INTEGRATION OF MACHINE LEARNING-BASED TYPE 2 DIABETES PREDICTION MODELS INTO CLINICAL WORKFLOW SYSTEMS

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ABSTRACT

Complications of diabetes mellitus are the main causes of morbidity, mortality, and increased health care costs. In recent years, machine learning-based prediction models, particularly Random Forest (RF) and Convolutional Neural Network (CNN), have shown promising capabilities in identifying diabetic patients who are at risk of complications. This systematic review aims to analyze the extent of integration of RF and CNN-based diabetes complication prediction models into clinical workflow systems, evaluate the operational feasibility of their implementation, and identify key barriers to their adoption. The study was conducted following the guidelines of PRISMA 2020 through a literature search on PubMed, Scopus, and Web of Science for publication in 2015-2026. Studies that meet inclusion criteria include the use of RF or CNN to predict diabetes complications in the context of health care, electronic health records, or clinical decision support systems. Data was synthesized using a thematic narrative synthesis approach. The results of the study show that most of the RF and CNN models are still in the non-integrated or semi-integrated stage. RF is easier to implement because it has better interpretability and computational efficiency, whereas CNN shows high predictive performance especially in medical imaging-based complications, but faces challenges related to computational needs and model transparency. Factors that affect the success of the implementation include system interoperability, data quality, infrastructure readiness, and user acceptance. Further implementation research is needed to support the continued integration of RF and CNN models in clinical practice.

Keywords: clinical workflow integration; complications of diabetes mellitus; convolutional neural network; electronic health records; random forest

INTRODUCTION

Diabetes mellitus (DM) is one of the non-communicable diseases that is a major global health challenge because its prevalence continues to increase from year to year (Hossain et al., 2024). According to estimates by the international diabetes federation, the number of people with diabetes is expected to continue to grow in line with the increase in obesity rates, lifestyle changes, urbanization, and population aging (Khan, 2025). In addition to causing chronic metabolic disorders, diabetes also contributes to high morbidity, mortality, and a significant economic burden on the health care system (Butt et al., 2024). The impact of this disease is not only felt by the individual who suffers from it, but also by the family, society, and state through the increased cost of long-term treatment. Despite various prevention and control efforts have been made, diabetes is still one of the leading causes of death and disability in various countries (Freihat et al., 2025). These conditions show that diabetes management requires a comprehensive and sustainable approach. One of the most important aspects of diabetes management is the prevention and early detection of complications that can worsen the patient's condition (Nikpour et al., 2022).

Complications of diabetes mellitus are the main cause of decreased quality of life in diabetic patients and are a contributing factor to high hospitalizations, permanent disabilities, and premature death (Ritonga et al., 2025). These complications can be differentiated into microvascular and macrovascular complications. Microvascular complications include diabetic kidney disease (DKD), diabetic retinopathy (DR), and diabetic neuropathy, while macrovascular complications include coronary heart disease, stroke, and peripheral artery disease (Yapislar & Gurler, 2024). Most complications develop slowly over the years and often do not cause obvious symptoms in the early stages. As a result, many patients are only diagnosed when significant organ damage has occurred, resulting in a lower chance of therapy success. Diabetic kidney disease can develop into terminal kidney failure that requires dialysis or kidney transplantation, while diabetic retinopathy is one of the leading causes of blindness in the productive age population (de Boer et al., 2022). Therefore, early identification of patients at risk of complications is an important step in improving the quality of diabetes services and preventing more severe clinical consequences (Ojurongbe et al., 2024).

Conventional approaches to predicting the risk of diabetes complications generally use statistical models based on a number of previously known risk factors. Although such approaches make important contributions in clinical practice, traditional statistical models have limitations in dealing with complex and nonlinear relationships between variables. The development of health information technology has resulted in the availability of large amounts of data from electronic health records (EHRs), laboratory test results, pharmaceutical data, hospital administrative data, and various other health information sources (Modi & Feldman, 2022). The data contains very valuable information to identify risk patterns of complications that are not easily recognized through conventional analysis methods. As artificial intelligence develops, machine learning is beginning to be used to leverage large and complex health data to produce more accurate and adaptive prediction models (Maleki Varnosfaderani & Forouzanfar, 2024). Machine learning's ability to automatically learn data patterns makes it one of the most promising approaches in the development of diabetes complication prediction systems (Flamino et al., 2021).

Among the various machine learning algorithms available, Random Forest (RF) is one of the most widely used methods in diabetes complication prediction research (Scheideman et al., 2025). Random Forest is an ensemble learning-based algorithm that combines a large number of decision trees to produce more stable and accurate predictions. This method has good ability to handle complex clinical data, large number of variables, and data containing missing values (Mohamadi et al., 2025). In addition, Random Forest is able to provide information about the level of importance of each predictor variable so that it makes it easier for health workers to interpret the results (Simsekler et al., 2021). Various studies show that Random Forest has a good performance in predicting diabetic kidney disease, diabetic neuropathy, cardiovascular complications, and various other clinical outcomes in diabetic patients (Cai et al., 2024). This capability makes Random Forest one of the most widely used algorithms in the development of risk prediction systems based on clinical data and electronic medical records (Song et al., 2021).

In addition to Random Forest, Convolutional Neural Network (CNN) is one of the deep learning approaches that is increasingly used in the healthcare sector due to its ability to automatically learn complex data patterns (Wang et al., 2025). Although CNN was originally developed for image processing, the development of deep learning architecture has made it possible to apply it to tabular data and structured clinical data. In the healthcare environment, data derived from electronic health records, laboratory test results, treatment history, demographic characteristics, and other risk factors produce multidimensional relationships that are often difficult to analyze using conventional methods (Stotz et al., 2025). CNN is able to perform feature extraction automatically through the convolutional layer so that it can identify nonlinear relationships and hidden patterns that contribute to the development of diabetes complications (Fan, 2025). Various studies show that CNN is able to produce high predictive performance in identifying the risk of diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, and cardiovascular complications based on a combination of complex clinical data (Gong et al., 2025). This ability makes CNN one of the technologies that has the potential to support the development of a more precise and personalized diabetes complication prediction system (Al Sadi & Balachandran, 2023).

Although Random Forest and CNN have shown promising predictive performance, most of the research still focuses on model development and validation in a research environment. The success of a prediction model is not only determined by the level of accuracy, sensitivity, specificity, or area under the curve (AUC), but also by the model's ability to be applied in actual healthcare practices (Mohamed et al., 2025). Many models with excellent performance fail to provide clinical impact because they are not integrated with the health information systems used by healthcare workers every day. Stand-alone models outside of the service system are often difficult to access, require additional data input processes, and have the potential to disrupt clinical workflows (Ghassemi et al., 2020). As a result, the benefits of prediction models cannot be optimally utilized in clinical decision-making. Therefore, aspects of system implementation and integration are important factors that need to be considered in the development of machine learning technology in the health sector (Yan et al., 2025).

The integration of machine learning models into clinical workflow systems allows the predictive results of diabetes complication risk prediction to be used directly by health workers in the patient service process (Wen et al., 2025). Clinical workflow systems include various activities related to patient data collection, clinical documentation, diagnosis, therapy planning, monitoring of patient conditions, and evaluation of service outcomes (Sutton et al., 2020). Integration with electronic health records and clinical decision support systems allows prediction models to work automatically using data already available in the system without requiring additional input from users (Solomon et al., 2023). Thus, health workers can obtain real-time risk information to support faster and more accurate decision-making. In addition to improving service efficiency, the integration also has the potential to improve the quality of care through early identification of patients who require more intensive interventions. Therefore, the integration of machine learning into clinical workflows is an important step in realizing the sustainable use of artificial intelligence in healthcare (Abd-Alrazaq et al., 2025).

Although the number of research on machine learning for the prediction of diabetes complications continues to increase, the scientific evidence specifically evaluating the integration of Random Forest and Convolutional Neural Network models into clinical workflow systems is still limited and scattered in various publications (Ljubic et al., 2020). Most previous studies have focused on algorithm performance, while implementation, interoperability, operational feasibility, and barriers to adoption have not been comprehensively discussed. In fact, understanding these factors is essential to bridge the gap between the development of technology and its application in clinical practice. Therefore, this systematic review aims to analyze the extent to which Random Forest and Convolutional Neural Network-based diabetes complication prediction models are integrated into clinical workflow systems, evaluate the factors influencing their successful implementation, and identify the main obstacles faced in the adoption of these technologies. The results of this study are expected to provide a scientific basis for the development of a more effective, sustainable, and integrated diabetes complication prediction system with the needs of modern health services.

METHOD

Research Design

This was a systematic review approach that aims to identify, evaluate, and synthesize scientific evidence related to the integration of machine learning-based diabetes mellitus complication prediction models into clinical workflow systems. The preparation of this systematic review follows the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 to ensure transparency, replication, and high quality reporting. This approach was chosen because it allows researchers to conduct a comprehensive study of various studies that have diverse designs, populations, and implementation contexts. This research not only focuses on the predictive performance of machine learning models, but also evaluates implementation aspects, level of system integration, operational feasibility, interoperability, and barriers to adoption in the healthcare environment. The main focus of the study was the Random Forest (RF) and Convolutional Neural Network (CNN) models used to predict various complications of diabetes mellitus, including diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, diabetic foot ulcer, and cardiovascular complications. Thus, this systematic review has a wider scope than technical research that only assesses the performance of algorithms. All stages of the research are designed to minimize bias and increase the validity of the resulting findings.

Data Sources and Search Strategies

Literature searches were conducted systematically on several major scientific databases relevant to the fields of health, health informatics, and artificial intelligence, namely PubMed, Scopus, and Web of Science. The selection of the three databases is based on the wide scope of publications in the fields of medicine, public health, computer science, and health information systems. Search strategies are developed using a combination of keywords and Boolean operators to improve the sensitivity and specificity of search results. Keywords used include terms related to machine learning, Random Forest, Convolutional Neural Network, diabetic complications, diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, cardiovascular complications, clinical workflow, clinical decision support system, electronic health record, healthcare integration, and implementation barriers. Keyword combinations are carried out using AND and OR operators according to the characteristics of each database. The publication range is limited to the period from 2015 to 2026 to obtain an overview of the latest developments related to the application of machine learning in the prediction of diabetes complications and its implementation in the health care system. In addition to the main search of the electronic database, a search of reference lists of relevant articles was also carried out to identify additional studies that met the inclusion criteria.

Inclusion and Exclusion Criteria

Inclusion criteria are established to ensure that the studies being analyzed have a high relevance to the research objectives. The studies included in the systematic review are studies that discuss the use of machine learning models, especially Random Forest or Convolutional Neural Networks, in predicting complications of diabetes mellitus. The study must have a clinical or healthcare context and evaluate the implementation, integration, or use of the model in electronic health records, clinical decision support systems, and clinical workflow systems. In addition, the study must be published in a reputable scientific journal or conference proceedings, available in English, and present adequate information regarding the research method and the results of the implementation of the system. In contrast, studies that focus only on algorithm development without addressing clinical implementation are excluded from the selection process. Articles in the form of editorials, comments, letters to editors, opinions, and narrative reviews are also not included in the analysis. Studies with incomplete data, not available in full-text form, or duplicate publications are also excluded. In addition, studies that only address the diagnosis of diabetes without evaluating the prediction of diabetes complications are also not included in the scope of this study. The determination of these criteria aims to maintain the quality, consistency, and relevance of the scientific evidence to be synthesized.

Study Selection Process

The study selection process was carried out through several systematic stages in accordance with the flow of PRISMA 2020. The first stage begins with the identification of articles based on search results from all databases used. Furthermore, duplicate articles are removed using reference management software to avoid counting the same study more than once. The remaining articles then undergo a screening process based on titles and abstracts to assess their initial suitability with the research objectives and inclusion criteria that have been set. Articles that meet the requirements at the screening stage are proceeded to a full-text review process to determine final eligibility. The entire selection process was carried out independently by at least two researchers to reduce the risk of subjective bias. If there is a difference of opinion in determining the feasibility of an article, a discussion is held until a mutual agreement is reached. In certain situations, a third researcher may be involved as a mediator to help resolve the difference. The entire selection process is documented in detail and presented in the form of a PRISMA flowchart to ensure transparency and ease of research replication.

Data Extraction

Data extraction is done using a standard form that has been prepared in the form of a structured table. The information collected includes the general characteristics of each study, such as the name of the author, the year of publication, the country where the study was conducted, and the design of the study used. In addition, information was also collected about the types of diabetes complications predicted, the type of machine learning model used, data sources, and the size of the research sample. Other data extracted included model evaluation parameters such as accuracy, sensitivity, specificity, area under the curve (AUC), precision, and recall. This study also collects information related to the level of system integration, including whether the model is used in a non-integrated, semi-integrated, or fully integrated manner in the health care system. The aspect of interoperability with electronic health records and other health information systems, the impact on clinical workflows, and factors that support or hinder implementation are also the main focus in the data extraction process. The entire extraction process was carried out independently by two researchers to improve the consistency and accuracy of the data. Any differences in extraction results are resolved through discussion until a mutual agreement is reached.

Study Quality Assessment

Methodological quality assessments were conducted to evaluate the validity and risk of bias of each study included in the systematic review. The instruments used were adjusted to the type of research being analyzed. Observational studies were evaluated using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist, while studies focused on system prediction or implementation were evaluated using instruments relevant to machine learning research and health technology implementation. Quality assessment covers a variety of important aspects, including clarity of research objectives, data representativeness, validity of analysis methods, transparency of reporting results, model evaluation process, and potential biases that may arise during the development and implementation of the system. The results of the assessment are then classified into high, medium, or low quality categories. This information is used to help interpret the results more critically so that findings from studies of low methodological quality can be considered proportionately. The approach aims to maintain a balance between the completeness of the scientific evidence and the methodological quality of the studies analyzed.

Data Analysis and Synthesis

The data that has been extracted is analyzed using the thematic narrative synthesis approach because there is considerable heterogeneity in the study design, the type of diabetes complications predicted, the characteristics of the data used, and the implementation methods reported in various studies. This approach allows for the integration of diverse research results without the need for quantitative meta-analysis. The analysis was conducted by grouping findings based on several key themes related to the level of integration of Random Forest and Convolutional Neural Network models in clinical systems, predicted characteristics of diabetes complications, factors affecting operational feasibility, barriers to adoption and implementation, factors supporting successful implementation, and impact of model integration on clinical workflow and clinical decision-making. Each theme is analyzed in depth to identify patterns, similarities, and differences between studies. In addition, critical interpretation of the findings is carried out to identify gaps in research and future development opportunities. The results of the synthesis are presented in the form of a narrative supported by a table of study characteristics and thematic classification so as to provide a comprehensive picture of the implementation of diabetes complication prediction models based on Random Forest and Convolutional Neural Network in modern healthcare systems.

RESULT AND DISCUSSION

Study Selection

Based on the results of literature searches on PubMed, Scopus, and Web of Science databases, a number of articles related to the use of machine learning for the prediction of diabetes mellitus complications and its implementation in the health care system were obtained.

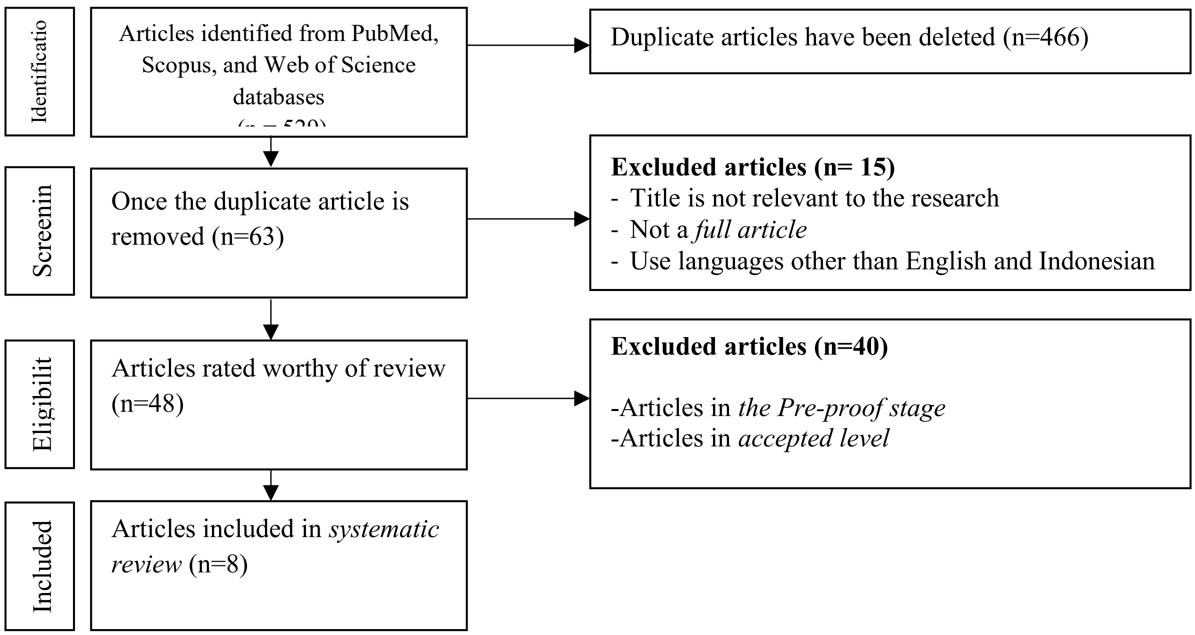

Figure 1. PRISMA Diagram

After the duplicate removal process, the remaining articles undergo a screening stage based on titles and abstracts. Studies that do not meet the inclusion criteria are eliminated, especially studies that focus only on the development of algorithms without addressing clinical context or implementation in the health system. Furthermore, articles that meet the initial criteria are evaluated through full-text review to ensure their suitability for the purpose of the study. The selection process was carried out according to the guidelines of PRISMA 2020. The final results showed that eight studies met all inclusion criteria and were included in the synthesis. The studies covered a wide range of diabetic complications, including diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, diabetic foot ulcer, as well as cardiovascular complications. The publications analyzed are from the period 2016 to 2026, which shows increasing attention to the use of machine learning to support the early detection of diabetes complications and their integration into the healthcare system.

Characteristics of the Analyzed Study

The eight studies analyzed came from different countries with diverse health system characteristics. Most studies use clinical data sourced from electronic health records (EHRs), multicenter databases, teleophthalmology systems, and medical image-based screening systems. Predicted complications include diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, diabetic foot ulcer, and cardiovascular complications related to diabetes mellitus. Of the eight studies analyzed, four studies used Random Forest as the primary prediction model, three used

Convolutional Neural Network (CNN), and one study combined Random Forest and CNN in the evaluation of various diabetes complications. Random Forest is widely used in structured clinical data derived from electronic health records due to its ability to process tabular data with a large number of variables. In contrast, CNN is more widely used on the analysis of medical image data such as retinal fundus photos and diabetic foot ulcer images, although some recent studies have also begun to apply CNN to tabular clinical data transformed into multidimensional representations.

A study by Lee et al. (2025) used Random Forest to predict diabetic kidney disease in type 2 diabetes mellitus patients based on multicenter electronic health records data. Gulshan et al. (2016) and Ting et al. (2017) developed a CNN model for the detection of diabetic retinopathy based on retinal images. Dagliati et al. (2018) used Random Forest to predict diabetic neuropathy and other chronic complications in a diabetes clinic setting. Meanwhile, Sait and Nagaraj (2025) developed a hybrid CNN–Vision Transformer model for digital-based identification of diabetic foot ulcers. The study of Huang et al. (2022) utilized CNN for the prediction of diabetic kidney disease using multicenter data, while Xie et al. (2026) evaluated the use of Random Forest and CNN for various diabetes complications in a clinical decision support system environment connected to electronic health records. Nicolucci et al. (2025) became the only study to report the full implementation of the Random Forest model in an EHR-based clinical workflow for the prediction of cardiovascular complications in diabetic patients.

Table 1.
Characteristics of the Study Analyzed

No	Author (Year)	Predicted Complications	Model	Integration Levels	Setting
1	Lee et al. (2025)	Diabetic Kidney Disease	Random Forest	Semi-integrated	Multicenter Electronic Health Records
2	Gulshan et al. (2016)	Diabetic Retinopathy	CNN	Non-integrated	System Screening Retina
3	Dagliati et al. (2018)	Diabetic Neuropathy dan komplikasi kronis	Random Forest	Prototype	Diabetes Clinic
4	Sait & Nagaraj (2025)	Diabetic Foot Ulcer	CNN (Hybrid CNN–Vision Transformer)	Prototype	DFU Image Analysis System
5	Huang et al. (2022)	Diabetic Kidney Disease	CNN	Non-integrated	Database Multicenter
6	Xie et al. (2026)	Diabetic Retinopathy, Diabetic Nephropathy, dan Cardiovascular Disease	Random Forest dan CNN	Semi-integrated	Clinical Decision Support & EHR-Based Systems
7	Ting et al. (2017)	Diabetic Retinopathy	CNN	Semi-integrated	Teleophthalmology System
8	Nicolucci et al. (2025)	Complications of cardiovascular diabetes	Random Forest	Fully Integrated	EHR-Based Clinical Workflow

Model integration level classification

Analysis of the level of integration shows that the implementation of machine learning models for the prediction of diabetes complications is still dominated by the non-integrated, prototype, and semi-integrated categories. Of the eight studies analyzed, only one study reported full integration into electronic health records-based clinical workflows, namely the study of Nicolucci et al. (2025).

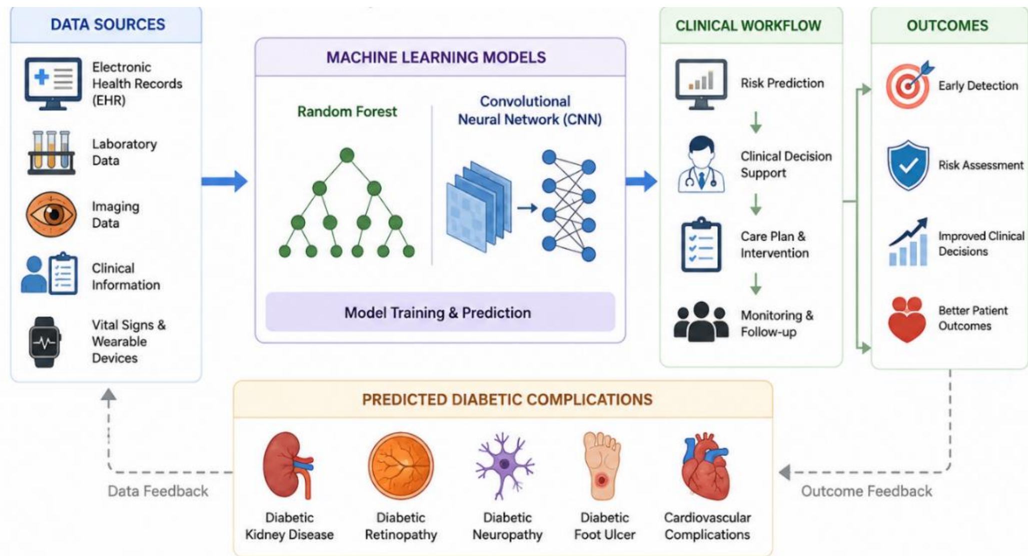

Figure 2. Framework for Integrating Random Forest and Convolutional Neural Network Models for Prediction of Diabetes Mellitus Complications in Clinical Workflow Systems

The Random Forest model shows a relatively higher level of integration than CNN. The studies Lee et al. (2025) and Xie et al. (2026) report on semi-integrated implementations that allow models to interact with electronic health records and clinical decision support systems. Meanwhile, Nicolucci et al. (2025) managed to fully integrate the Random Forest model into the clinical system so that complication risk predictions can be generated automatically during the patient care process. In contrast, most CNN implementations are still in the non-integrated or prototype stage. Gulshan et al. (2016) and Huang et al. (2022) developed a model that operates as an independent analytical system and is not yet directly connected to the hospital information system. Sait and Nagaraj (2025) also reported the use of Vision Transformer-based CNN which is still in the prototype stage. Only the study of Ting et al. (2017) showed the semi-integrated implementation through a teleophthalmology system that supports the screening process of diabetic retinopathy in a more integrated manner. These findings suggest that although CNN has high predictive capabilities, its integration into clinical systems still faces a variety of challenges compared to Random Forest.

Operational Feasibility

The operational feasibility of the diabetes complication prediction model is influenced by the interoperability of the system, data quality, computing needs, and readiness of the technological infrastructure. Studies using Random Forest show that the need for computing resources is relatively low, making it easier to apply in healthcare environments that already have electronic health records. Lee et al. (2025) show that the use of Random Forest on multicenter electronic health records data allows for efficient identification of diabetic kidney disease risk with relatively easy integration into health information systems. Similar findings were also reported by Nicolucci et al. (2025), where the model can be implemented in real-time in clinical workflows without disrupting service activities. In contrast, studies using CNN report greater computing needs, especially in medical image processing. Gulshan et al. (2016), Ting et al. (2017), and Sait & Nagaraj (2025) show that the successful implementation of CNN is highly dependent on the availability of high-performance hardware as well as adequate data storage infrastructure. In addition, complex data processing needs have led to the implementation of CNN being more common in healthcare centers with the support of more advanced technologies. Another factor that affects operational feasibility is the quality and completeness of the data. Multicenter studies using EHR data show that data standardization and interoperability between systems are important prerequisites for ensuring models can be used consistently in a variety of healthcare settings.

Barriers to adoption

Analysis of the analyzed studies shows that the obstacles to the implementation of machine learning models for the prediction of diabetes complications come from technical, organizational, and human factors. The most frequently reported technical barriers are the lack of interoperability between prediction models and electronic health records as well as variations in the quality of data available across various health institutions. In the CNN model, the main challenges have to do with the high computational requirements and the low interpretability of the model. Gulshan et al. (2016), Huang et al. (2022), and Sait & Nagaraj (2025) show that the results of CNN predictions are often difficult to explain to users because decision-making processes take place in complex neural networks. This condition can reduce the level of confidence in health workers in the predictive results provided by the system. On the other hand, while Random Forest is easier to interpret, barriers related to user acceptance and workflow changes are still found. Studies involving integration with clinical decision support systems show that healthcare workers tend to be more receptive to technology if the system can provide a clear explanation of the risk factors that affect predictive outcomes. In addition, regulatory limitations regarding the use of artificial intelligence in healthcare, implementation costs, and user training needs are also factors that contribute to the slow adoption of machine learning models in clinical practice.

Thematic synthesis

Thematic synthesis shows that Random Forest and Convolutional Neural Networks have great potential in supporting early detection of diabetes mellitus complications. Both approaches are able to identify high-risk patients before complications develop into more severe conditions to support faster and more informed clinical decision-making. Random Forest shows advantages in terms of ease of implementation, computational efficiency, and model interpretability. These characteristics make Random Forest more often used in systems that have been integrated with electronic health records and clinical decision support systems. In contrast, CNN offers a better ability to identify complex patterns, particularly in medical imaging data and multidimensional data. However, its implementation is still limited by high infrastructure requirements, complex system integration, and low model transparency. Overall, the synthesis results show that there is a considerable gap between the algorithm's performance and the actual clinical implementation. Factors such as system interoperability, data quality, infrastructure readiness, user trust, and regulatory support emerged as key determinants of successful implementation. These findings suggest that the successful integration of diabetes complication prediction models is determined not only by the accuracy of the algorithm, but also by the ability of the system to adapt to the needs of the user and the healthcare environment. Thus, the harmonization between technological innovation, organizational readiness, and clinical needs is the main key in realizing the sustainable implementation of machine learning in the field of diabetes.

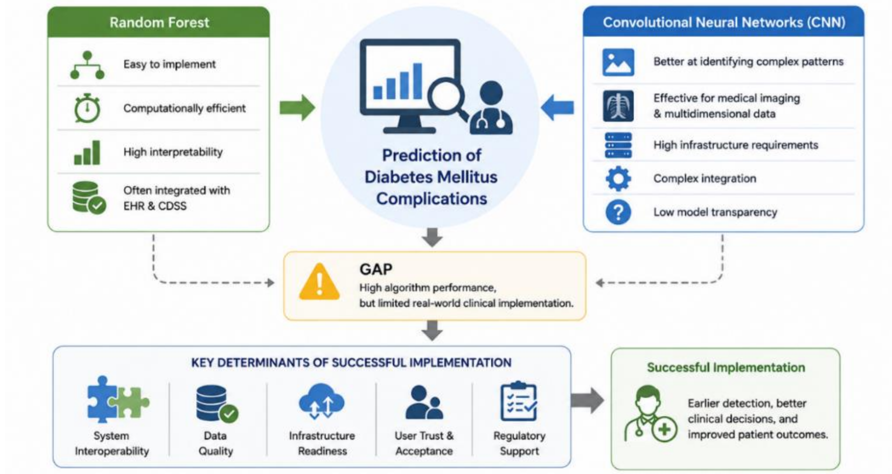

Figure 3. Thematic Synthesis of Machine Learning Integration for Diabetic Complication Prediction in Clinical Workflow Systems

Integration of Random Forest and Convolutional Neural Network Models in Clinical Workflows

The results of the systematic review show that the integration of machine learning models for the prediction of diabetes mellitus complications is still at various levels of implementation maturity. Of the eight studies analyzed, only one study reported a fully integrated implementation in an Electronic Health Records (EHR)-based clinical workflow system, namely a study by Nicolucci et al. (2025). Most research is still in the semi-integrated, prototype, or even non-integrated stage. These findings suggest that although the model's predictive capabilities have improved significantly, the process of translating the technology into everyday clinical practice still faces a variety of obstacles (Nicolucci et al., 2025). The Random Forest model appears to be more widely used in systems that have been connected to the clinical environment than CNN. The studies of Lee et al. (2025) and Xie et al. (2026) show that Random Forest is relatively easy to integrate into EHR systems because it has lower computing requirements, better interpretability, and high compatibility with structured clinical data (Lee et al., 2025). In contrast, most CNN implementations are still limited to research environments or prototype systems. Gulshan et al. (2016) and Huang et al. (2022) reported the use of CNN that is still in the non-integrated stage, while Sait and Nagaraj (2025) developed a CNN-Vision Transformer model that is still in the prototype stage for the analysis of diabetic foot ulcer images (Sait & Nagaraj, 2025). These findings are in line with socio-technical systems theory which states that the success of technology implementation is not only determined by the performance of the algorithm, but also by the suitability of the technology with the needs of existing organizations, users, and work processes. In the context of health services, the diabetes complication prediction system must be able to integrate harmoniously with the clinical documentation process, medical decision-making, and health information systems that have been used by health workers. Without adequate integration, even high-accuracy models will struggle to have a real impact on patient care (Islam et al., 2023).

In addition, the concept of a Clinical Decision Support System (CDSS) emphasizes that predictive information should be available at the right time in the clinical decision-making process (van Baalen et al., 2021). Therefore, the successful implementation of the diabetes complication prediction model depends not only on the algorithm's ability to generate accurate predictions, but also on the system's ability to present prediction results quickly, easily understandable, and relevant to the needs of clinicians (Aagaard et al., 2025). Based on these findings, it can be concluded that there is a considerable gap between the development of diabetes complication prediction algorithms and their implementation in clinical practice. Future development efforts need to focus more on the implementation, interoperability, and integration aspects of the system so that the benefits of technology can be felt directly by patients and healthcare workers.

Operational Feasibility of Diabetes Mellitus Complication Prediction Model

The analysis shows that operational feasibility is one of the main factors that determine the successful implementation of the diabetes complication prediction model in the healthcare environment. A variety of technical and non-technical factors affect a model's ability to be used sustainably in clinical practice. The Random Forest model shows a relatively high level of operational viability. In the study of Lee et al. (2025), Random Forest was able to be used to predict diabetic kidney disease using multicenter EHR data with relatively low computing requirements. The study of Nicolucci et al. (2025) even showed that the Random Forest model could be fully integrated into EHR-based clinical workflows. This shows that Random Forest has the right characteristics for healthcare environments that require processing speed, system stability, and ease of implementation (Loef et al., 2022).

In contrast, the CNN model offers superior capabilities in analyzing complex data, especially medical imaging data. Gulshan et al. (2016) and Ting et al. (2017) showed that CNN is able to produce excellent performance in the detection of diabetic retinopathy through retinal fundus analysis. Meanwhile, Sait and Nagaraj (2025) developed a hybrid CNN-Vision Transformer model that is able to automatically identify diabetic foot ulcers with a high level of accuracy. Nonetheless, CNN's implementation faces greater challenges than Random Forest. CNN requires high computing resources, large data storage capacity, and adequate technological infrastructure. In addition, the model training process requires a huge amount of data to produce optimal performance (Yang et al., 2025). This condition is a major obstacle, especially in health facilities in developing countries that have limited information technology resources. Interestingly, recent developments show that CNN is not only used for medical image analysis. Huang et al. (2022) and Xie et al. (2026) report that CNN is beginning to be adapted to analyze clinical tabular data through various modifications of deep learning architectures. This approach allows CNN to utilize complex non-linear relationships between various clinical variables to improve the predictability of diabetes complications (Singh et al., 2026). These developments open up new opportunities in the development of deep learning-based prediction models that are more flexible and can be applied to various types of health data. Thus, the operational feasibility of a model is determined not only by the level of prediction accuracy, but also by the readiness of the infrastructure, system interoperability, computational efficiency, and adaptability to the needs of the clinical environment (Cho et al., 2024).

Barriers to Adoption and Human Factors in the Implementation of Machine Learning Models

In addition to technical challenges, the barriers to the adoption of machine learning models also come from human and organizational factors. The results of the review show that low clinical trust in artificial intelligence-based systems is still one of the main obstacles in the implementation of the diabetes complication prediction model (Ayers et al., 2025). The Random Forest model is generally more acceptable to healthcare workers because it has a better level of interpretability. Clinicians can understand the contribution of each risk variable to the predicted outcome so that the decision-making process becomes more transparent. In the case of predictive diabetic kidney disease and cardiovascular complications, factors such as HbA1c, blood pressure, age, duration of diabetes, and kidney function can be identified as key predictors that contribute to model outcomes (Sabanayagam et al., 2023). In contrast, CNN is often considered a "black box" model because its decision-making process is difficult for users to understand. Although CNN is able to produce high accuracy in detecting diabetic retinopathy and diabetic foot ulcers, a lack of transparency in the prediction process can reduce the level of trust of health professionals in these systems (Das et al., 2023). This condition becomes more complex when predictive results are used as a basis for clinical decision-making that has the potential to affect patient safety.

In addition to the issue of interpretability, workflow changes are also an important obstacle. The implementation of diabetes complication prediction systems often requires changes in work procedures, user training, and adaptation to new technologies (Sadiq et al., 2025). Some healthcare workers may experience resistance because they feel the new system could increase their workload or reduce their clinical autonomy. Regulatory factors also play an important role in the adoption process. The use of artificial intelligence-based systems in healthcare requires legal certainty regarding clinical responsibility, patient data security, and model validity. Regulatory uncertainty can cause healthcare institutions to be hesitant to implement machine learning technology widely (Gaddas et al., 2025). Therefore, a human-centered design approach is very important in the development of diabetes complication prediction systems. The involvement of health workers from the design stage of the system can increase the suitability of technology to user needs while strengthening the level of acceptance of new technologies (Jeilani & Hussein, 2025).

Practical Implications and Future Research Directions

The results of the review show that research on the prediction of diabetes complications has progressed rapidly, particularly in the use of Random Forest and CNN. Nevertheless, most research still focuses on developing algorithms and improving model performance, while implementation research in real clinical settings is still relatively limited. Random Forest currently has a greater chance of implementation because it is easy to integrate with EHR systems and has better interpretability (Khodadadi et al., 2023). Therefore, this model can be the main choice for the initial implementation of diabetes complication prediction systems in routine health services. In contrast, CNNs have great potential in the processing of complex data, especially medical imaging and multimodal data, so that it can provide greater benefits in the future if technical and operational barriers can be overcome (Salehi et al., 2023). Future research needs to lead to the evaluation of the clinical impact of the implementation of diabetes complication prediction models. The focus of the research is not only on the value of accuracy, sensitivity, or area under the curve (AUC), but also on the influence of the system on early detection of complications, quality of service, work efficiency of health workers, and clinical outcomes of patients (Kumar et al., 2023). In addition, multimodal data integration that combines EHR data, laboratory data, medical imaging, wearable devices, and omics data has the potential to significantly improve the predictability of diabetes complications. The development of explainable artificial intelligence (XAI) is also an important research area to increase transparency and user trust in machine learning-based systems (Agrawal et al., 2025). The successful implementation of diabetes complication prediction models is determined not only by the sophistication of the algorithm, but also by the harmonization between technology, users, organizations, and health policies (Bai et al., 2026). A multidisciplinary approach involving researchers, clinicians, system developers, and policymakers is needed to ensure that machine learning innovations can provide tangible benefits for the prevention and management of diabetes mellitus complications.

CONCLUSION

This systematic review shows that machine learning models based on Random Forest and Convolutional Neural Network (CNN) have great potential in predicting various complications of diabetes mellitus, including diabetic kidney disease, diabetic retinopathy, diabetic neuropathy, diabetic foot ulcer, and cardiovascular complications. Random Forest tends to be easier to integrate into clinical systems because it has better interpretability and lower computational requirements, while CNN offers higher predictive capabilities on complex data, including medical images and clinical tabular data, but faces greater challenges related to infrastructure, computing, and model transparency. Although the predictive performance of both models is promising, most implementations are still at the non-integrated, prototype, or semi-integrated stages, so there is a gap between the development of the algorithm and its implementation in clinical workflows. The successful integration of diabetes complication prediction models into the healthcare system is determined not only by the accuracy of the model, but also by the interoperability of the system, readiness of infrastructure, user acceptance, and regulatory support. Therefore, further research needs to focus more on implementation studies and clinical impact evaluations to ensure that machine learning technology can provide tangible benefits in preventing diabetes complications and improving the quality of health care.

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