprietary database and its applicability in a variety of Machine Learning environments.**

Keywords—Retinal Blood Vessels; Segmentation; Fundus Scans;DataModeling;UNet;Metrics;DiceCoefficient;DiceLoss;Intersection over Union(IoU).

I. INTRODUCTION

The retina is the light-sensitive layer located in the back of the eye that enables vision. In addition, the retina gets oxygen and nutrients from the retinal blood vessels and the choroid, which sits underneath the retinal pigment epithelium. Moreover, arteries refer to the blood vessels that deliver oxygen and nutrients inside the retina. Through the optic nerve, the superior (upper) and inferior (lower) branches of the central retinal artery reach the eye. These then continue to branch out, similar to tree branches, until they form a capillary network of incredibly fine blood vessels. In addition, oxygen and nutrients leave the blood and enter the retina predominantly via the capillaries, whereas carbon dioxide and waste products leave the retina and enter the blood. The bulk of problems caused by illnesses affecting retinal blood vessels are attributable to either obstructed or leaky capillaries [1]. Asa consequence if a retinal vein or artery gets obstructed, then that section of the vision field will be impaired. This occurrence is generally known as an occlusion. There are many conventional deep learning various algorithms to examine and procure critical information regarding blood vessels in the retina, but none is more popular than a fully connected convolutional autoencoder, often known as UNet [2]. The suggested architecture is based on a fully convolutional network, which has been modified and enhanced to operate with less training images and provide more precise segmentations, thereby augmenting our understanding about the region of interest. Furthermore, the unique architecture provides precise localization, making it preferable than a typical convolutional neural network. Finally, during analysis, the suggested network provides critical features such as compatibility, customizability, adaptability, and much more.

II. RELATED WORK

U-Net topologies are prominent among Machine Learning researchers for segmenting biomedical images since they deliver precise results on challenging biomedical image datasets with relative ease. Furthermore, it has been established that these approaches provide comparable outcomes while consuming fewer resources. The research, which proposes an autonomous framework for segmentation of retinal blood vessels using a novel model dubbed weighted Res-UNet on two distinct datasets labeled DRIVE and STARE [3], yields comparable accuracies and sensitivities of 96.55%, 77.15%, and 96.93%, 74.66% respectively. In addition, the work which presents two novel effective strategies titled U-Net autoencoder and Fuzzy Classifier for segmentation of Retinal Blood vessels on the DRIVE database [4] achieves 95.72% accuracy with the Fuzzy system algorithm and 96.75% accuracy with the proposed U-Net autoencoder correspondingly. The study, which asserts a novel modified U-net architecture for segmentation of Retinal Blood vessels on four distinct databases labeled DRIVE, CHASE _DB1, STARE, and HRF [5], renders a diverse range of consistent sensitivity and specificity values respectively. In addition, the research reveals that the proposed method performs effectively on the dataset titled HRF in comparison to other versatile databases employed for this study.

III. DATASET

In this research, a custom database for segmenting retinal blood vessels was developed by integrating multiple prominent open-source datasets to promote heterogeneity and flexibility. In addition, the datasets 'ARIA', 'ChaseDB', 'DR-Hagis', 'DRIVE', 'HRF', 'IOSTAR', and 'ORVS' [6] were employed for model training and testing, whilst the dataset 'STARE' [7] were utilized for model validation. In addition, each discrete dataset employed form model training comprises of approximately 20 to 30 exceptional fluorescein angiography (fundus) scans with their respective masks spread across the folders titled train and test respectively, resulting in a custom training database housing approximately of 760 fluorescein angiography (fundus) scans and their corresponding masks for model analysis. Finally, the dataset dubbed 'STARE' comprises of roughly 397 exemplary fluorescein angiography (fundus) scans from which five randomly chosen fundus scans make up the validation database for model validation.

IV. PROJECT PLAN

In order to effectively segment the retinal blood vessels on any given fundus scan with ease ,the proposed project comprises of five distinct phases [8] titled 'Data Acquisition', 'Data Modelling', 'Model Development', 'Model Initialization and Hyperparameter Optimization', and 'Final Model Training and Evaluation'. The first phase, entitled "Data Acquisition," outlines the arduous process of acquiring and characterizing the nature of the diverse datasets employed for training and assessing the efficacy of the proposed model framework. In addition, the second phase titled "Data Modelling" highlights the automated task of pre-processing the images available in the raw database acquired in the preceding phase. The processing processes include, but are not limited to, Image resampling, Image formatting, Custom data partitioning into the Training and Validation database, as well as many more. In addition, the third phase, dubbed 'Model Development,' highlights the process of establishing distinct scripts for loading data, training, and testing a comparable UNet framework based entirely on TensorFlow [9]. In addition, the fourth phase titled 'Model Initialization and Hyperparameter Optimization' outlines the cumbersome process of troubleshooting issues encountered during training and testing the model on the presented training database. In addition, this phase includes the challenge of identifying suitable hyperparameters to enhance the generalization capability of a comparable model for validation analysis. The 'Final Model Training and Evaluation' phase describes the task of training/validating a comparable model retrofitted with distinct hyperparameters (obtained in the preceding phase) on the processed training and validation databases respectively . Table.1 represents the proposed project schedule, whereas figure.1 illustrates the proposed project's architecture.

TABLE I. PROPOSED PROJECT SCHEDULE

Objective	Timeline	Status
Topic Search	1.5 weeks	Completed
Initial Literature Review	2 weeks	Completed
Data Acquisition	1.5 weeks	Completed
Data Modelling	1 week	Completed
Model Development	2 weeks	Completed
Model Initialization	1.5 weeks	Completed
Hyperparameter Optimization	2 weeks	In-Progress
Final Model Training and Testing	2 weeks	To Be Completed
Final Model Validation	1 week	To Be Completed
Drafting Project Report & Project Presentation	2 weeks	To Be Completed

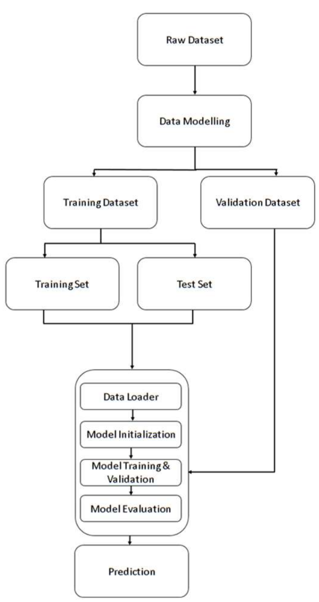

Fig. 1: Architecture of the proposed algorithm

V. PRELIMINARY RESULTS

Currently, the proposed model framework has been evaluated using the dice coefficient, dice loss, and intersection over union (IoU) [10] metrics. Furthermore, the proposed model has been reported to deliver consistent training and validation dice coefficients of 0.397 and 0.384, resulting in training and validation dice losses of 0.602 and 0.615, respectively. Moreover, the proposed model generates consistent training and validation IoU values of 0.248 and 0.238 accordingly. Figure 2 depicts preliminary validation results recorded by the algorithm when introduced to an anonymous but comparable validation dataset.

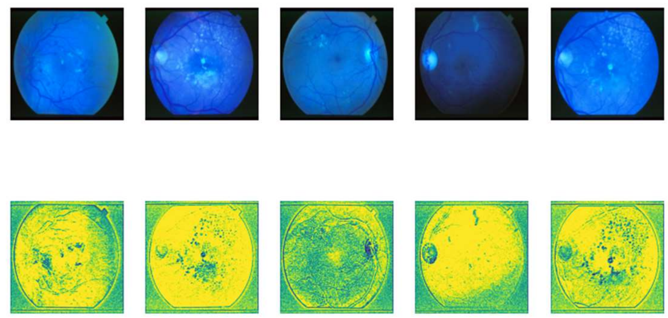

Fig. 2: Preliminary validation results recorded by the proposed model.

REFERENCES

[1] Sun Y, Smith LEH. Retinal Vasculature in Development and Diseases. Annu Rev Vis Sci. 2018 Sep 15;4:101-122. doi: 10.1146/annurev-vision-091517-034018. Retraction in: Annu Rev Vis Sci. 2020 Oct 15;0: PMID: 30222533; PMCID: PMC6326083.

[2] https://doi.org/10.48550/arXiv.1505.04597

[3] X. Xiao, S. Lian, Z. Luo and S. Li, "Weighted Res-UNet for High-Quality Retina Vessel Segmentation," 2018 9th International Conference on Information Technology in Medicine and Education (ITME), Hangzhou, China, 2018, pp. 327-331, doi: 10.1109/ITME.2018.00080.

[4] T. Mostafiz, I. Jarin, S. A. Fattah and C. Shahnaz, "Retinal Blood Vessel Segmentation Using Residual Block Incorporated U-Net Architecture and Fuzzy Inference System," 2018 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE), Chonburi, Thailand, 2018, pp. 106-109, doi: 10.1109/WIECON-ECE.2018.8783182.

[5] Afolabi, Oluwatobi & Nelwamondo, Fulufhelo & Mabuza, Gugulethu. (2020). Blood Vessel Segmentation from Fundus Images Using Modified U-net Convolutional Neural Network. Journal of Image and Graphics. 8. 21-25. 10.18178/joig.8.1.21-25.

[6] Galdran, Adrian, André Anjos, José Dolz, Hadi Chakor, Hervé Lombaert, and Ismail Ben Ayed. "The little w-net that could: state-of-the-art retinal vessel segmentation with minimalistic models." arXiv preprint arXiv:2009.01907 (2020).

[7] Krestanova, Alice, Jan Kubicek, and Marek Penhaker. "Recent techniques and trends for retinal blood vessel extraction and tortuosity evaluation: a comprehensive review." Ieee Access 8 (2020): 197787-197816.

[8] Albatayneh, Omar, Lars Forslöf, and Khaled Ksaibati. "Image retraining using TensorFlow implementation of the pretrained inception-v3 model for evaluating gravel road dust." Journal of Infrastructure Systems 26, no. 2 (2020): 04020014.

[9] Momin, Ahad. "Image Segmentation Using Deep Learning Tensorflow and Keras Implementation in Python." (2020).

[10] Liu, Yu-Cheng, Daniel Stanley Tan, Jyh-Cheng Chen, Wen-Huang Cheng, and Kai-Lung Hua. "Segmenting hepatic lesions using residual attention U-Net with an adaptive weighted dice loss." In 2019 IEEE International Conference on Image Processing (ICIP), pp. 3322-3326. IEEE, 2019.