The artificial intelligence driven on the development of diabetic retinopathy prognostic scoring tool among type 2 diabetes mellitus patients: A review

Muhammad Muaz Shahriman Teruna, MPH[1], Tajul Rosli Razak, PhD[2], Siti Munira Yasin, DrPH[1], Abdullah Ashraf Rafique Ali, MOPH[3], Mohamad Rodi Isa, DrPH[1]

[1]Department of Public Health Medicine, Faculty of Medicine, Universiti Teknologi MARA, Sungai Buloh, Selangor, Malaysia, [2]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia, [3]Department of Ophthalmology, Faculty of Medicine, Universiti Teknologi MARA, Sungai Buloh, Selangor, Malaysia

ABSTRACT

Introduction: Diabetic retinopathy, a major microvascular complication of type 2 diabetes mellitus, remains a leading cause of preventable blindness worldwide. Early identification of individuals at high risk is essential, yet conventional screening systems are limited by workforce shortages and delayed detection. Artificial intelligence, particularly machine learning, offers substantial potential to support prognostic scoring tools capable of predicting the development of diabetic retinopathy. This review summarises current evidence on AI-driven prognostic models for diabetic retinopathy among adults with type 2 diabetes mellitus.

Materials and Methods: A comprehensive PubMed search using Medical Subject Headings and free-text terms related to "Diabetic Retinopathy," "Type 2 Diabetes Mellitus," "Artificial Intelligence," "Machine Learning," and "Prognostic Model" was conducted. Original studies involving adults with T2DM that developed or evaluated AI- or ML-based prognostic or risk-scoring tools for DR were included. Extracted data included study design, sample size, artificial intelligence methods, predictors, and model performance, and were synthesised narratively.

Results: From 759 records, five studies met the inclusion criteria. Extreme Gradient Boosting consistently demonstrated the highest predictive performance, with area under the curve values between 0.803 and 0.966. Support Vector Machine also performed well in smaller cohorts. Key predictors across studies included HbA1c, duration of diabetes, renal function markers, blood pressure, lipid profile, and body mass index.

Conclusion: AI-driven prognostic tools show strong potential to enhance early diabetic retinopathy risk prediction. However, broader external validation and population-specific calibration are needed before routine clinical adoption.

KEYWORDS:
Type 2 Diabetes Mellitus, Diabetic Retinopathy, Prognostic Model, Artificial Intelligence, Risk Prediction

INTRODUCTION

Diabetic retinopathy (DR) is a significant and growing global health concern, recognized as a leading cause of vision loss among working-age populations. DR is a microvascular complication of diabetes mellitus, characterized by damage to the retinal blood vessels due to prolonged hyperglycaemia.[1] The global prevalence of DR among individuals with diabetes varies widely and is influenced by geographic location, socioeconomic status, and healthcare access. Recent studies estimate that approximately 34% to 40% of diabetic individuals worldwide are affected by DR, with this prevalence expected to rise alongside increasing rates of diabetes.[2] According to the National Diabetes Registry (NDR) of Malaysia, the proportion of patients diagnosed with DR increased from 10.6% in 2019 to 11.5% in 2020, illustrating a growing number of individuals at risk of visual impairment due to this complication.[3]

In Malaysia, DR screening is integrated into primary care, where all patients with diabetes undergo annual retinal assessment using non-mydriatic fundus cameras, which provide clearer images and higher diagnostic confidence compared to direct ophthalmoscopes.[4] Retinal images captured at Klinik Kesihatan are reviewed and will be graded as no DR, non-proliferative DR (mild to severe), proliferative DR, or diabetic macular oedema (DME). Patients with normal findings continue yearly screening, those with mild or moderate NPDR are referred non-urgently to ophthalmology, while severe NPDR, PDR, or suspected DME requires urgent referral.[5] However, constraints such as limited trained health personnel, equipment costs, and geographic accessibility challenges reduce DR screening efficiency.[6-8] Consequently, high-risk patients may remain unidentified until advanced stages of disease.

The use of artificial intelligence (AI), particularly machine learning (ML) models, for predicting and assessing the risk of DR among patients with type 2 diabetes mellitus (T2DM) has gained significant traction in recent years. ML models such as logistic regression, support vector machines, and deep learning techniques have shown promise in identifying risk factors associated with DR in T2DM patients. The performance of these models is often evaluated in terms of

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Corresponding Author: Mohamad Rodi Isa
Email: rodi@uitm.edu.my

accuracy, sensitivity, and area under the curve (AUC) metrics. For example, several studies reported construction and assessment of models that achieve accuracy rates exceeding 80% when leveraging extensive datasets.[9] Furthermore, previous study done noted that certain ML algorithms offer superior prediction capabilities compared to traditional clinical methods due to their ability to uncover complex patterns within the data.[10]

In the context of Malaysia, leveraging AI-driven tools could address significant challenges faced in diabetic care. The Malaysian healthcare system, despite its advancements, still deals with barriers such as limited resources and disparities in healthcare access.[11] AI-driven tools can serve to mitigate these challenges by providing cost-effective screening solutions that are both accurate and scalable to the needs of the population.[12] The pressing need to address the high prevalence of DR among T2DM in Malaysia, and with the advancements in AI technology for disease management, makes this review both timely and critical. The aim of this review is to summarise existing evidence on AI-driven DR prognostic scoring models.

MATERIALS AND METHODS

A comprehensive search strategy was developed for the PubMed database using a combination of Medical Subject Headings (MeSH) and free-text terms. The key MeSH terms included "Diabetic Retinopathy," "Diabetes Mellitus, Type 2," "Artificial Intelligence," "Machine Learning," and "Deep Learning." These were combined with free-text keywords such as "prognostic model," "prediction tool," "risk score," "scoring system," "survival prediction," "algorithm," and "AI-driven model." Boolean operators (AND/OR) were used to refine retrieval, and truncation was applied where appropriate to capture variations of each term. The search strategy was designed to ensure optimal sensitivity and specificity for studies focusing on AI-driven prognostic or risk-scoring tools specifically targeting DR outcomes in T2DM populations. No date restrictions were initially imposed to allow broad coverage of emerging and foundational literature. However, only articles published in English and involving human subjects were included.

Study selection was guided by predefined eligibility criteria. Articles were included if they (i) involved adults diagnosed with T2DM, (ii) focused on DR as an outcome of interest, (iii) applied artificial intelligence, machine learning, or deep learning approaches to develop, validate, or evaluate prognostic or risk-scoring tools for DR, and (iv) were original research articles (e.g., cohort, cross-sectional, modelling studies, algorithm-development papers). Studies were excluded if they focused solely on image-based DR classification without prognostic intent, did not differentiate T2DM from other diabetes types, lacked AI-based methodological components, or were review articles, case reports, editorials, or conference abstracts.

All search results were screened by title and abstract, followed by full-text assessment of potentially relevant articles. Data extraction focused on study characteristics (authors, country, sample size, study design), AI methods used (algorithm types, predictors, model architecture), performance metrics, and relevance to DR prognostic. Extracted information was synthesized descriptively and thematically to capture methodological trends, model performance, clinical applicability, and gaps in the existing evidence base.

RESULTS

The search initially yielded 759 articles from the PubMed database. After applying the free full-text filter, 405 articles were available for further assessment. Title and abstract screening of these records narrowed the pool to 77 studies that appeared to align with the inclusion criteria of this review. Following a comprehensive full-text review, five studies were identified as specifically reporting on the development of AI-driven DR prognostic scoring tool. These five studies were subsequently included in the analysis for this review. Table I presents the summary of the key points extracted from the papers.

Across the five included studies, AI and ML models demonstrated strong potential in predicting DR among adults with T2DM. Sample sizes varied significantly from small clinical cohorts of fewer than 400 participants to very large datasets exceeding 32,000 hospital records. Despite this variation, all studies consistently showed that ML approaches outperform traditional statistical modelling when applied to complex, multi-variable clinical datasets. Overall, Extreme Gradient Boosting (XGBoost) emerged as the most consistently high-performing model. In the large-scale Chinese cohorts by Li et al. and Zhao et al., XGBoost achieved excellent discriminative performance, with AUCs of 0.90 and 0.803–0.966, respectively.[13,14] These models identified key predictors such as elevated HbA1c, nephropathy, serum creatinine, insulin treatment, and lipid abnormalities. Importantly, Zhao et al., demonstrated that the XGBoost model could predict incident DR nearly three years before clinical diagnosis, highlighting its value for early intervention and risk stratification.[14]

In medium-sized datasets, such as the Romanian cohort by Roșu et al., XGBoost also outperformed other models, achieving an AUC of 0.72 after hyperparameter tuning.[16] Cardiovascular risk factors, particularly systolic blood pressure, low-density lipoprotein (LDL) cholesterol, and body mass index (BMI) were repeatedly identified as important predictors. In contrast, the UK-based study by Kotsiliti et al., found that gradient boosting machines and random forest models performed best, with AUCs between 0.73 and 0.77, especially when longer-term HbA1c and ACR trends were incorporated, demonstrating the value of longitudinal biochemical data.[15]

The Taiwanese dataset analysed by Tsao et al., further supports the strength of AI models, showing that Support Vector Machines (SVM) achieved an AUC of 0.839, outperforming artificial neural networks and logistic regression.[17] This study highlighted clinically interpretable predictors such as insulin use and duration of diabetes, reinforcing their relevance across both traditional and machine-learning approaches.

Table I: Characteristics of The Included Studies

Authors	Year	Country	Study Design	Sample Size	Machine Learning Models Used	Performance Measures	Key Outcomes
Kotsiliti et al.,[15]	2017	United Kingdom	Population-based retrospective cohort using NHS Diabetic Eye Screening data	n = 6,375	Logistic Regression (LASSO), Random Forest, Gradient Boosting Machine, Regularised Gradient Boosting	AUC 0.73 ± 0.03 (10-fold CV). With 5-year HbA1c & ACR data: AUC 0.77 ± 0.04	A gradient boosting machine model using duration of diabetes, HbA1c, and age as predictors achieved a cross validated AUC of 0.73 in predicting diabetic retinopathy.
Roșu et al.,[16]	2024	Romania	Retrospective cross-sectional study	n = 377	Random Forest, XGBoost, Support Vector Machine, Logistic Regression	RF AUC = 0.62; XGBoost AUC = 0.68, improved to 0.72 after tuning	The XGBoost model was identified as the best prediction model with the highest AUC (area under the curve value, 0.90).
Tsao et al.,[17]	2018	Taiwan	Retrospective clinical dataset analysis	n = 536	Support Vector Machine, Decision Tree, Artificial Neural Network, Logistic Regression	Accuracy 79.5%, AUC = 0.839 (80/20 split). Slightly lower AUC with 60/20/20 split	The XGBoost model achieved the highest predictive performance for the risk of diabetic retinopathy among patients with type 2 diabetes with an AUC, accuracy, sensitivity, and specificity of 0.803, 88.9%, 74.0%, and 81.1%, respectively.
Li et al.,[13]	2021	China	Retrospective cohort study using electronic medical records	n = 32,452	Logistic Regression, Random Forest, Support Vector Machine, XGBoost (best)	XGBoost AUC = 0.90. Key predictors: HbA1c > 8%, nephropathy, creatinine >100 μmol/L	The XGBoost machine learning model showed the best predictive performance, with AUC of 0.72 after tuning, and SBP, HDL cholesterol, and BMI were consistently identified as the most important predictors across models.
Zhao et al.,[14]	2022	China	Retrospective cohort study with longitudinal follow-up	n = 7,943	XGBoost (best), Random Forest, Logistic Regression, Support Vector Machine, KNN	AUC = 0.803, Accuracy = 88.9%, Sensitivity = 74.0%, Specificity = 81.1%. Follow-up AUCs = 0.834–0.966	Support vector machines performed better than the other machine learning algorithms and achieved 79.5% and 0.839 in accuracy and AUC.

Notes: XGBoost = extreme gradient boosting, AUC = area under curve, CV = cross-validation, ACR = albumin-to-creatinine ratio, WBC = white blood cell, BMI = body mass index

Collectively, the studies demonstrate that machine-learning models, particularly XGBoost and SVMs provide reliable and often superior predictive accuracy compared with conventional methods. Common high-impact predictors across studies include HbA1c, duration of diabetes, renal function markers (creatinine, eGFR, ACR), blood pressure, lipid levels, BMI, and insulin therapy. These findings support the integration of AI-driven prognostic tools into DR screening pathways to enable more targeted follow-up, earlier detection, and personalised diabetes care.

DISCUSSION

Recent advancements in AI and ML have significantly improved the accuracy and performance of predictive models for DR among patients with T2DM. Various studies have explored diverse algorithms and methodologies, showing that AI can enhance early detection and improve patient outcomes through timely intervention. For instance, Yang et al., demonstrated the feasibility of ML classifiers based on non-ocular data for identifying referable DR in a large-scale rural population, highlighting the strong performance of algorithms like XGBoost and random forest in achieving high accuracy rates.[18] Similarly, Jiang and Li compared different ML algorithms, including XGBoost and SVM, and demonstrated their efficacy in predicting DR in T2DM patients, thus providing an alternative to traditional diagnostic methods.[19]

Glycaemic control is prominently recognized as a critical predictor of DR. HbA1c, a standard measure of long-term glycaemic control, has been consistently linked to the development and severity of DR. Patients with higher HbA1c levels tend to show more advanced stages of DR, highlighting its role in disease progression and risk assessment.[20] Additionally, studies reveal that poor blood glucose control aggravates microvascular complications, including DR, which progresses from non-proliferative to proliferative stages as glycaemic control deteriorates.[21] Renal function is another essential predictor, as diabetic nephropathy and DR often coexist, reflecting microvascular damage. Prolonged diabetes duration significantly correlates with increased risk of both diabetic nephropathy and DR, with modelling studies showing that a 5-year increase in diabetes duration raises the risk for chronic kidney disease (CKD) and subsequent DR.[22] Furthermore, the presence of albuminuria serves as a critical marker of renal impairment, indicating a compounded risk for DR.[23]

Blood pressure also plays a pivotal role in predicting DR development. Hypertension has been established as a risk factor for DR, with several studies demonstrating that elevated systolic and diastolic blood pressure levels contribute to the progression of diabetic microvascular complications.[24] The interaction between hypertension, metabolic syndrome, and diabetes complicates the clinical picture, as patients often present with concurrent dyslipidaemia, further impacting vascular health and exacerbating the risk for DR.[25] Lipids, particularly cholesterol and triglycerides, are also implicated in the pathogenesis of DR. Dyslipidaemic states characterised by elevated levels of LDL cholesterol and triglycerides, as opposed to high-density lipoprotein (HDL) cholesterol, have been associated with worsened retinal outcomes.[26]

ML approaches have made significant advancements in the prognostic modelling of DR, contributing to more accurate and timely diagnosis, thereby effectively mitigating the risks associated with this sight-threatening condition. The ML frameworks enable the integration of patient data to generate predictive models tailored to individual risk profiles. For example, recent studies have developed systems capable of predicting the progression of DR from fundus images with high accuracy.[27] Furthermore, the adaptability of ML models in handling diverse datasets makes them a practical choice for prognostic modelling. They can be trained on various datasets encompassing different populations and disease severities, which increases their generalizability across different clinical setups.[28] This adaptability is critical in fields like DR, where variability in patient demographics can significantly affect outcomes.

The clinical and public health implications of utilising AI-driven prognostic scoring models for DR are substantial, potentially enhancing early detection, treatment accuracy, and management efficiency. AI ML models have demonstrated optimal accuracy in diagnosing DR, often outperforming traditional methods. Certain AI ML models have achieved diagnostic sensitivities and specificities that rival those of expert clinicians, particularly in interpreting retinal images for signs of DR.[29] Additionally, AI-driven models are particularly advantageous in resource-limited settings, where expert human resources are scarce. Automation lowers the costs of DR grading, with studies indicating potential reductions in annual screening costs per patient.[30] Moreover, the integration of AI in DR screening significantly enhances patient outcomes and public health management. The use of AI technologies has been associated with improved patient compliance with screening protocols and increased accessibility of diagnostic services, particularly in rural and underserved regions.[31]

However, several limitations persist in the applicability of these models, primarily stemming from issues related to external validation, dataset diversity, algorithmic transparency, and clinical integration. One significant limitation of existing evidence lies in the inadequate external validation of AI-driven models. Many studies focus on internal validation using small datasets, which raises concerns regarding the generalizability of the findings to broader populations. For instance, a national real-world evidence study noted that while AI models exhibit promise in detecting DR, performance frequently declines when models are applied to external datasets, highlighting the variability in the effectiveness of these algorithms across diverse populations.[32] This limited external validity can lead to the overfitting of models, which might perform excellently on training datasets but poorly in actual clinical environments.[33]

Future research should prioritise prospective, multicentre validation studies to confirm the generalisability and real-world applicability of current AI-driven prognostic models across diverse healthcare settings and populations. There is also a need to integrate clinical predictors with retinal imaging, biochemical markers, and longitudinal electronic health record data, allowing models to capture both structural and physiological determinants of DR progression. In the Malaysian context, future work should focus on the development of locally calibrated prognostic scoring tools that reflect the unique demographic, ethnic, and clinical characteristics of T2DM populations in the country. Finally, adopting explainable AI approaches such as Shapley Additive Explanations (SHAP) values or interpretable ML frameworks will be essential to enhance clinician trust, facilitate clinical decision-making, and support successful implementation of AI models into routine screening and public health programmes.

CONCLUSION

This review demonstrates that AI-driven prognostic models hold substantial promise for improving early prediction of DR among adults with T2DM. ML algorithms, particularly XGBoost, consistently outperform traditional statistical approaches by integrating diverse clinical predictors such as glycated haemoglobin, renal function markers, blood pressure, lipid levels, and duration of diabetes. These models offer meaningful opportunities to strengthen risk stratification, optimise screening intervals, and support earlier intervention. However, most existing models are limited by inadequate external validation and a lack of population-specific calibration, underscoring the need for future multicentre, real-world studies to enhance generalisability and clinical applicability.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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