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REVIEWPAPER

A Review on AI-Driven Approache for Diabetes Prediction in Female Populations via Risk Factor Analysis

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***Abstract*—Diabetes is fast emerging as a serious health challenge in the world, with countries around the globe spending huge resources on its management. At the same time it impacts the quality of life, especially among the female population in view of the hormonal, reproductive, metabolic and lifestyle-related risk factors. Early diagnosis and timely treatment are essential to minimize complications and enhance preventive healthcare. The present review paper presents the different artificial intelligence (AI) based strategies for the prediction of diabetes based on risk factors. The study focuses on the female-specific risk factors like gestational diabetes mellitus (GDM), polycystic ovary syndrome (PCOS), hormonal imbalance, obesity, genetic predispositions and socioeconomic factors related to the progression of diabetes. Furthermore, the survey examines how predictive accuracy can be improved by using machine learning (ML), deep learning (DL), federated learning, and cloud-based healthcare systems and how they can be used to personalize healthcare and facilitate early healthcare diagnosis. The results show that AI-based models, such as multimodal and DL models, outperform the traditional models in terms of prediction accuracy. However, there are a number of challenges that are still important research challenges for AI predictive systems for diabetes, such as limited data interpretability, privacy concerns, imbalanced data, and lack of female-specific data.**

Keywords—diabetes prediction, artificial intelligence, female health, risk factors, machine learning, personalized healthcare.

I. Introduction

The increasing prevalence of chronic diseases has become a major concern in healthcare systems globally, impacting public health, healthcare resources, and long-term patient care for various populations [1][2][3]. Diabetes is one of the major health issues nowadays and has affected many lives in the world. The prevalence of diabetes has been greatly increased due to urbanization, unwholesome lifestyle, obesity, aging and physical inactivity over the last few years [4]. According to the world health reports 90% of diabetes cases are Type II. It is more common in low- and middle-income countries, where there is less health-care coverage and later diagnosis, resulting in increased complications and mortality [5].

Diabetes mellitus is a metabolic disorder associated with abnormalities in hormone synthesis, secretion, and signal transduction, and in hormone receptor function, with insulin, glucagon, incretins, adipokines, and stress hormones being the major hormones involved in the disease. Treatment for diabetes extends beyond glucose control, and modern therapy does include consideration of preventative measures for the population, cardiovascular health, obesity, and kidney protection [6][7].

Early detection of diabetes is crucial for managing disease progression, minimizing the possibility of severe health consequences, and optimizing health outcomes. Early detection of high-risk individuals enables early interventions, including lifestyle changes, frequent monitoring and targeted treatment [8]. While traditional single-models prediction approaches may suffer from shortcomings in prediction accuracy and generalization, the powerful ensemble learning and AI approaches have the ability to deliver more reliable prediction performance [9]. For females, early diagnosis is especially critical as hormones, reproductive function and metabolism may make them more susceptible to developing diabetes and complications associated with the disease [10]. Hence, early prediction system guarantees the advent of improved preventive healthcare and personalized disease management strategies.

Diabetes disease burden, especially in females, has grown substantially in the past few decades and has emerged as a significant global public health problem [11]. While there have been studies that have taken a broad overview of the diabetes prevalence and trends in different age groups, there have been fewer studies that have specifically analyzed the diabetes process and progression across the female lifespan and its unique factors. Females' risk and burden of diabetes vary by stage of life, through the interplay of biological, hormonal, reproductive and lifestyle factors. Furthermore, population aging, obesity, and lifestyle changes worldwide are likely to continue to drive up the proportion of people with diabetes in females [12]. The lack of knowledge regarding modifiable risk factors and the progression of the disease over a lifetime in females indicates the need to conduct more research in females and implement preventive health interventions that are gender-specific.

AI has completely changed healthcare practices and disease forecasting through its advanced data-driven techniques. AI systems depend on electronic health records (EHRs) [13][14] and clinical data, medical imaging and lifestyle data to enhance their predictive capabilities and enable early detection of diseases [15][16]. Clinical decision support systems and disease prediction accuracy have increased since machine learning (ML) and deep learning (DL) techniques were incorporated into AI research [17]. AI-based technologies provide healthcare professionals with faster diagnostic results by detecting hidden disease patterns and connections in medical data that traditional diagnostic techniques fail to identify. AI and ML models have shown strong capabilities to detect high-risk diabetes patients who present with hormonal, reproductive, metabolic and lifestyle risk factors, especially among female patients [18][19]. These intelligent predictive systems support personalized healthcare, early intervention, risk assessment, and effective diabetes management among females. Risk factor analysis using AI-driven techniques enables the identification of significant biological, hormonal, genetic, behavioral, and lifestyle predictors of diabetes in female populations.

A. Structure of the Paper

This paper is organized as follows: Section II discusses Diabetes in Female Populations, Section III explains Female-Specific Risk Factors, Section IV describes AI-Driven Techniques for Diabetes Prediction, Section V highlights major challenges in AI-driven diabetes prediction, Section VI presents the Literature Review, and Section VII concludes the paper with Future Research Directions.

II. Diabetes in Female Populations

Diabetes mellitus is a chronic metabolic disorder characterized by low levels of insulin activity and/or production which cause poor blood sugar control. Among the factors affecting diabetes in female population are several biological, hormonal, reproductive and lifestyle factors affecting insulin sensitivity and glucose metabolism in the body. Females are also at risk of developing diabetes because of pregnancy-related issues, hormonal imbalance, obesity and polycystic ovary syndrome (PCOS). The main types of diabetes in the female population are Type I Diabetes, Type II Diabetes, and GDM which have varying causes, progression and health issues. There is a need for understanding diabetes in female populations for early prediction, prevention and effective management of diabetes with healthcare technologies and risk analysis approaches.

A. Types of Diabetes

Diabetes mellitus is a long-term metabolic disease in which the body's ability to control blood glucose levels is compromised by either inadequate insulin synthesis or defective insulin action. Type I, Type II, and Gestational Diabetes are the three primary forms of diabetes. The different types of diabetes have distinct causes, symptoms, risk factors and clinical management approaches, which particularly affect female populations.

Fig. 1. Classification of diabetes into type I diabetes, type II diabetes and gestational diabetes

Fig. 1 displays diabetes classification system for females, which encompasses Type I, Type II, and gestational diabetes, along with their respective causes, clinical features, symptoms and risk factors affecting females.

1) Type-I Diabetes

Insufficient insulin production is a characteristic of type I diabetes, formerly known as insulin-dependent diabetes or juvenile diabetes. It has to be managed with regular insulin shots. Type I diabetes affected an estimated 9 million persons globally as of 2017, with the majority of cases happening in high-income nations. It is still unknown what causes the disease and how to avoid it. Long before aberrant insulin secretion starts, type I diabetes (T1D) can be identified, and a gradual loss of insulin function can start at least two years before diagnosis. During this period, there is also a decrease in β-cell sensitivity to glucose. The late-phase insulin response increases as the initial insulin response decreases, perhaps compensating for the reduction. Once diagnosed, insulin responsiveness gradually deteriorates. A two-stage reduction in insulin secretion can be seen in the first few years, and first year is steeper than second. If identified, this decreased insulin production may persist for years, leading to little or non-existent insulin production. High glucose levels can indicate T1D even if it looks normal.

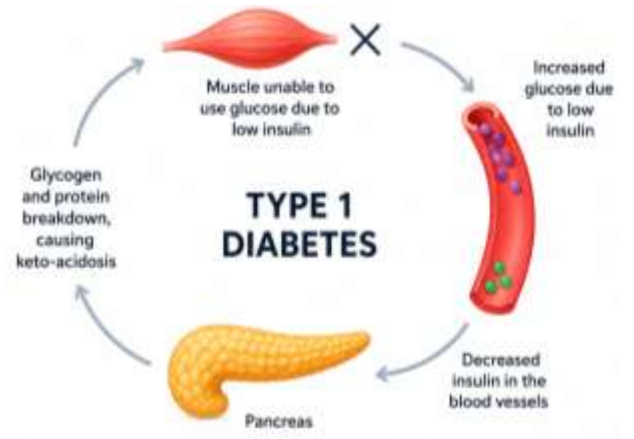

Fig. 2. Type-I Diabetes

The pathological mechanism of Type I diabetes (shown in Fig. 2) involves the pancreas failing to produce enough insulin, leading to the degradation of proteins and glycogen, decreased glucose absorption, and elevated blood glucose levels. This process eventually leads to ketoacidosis.

2) Type-II Diabetes

The disease known as type II diabetes occurs when the body improperly uses glucose (sugar) for energy. It disrupts the body's use of insulin and, if left untreated, can lead to elevated blood sugar. Uncontrolled type II diabetes can eventually cause major problems, especially harm to the blood vessels and nerves. In some people, diabetes of this kind can be avoided. Typical risk factors include being overweight, not exercising, and having a family history. The key to preventing serious health problems is early detection of type II diabetes. Regular medical examinations and blood tests with a health care provider are the best method to detect it early. Type II diabetes affects more than 95% of diabetics [20]. This was previously known as "adult" or non-insulin-dependent diabetes. In the past, it was a disease of adults, but now there is an increasing number of children with disease. High blood sugar levels severely impair body's ability to produce insulin and increase insulin sensitivity to other fuels. In the long-term, hyperglycaemia get worse and harder to control. Another characteristic of the progression of type II diabetes (T2D) is a gradual loss of β-cell function.

Fig. 3 illustrates how, with Type II diabetes, the insulin is still being secreted, but the glucose is not being utilized effectively, and this is caused by insulin resistance due to obesity, genetics and lifestyle factors, which all contribute to the increased blood glucose level.

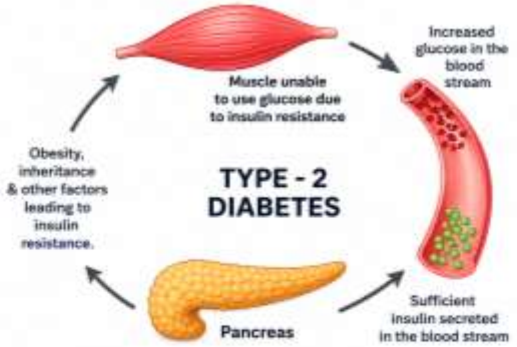

Fig. 3. Type-II Diabetes

3) *Gestational Diabetes Mellitus*

When blood glucose levels are elevated during pregnancy, a condition known as gestational diabetes mellitus (GDM) can develop. It occurs when the body can't make or use enough insulin to fulfill pregnancy's higher metabolic needs [21]. Hormonal changes that impact pancreatic β-cell activity and produce insulin resistance often happen in the second or third trimester. GDM is more likely to strike females who are overweight, over 40, have a family history of the disease, have had at least one GDM-affected pregnancy, have PCOS, and lead sedentary lifestyles [22]. GDM can adversely impact maternal and fetal health; complications like, As hypertension, preeclampsia, premature delivery and excessive growth. They lead to fetal growth and increased risk of cesarean section. Although it usually goes away after giving birth, it can be a significant condition. Raises mother's and baby's Type II diabetes risk the child. Early screening, glucose monitoring, lifestyle and preventive strategies. Treatment is required urgently, and the importance of modification is highlighted. for lowering long-term health issues and enhancing pregnancy outcomes.

Fig. 4. Maternal and Fetal Complications Associated with Gestational Diabetes Mellitus (GDM)

The main maternal and fetal problems linked to gestational diabetes mellitus are depicted in Fig. 4, including hyperglycemia, psychological stress, pre-eclampsia, cesarean delivery, macrosomia, and increased future risk of Type I or Type II diabetes.

B. Epidemiology and Prevalence in Females

The prevalence of diabetes among females has increased significantly worldwide due to factors such as urbanization, unhealthy eating patterns, a lack of exercise, and an increase in obesity rates. The burden of diabetes varies across age groups, ethnicities, and socioeconomic conditions. Females with diabetes are also at higher risk of long-term complications, including cardiovascular and reproductive health disorders [23]. Understanding the epidemiology and prevalence of diabetes in females is important for effective prevention, early diagnosis, and healthcare management strategies.

C. Diabetes Complications in Females

Diabetes complications in females differ significantly from those in males due to hormonal, physiological, and socio-economic factors. Females with diabetes are at greater risk of cardiovascular diseases [24], including coronary heart disease and stroke, compared to men. Additionally, gestational diabetes increases a woman's risk of Type II diabetes in the future. Other factors associated with female patients that lead to severe complications include delay in diagnosis, poor glycemic control, obesity and lack of access to healthcare [25]. Moreover, diabetic females are at increased risk of vascular complications and mortality. The gender-specific disparities underscore the need for early detection, effective disease management, and personalized healthcare strategies, achieved through AI, to enhance diabetes prediction and prevention in the female population.

D. Gender-Specific Challenges in Diagnosis and Management

Diabetes is different in men and women, it presents with different symptoms, different treatments and different long-term management. A diabetic female has a higher risk of cardiovascular problems, neuropathy, mental health disorders, and reproductive problems. Aside from this, changes in hormones, the conditions of pregnancy in females, and late diagnosis have been seen to exacerbate the disease. Furthermore, female omen is also more likely to have more serious problems from kidney disease, heart failure and stroke than men. The gender differences highlight the importance of tailored healthcare strategies [26], timely detection, and gender-specific management strategies to ensure better clinical outcomes and minimize diabetes-related complications in females, such as:

- **Cardiovascular Complications:** As their bodies lose important protective hormones and undergo accelerated atherothrombotic disease progression, diabetic females are at a greater risk of developing coronary heart disease, stroke, and vascular damage.
- **Heart Failure:** Heart failure in females is more frequently caused by diabetes, obesity, and hypertension, which frequently results in hypertrophic cardiomyopathy and maintained ejection fraction.
- **Diabetic Foot:** Men are more likely than women to have diabetic foot problems and amputations, whereas females exhibit distinct progression-related risk factors such as uric acid levels and insulin treatment.

- **Diabetic Retinopathy:** Gender-specific pathogenic abnormalities in diabetic retinopathy are not well-documented; both genders are similarly affected.
- **Diabetic Nephropathy:** However, diabetic female has a greater death rate during dialysis than men do, despite the fact that males undergo quicker disease progression.
- **Diabetic Neuropathy:** Painful neuropathy symptoms, such as paresthesia, sensory loss, and persistent nerve pain, are more common in females.
- **Diabetic Gastroparesis:** Gastroparesis is more common in females because of delayed stomach emptying, which also affects the metabolism and absorption of glucose.
- **Mental Health Disorders:** A diabetic female is more likely to have depression, anxiety, and eating disorders, which have a detrimental impact on their quality of life and ability to manage their disease.
- **Sexual and Reproductive Challenges:** Pre-pregnancy care is crucial since diabetic females have greater rates of unfavorable perinatal outcomes, pregnancy risks, and reproductive difficulties.

III. Female-Specific Risk Factors

There are risk factors in diabetes that are specific to females. Diabetes susceptibility and long-term complications of diabetes are influenced by a variety of conditions that affect insulin resistance and glucose metabolism, such as GDM, PCOS, hormonal imbalance, reproductive health disorders and lifestyle-related factors, all of which are significant contributors to this issue in female populations.

- **Pregnancy-related (Gestational Diabetes):** GDM is a common metabolic disease that develops during pregnancy, which is defined by abnormalities in glucose metabolism that develop during pregnancy. GDM has increased to 15.8% because of various factors such as increased age at childbearing, change in diet patterns, and pre-pregnancy obesity. GDM raised a pregnant woman's chance of macrosomia, premature delivery, and preeclampsia, among other unfavorable pregnancy outcomes [27] and also had a profound impact on the future health of their offspring, increasing the risk of obesity, type II diabetes and other metabolic disorders. Thus, early prediction and management of GDM may be an effective strategy in minimizing GDM and perinatal complications and thereby provide better care for the mother and baby in the perinatal period, and thereby improve long-term health outcomes.
- **Polycystic Ovary Syndrome (PCOS):** PCOS, sometimes called Stein-Leventhal syndrome, is a common endocrine disorder that raises the risk of diabetes in women who are fertile. Hyperandrogenism, ovulatory dysfunction and polycystic ovarian disease are the features of this condition. Increased androgen production and insulin resistance contribute to obesity, irregular menstruation, infertility, hirsutism, and metabolic disturbances. Type II diabetes and gestational diabetes are more common in females with PCOS [28], and cardiovascular complications.

Fig. 5 presents the common clinical symptoms of PCOS, including insulin resistance, obesity, irregular menstruation, infertility, ovarian cysts, acne, hirsutism, and reduced sexual drive-in female.

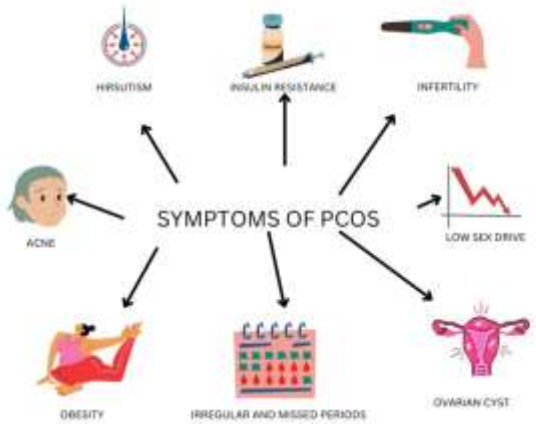

Fig. 5. Common Clinical Signs and Symptoms of PCOS

- **Hormonal imbalance:** Female hormonal imbalance is a major risk factor for the development and progression of diabetes. Hormones including cortisol, progesterone, estrogen, and androgens control glucose metabolism and insulin sensitivity. Any imbalance in these hormones can affect the way blood glucose is regulated and can result in diabetes. Menopause, pregnancy, thyroid disorders, and polycystic ovary syndrome (PCOS) are frequent hormones disruptions [29]. As a woman nears menopause, she may gain weight in the abdomen and lose sensitivity to insulin, which puts her at greater risk for Type II diabetes. Similarly, elevated androgen levels associated with PCOS can contribute to poor glucose tolerance and metabolic dysfunction. Hormonal changes during pregnancy may also lead to gestational diabetes mellitus (GDM). Therefore, hormonal imbalance plays an important role in diabetes risk among females and should be considered in early prediction and management.

A. General Risk Factors

Females are affected by several biological, genetic, hormonal, and lifestyle-related factors that influence diabetes development. These risk factors can be divided into non-modifiable, lifestyle-modifiable and medical-related risk factors [30]. These factors are crucial for early diabetes prediction, prevention and AI analysis in healthcare for females.

- **Age:** One of more significant risk factors for diabetes, especially Type II diabetes, is advancing age. Females above age of 45 are more likely to develop insulin resistance and impaired glucose metabolism. Hormonal changes, decreased activity and metabolic dysfunction are also linked to aging.
- **Obesity:** A significant risk for diabetes is obesity, especially belly fat. Obesity causes insulin resistance and a derangement of glucose metabolism.
- **Lifestyle:** Sitting for long periods of time and a lack of regular exercise are associated with an increased risk of diabetes and insulin resistance.
- **Genetic Predisposition:** If an individual has a family history of diabetes, it raises the likelihood of developing the disease. Females with diabetes in the family or close relatives are more likely to be

prediabetic or to develop insulin resistance and abnormal glucose levels.

B. Socioeconomic and Behavioural Factors

Females' socioeconomic and behavioral factors are significant determinants of diabetes development and progression. Opportunities for early diagnosis, treatment, and proper disease management can be reduced due to limited access to healthcare, low education, poor economic conditions and lack of health awareness. Females with low-income levels may face difficulties in maintaining a healthy diet, attending regular medical check-ups, and accessing diabetes treatment services [31]. In addition, lifestyle-related elements such alcohol use, smoking, obesity, and physical inactivity, stress, and sleep disorders significantly increase the risk of diabetes. Sedentary behavior and excessive consumption of processed foods contribute to obesity and insulin resistance, which is one of main causes of Type II diabetes. Furthermore, psychological stress and depression can affect the balance of hormones and can adversely affect glucose metabolism. Hence, socioeconomic status and lifestyle are significant factors to be taken into account in diabetes prediction and prevention, especially for females.

IV. AI Techniques for Diabetes Prediction

AI-based methods significantly contribute to enhancing diabetes prediction, early detection, and personalized management of diabetes [32]. AI-based models analyze clinical, demographic, lifestyle, and medical data to identify high-risk individuals with high accuracy. ML, DL, and federated cloud-based systems enhance predictive performance, support clinical decision-making, and enable secure healthcare analytics [33][34].

A. Machine Learning Approaches

ML techniques can help systems learn from healthcare data to detect patterns in disease without explicit programming. ML algorithms can be used in diabetes prediction to screen out high-risk patients based on clinical, demographic, and lifestyle-related factors [35]. Some common ML algorithms include KNN, RF, LR, SVM, DT, and ensemble models. They are used to assist in predicting diabetes at early stages, assessing diabetes risk and for clinical decision-making, especially in females.

B. Deep Learning Approaches

A more sophisticated type of ML called DL uses ANN to examine big and intricate healthcare datasets [36]. DL models perform very well in automatically learning complex relationships and patterns of medical data. Popular DL architectures include CNNs, RNNs and LSTM networks. In the medical field, these techniques are used in medical image analysis, EHR processing, and time-series forecasting to aid in accurate diabetes prediction and personalized healthcare management.

C. Federated and Cloud-Based AI Systems

AI systems that are federated and cloud-based have been successful in diabetes prediction and healthcare analytics for secure and scalable applications [37]. Federated Learning (FL) also enables decentralized model training, which helps protect privacy and is compliant with HIPAA and other healthcare regulations, thereby helping to safeguard sensitive patient information without direct data sharing [38][39]. It also helps to facilitate collaboration among healthcare organizations, minimizes bias due to single-center datasets, and enhances model generalizability. FL has been found effective in glucose control optimization and EHR analysis of different patient populations in diabetes prediction [40].

Cloud-based AI systems can help manage vast healthcare data, process it efficiently, and analyze it in real-time [41]. These systems allow for remote patient monitoring, shared care co-ordination and the incorporation of multimodal data such as activity tracking, insulin pump data, CGM and genetic data. Furthermore, the use of multimodal AI and self-supervised learning techniques enables the discovery of previously unknown connections between clinical features, further enhancing the predictive power. Intelligent systems can assist in personalized diabetes prediction and management, especially in the case of females with complex hormonal, metabolic and reproductive risk factors.

V. Challenges in AI-Driven Diabetes Prediction

Diabetes prediction systems exist based on AI, but they have several technical, ethical, and clinical issues, including that they impact prediction accuracy and healthcare uptake rates [42][43]. The key obstacles for the development of women-centric diabetes prediction and management system are summarized in Table I.

TABLE I. Major Challenges in AI-Based Diabetes Prediction for Female Populations

Challenge	Description	Impact on Female Diabetes Prediction
Limited Female-Specific Data	Most healthcare datasets lack female-specific information such as hormonal, reproductive, and pregnancy-related factors.	Reduces prediction accuracy for conditions like PCOS, gestational diabetes, and menopause-related diabetes risks.
Data Imbalance and Missing Values	Medical datasets often contain incomplete records and uneven class distribution.	Leads to biased learning, reduced model performance, and inaccurate prediction outcomes in females.
Privacy and Security Issues	AI systems use sensitive patient information including EHRs, genomic data, and lifestyle records	Creates challenges in secure data sharing, patient confidentiality, and regulatory compliance in female healthcare data.
Ethical and Bias Concerns	AI models may develop bias due to unequal representation of gender and socioeconomic groups in datasets.	Can produce unfair or unreliable predictions for female patients and reduce trust in AI systems.
Clinical Deployment Challenges	Real-world implementation of AI models requires infrastructure, validation, and healthcare professional acceptance.	Restricts the practical application of AI-based diabetes prediction systems in a female-focused healthcare environment.

VI. Literature Review

The literature section emphasizes the increasing role of AI and ML in diabetes prediction, particularly in identifying risk factors, leveraging multimodal data, and enabling personalized healthcare. There are still a few areas of concern, however, that include lack of interpretability, dataset imbalance, and lack of analysis by gender.

X. Xie et al. (2026) Clinical decision support and risk prediction in diabetes management have been improved because to AI. Research on AI-based prediction of cardiovascular disease (CVD), diabetic retinopathy (DR), and nephropathy (DN) from PubMed, Web of Science, and Scopus published between 2015 and 2025 is examined in this review. A total of 58 studies were analyzed, covering clinical, omics, imaging, and multimodal data. Multimodal data fusion shows improved performance over single-modality approaches. A summary of the development of DL and big language models from conventional ML is also provided, emphasizing their advantages and uses [44].

W. Meng et al. (2025) provide a way for predicting a woman's risk of developing diabetes using an enhanced artificial neural network (ANN) model based on Pima Indians Diabetes, with intention of improving prediction accuracy and acting as a clinical diagnostic guide. In order to avoid overfitting, the conventional ANN model is adjusted in this study by modifying the neural network's hyperparameters include number of layers, neurons, activation function, and dropout rate. Additionally, an early halting mechanism and L2 regularization are employed [45].

A. Tanwar and P. K. Bhatia (2024) people all across the world are affected by the chronic disease known as diabetes. Once a person contracts this ailment, it is a lifetime affliction. It is among top 10 deadliest diseases in world, according to the WHO. Heart disease, renal disease, neurological issues, and many other high-risk conditions can be brought on by having too much glucose in the blood. However, if diabetes is not adequately managed, it can become a dangerous disease. With good management and routine examinations, many of these problems may be avoided. By using the analysis of massive datasets to find trends and risk factors, ML and data mining techniques have become effective tools for diabetes prediction [46].

M. V. Prashanth et al. (2024). Early prediction of diabetes helps to avoid complications like diabetic retinopathy which leads to blindness. There is a 13% higher risk of death among people with diabetes, especially in female, cardiovascular disease caused by diabetes attributes to 50% higher risk of death, coronary heart disease caused by diabetes contributes to a 58% higher risk of death. The proposed research work aims to predict diabetes from the symptoms a patient exhibits. The proposed system is a healthcare assisting system that is accessible to patients as well as medical practitioners [47].

F. Hanna, P. Wu, A. Heald, and A. Fryer (2023). International guidelines recommend screening for type II diabetes; current screening strategies face major challenges. There is no consensus on the type and frequency of tests, leading to inconsistent guidance for healthcare professionals. Furthermore, compliance with screening recommendations remains low, and current efforts to improve screening largely rely on technology-based reminder systems that fail to consider patients' convenience or risk. Most importantly, current strategies are overly generic and rely on tests that detect abnormalities too late to enable effective prevention. Risk factors vary widely among individuals, and insulin sensitivity and β-cell dysfunction often appear during the pre-diabetes stage, before the onset of diabetes [48].

E. Dritsas and M. Trigka (2022) prevalence of diabetes has dramatically grown as a result of modern living. Consequently, early disease diagnosis is essential. ML has grown in popularity among medical professionals due to its powerful ability to provide practical tools for risk assessment, diagnosis, management, and treatment of a range of illnesses. This paper describes a supervised learning approach for creating high-efficiency type II diabetes risk prediction tools. To assess their significance and investigate their relationship with diabetes, a feature analysis is carried out. Several ML models are trained and evaluated using these characteristics, which are typical signs of diabetes and frequently appear gradually [49].

Table II presents recent studies on AI-driven diabetes prediction, highlighting their methodologies, contributions, challenges, and limitations related to female-focused risk analysis.

TABLE II. A SUMMARY OF THE STUDY ON AI-DRIVEN FOR DIABETES PREDICTION IN FEMALE POPULATIONS USING RISK FACTOR ANALYSIS

Reference	Focus Area	Key Findings	Challenges	Key Contribution	Limitation and Future Work
X. Xie et al. (2026)	AI-based prediction of DR, DN, and CVD using multimodal data	Multimodal AI models achieved better prediction performance than single-data approaches	Limited interpretability and integration of heterogeneous datasets	Highlighted the evolution from ML to DL and LLM-based diabetes prediction systems	Gender-specific prediction models were limited.
W. Meng et al. (2025)	ANN-based diabetes prediction for female	Optimized ANN improved prediction accuracy using hyperparameter tuning and regularization	Risk of overfitting and limited dataset diversity	Proposed an enhanced ANN framework for female diabetes risk prediction	Limited explainability and clinical validation
A. Tanwar and P. K. Bhatia (2024)	ML and data mining for diabetes prediction	ML techniques effectively identified diabetes risk factors from large datasets	Difficulty in handling complex and real-time clinical data	Demonstrated the usefulness of AI techniques in early diabetes prediction	Female-specific risk analysis was not considered
M. V. Prashanth et al. (2024)	Early diabetes prediction using symptom-based AI system	Early detection can reduce severe complications and mortality risks in females	Dependence on symptom-based inputs may reduce generalization	Developed a healthcare assistance system for patients and practitioners	Lifestyle and genetic factors were not included
F. Hanna, P. Wu, A. Heald, and A. Fryer (2023)	Diabetes screening and risk assessment strategies	Current screening methods are inconsistent and detect disease at later stages	Lack of personalized and patient-centric prediction approaches	Emphasized the need for individualized AI-driven early prediction systems	Screening strategies remained generalized
E. Dritsas and M. Trigka (2022)	ML-based risk prediction for type II diabetes	Feature analysis improved understanding of diabetes-associated symptoms	Limited explainability and dataset imbalance issues	Introduced supervised ML models for efficient diabetes risk prediction	Female health indicators were not included

VII. Conclusion and Future Work

The prevalence of diabetes has become a major global health challenge, particularly among females due to hormonal, reproductive, metabolic, and lifestyle-related risk factors. This survey paper reviews recent studies on diabetes prediction using AI techniques with consideration of female-specific risk factors. The reviewed studies indicate that AI, ML, DL, and federated healthcare systems contribute to early prediction, risk assessment, and personalized healthcare management. The findings also suggest that multimodal data integration and intelligent predictive models perform better than several conventional approaches. In addition, the survey identifies major research challenges, including limited female-specific datasets, data imbalance, privacy concerns, restricted interpretability, and issues related to clinical deployment. Overall, AI-driven predictive systems demonstrate strong potential for improving early intervention, preventive care, and personalized diabetes management among females.

Future research should focus on using large-scale female healthcare datasets to develop gender-specific and explainable AI models. The integration of multimodal clinical data, wearable devices, federated learning, and real-time monitoring systems may improve predictive performance, personalized treatment, and early Type II Diabetes Prevention in Various Female Populations.

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