A Depth Learning-Based Approach for Vision Prevention and Detection Utilized on Mobile Devices

Yichuan Huang

School of Information Technology, Beijing Normal University, Zhuhai, China
1801030042@mail.bnuz.edu.cn

Abstract. Vision, one of humanity's paramount senses, plays a pivotal role in our lives and learning. Maintaining a pair of healthy eyes is of utmost significance. Conventional vision assessments typically necessitate the expertise of ophthalmologists or optometrists to diagnose myopia. Unfortunately, this approach is fraught with substantial delays. Once myopia is confirmed post-refraction, the removal of eyeglasses becomes a formidable challenge. In recent years, the prevalence of myopia, especially among school-age children, has surged, resulting in a widespread reliance on corrective lenses.The imperative for vision preservation and safeguarding has never been more apparent. In light of the rapid advancements in computer vision and artificial intelligence technologies, this paper introduces an AI-based method, designed for deployment on mobile devices, for vision prevention and assessment. Integrating artificial intelligence image processing and pattern recognition techniques, this approach enables expeditious and precise evaluation of visual acuity through analysis of the subject's ocular images. It presents a novel solution for ocular health maintenance and disease diagnosis.

Keywords: Visual Acuity Assessment, Image Processing, Deep Learning

1 Introduction

Vision holds paramount significance in the realm of our daily existence and scholastic pursuits. Nevertheless, recent years have witnessed an escalating prevalence of myopia, notably within the demographic of children and adolescents, evincing a conspicuous surge in the number of myopic individuals. Impairments in visual acuity not only encumber personal learning and work efficacy but also have the potential to instigate ancillary health maladies, such as headaches, ocular fatigue, and myopic retinopathy. Thus, the timely detection and amelioration of visual impairments are pivotal to the preservation of ocular health and the augmentation of life quality.

Traditional methods for the assessment of visual acuity typically entail the involvement of specialized medical practitioners or optometrists, employing techniques such as subjective refraction with phoropters and computerized optometry. Despite their widespread application in medical institutions and a variety of optical establishments, these methods are confronted with certain challenges when applied to large-scale vision screenings and the dissemination of ocular healthcare. These issues

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arise from the necessity for specialized personnel, time-intensive procedures, and susceptibility to subjective factors attributable to the examinees.

In tandem with the expeditious evolution of computer vision and artificial intelligence technologies, AI-driven image processing methods have burgeoned as a focal point of investigation. Computer vision technologies proffer intelligent image manipulation and analysis, whereas deep learning algorithms facilitate the extraction of salient information from images, thereby enabling the assessment of visual acuity. Through the confluence of these technologies, the prospect of realizing automated, rapid, and precision-driven visual acuity assessments beckons. This augments the repertoire of solutions available for vision assessment and ocular healthcare.

This exposition proffers a deep learning-based methodology for the prevention and assessment of visual acuity, synergizing computer vision and pattern recognition techniques to facilitate the rapid self-assessment of visual acuity in examinees. The proposed approach holds the promise of ushering in innovative solutions for the assessment of visual acuity and ocular healthcare, thereby assisting a wider spectrum of individuals in the early detection and mitigation of visual impairments, thereby enhancing the ocular health quotient of society at large.

2 Visual Acuity Detection Method

This chapter provides an in-depth exploration of contemporary techniques employed in the assessment of visual acuity. Traditional methodologies encompass comprehensive optometry [1] and computerized optometry tests [2]. Despite their extensive application in clinical settings, these methods, owing to their dependence on skilled personnel, susceptibility to subject cooperation and subjectivity, and constraints in large-scale screenings, continue to pose certain challenges.

2.1 Comprehensive Optometry Examination

Comprehensive optometry, a widely embraced modality in ophthalmic diagnosis and visual acuity assessment, seamlessly integrates diverse optical techniques to holistically evaluate ocular health and visual status. Typically, the procedural workflow of comprehensive optometry entails the following steps: firstly, the apparatus autonomously conducts diopter measurements to identify refractive anomalies such as myopia, hyperopia, and astigmatism. Subsequently, by gauging corneal curvature, the comprehensive optometry instrument can assess corneal health and detect irregularities such as corneal distortion. Following this, measurements of the anterior and posterior axial lengths of the eye enable precise assessment of axial length, a pivotal parameter for myopia evaluation. Moreover, the instrument can determine the degree and orientation of astigmatism, providing essential data for corrective lens prescriptions. In the visual acuity assessment phase, the instrument is typically equipped with various visual acuity test patterns, such as Snellen charts or E charts, where subjects report the smallest line they can read with clarity, thus yielding their visual acuity levels. Furthermore, comprehensive optometry encompasses contrast sensitivity tests, evaluating subjects' perceptual capabilities regarding varying levels of contrast, further elucidating their visual status. Additionally, eye position and eye movement tests are integral to the examination process, particularly for assessing ocular alignment issues like strabismus. Comprehensive optometry automatically analyzes acquired data and generates a comprehensive visual acuity report, encompassing diopter values, visual acuity levels, corneal curvature, among other information. This array of procedures empowers ophthalmologists with a comprehensive understanding of ocular health and visual status, furnishing a reliable foundation for precise visual correction and early detection of ocular issues. This methodology plays an indispensable role in ophthalmic clinical diagnostics and visual health management.

2.2 Astigmatism Assessment

Astigmatism assessment serves as a diagnostic modality to ascertain the presence of irregular ocular shapes leading to inaccurate light focusing. Astigmatism, a common visual anomaly, if left uncorrected, may result in visual blurriness and discomfort. The advantage of astigmatism assessment resides in its paramount role in the early detection and correction of astigmatism. During the examination, specialized ophthalmologists employ specific devices for precise measurement of astigmatism degree and orientation, facilitating tailored corrective interventions. Nonetheless, it's worth noting that astigmatism assessment necessitates the expertise of specialized ophthalmologists, specific examination equipment, and is relatively intricate, rendering it unsuitable for routine visual screenings. Furthermore, astigmatism assessment primarily addresses irregularities in eye shape, thereby necessitating a comprehensive consideration of other visual parameters and real-world application scenarios when conducting visual acuity evaluations.

2.3 Computerized Optometry

Ophthalmic optical biometry, as a specialized apparatus, is employed for the measurement and analysis of various optical parameters of the eye. These parameters encompass diopter values, astigmatism degrees, corneal curvature, and pupil diameter, among others. Below is an elucidation of the operational principles of ophthalmic optical biometry:

Automatic Diopter Measurement. Ophthalmic optical biometry facilitates automatic diopter measurement, also referred to as automatic refractometry or automatic refractometry. In this functionality, the examinee maintains a stable head position by resting their chin and forehead on the instrument's support. Subsequently, the examinee fixates on an internal target or pattern within the instrument, as illustrated in Figure 1.

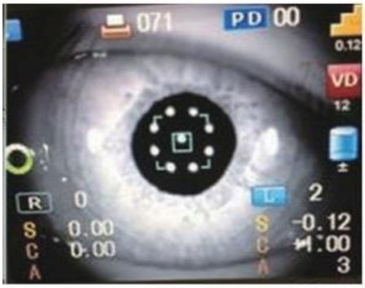

Fig. 1. Eye focus state diagram [1]

The instrument emits a beam of light through the examinee's eye while simultaneously capturing and analyzing the refraction of light as it passes through the eye. Utilizing optical principles and computations, the instrument can quantify the diopter values of the eye, as depicted in Figure 2, which corresponds to the eye's refractive power. This process is automated, requiring examinees only to gaze at the target; the instrument autonomously conducts optical measurements and data analysis, thereby accurately determining diopter values.

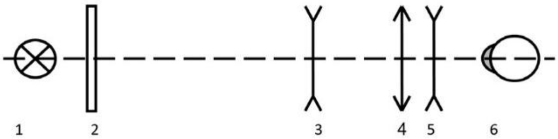

Fig. 2. Schematic diagram of diopter measurement of computer refractometer [2]

Within a variable-focus system composed of three lenses, including a movable concave lens, a fixed convex lens, and a concave lens with absolute focal lengths equal, the second principal point of the system remains stationary with respect to the eye position. Thus, as the focal power of the first lens system within the movable system changes, the variation Δf is linearly related to the displacement x. This linear relationship, i.e.

$$f=kx \tag{1}$$

where f denotes focal length, is inherent to diopter measurements. According to the definition of diopter, the reciprocal of focal length is diopter or refractive power, which varies linearly with the adjustment of the far point, i.e.,

$$D = 1/f. \tag{2}$$

Substituting (1) into (2) yields

$$D = 1 /kx \tag{3}$$

Hence, the measurement of the displacement x of the first lens system allows for the determination of an individual's diopter value.

The fixation visual pathway serves the purpose of achieving focus alignment by moving the lens to produce displacement x once focus alignment has been achieved. Consequently, the examinee obtains a clear visual target within their field of view, and this displacement signal is converted into a voltage signal. Subsequently, the electronic computer system processes the acquired data, digitally displays the measurements, and can print the data using a thermal printer. The correspondence between the fixation target and diopter value is illustrated in Figure 3.

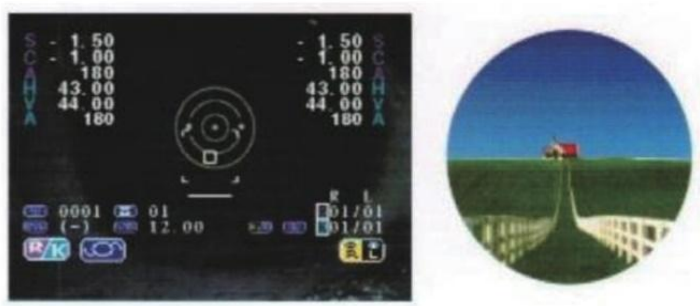

Fig. 3. Correspondence between fixation icon and diopter [3]

Automatic Astigmatism Testing. Ophthalmic optical biometry also facilitates automatic astigmatism testing, also known as automatic corneal curvature measurement. Examinees similarly maintain a stable head position by resting their chin and forehead on the instrument's support while fixating on an internal target within the instrument. The instrument measures corneal curvature by emitting light and analyzing the refraction of light as it traverses the cornea, quantifying the curvature of the cornea. Corneal curvature significantly influences the eye's refractive power and is associated with astigmatism. By measuring corneal curvature, ophthalmologists can ascertain irregular ocular shapes, as depicted in Figure 4, thereby determining the degree and orientation of astigmatism.

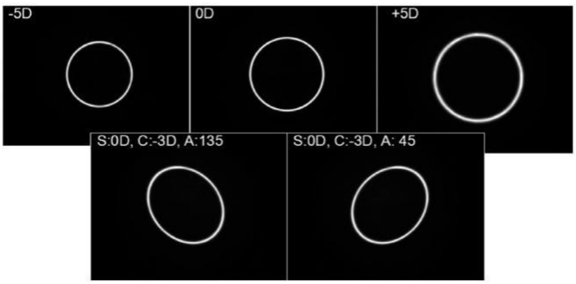

Fig. 4. Simulated eye ring image (Photo/Picture credit :Original)

2.4 Summary and Limitations

However, comprehensive optometry, computerized optometry, and astigmatism testing all exhibit certain limitations in the realm of vision assessment. These limitations encompass the impact of examinee cooperation, subjectivity in test results, and constraints imposed by testing equipment and specialized personnel. To mitigate these shortcomings, this paper proposes a contemporary image processing-based vision assessment method. Leveraging computer vision and artificial intelligence technologies, this method conducts automated, rapid, and precise vision assessment by capturing real-time images of the eye through cameras on smart devices such as smartphones and tablets. This approach offers a more convenient solution for vision health, augmenting ocular healthcare accessibility.

3 Deep Learning-Based Vision Prevention and Detection Methods

Traditional methods of vision assessment are constrained by location and equipment, limiting their ability to provide real-time monitoring of eye health. This paper introduces a novel vision assessment method utilizing the cameras of devices such as smartphones and tablets. By employing deep learning algorithms for image enhancement, clear eye images are obtained, allowing for real-time monitoring of individuals' eye conditions. This system serves as a preventive measure, issuing alerts when individuals overstrain their eyes.

3.1 System Structure

This paper proposes a straightforward eye vision assessment system. Pupil images are captured using a camera, and deep learning techniques are applied for image recognition. Threshold segmentation is then utilized to segment the image, ultimately calculating the refractive power of the eye. The system comprises hardware for image acquisition and software for digital image processing and refractive power calculation. The overall structure consists of both hardware and software systems, as depicted in Figure 5.

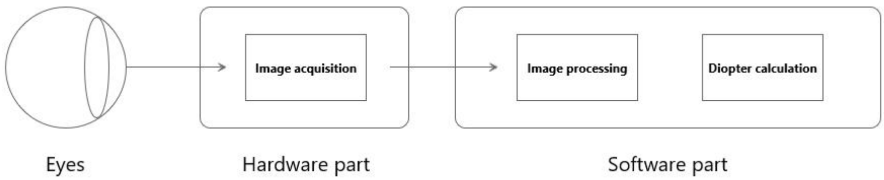

Fig. 5. Vision detection system structure (Photo/Picture credit: Original)

3.2 Eccentric Photography Refraction Technique

The fundamental principle behind screening for myopia and strabismus eye diseases using iris images is based on the Eccentric Photography Refraction Technique [3]. Light enters the eye and reflects from the retina, with the degree of deviation of the corneal reflection point varying with the eye's refractive state. Characteristic parameters of refractive power are exhibited in the pupil area and recorded. The captured iris images are shown in Figure 6.

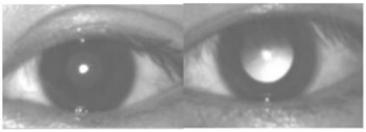

Fig. 6. Emmetropia and myopia images [4]

Emmetropic Eye: In images of emmetropic eyes, the corneal reflection point lies in the center of the pupil, with no crescent-shaped bright area beneath the pupil.
Myopic Eye: For patients with myopia, crescent-shaped bright areas appear in the lower or left portion of the pupil images (as shown in the figure). The ratio of the bright area's size to the pupil area indicates the degree of myopia.
Eccentric Photography Refraction (EPR) Figure 7 is a fundamental technique for assessing refractive errors like myopia and hyperopia based on the crescent-shaped images formed in the pupil. The refractive error can be quantified using the following formula:

$$D = E / (2 \cdot A \cdot R \cdot DF) \tag{4}$$

Where:
D represents the refractive error (diopters).
A is the distance from the eye's principal plane to the camera lens's principal plane.
R is the radius of the eye's pupil.
DF signifies the ratio of the height of the bright area formed by the highest reflected light ray to the diameter of the entire pupil.
E denotes the eccentric distance from the center of the point light source to the edge of the camera's aperture.

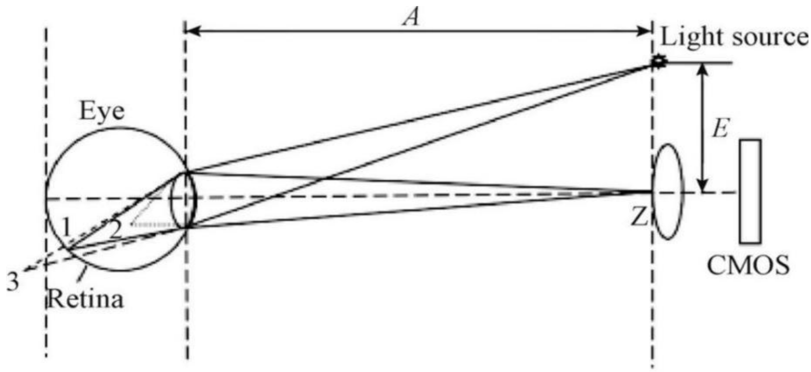

Fig. 7. The eccentric photography optometry system structure (Photo/Picture credit: Original)

3.3 Image Capture and Localization

The contraction of the pupil in response to light stimulation is a pupillary nerve reflex [4]. Electronic devices such as smartphones and tablets can locate and capture the pupil based on the reflection of light by the pupil. Images are taken from various angles, as shown in the Figure 8.

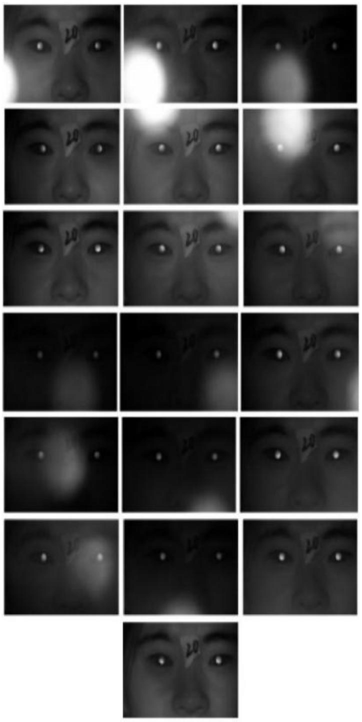

Fig. 8. Light reflection photography [5]

3.4 Faster R-CNN Image Detection

The complexity of object detection arises from two factors: the need to process a large number of candidate bounding boxes, and the fact that the initial localization of these bounding boxes is coarse and requires fine-tuning. In reference [5], a pupil center localization method based on Unet was proposed, which could rapidly locate the pupil but exhibited significant errors in the presence of occlusions. Reference [6], on the other hand, introduced an approach that integrates the proposal network (RPN) and detection network (Fast R-CNN) of Faster R-CNN into a unified network architecture to address the aforementioned issues more effectively. The RPN generates region proposals considered as potential object regions, and the Fast R-CNN detector employs these proposed regions for classification and bounding box refinement.

In this study, after preprocessing the images captured by the pupil reflection camera, a Faster R-CNN model is utilized for pupil recognition on facial images. The recognized pupils are then segmented, and the segmentation results, as shown in Figure 9, are provided for 19 different captured images corresponding to different illumination conditions. For the sake of clarity, only the left eye is selected as an example.

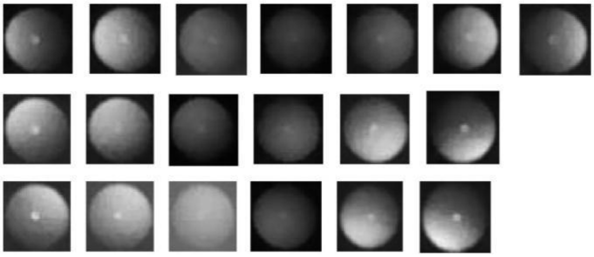

Fig. 9. Left eye test result (Photo/Picture credit :Original)

3.5 Image Processing and Segmentation

In the field of image processing, image recognition technology has been rapidly evolving, achieving continuous breakthroughs. The most classical approach for rapid localization primarily relies on the Hough transform, as discussed in references [7, 8]. However, this algorithm is computationally intensive, resulting in relatively long processing times. Therefore, the current demand is to identify suitable algorithms that can enhance the efficiency while maintaining the precision of pupil detection. Consequently, this paper employs deep learning, specifically Faster R-CNN, to ensure efficient and accurate pupil detection. Nonetheless, the acquired iris images cannot be directly utilized. Therefore, in the image processing stage, the images need to be enhanced. Traditional image denoising methods can be broadly categorized into two classes: spatial domain denoising and frequency domain denoising. This paper adopts the adaptive enhancement algorithm for uneven illumination images proposed by Li

Haoran et al. [9]. This method is primarily utilized to address the issue of non-uniform illumination in the acquired pupil images. Pupil images may be affected by variations in lighting, resulting in some regions of the image being too dark or too bright. Through this algorithm, pixel brightness and contrast are adaptively adjusted based on the local characteristics of the image, thereby enhancing image clarity and quality. This is crucial for subsequent image segmentation and vision testing, as clear pupil images better reveal eye features, aiding in accurate diopter measurement, as shown in Figure 10.

During the image segmentation stage, the paper applies the concept of the adaptive threshold-based iris segmentation algorithm proposed by Li Peng et al. [10]. Although this algorithm was originally designed for iris segmentation, this paper adapts it for edge detection and segmentation of pupil images. By leveraging the edge information of the pupil's distinct features in the image, the adaptive threshold algorithm separates the pupil from the background, resulting in a binary Figure 11.

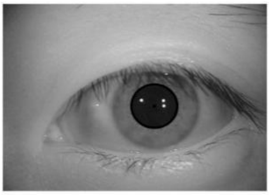

Fig. 10. Clear picture of eyes [9]

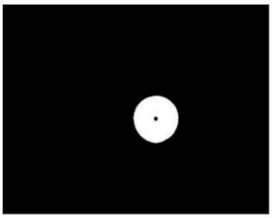

Fig. 11. Binarized image [10]

Combining these two steps with pupil images and myopia prevention allows for the extraction of clear pupil images from the captured eye images and precise edge segmentation. This provides a reliable data foundation for subsequent visual acuity assessment and prevention. By calculating refractive error and applying the theoretical formula of the eccentric photography refraction (EPR) method, it is possible to accurately determine whether the test subject has myopia and, furthermore, provide tailored recommendations for myopia prevention.

3.6 Feature Parameter Extraction

In this paper, the key criterion for screening myopia and strabismus is the crescent-shaped bright area and the eye deviation caused by corneal reflection points. When myopia patients are exposed to the light source emitted by the pupil camera, the incoming light converges in front of the retina, forming a crescent-shaped area within the pupil image [11]. The position of the light source within the camera and the aperture is illustrated in the diagram. In the reflected images obtained by the pupil camera, a crescent-shaped area is formed inside the pupil, creating a clear boundary line between the two sides. Based on clinical experiments, there exists a proportional relationship within a certain range between the degree of myopia in eye disease patients and the brightness boundary line produced by the crescent-shaped area within the pupil. This relationship indicates that as the degree of myopia increases, the proportion of the crescent-shaped area rises, resulting in an increase in the height of the brightness boundary line. Conversely, as the degree of myopia decreases, the proportion of the crescent-shaped area decreases, leading to a decrease in the height of the brightness boundary line. The myopia eye model is depicted in the Figure 12 below.

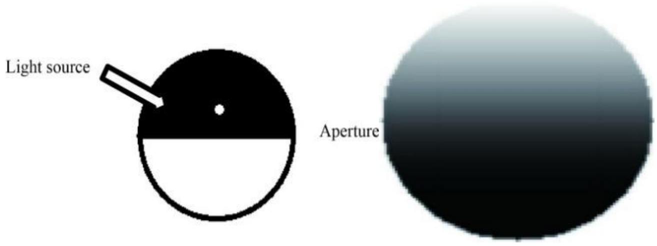

Fig. 12. Myopia model (Photo/Picture credit: Original)

This paper employs a method of feature extraction for the pupil area in eye images by calculating the area of its connected components. The procedure for feature extraction of the pupil region in the eye images is outlined as follows:

The eye images, pre-processed in advance, are binarized by adjusting the threshold parameters. Subsequently, a threshold segmentation is applied to these binarized eye images, and the pupil region is subjected to feature extraction. The pupil region is then labeled as the largest connected component.

The largest connected component within the eye image is identified and marked, while all other regions outside this component are set to 0. Based on the extracted pupil region in the eye image, the area of this connected component is calculated, as illustrated in the Figure 13.

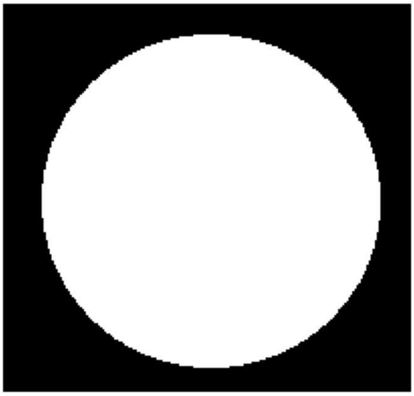

Fig. 13. Extraction of pupil area (Photo/Picture credit: Original)

Regarding the feature extraction method for the crescent-shaped bright area in the pupil images, the steps are as follows: Enhancement techniques, such as adjustments to brightness and contrast, are individually applied to the pre-processed the pupil image. The enhanced images are then subjected to binarization to initially extract the crescent-shaped regions within the pupils.

The sizes of connected components are extracted from the images obtained in step 1). Let S denote the area of the pupil region, and all connected regions with an area greater than S/100 are marked as the smallest connected component.

The smallest connected component is identified, and all regions outside this component are set to 0, facilitating the extraction of corneal reflection points, as shown in the Figure 14.

Connected component size extraction is again applied to the images obtained in step 1), with the largest connected component in the image being marked while the other connected components are set to 0. The crescent-shaped regions corresponding to the pupil images are separately extracted, and the area of this connected component is determined, as illustrated in the Figure 15.

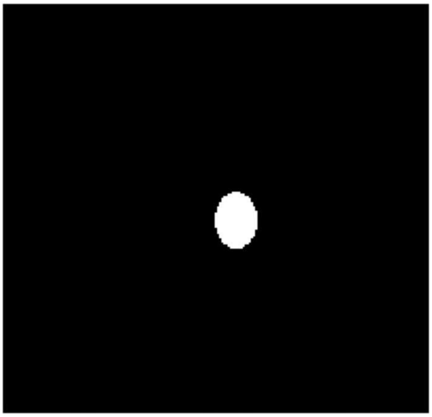

Fig. 14. Corneal reflection point region extraction (Photo/Picture credit: Original)

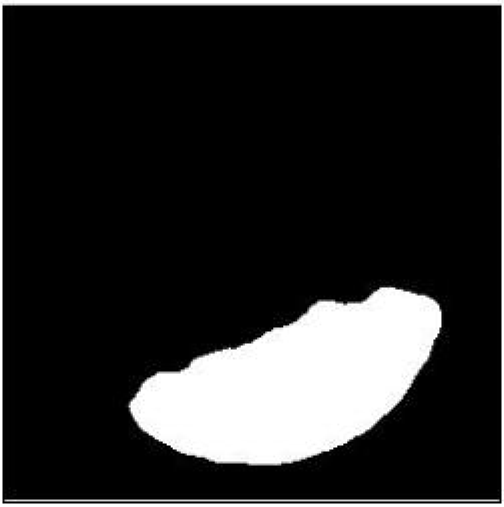

Fig. 15. Crescent region extraction (Photo/Picture credit: Original)

3.7 Results

A test case with an actual refractive power of 250° in the left eye is selected, and the measurement results are presented in the Table 1. The test values closely align with the actual values.

Table 1. This method measures the degree of myopia in the left eye

Count	1	2	3	4	5	6
Detection value	220	309	233	239	224	242
Error value	30	59	17	11	26	8

Through these steps, a smartphone-based method for myopia prevention and detection can be realized. The validity of the prediction relies on the efficiency and accuracy of deep learning techniques, combined with the advantages of multiple algorithms. However, considering individual differences and lighting conditions, further validation and verification may be required in clinical experiments.

4 Conclusion

In the current era of widespread adoption of mobile smart devices, the application of deep learning-based methods for myopia prevention and detection to portable electronic devices such as smartphones and tablets presents a range of unique advantages. Firstly, the convenience of this approach is noteworthy. Nowadays, people carry smartphones and similar devices with them wherever they go, enabling on-the-spot vision assessment. Users can easily conduct vision tests at home, school, or work by simply capturing facial photos with their devices, eliminating the need for cumbersome visits to medical facilities. Secondly, the use of deep learning technology allows for rapid processing of image data, ensuring real-time results. Users can obtain accurate test results in a short time, facilitating the early detection of vision issues and the implementation of corresponding preventive measures. Furthermore, conducting vision tests through devices like smartphones reduces the costs associated with traditional healthcare facilities, alleviating the economic burden. The method's widespread accessibility is also a significant advantage, as nearly everyone possesses a mobile device, making it possible to promote awareness of visual health. Personalized analysis further enhances the value of this method by providing customized vision data and healthcare recommendations based on individual pupil images and characteristics. Most importantly, this approach encourages the formation of a prevention mindset. With real-time data acquisition, users can make targeted adjustments to their eye usage habits, effectively preventing the deterioration of myopia issues.

Looking ahead, the research directions in the field of myopia prevention and control using artificial intelligence and visual technology are extensive. As technology continues to advance, developers can further improve algorithms to enhance detection accuracy and even achieve real-time remote vision monitoring through mobile applications. While this method has some limitations, it offers a new perspective on promoting visual health and provides valuable insights for future research.

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