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Artificial Intelligence, Cybersight Detection of Diabetic Retinopathy in the Elderly in Vietnam

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Abstract

Diabetic retinopathy (DR) is a highly prevalent cause of vision loss worldwide. Detection of DR requires substantial human resources and high medical costs. Therefore, the use of diagnostic software has been recently explored. The study aimed to assess the results of DR diagnoses by Cybersight, an artificial intelligence software. A total of 1,012 patients with type 2 diabetes mellitus (1,943 eyes) with a mean age of 74.61 ± 6.73 years were included. Comprehensive demographic and clinical data were gathered, and all patients underwent color fundus photography following Cybersight's standardized protocols. The study compared Cybersight's accuracy with that of ophthalmologists in identifying key DR lesions, including retinal microvascular changes, exudates, hemorrhages, the diagnosis and staging of DR, using sensitivity, specificity, and weighted Kappa metrics. The prevalence of DR was 16.2%. A high level of agreement was found between Cybersight and ophthalmologists in DR diagnosis, with a sensitivity of 85.0%, specificity of 95.8%, and a weighted Kappa of 0.78. The presence of cataracts and the degree of pupil dilation notably impacted on the accuracy of DR diagnosis. The results have important implications for the potential application of Cybersight as a low-cost and effective tool for diabetic eye screening.

Keywords: *Cybersight; artificial intelligence; diabetes; diabetic retinopathy*

1. Introduction

Diabetes mellitus (DM) is a prevalent chronic disorder that affects glucose metabolism. It is estimated that, as of 2021, there were 530 million people worldwide living with diabetes, with projections indicating this number could rise to 1.3 billion by 2050 (Ong et al., 2023). In Vietnam, the incidence of DM has surged to an estimated 7 million individuals, 50% of whom remain undiagnosed and untreated. By 2022, the prevalence of DM in the population had reached 7.3%, compared to 5.4% in 2012 (Phan et al., 2022).

Type 2 diabetes mellitus (T2DM) is characterized by a few noticeable symptoms until it progresses to a severe stage (Manosroi et al., 2023). Without prompt detection and intervention, patients become vulnerable to potentially life-threatening complications, including infections, cardiovascular disorders, renal failure, nerve damage, and eye conditions (Farmaki et al., 2020). Diabetic retinopathy (DR) stands out as a common complication that can lead to vision impairment and blindness among people with T2DM. A 2013 study in 33 countries revealed that the prevalence of DR in cases with known T2DM and newly diagnosed T2DM was 27.9% and 10.5%, respectively. Notably, this rate was higher in developing countries compared to developed countries (Ruta et al., 2013).

DR poses a significant risk of cardiovascular disease and mortality among individuals with T2DM. Therefore, early screening and diagnosis of DR are crucial (Xu et al., 2020). In recent years, numerous studies have explored the potential of artificial intelligence (AI) in medical applications, including diagnosis, disease monitoring, and treatment recommendations across various clinical conditions (Pechprasarn et al., 2024; Srisubat et al, 2023; Pechprasarn et al., 2023; Ruamviboonsuk, 2022; Ausawalaithong et al., 2018; Yang, & Garibaldi, 2015). In the field of ophthalmology, AI has shown promise in detecting diseases such as retinopathy of prematurity, age-related macular degeneration, and diabetic retinopathy (Cole et al., 2022; Vought et al., 2023).

Despite the potential benefits of AI in diagnosing DR, its widespread implementation for initial detection is still limited (Gu et al., 2024; Lupidi et al., 2023; Uy et al., 2023). In Vietnam and many developing countries where DM prevalence continues to escalate, most patients receive treatments focused on glycemic management but lack systematic screening for complications, including ophthalmic conditions, due to constraints such as a shortage of ophthalmologists and limited resources. As a result, there is a growing need for accessible and efficient measures to support early detection of DR (Dimore et al., 2023).

2. Objectives

This study aims to evaluate the effectiveness of Cybersight, an AI software, in detecting DR among people with DM in an outpatient setting by comparing the performance of Cybersight with ophthalmologists' evaluations.

3. Materials and Methods

3.1 Study Design and Sample

The present study was approved by the Scientific Committee of Hanoi Medical University on August 29, 2022, and obtained ethical approval from the Ethics Committee of Hanoi Medical University (No. IRB-VN01.001/IRB00003121/FWA 00004148) on April 4, 2023. All patients with T2DM who visited the Ophthalmology or Endocrinology clinics at Thai Nguyen National Hospital in Vietnam from April to July 2023 were selected for inclusion. We excluded patients younger than 40 years of age, as well as individuals with prior corneal transplantation, acute ocular surface diseases, or media opacity that could interfere with fundus photography, such as cataracts graded 3-4. The final analysis included 1,012 individuals.

3.2 Measurements

Diagnosis of DR was based on the International Council of Ophthalmology Guidelines, which include proliferative and non-proliferative DR, with the latter further classified into mild, moderate, and severe categories (Wong et al., 2018).

Table1 International Classification of Diabetic Retinopathy

Diabetic retinopathy	Findings Observable on Dilated Ophthalmoscopy
No apparent DR	No abnormalities
Mild nonproliferative DR	Microaneurysms only
Moderate nonproliferative DR	Microaneurysms and other signs (e.g., dot and blot hemorrhages, hard exudates, cotton wool spots), but less than severe nonproliferative DR
Severe nonproliferative DR	Moderate nonproliferative DR with any of the following: intraretinal hemorrhages (≥20 in each quadrant); definite venous beading (in 2 quadrants); intraretinal microvascular abnormalities (in 1 quadrant); and no signs of proliferative retinopathy
Proliferative DR	Severe nonproliferative DR and 1 or more of the following: neovascularization, vitreous/preretinal hemorrhage

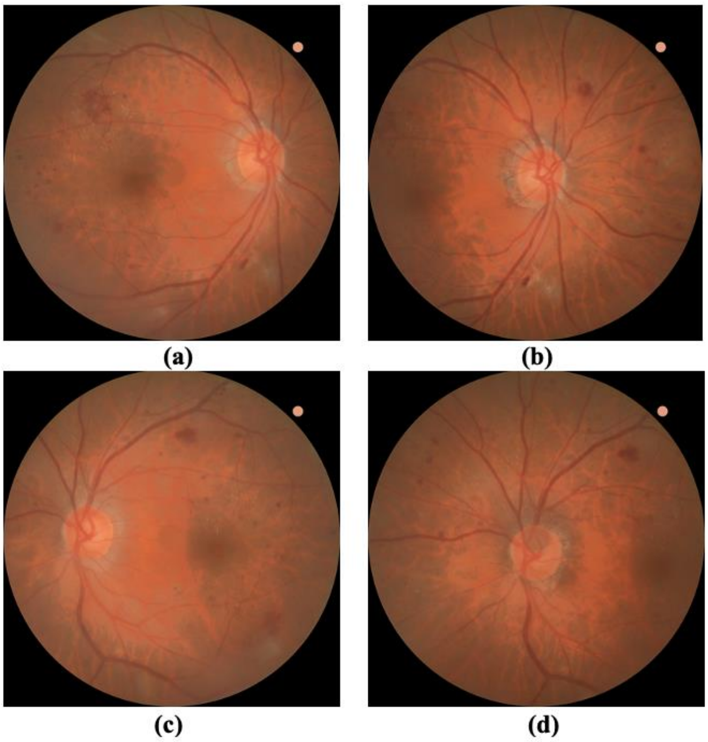

Figure 1 Fundus images. (a) Macular-centered right eye, (b) Optic disc-centered right eye, (c) Macular-centered left eye, (d) Optic disc-centered left eye.

All patients underwent color fundus photography following the standards as determined by Cybersight, a cloud-based AI software developed by Orbis International. Cybersight is a not-for-profit telemedicine and e-learning platform designed to advance the knowledge, skills, and expertise of eye health professionals worldwide (Mathenge et al., 2022; Whitestone et al., 2024). For each eye, two color fundus images were taken: one centered on the optic disc and the other centered on the macula. These images were then uploaded to the Cybersight AI software for DR diagnosis (Figure 1). The ophthalmologist did not see the result of AI interpretation before examining the DM patients. Two ophthalmologists were involved in examining and diagnosing the DR patients. One additional ophthalmologist was responsible for taking fundus pictures and uploading them to the web. Subsequently, we compared the accuracy in detecting key lesions such as retinal microvascular changes, retinal exudates, hemorrhages, cataracts, and pupil dilation level, as well as staging of DR between Cybersight and ophthalmologists.

The respondents' demographic and clinical information was collected, including age (40-60 years, >60 years); sex (male and female); duration of DM (<5 years, 5-10 years, and >20 years); comorbidities (cardiovascular diseases, dyslipidemia, Stroke, Obesity, and chronic kidney disease). Glycemic control was classified as good with HbA1c < 7% and poor when HbA1c ≥ 7% (American Diabetes Association, 2022). Visual acuity was classified as normal vision (≥ 20/40), mild vision impairment (≥ 20/70 to < 20/40), moderate vision impairment (≥ 20/200 to < 20/70), severe vision impairment (≥ 20/400 to < 20/200), and blindness (≥ 20/1200, light perception < 20/200, or no light perception) (World Health Organization, 2019). Pupil dilation was classified as good (≥ 6 mm) and poor (< 6 mm) (Feldman et al., 2024). Cataract grading was classified into Grade 1, where the nucleus is clearer than the anterior/posterior sections, and Grade 2, where the nucleus is as opaque as the anterior/posterior sections throughout (World Health Organization, 2002).

3.3 Statistical Analysis

Data from the study were processed using SPSS 20.0, STATA 11, and OPEN EPI 2.4. Continuous variables are presented as mean and standard deviation, while categorical variables as frequencies and proportions. DR diagnostic performance by Cybersight was evaluated with sensitivity, specificity, and weighted Kappa values (Cohen, 1968).

4. Results

4.1 Patients' s Characteristics

A total of 1,012 patients with T2DM (1,943 eyes) participated in this study. Table 1 provides the demographic and clinical characteristics of the cohort. Mean age of the patients was 74.6 ± 6.7 years. Only 3% of the patients were aged between 40 and 60 years, while the majority (97%) were over the age of 60 years. 50.8% of the cohort was female. Regarding disease duration, 39.43% of patients had the disease for 5 to 10 years, 29.64% for 10 to 20 years, 23.52% for less than 5 years, and 7.41% for more than 20 years. The most prevalent comorbidities were cardiovascular disease, which affected 854 patients (84.4%), and dyslipidemia, affecting 562 patients (55.4%). Among the cohort, 439 patients exhibited good glycemic control (43.4%), while 573 patients had poor glycemic control (56.6%). Severe vision impairment was the most common visual acuity classification, observed in 49.3% of the patients.

4.2 Diagnosis of Diabetic Retinopathy

In Table 3, 314 out of 1,943 eyes (16.2%) were diagnosed with DR. The most common lesions were microvascular damage (14.2%), exudates (8.0%), and hemorrhages (10.4%). Among the 254 eyes with nonproliferative diabetic retinopathy (NPDR), 20.5% exhibited mild NPDR, 57.5% had moderate NPDR, and 22.0% had severe NPDR. Sixty eyes (19.1%) exhibited proliferative diabetic retinopathy (PDR).

Table 2 Demographic and Clinical Characteristics of the Cohort

Characteristic	N (%)
Age	
40 – 60	30 (3.0)
> 60	982 (97.0)
Sex (Female)	514 (50.8)
Duration of Diabetes mellitus	
< 5 years	238 (23.52)
5-10 years	399 (39.43)
10-20 years	300 (29.64)
> 20 years	75 (7.41)
Comorbidities	
Cardiovascular diseases	854 (84.4)
Dyslipidemia	562 (55.4)
Stroke.	92 (9.1)
Obesity	76 (7.5)
Chnonic kidney disease	185 (18.3)
Glycemic control	
Good*	439 (43.4)
Poor**	573 (56.6)
Visual acuity	
Normal vision (≥ 20/40)	85 (4.2)
Mild vision impairment (≥20/70 to <20/40)	326 (16.1)
Moderate vision impairment (≥ 20/200 to <20/70)	360 (17.8)
Severe vision impairment (≥ 20/400 to <20/200)	997 (49.3)
Blindness (≥ 20/1200, LP (+) to <20/200, NLP) ***	256 (12.6)

* HbA1c < 7%
**HbA1c ≥ 7%
***LP: Light perception, NLP: No light perception

Table 3 Diagnosis of diabetic retinopathy by Cybersight AI software

Diagnosis	N (%)
Microvascular Damage	
Yes	276 (14.2)
No	1667 (85.8)
Exudates	
Yes	155 (8.0)
No	1788 (92.0)
Hemorrhages	
Yes	202 (10.4)
No	1741 (89.6)
Diabetic Retinopathy	
Yes	314 (16.2)
Nonproliferative	254 (80.9)
Proliferative	60 (19.1)
No	1629 (83.8)
Stages of Nonproliferative Diabetic Retinopathy	
Mild	52 (20.5)
Moderate	146 (57.5)
Severe	56 (22.0)

Table 4 Performance of Diabetic Retinopathy Diagnosis between Cybersight AI and Ophthalmologists

Diagnosis	Sensitivity (%)	Specificity (%)	Weighted Kappa
Microvascular damage	96.3	90.6	0.50
Exudates	64.8	99.2	0.74
Hemorrhages	92.1	97.1	0.81
Diabetic Retinopathy	85.0	95.8	0.78
Cataracts			
Grade 1	90.1	84.3	0.82
Grade 2	75.0	88.4	0.68
Dilated pupil level			
Good level	91.6	95.8	0.83
Poor level	85.6	98.2	0.78
Stages of diabetic retinopathy			
Non diabetic retinopathy	95.0	85.0	0,75
Mild nonproliferative diabetic retinopathy	15.1	98.0	0.18
Moderate nonproliferative diabetic retinopathy	68.9	94.9	0.48
Severe nonproliferative diabetic retinopathy	41.0	99.0	0.43
Proliferative	65.1	97.9	0.38

Table 5 Comparing the accuracy of CyberSight AI diagnosis with that of ophthalmologists

Ophthalmologists / Cybersigh AI	Non - DR	Mild NPDR	Moderate NPDR	Severe NPDR	Proliferative	Total
Non - DR	**1590**	34	5	0	0	1629
Mild NPDR	28	**17**	4	3	0	52
Moderate NPDR	36	46	**59**	5	0	146
Severe NPDR	0	3	12	**32**	9	56
Proliferative	22	10	6	5	**17**	60
Total	1676	110	86	45	26	**1943**

Abbreviations: DR, diabetic retinopathy; NPDR, non-proliferative diabetic retinopathy

Table 6 Comparison of some recent studies using artificial intelligence software for diagnosed diabetic retinopathy

Study	Software	Sensitivity (%)	Specificity (%)	Weighted Kappa
(Bellemo et al., 2019)		92.3	89.0	
(Ipp et al., 2021)	EyeArt	95.5	85	
(Malerbi et al., 2022)	Phelcom Eyer	97.8	61.4	
(Vought et al., 2023)	EyeArt	74	87	0.69
(Whitestone et al., 2024)	CyberSight	92	85	

4.3 Comparison of Diabetic Retinopathy Detection Rate between Cybersight AI and Ophthalmologists

From Table 4, the comparison of DR diagnostic accuracy between Cybersight and ophthalmologists demonstrates a high level of agreement. The sensitivity for diagnosing DR was 85.0%, with a specificity of 95.8% and a weighted kappa of 0.78. Specifically, the "non-diabetic retinopathy" stage showed a high level of agreement, with a sensitivity of 95%, a specificity of 85%, and a weighted kappa of 0.75. In contrast, the "mild nonproliferative diabetic retinopathy" stage had the lowest agreement, with a sensitivity of 15.1%, specificity of 98%, and a weighted kappa of 0.18. Other stages of diabetic retinopathy exhibited weighted kappa values ranging from 0.38 to 0.48. Among the specific types of retinal damage, hemorrhages demonstrated the highest level of diagnostic concordance, with a sensitivity of 92.1%, specificity of 95.8%, and a weighted kappa of 0.81.

Furthermore, patients with grade 1 cataracts exhibited a sensitivity of 91% and a specificity of 85%, with a weighted kappa of 0.82. In contrast, patients with grade 2 cataracts showed a sensitivity of 75%, a specificity of 88.4%, and a weighted kappa of 0.68. Regarding pupil dilation, patients with a higher level of dilation demonstrated greater diagnostic concordance compared to those with a poorer level. Specifically, the sensitivity for patients with good pupil dilation was 91.6%, with a specificity of 95.8% and a weighted kappa of 0.83 (Table 4).

Table 5 presents the confusion matrix for the diagnosis of DR, including non-DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative DR. The concordance rate between Cybersight AI and ophthalmologists was 1715 out of 1943, yielding a rate of 88.3%.

5. Discussion

With the rapid increase in the number of patients with DM, the control of systemic complications, including those in the eyes, still faces many difficulties, particularly the lack of ophthalmologists. Therefore, it is important for endocrinologists to make an initial preliminary classification using AI, and the model should be widely replicated in diabetes clinics.

In our study, we found that the prevalence of DR was 16.2%, with 80.9% classified as NPDR and 19.1% classified as proliferative DR. This finding is comparable to other studies, including one by Bhaskaranand and colleagues where DR was found in 19.3% among 101,710 patients with DM using the EyeArt System for diagnosis (Bhaskaranand et al., 2019). According to Abràmoff et al., (2018) the prevalence of DR was 21.9% among 892 patients (Abràmoff et al., 2018). In a study conducted by Vought and colleagues, the incidence of DR detected by AI was 81% when analyzed across 124 eyes. However, this study included patients already diagnosed with DR for re-evaluation using the EyeArt software, resulting in a higher DR detection rate compared to our study (Vought et al., 2023). Another study showed that 16.3% of patients with DR were detected by AI, with a sensitivity of 90.79%, a specificity of 98.5%, and an area under the curve of 0.964, as compared with the ophthalmologist's diagnosis (He et al., 2020).

When assessing the agreement of diagnostic outcomes for DR between the Cybersight AI software and ophthalmologists, we observed a substantial level of similarity with a weighted Kappa of 0.78, a sensitivity of 85%, and specificity of 95.8%. Notably, our study yielded results akin to those reported by Bellemo et al., (2019) and Ipp et al., (2021), highlighting the AI system's heightened sensitivity and specificity in DR detection, particularly excelling in diagnosing beyond mild DR. In Malerbi's study involving 824 individuals with type 2 diabetes, the sensitivity and specificity of the artificial intelligence results were 97.8% and 61.4%, respectively (Malerbi et al., 2022). However, in this study, the author utilized artificial intelligence in conjunction with a handheld smartphone-based retinal camera. In a separate study conducted by Vought et al., (2023), there was a 79% overall agreement in the diagnosis of DR, with a Kappa value of 0.69 (95% confidence interval 0.61-0.77), signifying substantial agreement in diagnostic concordance. However, when considering AI's disease stage classification for individual patients with diabetic retinopathy, the sensitivity and weighted Kappa were not as high (Table 4). Our findings differ from an earlier study that reported a sensitivity of 95.5% and a specificity of 85.0% for AI detection of DR at each stage of the disease (Ipp et al., 2021). In another study comparing AI with human grading, the sensitivity of the AI for referable DR was 92% and the specificity was 85% (Whitestone et al., 2024). In our study, the majority of patients exhibited poor visual acuity (Table 2), with a higher mean age of 74.61 ± 6.73 years compared to 53.9 ± 15.2 years in Ipp's research. Furthermore, our patients presented with diverse levels of cataracts, which may have influenced the quality of the fundus photos utilized for AI disease stage classification.

In the evaluation of DR lesions, Cybersight's sensitivity for detecting exudates was determined to be 64.8%. Several factors could contribute to this lower-than-desired sensitivity level. Firstly, variability in exudate characteristics, such as differences in appearance, size, and location within the eye, can pose challenges for AI in accurately detecting all types of exudates, especially since the software only requires two images of the central posterior retina. This limitation may result in certain types of exudates being overlooked. Additionally, sensitivity may be influenced by the threshold settings used to identify exudates, as adjusting these settings can impact the balance between true positives and false negatives, thereby affecting sensitivity levels. Notably, in previous studies utilizing Cybersight AI software for DR diagnosis, the specific issues of variability in exudate characteristics and the influence of threshold settings on sensitivity were not explicitly addressed by the authors, highlighting areas for further investigation and improvement in diagnostic accuracy (Whitestone et al., 2024).

Furthermore, our study revealed that the severity of cataracts and the degree of pupil dilation influenced the performance of the AI system in DR detection. James Rice showed that the severity of cataracts can impede the comprehensive examination or treatment of the retina in patients with diagnosed or suspected severe non-proliferative and proliferative DR (Rice, 2011). Therefore, we excluded patients with cataract grades 3 and 4, even though ophthalmologists are still able to diagnose DR in such instances. Based on Ronald Klein's research, pharmacological dilation of the pupils enhances the sensitivity of detecting DR twofold compared to an examination of the retina without dilation (Klein et al., 1985). In our study, we observed that a satisfactory level of pupil dilation was associated with higher sensitivity, specificity, and weighted Kappa values compared to cases with inadequate pupil dilation when assessing the concordance between the AI system's diagnosis and that of ophthalmologists. This finding aligns with real-world scenarios where the diagnosis of DR in clinical settings, as well as through the evaluation of fundus images using the CyberSight AI software, exhibit similar trends. Overall, the accuracy of CyberSight AI was 88.3%, indicating a high level of reliability in its diagnostic capabilities.

The effectiveness of using AI in early diagnosis and prevention of DR has been demonstrated in many studies. Previous studies have reported the results of applying AI in screening for DR in Vietnam and primary care clinics for DR patients (Cao et al., 2023; Gilbert, & Sun, 2020; Gu et al., 2024; Lupidi et al., 2023).

Several studies have shown that using point-of-care DR screening with the AI system is especially helpful for the diagnosis of DR and triage of patients with T2DM. In a study of 893 patients with DM, the authors found that 31.1% needed to see an ophthalmologist. Therefore, most patients did not require referrals, reducing the diagnostic burden on eye care specialists and saving time for patients (Ipp et al., 2021). AI could also help reduce the cost of screening for DR. One study in Scotland showed a 46.7% cost reduction by replacing first-level human assessment with AI assessment in a national screening program for DR. Another study from the United Kingdom reported cost savings of 12.8-21.0% (Scotland et al., 2007; Tufail et al., 2017).

This study exhibits various strengths, notably its execution in a well-equipped large hospital setting, enabling the utilization of modern equipment. The inclusion of a substantial number of patients with T2DM` facilitated the selection of a large sample size for robust statistical analysis. Furthermore, classifying DR according to the latest international guidelines enhances the study's clinical relevance and comparability. However, a significant limitation of this research lies in its exclusive focus on patients with T2DM, thereby restricting the generalizability of the findings across all DM types. Additionally, excluding eyes with severe cataracts due to the software's limitations in generating accurate results represents a notable drawback. Nonetheless, the study reaffirms the early diagnostic efficacy of AI software, underscoring its utility in the prompt detection of DR.

6. Conclusion

While AI and ophthalmologists were working separately, this study demonstrated the reliable and precise clinical efficacy of the Cybersight AI Software in autonomously detecting DR without ophthalmologist intervention. Implementing this AI system holds promise for enhancing DR screening and monitoring among individuals with T2DM by non-ophthalmic healthcare providers, facilitating accurate identification of DR for timely referrals in clinical settings. These findings underscore the practicality of this automated tool for endocrinologists, diabetologists, and ophthalmologists in addressing the escalating need for DR screening and monitoring.

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