Artificial Intelligence for Diabetes Diagnosis and Prediction: Methods and Challenges

Yukang Wang *

College of Medicine and Biological Information Engineering, Northeastern University, Shenyang, 110819, China

* Corresponding Author Email: wangyk10@mails.neu.edu.cn

Abstract. Diabetes Mellitus is a worldwide disease that affects the body's metabolism and is considered a public health disaster resulting in great loss. Proper diagnosis and estimation of Diabetes Mellitus (DM) is crucial to enhance the patient's diagnosis and upgrade the health care system. This review provides a systematic review of advances in diabetes diagnosis and prediction. This paper also talks about traditional diagnostic methods and risk prediction models and compares them clinically in both sensitivity and coverage, on the scale of application outside health. It further explores the application of artificial intelligence (AI) in clinical applications for DM patients. Open-ended questions in explainability and clinical translations are also discussed. Furthermore, this paper also discuss limitations in current presentation and conclude by suggesting future research agendas. These future agendas include but are not limited AI techniques in mathematical applications. The review discusses the potential use of Artificial intelligence in providing personalized diabetes care further aiding the DM patients as well as improving diagnosis. Artificial intelligence would tie together methodological excellence with clinical practice solutions.

Keywords: Diabetes diagnosis and prediction; Machine learning; Deep learning; Artificial intelligence in healthcare; Clinical decision support.

1. Introduction

Diabetes is a disease that can be separated into different types based on different factors. These types include Type 1 diabetes, Type 2 diabetes, and gestational diabetes [1]. Diabetes is a disease where the body cannot control its sugar levels because the body either has a problem producing insulin or there is a problem using insulin to control sugar. There have been more people who have diabetes. [2] found that there were around 8.4 million adults with type 1 diabetes in 2021. This alarming number is projected to keep increasing in the next few decades. Diabetes has been shown to be a major factor in death. It can be a direct cause or it can also decrease the quality of life by decreasing the body's function. Other effects include cardiovascular disease, nephropathy, neuropathy and retinopathy, it can take around 3 years off a person's life and it can have a big social and economic effect [3]. Diabetes is not curable, so it requires continuous treatment and health care management for most patients' lives. This increases the resources used in the healthcare system.

The causes for diabetes can come from a mix of different factors including genetics, exposure to different environmental factors and lifestyle choices that are influenced by the previous two factors. Other reasons that can cause diabetes include being overweight, not being active and eating poorly, as well as the increase in the likelihood of developing diseases as a person ages. The complexity of the number of factors involved makes diagnosing this disease more complicated [4]. The current way to diagnose diabetes involves fasting blood glucose (FBG), oral glucose tolerance test (OGTT) and HbA1c [5]. Even though this is the most used VAI, it is expensive to conduct this test and the result may not be valid and testing is very sensitive, with a high likelihood of not detecting the disease (early stages). The accuracy for diagnosis is very low and that leads to high-risk patients not being put under the right care. Because the condition worsens over time, it is key to find new ways to improve the system. "Early prevention for the individual would be slowing down their disease by addressing their lifestyle as well as starting preventive medicines; early prevention at a societal and healthcare level would mean reducing chronic future burden and optimizing resource usage. As a result, early diagnostic and prognostic strategies with higher sensitivity and scalability are urgently needed.

Recent advancements in artificial intelligence have made new approaches possible in this field. ML and DL are one of the fields where they allow researchers to combine all information that is included in their electronic medical record, Lab test, radiology image, but also from wearable equipment and now even genomic data. Besides, these approaches can represent complex nonlinear relationships that would otherwise be hard to identify by conventional statistical models. The accuracy for predicting risk and personalized risk stratification has dramatically improved for these types of models. But at present, these models do not have enough explanation and experimental verification that their practical clinical use can be unavoidable. On this basis, the purpose of this article is to systematically review and critically analyze research progress on the diagnosis and prediction of diabetes. It will analyze them from each compared to the traditional methods, machine learning models, and deep learning technologies. From different aspects of data types to methodological pros and model performance.

Finally, it will also summarize the present difficulties and point out the future development trend. In this paper, the three critical questions: which data resource is the most useful, what kind of methodology is the best at prediction and how to push these methods for real application in the clinic will be addressed.

2. Traditional Diabetes Diagnosis and Prediction

People have been using tests in clinics and labs to diagnose diabetes. These tests are the most important medical tests to control the disease. The best test tools used are fasting plasma glucose (FPG), the oral glucose tolerance test (OGTT), and glycated hemoglobin A1c (HbA1c) [6]. Now, these ways of testing are used around the world because the WHO and American Diabetes Association (ADA) have made them the standards of testing [7].

The test most used in clinics is fasting blood glucose (FBG) because it is easier to use and not expensive to do, so it is often used in family care. But this test is not stable because it can be easily changed by eating, lifestyle, and other factors. Another test is the oral glucose tolerance test (OGTT), which is believed by many to be more sensitive in finding out early diabetes levels and can show the blood sugar level in body. The OGTT test takes a long time and requires patients to work together, so it is hard to use for a lot of people. Glycated hemoglobin (HbA1c) can show the overall blood sugar level in people for 2-3 months. This test is less affected by other things, and the results are controlled. So, people started using this as a key test. But this test is expensive, and the result is easily affected by other things like anemia and kidney problems.

All the traditional ways and test tools must be used so operators can get accurate information. In checking the prediction, the old way is to use the statistics model and risk score. The best example is the risk factor model made by checking people, like the Finnish Diabetes Risk Score (FINDRISC) [8]. These kinds of tools check the result by looking at a person's age, BMI, hereditary history, blood pressure, and blood lipids. These tools are good because the results are easy to see and are simple to use, making them best for basic clinics and large groups of people. But the problem is that because these models don't use enough data, they can't check the relationship between the main features. The most important problem is that when the model is used in different countries or groups, the tool's value decreases.

For a long time, the traditional way was the best way to check and control diabetes. They have simple knowledge and can be easily used. They also give a lot of important information for later AI research. But, now, because of older people, changes in life eating, and big data, using the old methods is not good enough. Things must be made to add more, so the prediction is better while keeping the old way of being simple and easy to understand.

3. Diabetes Diagnosis and Prediction Based on Machine Learning

As medical data gets larger and larger, the shortcomings of traditional diagnostic and risk scoring models have become increasingly prominent. Although traditional models also have advantages in interpretability and operability, the shortcomings of high-dimensional, nonlinear, multi-modal data are also difficult to overcome. In this context, machine learning methods have begun to be introduced into diabetes research. Compared with traditional models, machine learning not only adapts to large, complex, and diverse data structures, but also can automatically learn the underlying feature relationship through algorithms rather than relying on researchers' prior assumptions, thereby having higher predictive performance. The flexibility and adaptability of different types of data show greater potential.

From the perspective of specific methods, the tree model family is undoubtedly the most widely used method category. Single decision trees have been widely used in clinical practice due to their intuitiveness and interpretability, but the problem of overfitting is difficult to avoid. Random forest integrates multiple trees for voting, which greatly improves the stability and generalization performance of the model, so it has been widely used in the risk stratification task of high-risk populations of diabetes. Gradient boosting trees have stronger fitting capabilities, among which XGBoost and LightGBM have also become research hotspots in recent years. The former uses second-order gradient optimization and regularization strategies to greatly accelerate the training process and improve Prediction accuracy; the latter uses a histogram algorithm and efficient parallel strategy, which makes it possible to quickly model massive electronic medical record data, thus adapting to the trend of expanding data scale in modern medical systems. A large number of empirical studies have shown that this type of model is often better than traditional methods in terms of discrimination metrics such as AUC, sensitivity, and specificity and performs better in terms of calibration robustness [9]. In addition to tree models, support vector machines (SVMs) have also been proven to be good at processing high-dimensional small sample data. SVMs construct optimal hyperplanes to achieve classification, which is very suitable for high-dimensional cases such as metabolomics or laboratory indicators. For prediction tasks, multiple studies have found that SVM-based diabetes prediction models often achieve higher accuracy and sensitivity in distinguishing patients from non-patients, while the K-nearest neighbor (KNN) algorithm is based on the "proximity principle".

In recent years, ensemble learning has further expanded the model boundaries of machine learning in the field of diabetes prediction. Some researchers have used stacking or blending methods to combine different base models such as logic regression, random forest, and SVM, and integrate various predictive models. The model's complementary capabilities have achieved better performance improvements, which are particularly good at predicting patient complications. For example, for tasks such as predicting the risk of retinopathy or nephropathy, ensemble methods have shown significantly better effects than single models. Good stability and generalization capabilities, and some researchers even combined feature selection algorithms and ensemble prediction frameworks and found that they can achieve more accurate results while interpreting variable importance to a certain extent.

Machine learning has helped us learn how to combine different types of health data. Old prediction models only used patients' basic information. Now, researchers are finding ways to include genetic information and medical images in prediction tools. This new research has given doctors more information about how to treat diabetes patients. Machine learning models can also work with thousands of variables at once, instead of just a few.

But machine learning has a lot of problems. Patient information has problems, like missing data or unclear numbers and notes. These problems make machine learning models less stable and sometimes not trustworthy. It's also very common for machine learning models not to work well for diabetes prediction. When there is a lack of data from enough high-risk diabetes patients, high-risk patients are often not identified by the model, while the majority of the population is more easily identified. Hence, models don't really find those who need doctors' help. Another big problem is that researchers use data sets from only one hospital, so it is difficult to tell if a model would work for different types of patients at another hospital. Moreover, understanding how machine learning models work will take up a significant amount of time for doctors. Due to patient privacy, it's hard to get data from other clinics.

In general, machine learning is better than early models and has taught us a lot about diabetes. It can deal with more complicated information than anything before and usually predicts better than older models. But for these tools to help real patients, researchers still need to work on many details. Like finding ways to improve the quality of patient data, making machine learning easier to understand, finding ways to test machine learning in different patient groups, and figuring out how to protect patient privacy. Only after researchers solve these problems can machine learning help doctors help patients with diabetes.

4. Diagnosis and Prediction Based on Deep Learning

Machine learning tools have helped doctors predict who is at risk for diabetes and diagnose early, but they can't work if researchers don't choose the right information from patients. They also can't figure out how to use complicated patient information. New tools, called deep learning, help with this problem. Unlike some machine learning models, deep learning tools can "learn" how to use different types of patient information, like doctors' notes. They can also figure out why one feature matters more than another.

Another big difference from machine learning is that deep learning tools can be used with medical images, doctors' notes, and genetic information. In other words, it is unnecessary to have to figure out which patient information to use with the prediction tool. The tool can learn to "read" patient information, tell us what matters the most, and explain why it chose a certain patient as someone who is at high risk for developing diabetes. In the past, which patient information was most important could only be guessed. New deep learning tools can tell us what patient information to consider when guessing about who will develop diabetes.

For these reasons, deep learning tools like convolutional neural networks (CNNs) work well for reading retina images and predicting who will get diabetic retinopathy (DR). Now, in some countries, CNNs have been as good, or even better than, eye doctors and some clinics now use these tools. For clinics that don't have enough specialists, these deep learning tools can look at retina pictures and predict which patients will get DR [10-12].

Time series modeling mainly includes recurrent neural network (recurrent neural network, RNN) and its improved architecture-long short-term memory neural network (long short-term memory, LSTM). They are often used in continuous glucose monitoring (CGM) data and long-term electronic medical records. It can capture the dynamic characteristics of blood glucose fluctuations and predict future trends, thereby achieving early warning of disease progression and personalized intervention. For example, [13] established an LSTM model based on CGM data from multiple populations, which can not only achieve accurate prediction but also maintain good performance on external test data. Compared with machine learning methods based on static variables, RNN and LSTM can reveal the dynamic evolution process of diabetes to a greater extent. After the Transformer architecture achieved breakthrough results in natural language processing, it has also begun to be used in the analysis of medical data. The multi-head attention mechanism of Transformer has shown outstanding results in long-sequence data and multi-modal fusion tasks. Some studies have integrated laboratory parameters, medical record information and medical images into the same Transformer model and achieved higher-accuracy prediction of risk stratification. Its exploratory significance lies in fully demonstrating that deep learning can not only achieve breakthroughs in a single data type, but also has the potential to integrate multiple sources of data to construct a patient's multi-modal portrait. In addition, the emergence of self-supervised learning and transfer learning has partially alleviated the problem of insufficient labeling of medical data. Pre-training on a large amount of unlabeled data can still maintain model performance under limited annotations. Transfer learning can transfer model features learned in other fields to diabetes-related research, greatly reducing the demand for a large amount of labeled data. These two technologies may make deep learning feasible in health care settings with limited resources. Of course, deep learning is far from maturity in the field of diabetes diagnosis and prediction. Model training has high requirements for data volume and computing resources. At the same time, clinical data is often subject to privacy protection and data sharing restrictions, making it difficult to achieve multi-center collaborative research. Even though attention mechanisms and interpretability research have developed rapidly, it is still difficult to fully clarify the decision-making process of deep neural networks, making it difficult for doctors to trust them in clinical practice. The stability of the model also deserves attention. In practical applications, deep learning algorithms may have different degrees of performance degradation due to data noise, adversarial samples, or cross-population differences, thus weakening their clinical credibility [14]. In addition, the real-world verification of the model is still insufficient, and how to truly "get out of the laboratory" and achieve large-scale clinical application is still a huge challenge faced by current research in this field. In summary, deep learning has brought new opportunities for the diagnosis and prediction of diabetes. Its characteristics of automatic feature extraction, dynamic modeling, and multi-modal integration make up for some of the shortcomings of machine learning to a certain extent. With future breakthroughs in data sharing, model lightweighting, and interpretability, this series of methods is expected to truly move to the clinic and become an important technical support for diabetes prevention and control.

5. Current Limitations and Prospects

In recent years, research on diabetes diagnosis and prediction has made significant progress. The introduction of machine learning and deep learning has improved the accuracy and flexibility of models. However, the application of these methods in clinical practice still faces numerous obstacles, such as spanning data, methods, and applications.

At the data level, medical information comes from complex sources and inconsistent standards, with widespread issues of missing values and noise, making it difficult for models to maintain stability across regions and institutions. Diabetes-related data also often suffer from an imbalance in sample sizes across categories. Insufficient samples of high-risk groups or early-stage patients can bias model predictions towards the majority category, making it difficult to identify the groups truly requiring attention. Furthermore, privacy and ethical constraints hinder multi-center data sharing and large-scale joint modeling. At the methodological level, many models lack validation and real-world evaluation, making them difficult to meet clinical standards. While deep learning reduces reliance on feature engineering, its complex structure and opaque decision-making processes make it difficult to gain full trust from physicians, even with the introduction of interpretability techniques. Furthermore, its demand for computing resources limits its widespread adoption in primary care settings. At the application level, most models remain in the academic research stage and lack effective integration with electronic medical record systems and clinical decision support tools. Clinicians require not only predictions but also reasonable explanations. However, existing research often overlooks cost, usability, and patient acceptance, factors that are crucial to the long-term success of a technology.

Future research needs to be jointly promoted in multiple aspects. In terms of data, standardization and multi-center cooperation should be strengthened. Technologies such as privacy-preserving computing and federated learning can help different institutions share data securely. In terms of methods, external validation and model calibration should become routine links. At the same time, the development of explainable artificial intelligence and causal reasoning should be promoted to improve the transparency and credibility of the model. In terms of application, the model needs to be verified in a real clinical environment for a long time and deeply integrated with the existing medical process. Fairness is equally important. The model must maintain stable performance across different genders, ages and races to avoid exacerbating medical inequalities. Overall, diabetes diagnosis and prediction are at a critical stage from proof of concept to clinical implementation. Only by making breakthroughs in data quality, method transparency, clinical adaptability and fairness can artificial intelligence models truly move out of the laboratory and become a powerful tool for diabetes prevention and control.

6. Conclusions

Diabetes is a chronic illness that harms the world. It not only makes life worse for patients but also causes financial problems. More precise diagnosis and risk prediction have always been at the heart of public health and clinical research. This paper provides a comprehensive review of research progress in the field of diabetes diagnosis and prediction, from traditional diagnosis and risk scores. It also covers machine learning models and the emerging deep learning methods in recent years. By systematically sorting out and analyzing a large amount of multi-source data, including laboratory indicators, electronic medical records, medical imaging, and wearable devices, different methods were compared while exploring their potential value in early detection and personalized risk stratification.

Existing studies have shown that AI methods, especially deep learning, can leverage complex, high-dimensional data and recognize nonlinear patterns that are difficult for traditional methods to handle. This shows great potential in terms of predictive accuracy and generalization. However, uneven data quality, unbalanced sample distribution, insufficient interpretability of models, limited external verification, and difficulty in clinical integration are still the main bottlenecks that limit their translational application. The above limitations remind us that pursuing performance indicators is not the ultimate goal. Ensuring the stability and applicability of models in different populations and medical settings may be more important.

In terms of future prospects, diabetes research needs cooperation from many different fields. At the data level, cross-institutional standardization and privacy protection technologies will be key to improving data quality and sharing. At the methodology level, emerging areas such as explainable AI, causal inference, and federated learning are expected to improve model transparency and fairness. At the application level, deep integration into clinical workflows, combined with prospective research and real-world validation, will determine the technology's ultimate success. Only by truly integrating data, algorithms, and clinical practice can AI-driven diagnosis and predictive tools become a strong support for diabetes prevention and control.

References

[1] Campanella S, Paragliola G, Cherubini V, Pierleoni P, Palma L. Towards personalized AI-based diabetes therapy: a review. IEEE Journal of Biomedical and Health Informatics, 2024, 28(11): 6944–6957. DOI: 10.1109/JBHI.2024.3443137.

[2] Gregory G A, et al. Global incidence, prevalence, and mortality of type 1 diabetes in 2021 with projection to 2040: a modelling study. Lancet Diabetes & Endocrinology, 2022, 10(10): 741–760. DOI: 10.1016/S2213-8587(22)00218-2.

[3] Guo H, Wu H, Li Z. The pathogenesis of diabetes. International Journal of Molecular Sciences, 2023, 24(8): 6978. DOI: 10.3390/ijms24086978.

[4] Lovic D, Piperidou A, Zografou I, Grassos H, Pittaras A, Manolis A. The growing epidemic of diabetes mellitus. Current Vascular Pharmacology, 2020, 18(2): 104–109. DOI: 10.2174/1570161117666190405165911.

[5] Ortiz-Martínez M, González-González M, Martagón A J, Hlavinka V, Willson R C, Rito-Palomares M. Recent developments in biomarkers for diagnosis and screening of type 2 diabetes mellitus. Current Diabetes Reports, 2022, 22(3): 95–115. DOI: 10.1007/s11892-022-01453-4.

[6] ElSayed N A, et al. Classification and diagnosis of diabetes: standards of care in diabetes—2023. Diabetes Care, 2023, 46(Suppl. 1): S19–S40. DOI: 10.2337/dc23-S002.

[7] American Diabetes Association Professional Practice Committee. Diagnosis and classification of diabetes: standards of care in diabetes—2025. Diabetes Care, 2024, 48(Suppl. 1): S27–S49. DOI: 10.2337/dc25-S002.

[8] Arnardóttir E, Sigurðardóttir Á K, Graue M, Kolltveit B-C H, Skinner T. Using HbA1c measurements and the Finnish diabetes risk score to identify undiagnosed individuals and those at risk of diabetes in primary care. BMC Public Health, 2023, 23(1): 211. DOI: 10.1186/s12889-023-15122-y.

[9] Almutairi E S, Abbod M F. Machine learning methods for diabetes prevalence classification in Saudi Arabia. Modelling, 2023, 4(1): 37–55. DOI: 10.3390/modelling4010004.

[10] Thanikachalam V, Kabilan K, Erramchetty S K. Optimized deep CNN for detection and classification of diabetic retinopathy and diabetic macular edema. BMC Medical Imaging, 2024, 24(1): 227. DOI: 10.1186/s12880-024-01406-1.

[11] CNN-based integrated framework for enhanced diabetic retinopathy detection. Recent Advances in Computer Science and Communications, 2025, 18(3). DOI: 10.2174/0126662558293742240925044450.

[12] Zhang W, Belcheva V, Ermakova T. Interpretable deep learning for diabetic retinopathy: a comparative study of CNN, ViT, and hybrid architectures. Computers, 2025, 14(5): 187. DOI: 10.3390/computers14050187.

[13] Carvalho C F, Liang Z. Glucose prediction with long short-term memory (LSTM) models in three distinct populations. Engineering Proceedings, 2024, 82(1): 87. DOI: 10.3390/ecsa-11-20513.

[14] Javed H, El-Sappagh S, Abuhmed T. Robustness in deep learning models for medical diagnostics: security and adversarial challenges towards robust AI applications. Artificial Intelligence Review, 2024, 58(1): 12. DOI: 10.1007/s10462-024-11005-9.