A Deep-Learning-Enabled Monitoring System for Ocular Redness Assessment

Yuxing Li
Dept. of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam, Hong Kong
yuxingli@hku.hk

Pak Wing Chiu
LKS Faculty of Medicine
The University of Hong Kong
Pokfulam, Hong Kong
u3537023@connect.hku.hk

Yanmin Zhu
Dept. of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam, Hong Kong
ymzhu19eee@connect.hku.hk

Vincent Tam
Dept. of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam, Hong Kong
vtam@eee.hku.hk

Allie Lee
Dept. of Ophthalmology
The University of Hong Kong
Pokfulam, Hong Kong
allieleehk@gmail.com

Edmund Y. Lam
Dept. of Electrical and Electronic Engineering
The University of Hong Kong
Pokfulam, Hong Kong
elam@eee.hku.hk

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***Abstract*—Ocular redness is a common symptom of numerous eye conditions and serves as an essential diagnostic indicator requiring accurate and timely assessment. However, the conventional manual evaluation of ocular redness is inherently subjective, inefficient, and error-prone due to inter-observer variability. To address these limitations, we present an automatic ocular redness monitoring system (AORMS) that utilizes deep learning models for objective and consistent quantification of ocular redness. In this work, we propose an approach for effectively classifying and monitoring ocular redness caused by subconjunctival hemorrhage (SCH) and conjunctivitis. To ensure robustness, we employ transfer learning and image processing techniques to maximize the utilization of a limited dataset comprising external eye photos. Additionally, a complete pipeline is implemented to facilitate the seamless integration of our system into clinical workflows. The proposed method achieved $98.3\,\%$ accuracy in class classification and $96.2\,\%$ accuracy in SCH area identification.**

***Index Terms*—ocular redness, deep learning, classification, measurement, monitoring system**

I. Introduction

Ocular redness is a common symptom that presents an abnormal reddish hue or increased prominence of blood vessels in the eye. This redness is a characteristic feature of numerous ocular conditions, including but not limited to conjunctivitis, subconjunctival hemorrhage (SCH), dry eye disease, and ocular allergies [1]. As a crucial diagnostic indicator, ocular redness aids in detecting and monitoring the progression of various eye diseases, as well as evaluating the effectiveness of treatments [2]. However, traditional visual inspection methods can be limited by the availability of experienced medical professionals and inter-observer variability, leading to inconsistencies in diagnosis and patient care. Thus, there is a growing need for an automated, objective, and reliable system for ocular redness assessment.

Recent advances in the evaluation of ophthalmic diseases using neural networks offer a promising path toward data-driven automation design [3], [4]. However, few studies in the literature addressed the introduction of deep learning into automatic evaluation in external eye images. For instance, machine learning methodologies, such as random forests [5] and multi-layer perceptron [6], have proven effective in assessing external eye redness. These techniques have been applied to segment the sclera area and grade conjunctival hyperemia. Researchers have also employed deep learning techniques, specifically convolutional neural networks (CNNs), to classify red eyes from healthy ones [7] and extract redness based on image [8] or video [9] features. The development of ocular redness image processing techniques has been gradually developed with the goal of achieving automated detection [10]. In addition to these advancements, telemedicine offers a promising approach to diagnosing ocular redness, improving access to ophthalmic care, especially with the increasing popularity of smartphones [11].

In this paper, we propose the automatic ocular redness monitoring system (AORMS) based on a complete pipeline, various image processing techniques, and deep learning models for efficient and consistent quantification of ocular redness. Our approach aims to improve the classification and monitoring of ocular redness patterns caused by SCH and conjunctivitis, ultimately enhancing patient care and clinical decision-making.

II. Methods

The system architecture, illustrated in Fig. 1, consists of three main components: data preprocessing engines, the CNN model, and post-processing. The dataset photos undergo an initial screening based on resolution, contrast, and intensity, and are then labeled as normal, SCH, or conjunctivitis. The system applies image preprocessing techniques such as resizing and augmentation, white balance adjustment, contrast enhancement, and sclera segmentation. The processed data is subsequently fed into the customized model for classification and diagnosis. After classification, specified measurements are conducted accordingly, and treatment parameters are pro-

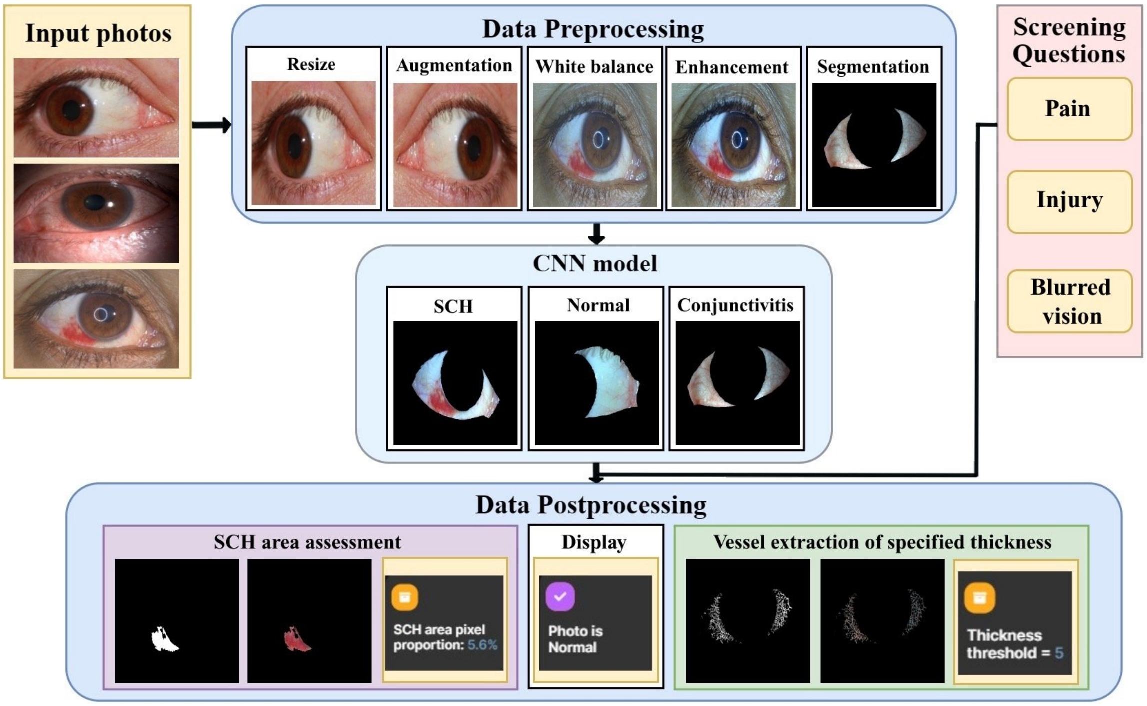

Fig. 1. The pipeline of AORMS is decomposed into three steps: data preprocessing, ocular redness diagnosis by CNN model, and data postprocessing.

vided based on the diagnosis. The proposed framework's effectiveness is evaluated in terms of scleral segmentation, redness classification, SCH area measurement, and extraction of vessels with certain thicknesses.

A. Data Preprocessing

1) Image resizing, contrast enhancement, and white-balancing adjustment: To achieve a uniform image size, we resized all photos to 640×640 pixels. The image quality significantly impacts the system's evaluation, and evaluating image details becomes more challenging in low-contrast images. Consequently, the global contrast of images was enhanced using histogram equalization, particularly when the usable data of the image was represented by close contrast values [12].

Images of different patients may be taken in various lighting conditions, causing differences in brightness and color temperature levels. These differences can affect the judgment and diagnosis of ocular redness. To solve this problem, we used automatic white balance algorithms that estimated the light source's color temperature and adjusted the image colors accordingly [13]. By applying the gray world assumption, different images were ensured to have similar color temperatures.

2) Image Augmentation: Image augmentation was employed to expand the dataset, thereby improving the network's training. We increased the dataset's diversity and size by applying various transformations such as rotation, scaling, and flipping. This enhanced dataset helps the model generalize better and reduces overfitting [14].

3) Segmentation of the Scleral Region: External eye image processing can be influenced by interference from skin and eyelashes. Hence, accurately segmenting the scleral region is crucial before proceeding with further classification. CNNs have demonstrated superior performance over traditional methods in semantic image segmentation tasks [15]. In particular, the U-Net architecture is widely employed in biomedical image segmentation [16]. In this work, we utilized the U-Net architecture to segment the scleral region and referred to this network as SU-Net to avoid ambiguity.

The SU-Net was trained using external eye images and corresponding annotations of scleral regions. The binary cross-entropy loss served as the loss function, while the ADAM optimizer was employed to train the network [17]. During the inference process, the network generated a binary mask of the scleral region. This binary mask was subsequently applied to extract the isolated scleral region from the external eye photo, resulting in the scleral image.

B. CNN Model

Among various CNN models, YOLOv5 is lightweight and capable of running on portable electronic devices equipped with only a CPU [18]. Therefore, to achieve a more efficient system, we primarily utilize YOLOv5 for image classification. Transformers are well-known architectures with robust self-attention mechanisms [19]. TransUNet combines the strengths of both Transformers and U-Net, making it a powerful alternative for medical image segmentation and one of the current state-of-the-art methods [20]. In this work, we customized the TransUNet model to perform automatic and accurate segmentation of the reddish area in the classified SCH images

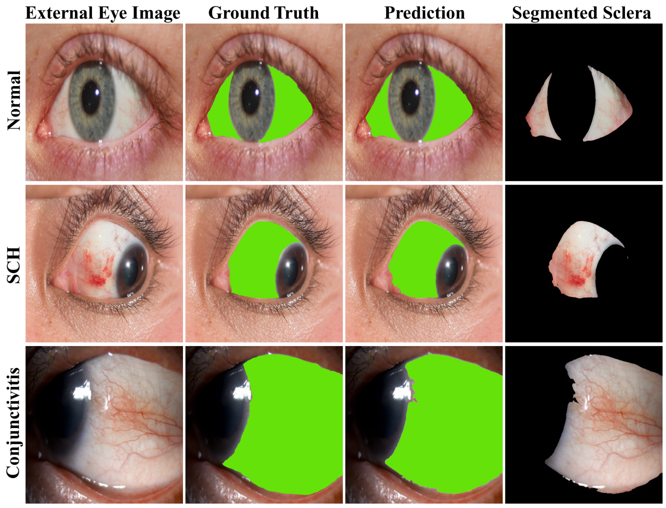

Fig. 2. Prediction by SU-Net and scleral segmentation in three kinds of external eye images.

and predict the vessel map in the classified conjunctivitis images.

The pre-trained weight from ViT was employed to initialize the TransUNet model. This approach not only accelerates the training process but also improves the model's performance. Next, the model was further fine-tuned and a manual grid search was performed in order to optimize the hyperparameters, including learning rate, batch size, and the application of augmentations.

C. Image Postprocessing

1) SCH Area Measurement and Vessel Extraction: For comprehensive eye care, our approach involved assessment after classification. If the input image is identified as SCH, the area of the SCH region is calculated using a self-developed Python script. Subsequently, the SCH-area pixel proportion in the scleral region is further determined to monitor daily changes. If the image is classified as conjunctivitis, the vessels of specified thickness are extracted for accurate measurements [21]. A tailored script takes in the predicted vessel map and returns a binary image that contains the vessels of specified thickness as output. For this purpose, we employed a series of image-processing techniques including morphological operations and filtering [22].

This approach allows for comparisons of the SCH area or dilated vessels in photos taken on different days. The aim of these measurements is to enable long-term monitoring, thereby providing a more organized and logical analysis.

2) Care Suggestions and System Integration: When input images display conjunctivitis and are accompanied by pain or injuries, as indicated by the screening questionnaires in Table I, a warning will be issued in the system. In such cases, patients are advised to consult an ophthalmologist [23]. Conversely, if the input images appear normal white, this suggests that the patient is normal and not currently experiencing issues related to conjunctivitis or SCH (Fig. 1).

TABLE I
SCREENING QUESTIONS

No.	iCare Questions
1	Have you noticed any redness, swelling, or discharge in your eyes?
2	Are you experiencing any discomfort or pain in your eyes? If so, can you describe the intensity, frequency, and duration of the pain?
3	Have you had any recent eye injuries or accidents that may have affected your vision or eye health?
4	Have you experienced any changes in your vision, such as blurriness, double vision, or difficulty focusing? If so, can you describe the intensity, frequency, and duration of the pain?

To improve daily eye care and support clinical decision-making, the system has been incorporated into a smartphone app called iCare. The user interface was designed using Uizard, as shown in Fig. 4.

III. Experimental Results

A. Dataset Description and Experimental Setup

Two datasets were used in this work: the External Eye Photo (EEP) dataset collected from the Lo Fong Shiu Po Eye Centre (LFSC) in Hong Kong, and the publicly available Sclera Blood Vessels, Periocular and Iris (SBVPI) dataset [24]. The different datasets enhance the generalization capability of the system and ensure the performance of the system is not biased. The EEP dataset consists of 600 external eye images (2576×1934) of 3 different kinds (SCH 200, conjunctivitis 200, and normal 200). The SBVPI dataset consists of 1840 external eye images (3000×1700) belonging to 55 subjects [25].

The task involved classifying segmented sclera photos into three categories: normal, SCH, and conjunctivitis, followed by further area measurements and vessel extraction. For all experiments, the deep learning models were implemented with PyTorch and trained on an Nvidia RTX 4090 graphic card.

B. Segmentation of Sclera

The performance of the SU-Net was evaluated using the SBVPI dataset. We trained the model with a learning rate of 0.0005 and assessed its performance by calculating the accuracy score (Acc), Intersection over Union (IOU), and F1 score. These metrics are defined as follows: Acc = (TP + TN) / (TP + TN + FP + FN), IOU = TP / (FP + FN + TP), and F1 score = 2 $\times$ Precision $\times$ Recall / (Precision + Recall), where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. On the SBVPI dataset, SU-Net achieved an Acc of 0.992, an IOU of 0.977, and an F1 score of 0.982. These metrics, coupled with the data presented in Table II, further indicate that SU-Net provides enhanced performance for this task. Fig. 2 shows representative external eye images of three types, along with their scleral ground truth and scleral segmentations obtained from the SU-Net. The sclera area is extracted from the original images using a customized algorithm. The segmented images effectively eliminate interference from eyelashes and skin, thereby facilitating subsequent classification.

TABLE II
SEGMENTATION PERFORMANCE BASED ON THE SBVPI DATASET

Algorithm	Precision	Recall	F1 score
RefineNet-50 [25], [26]	0.960	0.960	0.960
Sclera-Net [27]	0.944	0.982	0.962
SU-Net	**0.993**	**0.971**	**0.982**

C. Three-class Classification

In our study, the YOLOv5 model was fine-tuned to classify three types of eye conditions: normal white eyes, conjunctivitis eyes, and SCH eyes. A normal white eye represents a healthy eye with a clear white sclera, while conjunctivitis eyes are characterized by inflammation, redness, and often discomfort. SCH eyes exhibit a noticeable accumulation of blood on the sclera's surface.

The evaluation results revealed that the model is effective in distinguishing the different eye conditions, consistently achieving an Acc of 98.3 %. This highlights the potential applicability of the YOLOv5 algorithm for automated eye condition diagnosis, ultimately contributing to the early detection and timely treatment of various eye disorders. Furthermore, the model can be easily integrated into systems using an application programming interface (API) module [28].

D. Post-assessment

The system provides a quantitative assessment of the detailed hemorrhage area for images classified as SCH, utilizing self-developed algorithms, as shown in Fig. 3(a).

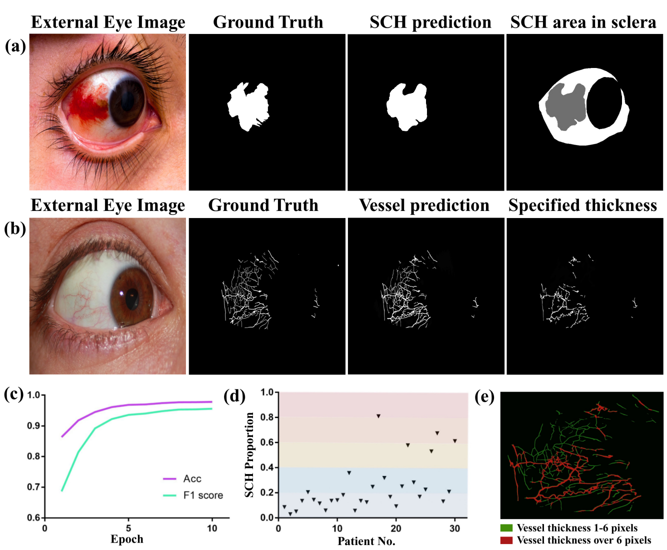

Fig. 3. (a) SCH segmentation and area measurement in the scleral region. (b) Vessel prediction and thickness extraction. (c) Training accuracy (Acc) and F1 score. (d) Patients of different SCH area proportion and severity groups. (e) Closeup visualizations of extracted vessels.

This assessment was compared with ground truth by manual annotations. The system achieved an Acc of 96.2 % (Fig. 3(c)). Additionally, the proportion of SCH area pixels in the scleral region is counted. These results demonstrate the system's accuracy in quantifying SCH severity and offering a more objective evaluation of ocular redness (Fig. 3(d)).

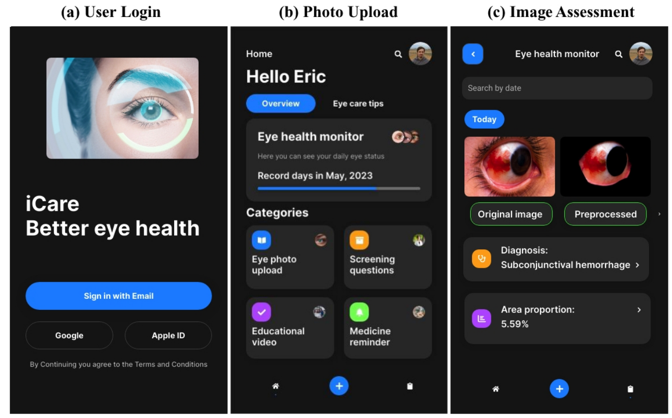

Fig. 4. The user interface of the integrated system, named iCare.

For images classified as conjunctivitis, the system extracts dilated vessels exceeding a specific thickness. This extraction allows for a clearer visualization of the most dilated blood vessels while minimizing the visual interference from smaller blood vessels (Fig. 3(b)). The vessel extraction steps can be conveniently tailored to suit the nature of the vessels of interest. As illustrated in Fig. 3(e), vessels with a thickness of more than 6 pixels are extracted.

E. Monitoring System

We have been designing a mobile app named iCare that enables patients to upload eye photos using their phones. The screening questions (Table I) were integrated into the system, allowing for comprehensive sorting in conjunction with the corresponding eye images [2]. Furthermore, once the ophthalmologist has made a diagnosis, patients can conduct long-term self-monitoring at home by creating a condition log, as shown in Fig. 4. This feature allows patients to track their progress and maintain a record of their eye health.

IV. CONCLUSIONS

In this work, we propose a comprehensive system for classifying and quantifying external eye photographs, specifically focusing on the identification of SCH and conjunctivitis. Our system is capable of measuring the affected area of SCH and extracting vessels of specified thickness, providing accurate and efficient analysis. We apply deep learning models and achieve a classification accuracy of 98.3 % and an area identification accuracy of 96.2 %. To facilitate long-term monitoring, we incorporate the assessment into a user-friendly app. This comprehensive system enables at-home inspection, reducing costs and improving efficiency in the diagnosis and monitoring of eye conditions.

REFERENCES

[1] S. Bonini, "The red eye," *European Journal of Ophthalmology*, vol. 31, no. 6, pp. 2843–2849, 2021.

[2] H. Cronau, R. R. Kankanala, and T. Mauger, "Diagnosis and management of red eye in primary care," *American Family Physician*, vol. 81, no. 2, pp. 137–144, 2010.

[3] Z. Wang, P. A. Keane, M. Chiang, C. Y. Cheung, T. Y. Wong, and D. S. W. Ting, "Artificial intelligence and deep learning in ophthalmology," in *Artificial Intelligence in Medicine*. Springer, 2022, pp. 1519–1552.

[4] P. Kumar, R. Kumar, and M. Gupta, "Deep learning based analysis of ophthalmology: A systematic review," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 7, no. 29, 2021.

[5] E. Sirazitdinova, M. Gijs, C. J. Bertens, T. T. Berendschot, R. M. Nuijts, and T. M. Deserno, "Validation of computerized quantification of ocular redness," *Translational Vision Science & Technology*, vol. 8, no. 6, pp. 31–31, 2019.

[6] L. S. Brea, N. B. Rodriguez, A. M. González, and K. Evans, "Assessment of the repeatability in an automatic methodology for hyperemia grading in the bulbar conjunctiva," in *2017 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2017, pp. 1673–1680.

[7] S. Verma, L. Singh, and M. Chaudhry, "Classifying red and healthy eyes using deep learning," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 7, 2019.

[8] P. Ostheimer, A. Lins, B. Massow, B. Steger, D. Baumgarten, and M. Augustin, "Extraction of eye redness for standardized ocular surface photography," in *Ophthalmic Medical Image Analysis: 9th International Workshop, OMIA 2022, Held in Conjunction with MICCAI 2022, Singapore, Singapore, September 22, 2022, Proceedings*. Springer, 2022, pp. 193–202.

[9] H. Abdelmotaal, R. Hazarbasanov, S. Taneri, A. Al-Timemy, A. Lavric, H. Takahashi, and S. Yousefi, "Detecting dry eye from ocular surface videos based on deep learning," *The Ocular Surface*, vol. 28, pp. 90–98, 2023.

[10] N. Curti, E. Giampieri, F. Guaraldi, F. Bernabei, L. Cercenelli, G. Castellani, P. Versura, and E. Marcelli, "A fully automated pipeline for a robust conjunctival hyperemia estimation," *Applied Sciences*, vol. 11, no. 7, p. 2978, 2021.

[11] J. Sink, S. Blatt, D. Yoo, M. Henry, S. D. Yang, R. Vasaiwala, L. Ghadiali, W. Adams, and C. S. Bouchard, "A novel telemedicine technique for evaluation of ocular exam findings via smartphone images," *Journal of Telemedicine and Telecare*, vol. 28, no. 3, pp. 197–202, 2022.

[12] R. Dorothy, R. Joany, R. J. Rathish, S. S. Prabha, S. Rajendran, and S. Joseph, "Image enhancement by histogram equalization," *International Journal of Nano Corrosion Science and Engineering*, vol. 2, no. 4, pp. 21–30, 2015.

[13] E. Y. Lam, "Combining gray world and retinex theory for automatic white balance in digital photography," in *Proceedings of the Ninth International Symposium on Consumer Electronics, 2005.(ISCE 2005)*. IEEE, 2005, pp. 134–139.

[14] J. Wang, L. Perez *et al.*, "The effectiveness of data augmentation in image classification using deep learning," *Convolutional Neural Networks Vis. Recognit*, vol. 11, no. 2017, pp. 1–8, 2017.

[15] A. Garcia-Garcia, S. Orts-Escolano, S. Oprea, V. Villena-Martinez, and J. Garcia-Rodriguez, "A review on deep learning techniques applied to semantic segmentation," *arXiv preprint arXiv:1704.06857*, 2017.

[16] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18*. Springer, 2015, pp. 234–241.

[17] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[18] G. Jocher, A. Chaurasia, A. Stoken, J. Borovec, Y. Kwon, K. Michael, J. Fang, C. Wong, Z. Yifu, D. Montes *et al.*, "ultralytics/yolov5: v6. 2-yolov5 classification models, apple m1, reproducibility, clearml and deci. ai integrations," *Zenodo*, 2022.

[19] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[20] J. Chen, Y. Lu, Q. Yu, X. Luo, E. Adeli, Y. Wang, L. Lu, A. L. Yuille, and Y. Zhou, "Transunet: Transformers make strong encoders for medical image segmentation," *arXiv preprint arXiv:2102.04306*, 2021.

[21] A. De Silva, M. V. Perera, N. Wijethilake, S. Jayasinghe, N. D. Nanayakkara, and A. De Silva, "A thickness sensitive vessel extraction framework for retinal and conjunctival vascular tortuosity analysis," *arXiv preprint arXiv:2101.00435*, 2021.

[22] W. Dong, H. Zhou, and D. Xu, "A new sclera segmentation and vessels extraction method for sclera recognition," in *2018 10th International Conference on Communication Software and Networks (ICCSN)*. IEEE, 2018, pp. 552–556.

[23] P. Mukherjee, I. Bhattacharyya, M. Mullick, R. Kumar, N. D. Roy, and M. Mahmud, "i condet: An intelligent portable healthcare app for the detection of conjunctivitis," in *Applied Intelligence and Informatics: First International Conference, AII 2021, Nottingham, UK, July 30–31, 2021, Proceedings*. Springer, 2021, pp. 29–42.

[24] P. Rot, M. Vitek, K. Grm, Ž. Emeršič, P. Peer, and V. Štruc, "Deep sclera segmentation and recognition," *Handbook of Vascular Biometrics*, pp. 395–432, 2020.

[25] M. Vitek, P. Rot, V. Štruc, and P. Peer, "A comprehensive investigation into sclera biometrics: A novel dataset and performance study," *Neural Computing and Applications*, vol. 32, pp. 17 941–17 955, 2020.

[26] G. Lin, A. Milan, C. Shen, and I. Reid, "Refinenet: Multi-path refinement networks for high-resolution semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 1925–1934.

[27] R. A. Naqvi and W.-K. Loh, "Sclera-net: Accurate sclera segmentation in various sensor images based on residual encoder and decoder network," *IEEE Access*, vol. 7, pp. 98 208–98 227, 2019.

[28] M. A. Muhammad, Y. Mulyani *et al.*, "Library attendance system using yolov5 faces recognition," in *2021 International Conference on Converging Technology in Electrical and Information Engineering (ICCTEIE)*. IEEE, 2021, pp. 68–72.