An Intelligent and Handheld Device for Early Identification of Meibomian Gland Irregularities

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ABSTRACT

Meibomian gland dysfunction (MGD) is a significant cause of evaporative dry eye disease, occurring when the meibomian glands (MGs) in the eyelids produce abnormal lipid amounts. MG morphological features are crucial indicators of MG function and dry eye symptoms. However, the relationship between MG morphological irregularities and MGD remains unclear. To address this, we develop an integrated deep-learning-enabled monitoring system within a portable meibography device, enabling early identification and quantification of irregularly-shaped MGs. Our approach comprises two key technical components. First, a customized model is fine-tuned to classify MG irregularities into four types: overlapping, shortening, thickening, and tortuosity. We then quantitatively analyze MG irregularity ratios among four meiboscore groups of varying MG atrophy degrees and examine their connection to Ocular Surface Disease Index (OSDI) indexes from a subjective symptom perspective. From meiboscore 0 to 3, the overlapping MG ratio decreases by 17 %, and the shortening MG ratio increases by 12 %. Furthermore, we've built a handheld device equipped with infrared (IR) LED arrays and a USB camera to facilitate long-term and dynamic assessment. This meibography technology is compatible with common operating systems and can be integrated into a smartphone. The high-resolution images captured by this device can be used to assess various types of irregularities. This intelligent portable system offers an automatic and efficient quantitative evaluation of MG morphological irregularities, enabling home inspection and reducing costs. It has the potential to be applied in diagnosing and monitoring MG conditions, facilitating the management of MGD.

Keywords: Meibography, dry eye, early identification, handheld device, precision eye healthcare

1. INTRODUCTION

Dry eye disease is one of the most common eye disorders, impacting millions of people worldwide. The global prevalence ranges from 5 % to 50 %.[1] Meibomian gland dysfunction (MGD) is a significant cause of evaporative dry eye disease, which occurs when the meibomian glands (MGs) in the eyelids produce abnormal amounts of lipids.[2] Moreover, 80 % - 90 % of dry eye patients exhibit signs of MGD.[2] MGD may result in changes to the composition of the tear film, the development of ocular surface disorders, discomfort in the eye and eyelid, as well as the onset of evaporative dry eye.[3]

The assessment of MG health plays a crucial role in the diagnosis and management of MGD. At present, a widely used and intuitive measure for evaluating MGD is the extent of MG atrophy, which is both prevalent and subjective.[4] Recently, researchers have employed learning-based methods to characterize the dropout rate of MGs.[5,6] To quantify the status of glands, different clinically relevant metrics are proposed, such as number, tortuosity, width, and length.[7] Furthermore, early indicators of subsequent dropouts include MG morphological irregularities such as truncation, angulation, and dilatation.[3,8,9] However, the relationship between these morphological irregularities and MGD remains unclear, which poses a considerable challenge in terms of early diagnosis and the development of intelligent measurement indicators.

To efficiently monitor the status of the meibomian glands, various devices have been developed to provide accurate and detailed evaluations. These devices employ advanced imaging techniques, such as infrared meibography[10] and confocal microscopy,[11,12] to visualize the gland structure and assess gland functionality. Given

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that MGDs are chronic in nature, continuous monitoring becomes vital in ensuring appropriate treatment and symptom management. Unfortunately, the majority of available diagnostic tools and monitoring techniques are clinic-based, requiring patients to visit eye care professionals, which may not be feasible for continuous monitoring. This limitation not only places a burden on patients and eye care systems but also makes it difficult to track the progression of these conditions and assess the effectiveness of various treatments. For example, it's reported that only 33.6 % of dry eye patients received a follow-up examination within 6 months, highlighting the challenge of maintaining long-term monitoring in clinical settings.[13]

In this work, we develop a deep-learning-enabled approach to classify MG irregularities into four types: overlapping, shortening, thickening, and tortuosity. We quantitatively analyze their relations to meiboscores of varied MG atrophy severity degrees and examine their connection to Ocular Surface Disease Index (OSDI) indexes from a subjective symptom perspective. Additionally, we have developed a handheld device that utilizes infrared (IR) LED arrays and a USB camera to facilitate long-term and dynamic assessment. This comprehensive system enables home inspection, reducing costs and improving efficiency in diagnosing and monitoring MG conditions.

2. METHODS

A total of 1200 IR meibography images were collected from 378 patients. 200 IR meibography images (820 $\times$ 615) were obtained from 58 patients who visited LFSC for a dry eye examination. In addition, the public MGD-1K dataset comprised 1000 images (1280 $\times$ 640) from 320 patients (467 images from the upper eyelids and 533 images from the lower eyelids).[5] The IR meibomian gland (MG) images were obtained with the LipiView interferometer (Johnson & Johnson Inc., Jacksonville, FL). All data is anonymized to ensure patient privacy, and Institutional Review Boards (IRB) approvals have been secured to protect human research subjects' rights.

A deep learning model is developed to accurately segment both the eyelid and meibomian gland (MG) regions within meibography images. This is achieved by calculating various morphometric parameters, including the number of glands, as well as their length, width, and area ratio for each segmented gland. To further enhance the identification of abnormal MGs, which serve as early indicators of potential dropouts, a customized TransUNet model is employed.[14] This model is initialized using pre-trained weights from the Vision Transformer (ViT) and is subsequently fine-tuned for the specific task of detecting abnormal MGs.

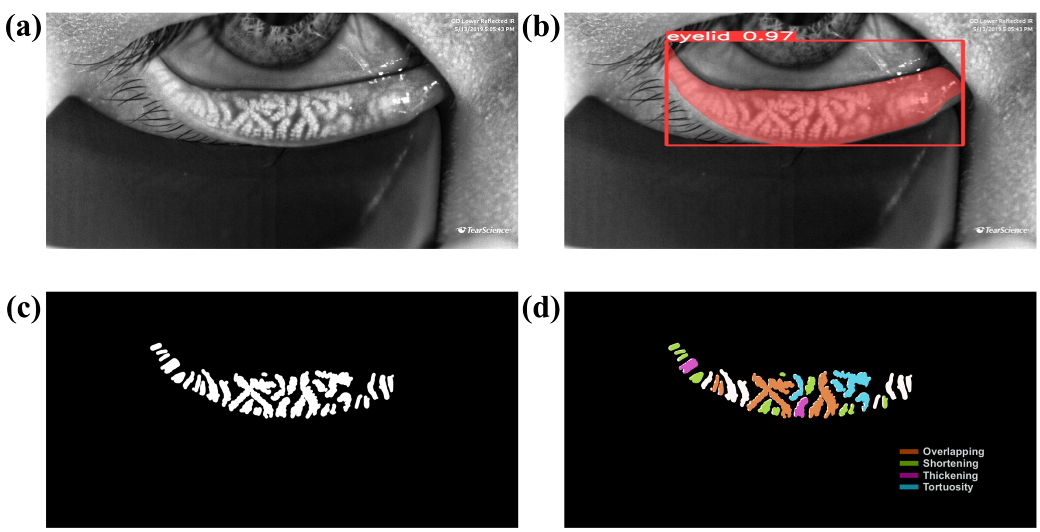

Figure 1. (a) Meibography image. (b) Predicted eyelid. (c) Binary segmented MG image. (d) Identified MG irregularities.

The meibomian gland irregularities are classified into four distinct types: overlapping, shortening, thickening, and tortuosity. In order to analyze these irregularities, meibography images are categorized into four separate groups based on the meiboscore, which ranges from 0 to 3. By examining the meibomian gland irregularity ratios within each group, a more comprehensive understanding of the glandular abnormalities can be achieved, ultimately aiding in the early detection and effective management of meibomian gland dysfunction and related ocular surface diseases.

The processing pipeline for MG assessment is incorporated into a handheld device, which is equipped with a 2.0-megapixel infrared (IR) USB camera featuring a 90-degree angle-of-view (AOV) module. To enhance image capture, the device also includes an array of six LED lights with a wavelength of 850 nm (Aoke Tech, 3206-1080P) and a narrow band filter. This compact and portable meibography technology has a working distance of approximately 5 cm, making it convenient for use in clinical settings.

The handheld device is designed for seamless compatibility with common operating systems such as Windows OS and Android OS, requiring no additional setup or drivers for integration. This compatibility extends to smartphones, allowing for easy pairing and enhancing the device's portability and user-friendliness. By combining advanced imaging capabilities with a portable and easy-to-use design, this meibography technology offers a practical solution for eye care professionals seeking to assess meibomian gland health and diagnose related ocular surface disorders efficiently.[15,16]

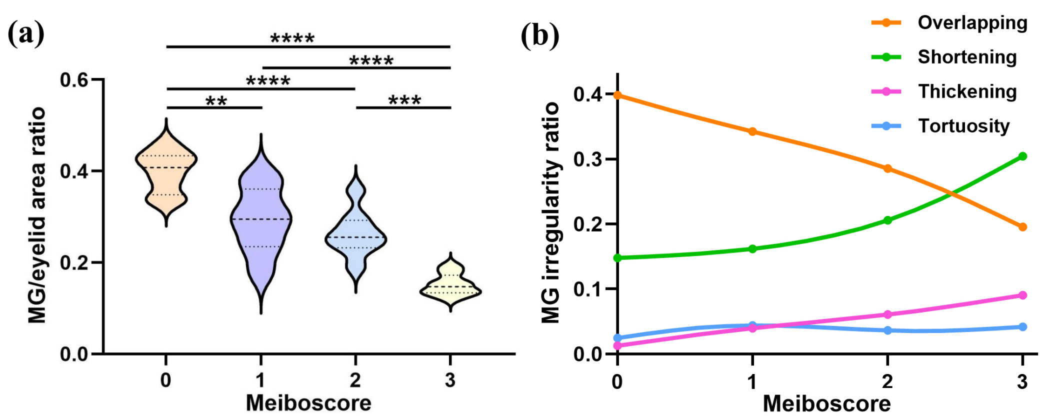

Figure 2. (a) MG-to-eyelid area ratio across meiboscore groups. (b) Irregular-shaped MG types and corresponding ratios.

3. RESULTS

The dataset was split into training-validation-test with a ratio of 8:1:1. The eyelid segmentation achieves an accuracy of 99 %, effectively avoiding interference from skin and eyelashes in the meibography (Figure 1(a) and (b)). The algorithm attains an overall accuracy of 97 % MG segmentation (Figure 1(c)). The four kinds of irregularities (overlapping, shortening, thickening, and tortuosity) are detected with a mean accuracy of 84 %, as illustrated in Figure 1(d). As the meiboscore increases, the ratio of the MG area to the total analyzed eyelid area decreases (Figure 2(a)). From meiboscore 0 to 3, the overlapping MG ratio decreases by 17 %, and the shortening MG ratio increases by 12 %, as shown in Figure 2(b). Moreover, OSDI indexes exhibit a positive relationship with the MG irregularity ratio in terms of dry eye symptoms. The morphological parameters also noticeably change among the four meiboscore groups (data not shown).

A USB camera equipped with 850 nm IR LED arrays enables the capture of high-contrast meibography images, making the portable device a convenient tool for daily self-checks (Figure 3(a)). Encased in a handheld metal container, as depicted in the red box in Figure 3(b), the system can be easily attached to a smartphone. The images captured by this device are of high quality and can be used to assess various types of irregularities (Figure 3(c)). Furthermore, the corresponding smartphone app allows users to adjust parameters such as intensity and contrast, resulting in a more user-friendly experience while achieving optimal image quality. Furthermore, the images will be processed to identify the irregularities.

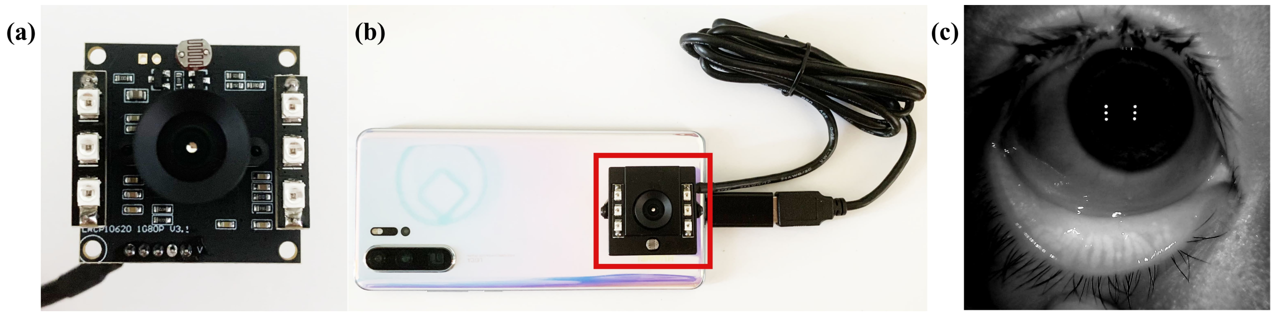

Figure 3. (a) USB-based imaging sensor equipped with an integrated IR LED array. (b) Portable meibography device (highlighted in red box) connected to a Huawei P30 Pro smartphone. (c) Meibography image captured by the smartphone.

4. DISCUSSION AND CONCLUSION

At present, only a few commercially available portable IR meibographers, such as MeiboVue and Ezer Sapphire, are capable of capturing MG images.[17] Although these devices offer high-resolution meibography for diagnostic purposes, they fall short in providing accurate measurement and quantification of MG morphology. Furthermore, these devices lack automated algorithms for the early detection of MG irregularities and are unable to offer patients personalized recommendations based on their specific conditions.

In summary, this study proposes a deep-learning-enabled approach that provides an automatic and efficient quantitative evaluation of MG morphological irregularities. This approach has potential applications in MGD disease monitoring and research and may support further clinical investigation of early dry eye biomarkers from the perspective of precision medicine.

REFERENCES

[1] Stapleton, F., Alves, M., Bunya, V. Y., Jalbert, I., Lekhanont, K., Malet, F., Na, K.-S., Schaumberg, D., Uchino, M., Vehof, J., et al., "Tfos dews ii epidemiology report," *The ocular surface* **15**(3), 334–365 (2017).

[2] Daniel, E., Maguire, M. G., Pistilli, M., Bunya, V. Y., Massaro-Giordano, G. M., Smith, E., Kadakia, P. A., Asbell, P. A., et al., "Grading and baseline characteristics of meibomian glands in meibography images and their clinical associations in the dry eye assessment and management (dream) study," *The ocular surface* **17**(3), 491–501 (2019).

[3] Chhadva, P., Goldhardt, R., and Galor, A., "Meibomian gland disease: the role of gland dysfunction in dry eye disease," *Ophthalmology* **124**(11), S20–S26 (2017).

[4] Zhang, Z., Lin, X., Yu, X., Fu, Y., Chen, X., Yang, W., and Dai, Q., "Meibomian gland density: An effective evaluation index of meibomian gland dysfunction based on deep learning and transfer learning," *Journal of Clinical Medicine* **11**(9), 2396 (2022).

[5] Saha, R. K., Chowdhury, A. M., Na, K.-S., Hwang, G. D., Eom, Y., Kim, J., Jeon, H.-G., Hwang, H. S., and Chung, E., "Automated quantification of meibomian gland dropout in infrared meibography using deep learning," *The Ocular Surface* **26**, 283–294 (2022).

[6] Setu, M. A. K., Horstmann, J., Schmidt, S., Stern, M. E., and Steven, P., "Deep learning-based automatic meibomian gland segmentation and morphology assessment in infrared meibography," *Scientific reports* **11**(1), 7649 (2021).

[7] Prabhu, S. M., Chakiat, A., Shashank, S., Vunnava, K. P., and Shetty, R., "Deep learning segmentation and quantification of meibomian glands," *Biomedical signal processing and control* **57**, 101776 (2020).

[8] Lin, X., Fu, Y., Li, L., Chen, C., Chen, X., Mao, Y., Lian, H., Yang, W., and Dai, Q., "A novel quantitative index of meibomian gland dysfunction, the meibomian gland tortuosity," *Translational Vision Science & Technology* **9**(9), 34–34 (2020).

[9] Singh, S., Naidu, G. C., Vemuganti, G., and Basu, S., "Morphological variants of meibomian glands: correlation of meibography features with histopathology findings," *British Journal of Ophthalmology* **107**(2), 195–200 (2023).

[10] Wise, R. J., Sobel, R. K., and Allen, R. C., "Meibography: A review of techniques and technologies," *Saudi Journal of Ophthalmology* **26**(4), 349–356 (2012).

[11] Maruoka, S., Tabuchi, H., Nagasato, D., Masumoto, H., Chikama, T., Kawai, A., Oishi, N., Maruyama, T., Kato, Y., Hayashi, T., et al., "Deep neural network-based method for detecting obstructive meibomian gland dysfunction with in vivo laser confocal microscopy," *Cornea* **39**(6), 720–725 (2020).

[12] Li, Y., Liu, X., Xia, C.-h., FitzGerald, P. G., Li, R., Wang, J., and Gong, X., "Cp49 and filensin intermediate filaments are essential for formation of cold cataract," *Molecular Vision* **26**, 603 (2020).

[13] Uchino, M., Yokoi, N., Kawashima, M., Ryutaro, Y., Uchino, Y., and Tsubota, K., "Treatment trends in dry eye disease and factors associated with ophthalmic follow-up discontinuation in japan," *Journal of Clinical Medicine* **8**(8), 1120 (2019).

[14] Chen, J., Lu, Y., Yu, Q., Luo, X., Adeli, E., Wang, Y., Lu, L., Yuille, A. L., and Zhou, Y., "Transunet: Transformers make strong encoders for medical image segmentation," *arXiv preprint arXiv* **2102**(04306) (2021).

[15] Wang, D. N., Patel, Y., and Luong, M., "Portable meibography technology using a smartphone device," *Canadian Journal of Ophthalmology* **55**(6), e211–e213 (2020).

[16] Li, Y., Chiu, P. W., Zhu, Y., Tam, V., Lee, A., and Lam, E. Y., "A deep-learning-enabled monitoring system for ocular redness assessment," in [*2023 IEEE Biomedical Circuits and Systems Conference (BioCAS)*], In Press, IEEE (2023).

[17] Retana, H., Bojorges, E., and Quintela, E., "Development of alpha prototype of handheld device for meibography," in [*Congreso Nacional de Ingeniería Biomédica*], 448–458, Springer (2022).