International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Ai-Powered Insights into Diabetes Mellitus: A Comprehensive Systematic Review

[1]Dr. Vikas J. Magar, [2]Dr. Sachin B. Bhoite, [3]Dr. Rajivkumar S. Mente, [4]Dr. Tulashiram B. Pisal

Submitted: 07/02/2024 **Revised**: 15/03/2024 **Accepted**: 21/03/2024

Abstract: This comprehensive systematic review delves into the current landscape of artificial intelligence (AI) applications to illuminate the intricate metabolic processes and facets of diabetes mellitus. The primary objective is to thoroughly scrutinize and assess the existing body of studies to uncover potential benefits that AI may offer in identifying diabetes mellitus. This study delves into AI's potential for diabetes management, from early detection and personalized therapy to predictive modeling. It critically assesses both the benefits and drawbacks of AI integration, paving the way for responsible future advancements in this complex field. By uncovering AI's potential in diabetes research and exploring its impact on healthcare, this analysis ignites a transformation in how technology shapes both research and treatment.

Keywords: *Artificial Intelligence, Diabetes Mellitus, Machine Learning, Healthcare, Clinical Insights*

1. Introduction

As diabetes mellitus rises as a global health titan, the potential of AI to revolutionize healthcare emerges as a beacon of hope. This research, driven by AI's transformative power in managing this disease, aims to illuminate a path forward through a comprehensive review of existing knowledge, paving the way for novel strategies and reshaping future studies in this critical domain. [1]. Machine learning, deep learning, and data mining - these are the mighty tools wielded by AI, its capacity to devour, decipher, and illuminate vast landscapes of data proving invaluable in simplifying the complexities of diabetes. Through these cutting-edge techniques, AI sheds light on diagnosis and treatment, offering patients and healthcare professionals alike a clearer path forward [2]. The potential application of artificial intelligence (AI) in diabetes research offers promise for enhanced understanding and more effective clinical strategies. However, a gap exists between theoretical potential and practical implementation. This systematic review aims to address this gap by providing a comprehensive synthesis of the scientific literature, identifying trends in AI methodologies, evaluating their efficacy, and highlighting areas in need of further investigation. Understanding the role and function of AI in diabetes research will have pragmatic consequences for healthcare practitioners, as AI-driven insights can potentially improve early identification, personalized treatment planning, risk assessment, and informed decision-making, ultimately leading to better patient outcomes and a more efficient healthcare system [3]. To catalyze breakthroughs in AI-powered diabetes treatment, this review delves deep into the existing body of knowledge, unearthing the strengths and weaknesses of current approaches. By pinpointing areas for improvement, it serves as a roadmap for researchers, guiding them toward filling knowledge gaps and developing innovative strategies. This detailed assessment of effectiveness, benefits, challenges, and future directions equips the scientific community with the tools needed to refine AI's role in diabetes management and accelerate progress toward better patient outcomes. Artificial Intelligence (AI) holds profound significance in the realm of Diabetes Mellitus for several compelling reasons[4]. Diabetes Mellitus, commonly referred to as diabetes, is a chronic metabolic disorder characterized by elevated blood glucose levels resulting from either insufficient insulin production or ineffective utilization of insulin by the body [5]. This situation affects billions of individuals globally and presents substantial healthcare challenges attributed to its potential complications. The significance of AI in diabetes management and research has garnered considerable attention, driven by its potential to transform various aspects of diabetes care, and understanding. Early detection and risk prediction, improved disease management, research advancements, predictive modeling, remote monitoring, and telemedicine

[1]*Assistant Professor, Department of Computer Science and Applications, Dr. Vishwanath Karad MIT World Peace University, Pune India*
Email: magarvjresearch@gmail.com
[2]*Associate Professor, Department of Computer Science and Applications, Dr. Vishwanath Karad MIT World Peace University, Pune*
Email: sachintenjuly@gmail.com
[3]*Associate Professor, School of Computational Sciences, P. A. H. Solapur University Solapur*
Email: rsmente@sus.ac.in
[4]*Assistant Professor, Green fingers College of Computer and Technology Shankarnagar-Akluj*
Email: pisaltbresearch@gmail.com

are some of the commonly listed significances of Artificial Intelligence in Diabetes Mellitus [6].

The primary objective of the research is to carry out a thorough evaluation and analysis of studies about the use of artificial intelligence (AI) in the setting of diabetes mellitus. The purpose of this study is to provide a comprehensive review of the application of artificial intelligence (AI) technologies in numerous facets of diabetes care, including diagnosis, prevention, and treatment. By synthesizing the available data, the paper seeks to shed light on the potential benefits, challenges, and future directions of AI-powered solutions in the fight against the diabetes pandemic. The primary objectives of the study are as to conduct a meticulous and comprehensive analysis of published studies, clinical trials, and pertinent data related to the application of AI in the field of diabetes mellitus. To do this, research from a range of sources will be examined, such as those from medical journals, conference proceedings, and healthcare databases. denouncing the diabetes pandemic. Second objective is to categorize and classify the various AI applications in diabetes management. Identify the different domains where AI has been applied like Diagnosis and early detection, Disease risk prediction and prevention, Personalized medicine, Treatment optimization, Monitoring and self-management, Patient education and engagement, and Monitoring and self-management in the domain of diabetic mellitus. Third objective is lead to identifying gaps in research and practical difficulties in putting AI-powered diabetic care approaches into practice. Throughout this study it is provided the potential recommendation to utilize AI-based technology in diabetic care management. It Suggests AI-based research areas for further development. Another objective is study gives the review of the possible improvements and prospect strategies for AI-powered diabetes care while judging current trends and advancing technology. Finally, study will contribute to the amount of knowledge on AI in healthcare, particularly in relation to diabetes, by offering a thorough and current synthesis of the information and insights that are accessible.

1.1 Theoretical framework: AI, Machine Learning, and Deep Learning

A theoretical framework is abstract configuration that provides a foundation for understanding and studying a particular topic or field. The theoretical framework in AI, machine learning, and deep learning corresponds to the fundamental concepts, precepts, and models that constitute the basis of these fields [7], [8]. Below is an overview of the theoretical underpinnings of deep learning, machine learning, and AI. Artificial Intelligence is the broad field of computer science that focuses on creating systems or machines that can perform tasks that typically require human intelligence, such as problem-solving, learning, decision-making, and understanding natural language [9]. Theoretical frameworks in AI include symbolic AI, connectionist AI (neural networks), and probabilistic reasoning [10]. These frameworks provide different approaches to modeling and simulating human-like intelligence. Knowledge representation, reasoning, problem-solving, planning, and natural language processing are the key concepts of Artificial Intelligence [11]. Machine learning is a subset of AI that pacts with the extension of algorithms and models that facilitate computers to acquire from data and make estimates or decisions without being plainly programmed [12].Theoretical frameworks in machine learning embody several learning paradigms, including supervised learning, unsupervised learning, and reinforcement learning. Incorporate feature engineering, model selection, optimization, and assessment metrics are the key concepts in machine learning [13].The theoretical framework deep learning is applied to manage and interpret complicated data, an area of artificial intelligence. Deep learning models are the neural networks of the human brain [14]. It employs multi-layered deep neural networks to extract hierarchical characteristics from input, which makes it very useful for applications like modelling predictions, natural language processing, and imagine and audio recognition Deep Learning is an essential component in many industries, especially self-driving vehicles, healthcare, finance and banking [15]–[17]. Its success is attributable to being able to automatically learn representations from raw data. Deep Learning is an essential component in many industries, especially self-driving vehicles, healthcare, and finance. Its success is attributable to being able to automatically learn representations from raw data [18]. The synergistic potential of Artificial Intelligence (AI), Machine Learning (ML), and Data Mining forms an especially potent combination. For the expansion of intelligent systems that can predict events, adjust to changing circumstances, and harvest information from enormous databases, artificial intelligence (AI) frequently utilizes the usage of Machine Learning and Data Mining techniques. Following figure 1, represents the relationship between AI, ML and Deep Learning [19].

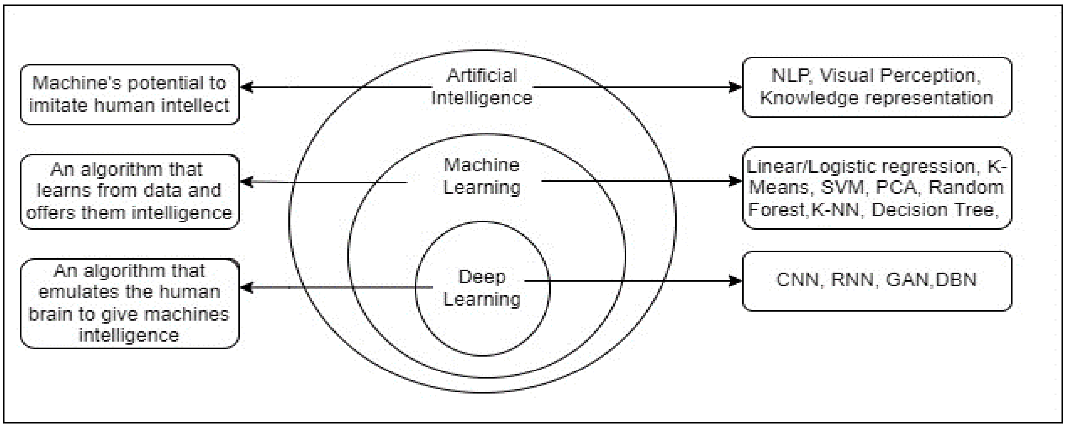

Fig 1. Interconnections Among AI, Machine Learning, and Deep Learning

In turn, data mining is employed by machine learning algorithms to extract pertinent characteristics and patterns from data that are then utilized for predictive modeling and decision support [20]. Considering all factors, the theoretical underpinning of Artificial Intelligence, Deep Learning, Machine Learning, and data mining is dynamic and continually evolving with the emergence of new findings and advancements in these domains. Together, professionals and academics in these fields develop more complex and sophisticated systems that can handle a wide range of real-world issues and difficulties [21].

1.2 Structure of the paper:

The research paper's structure is intended to offer an in-depth investigation of the application of artificial intelligence (AI) for controlling diabetes mellitus. Defining the history and emphasizing the significance of AI in the setting of diabetes is the first step in the Introduction (Section 1). It establishes the framework for a targeted investigation by describing the goals and objectives of the systematic review. The theoretical framework additionally investigates the fundamental ideas of Deep Learning, Machine Learning, and Artificial Intelligence, providing a theoretical groundwork for the discussions that follow. In addition, this section ends by outlining the paper's general structure. Section 2 delves into the Methodology, detailing the systematic approach taken to gather and analyze relevant literature. The paper comprises subsections such as "Search Strategy and Data Sources," delineating the parameters of the literature search, and "Inclusion and Exclusion Criteria," which establish the criteria for the selection of articles.

Sections 3 and 4 offer an overview of diabetes mellitus, exploring its types, key concepts, and associated complications. Section 4 then narrows the focus to the scope of AI-based approaches in diabetes, setting the stage for the subsequent in-depth analysis of AI techniques in diabetic mellitus treatment (Section 5). This section provides a critical review of prominent techniques such as Decision Tree, Neural Network, Support Vector Machine, Random Forest, and Case-Based Reasoning. Additionally, it examines commonly used datasets. Section 6 scrutinizes the constraints and challenges accompanying the application of Artificial Intelligence in diabetes management, providing a balanced perspective on the technology's constraints. Section 7 delves into future directions, offering insights into emerging technologies and potential research trajectories. The subsequent sections, 8 (Discussion) and 9 (Conclusion), synthesize the findings, discuss their implications, and draw conclusions, ensuring a comprehensive consideration of the current state and future possibilities in the realm of AI-powered insights into diabetes mellitus. The References section documents the sources cited throughout the paper, ensuring transparency and scholarly rigor.

2. Methodology

To find the vast field of artificial intelligence related to diabetes mellitus, we do a Google Scholar search (https://scholar.google.com). We use relevant keyword combinations, such as "Artificial Intelligence + Diabetic Mellitus," "Machine Learning + Diabetic Mellitus," "Support Vector Machine + Diabetic Mellitus," "Neural Network + Diabetic Mellitus," "Decision Tree + Diabetic Mellitus," "Random Forest + Diabetic Mellitus," and "CBR + Diabetic Mellitus," to search for the article using the Google Scholar search engine. We first carefully review the papers by inspecting the titles and abstracts. We then choose the articles based on machine learning and diabetic mellitus. Research articles which include the description of diabetic mellitus, machine learning, artificial intelligence, neural network, and Choice based reasoning. For this study we considered articles mostly from reputed journal/Publications like Springer Nature, Science Direct, IEEE, Taylor, and Francis etc.

2.1 Inclusion and Exclusion Criteria for article selection

This article provides the inclusion and exclusion criteria for the systematic review "AI-Powered Insights into Diabetes Mellitus." The systematic review aims to comprehensively examine and synthesize the existing body of studies on the application of artificial intelligence

(AI) to shed light on diabetes mellitus. Defining clear criteria is crucial to maintaining the review's neutrality, relevance, and thoroughness to include the research articles. The review's inclusion criteria encompass a broad spectrum of academic papers, conference proceedings, and clinical trials that were published in English between January 2000 and the present, with a focus on artificial intelligence (AI) applications related to diabetes mellitus. This group includes studies of adults and children with diabetes mellitus, together with diabetic type 1 and type 2. The studies under review must address the implementation of artificial intelligence (AI) or machine learning algorithms in diabetes management, diagnosis, risk assessment, monitoring, or treatment in a variety of settings. Several study designs are covered by the review, such as prospective or retrospective observational studies, case-control studies, cross-sectional studies, cohort studies, systematic reviews, meta-analyses, and randomized controlled trials. This inclusion criterion only applies to research that discusses AI applications concerning diabetes mellitus. Additionally, the review investigates a wide range of AI techniques that are used to forecast results, extract insights, or support clinical decision-making in the context of diabetes. These techniques consist of machine learning, image analysis, deep learning, natural language processing, and other people. Performance metrics that are relevant to the impact of artificial intelligence (AI) applications on diabetes management and associated outcomes, such as the area under the receiver operating characteristic curve (AUC-ROC), F1-score, sensitivity, specificity, and predictive values, accuracy, and other relevant indicators, should be explicitly disclosed by the studies the fact that are included in the review.

The objective of the review's exclusion criteria is to make sure that high-caliber, relevant research gets reviewed while filtering out studies that do not adhere to strict rules. Grey literature, conference abstracts, letters, views, posters, and other non-peer-reviewed materials will not be accepted. Studies that do not address the use of AI in diagnosing, treating, or managing diabetes mellitus will be disregarded, as will those that don't include significant outcome statistics. To make sure the review maintains demanding, the research team will disregard studies that do not meet the required standard of methodological quality, case reports, case series, expert feedback, qualitative studies, and studies that have an inadequate study design. Non-English language articles will also not be included because translation resources are limited. Furthermore, the papers we selected are primarily published by reputable publishers including IEEE, Elsevier, and Springer, and we classified them based on how specifically they are used in the medical area. In summary, we identified 100 publications that are relevant to our study, particularly the portion on the uses Artificial Intelligence in diabetic mellitus. We focused primarily on works published within the last 10 years and have visualized the overall distribution of papers over time in Figure 2. Additionally, the chosen papers predominantly originate from reputable publishers, including IEEE, Elsevier, and Springer, as depicted in Figure 3.

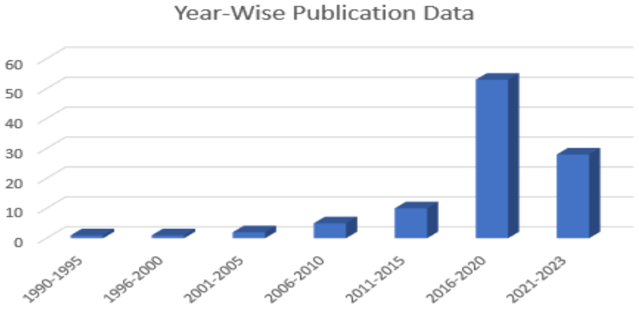

Fig. 2 Article Distribution according to Publication year

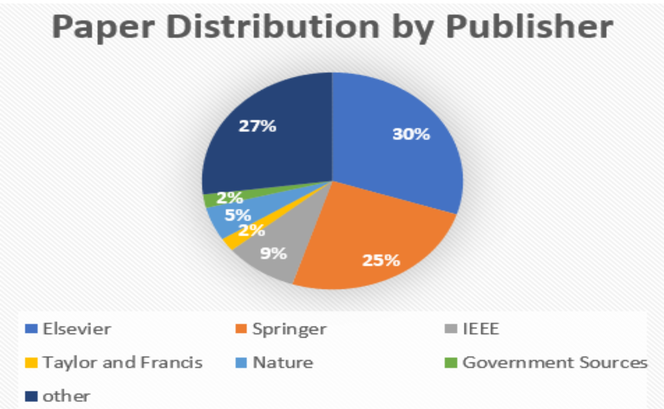

Fig. 3 Article Distribution according to Publication

To sum up our findings, we have identified 100 articles pertinent to our study. These 100 articles cover the study of various techniques belonging to artificial intelligence to predict diabetic mellitus. The compiled articles encompass a diverse range of studies focused on various aspects of Artificial Intelligence in diabetic management. These include examinations of diabetic retinopathy, investigations into risk factors associated with diabetes, explorations of diabetic mellitus and awareness, and innovative approaches employing data-driven and deep learning methods to measure the thickness of diabetic macular. Moreover, the compilation includes studies on the advancement of decision support systems for predicting diabetes and the effort of artificial neural networks (ANN) for the continuous guess of blood glucose levels. The breadth of these studies contributes to a comprehensive understanding of the intersection between Artificial Intelligence and diabetes-related challenges.

3. Overview of Diabetes Mellitus

Diabetes Mellitus, sometimes known as diabetes, is a long-term metabolic condition characterized by high levels of glucose in the blood (sugar) [22]. The condition occurs when the body has difficulty regulating blood sugar levels because of issues with insulin, a hormone that helps in blood glucose regulation [23]. Type 1, Type 2, and gestational diabetes are the most frequent varieties of the disease, which is a significant global health issue [24], [25]. Diabetic mellitus is divided into four categories like prediabetic, type 1, type 2 diabetic and gestational diabetics. In the case of prediabetic, blood sugar levels have over average but not yet high enough for a doctor to diagnose diabetes are known as prediabetes [22]. The likelihood of developing type 2 diabetes and cardiovascular illnesses increases with prediabetes[26]. Regular exercise and weight loss, often ranging from five to seven percent of one's body weight, may significantly decrease these risks.[27], [28]. Type 1 diabetic is insulin-dependent diabetes mellitus (IDDM) is a popular term used to describe type 1 diabetes [22] . Because it tends to occur in childhood, it is also described as juvenile-onset diabetes. An autoimmune condition called type 1 diabetes happens when the pancreas is attacked by the body's immune system using antibodies, impairing the organ's capability to produce insulin. In addition to family history, problems affecting the pancreatic cells in charge of generating insulin may also contribute to this sort of diabetes [29]. Type-1 diabetes is characterized as an autoimmune disorder where the body's immune system erroneously targets and eliminates the insulin-producing beta cells located in the pancreas. Although the precise cause is not fully comprehended, this condition frequently manifests early in life. Typically, this diabetic is found in children, adolescents, or young adults. People having Type 1 diabetes need permanent insulin therapy to restrain their blood sugar levels. Insulin is typically administered through injections or an insulin pump. Type 2 diabetic is non-insulin-dependent or diabetes that develops in adults are additional popular titles [22]. However, during the last 20 years, it has become more prevalent among kids and teens, mostly because of the rise in the number of young people who are overweight and obese. Type 2 diabetes now affects 90% of diabetic patients [24]. Type 2 diabetes is defined as insulin resistance, a condition in which the body's cells exhibit reduced responsiveness to insulin, coupled with a gradual decline in insulin production by the pancreas. Genetic factors, obesity, poor diet, and a sedentary lifestyle are key risk factors. While commonly emerges in adulthood, the diagnosis of Type 2 diabetes is becoming more prevalent among children and adolescents, primarily attributable to the escalating rates of obesity. For the treatment initially need to change lifestyle, including diet and exercise. In some cases, oral medications or insulin may be necessary to manage blood sugar levels. Another type of diabetic is gestational diabetes. It is a kind of diabetes that happens to pregnant women who have never suffered from the disease before [30]. In some women, gestational diabetes develops during many pregnancies. Gestational diabetes often presents during the middle of pregnancy [31]. When the body lacks the ability to generate enough insulin to satisfy the increased demands during pregnancy, gestational diabetes develops. Although it typically goes completely after childbirth, it enhances the chance of developing Type 2 diabetes in adulthood. This diabetic diagnosed mostly in the second or third trimester of pregnancy. This diabetic is managed through diet, medication, and exercise. Symptoms of Diabetics may include unexpected weight loss, increased thirst and frequent urination, fatigue and weakness, recurrent infections, tingling or numbness in the limbs (neuropathy), fatigue and weakness, and poor wound healing [32]. Heart disease, stroke, kidney failure, neuropathy, retinopathy (eye damage), and problems with circulation that may require amputations are merely a few of the long-term conditions that may affect multiple organs [33]. Hypoglycemia (low blood sugar) and hyperglycemia (high blood sugar) crises are examples of short-term problems that, if not correctly treated, can be fatal [34].

To avert complications, the management of diabetes care necessitates maintaining blood sugar levels within a specific range. Foundational lifestyle changes include engaging in regular physical activity, maintaining a healthy weight, and adopting a balanced diet several factors, including the type of diabetes and the patient's needs, medications like insulin or oral antidiabetic drugs may be performed. Type 2 diabetes is frequently avoided by making lifestyle changes like managing your weight, consuming a balanced diet, and participating in regular exercise [35]. Anticipation of the emergence of Type 2 diabetes involves timely identification and treatment of prediabetes. In conclusion, diabetes mellitus is a chronic disease characterized by elevated blood sugar levels and is associated with various health issues. To live healthy lives and lower the risk of complications, people with diabetes need early diagnosis, appropriate care, and lifestyle adjustments. Initiatives related to public health are essential for preventing and educating people about diabetes.

4. Scope of the Ai Based Approaches in Diabetic Mellitus

Artificial intelligence (AI) has an extensive number of applications in the field of diabetes mellitus and has significant promise to improve patient care, research, and healthcare system effectiveness [36]–[38]. Early detection and risk assessment play crucial roles in recognizing individuals at risk of developing diabetes. In this process, artificial intelligence (AI) plays a key role by evaluating a variety of datasets, including genetic, lifestyle, and electronic health records (EHRs)[4]. Healthcare workers may proactively detect possible dangers by utilizing AI, which enables early intervention and the use of preventative measures. In addition to improving risk assessment accuracy, this integrated method gives healthcare practitioners the ability to customize therapies based on patient-specific data [39]. Ultimately, leveraging AI for risk assessment and early identification holds the probable to enhance outcomes and mitigate the overall impact of diabetes through the implementation of timely and targeted treatments. Artificial intelligence systems aid in the early identification of diabetes by using blood test results, imaging studies such as retinal scans, and other diagnostic data [39]. Artificial intelligence based applications are able to monitor continues glucose in real-time and suggest for insulin dosing [40]. AI has the capability to personalize a patient's treatment by considering their health information, lifestyle, and therapeutic responses, encompassing aspects such as medication dosage, timing, and choice[41].

In contemporary healthcare, AI-enabled telehealth technologies have emerged as invaluable tools for the remote monitoring of individuals with diabetes. These technologies offer a thorough and continuous assessment by offering real-time surveillance of symptoms, blood sugar levels, and general health [42]. By using artificial intelligence (AI) models, these systems can predict fluctuations in blood sugar levels and possible health problems. This enables prompt interventions and modifications of treatment plans that enhance patient outcomes [43]. Furthermore, by providing personalized food recommendations based on each user's unique health status, chatbots, and AI-powered applications are essential in encouraging better dietary habits[44]. AI is being used in healthcare in methods that go beyond monitoring to solve issues with drug adherence. Artificial intelligence (AI)-enabled applications and instruments alert medical staff to problems with patient adherence, remind patients to take their medications and track adherence levels over time, all of which enhance overall patient care and treatment performance [45]. As technology develops and research moves forward, the application of AI in diabetes care keeps increasing. Artificial intelligence (AI) possesses the potential to reduce healthcare expenditures, improve patient outcomes, and broaden our understanding of diabetes. To promote safe and effective AI integration into the surveillance and management of diabetes, it is essential to solve regulatory, ethical, and privacy concerns.

5. Literature Review of Ai Based Techniques for Diabetic Mellitus Treatment

AI has ushered in a new age in diabetes care, boosting possibilities for diabetes diagnosis significantly beyond the traditional dependency on a small number of blood glucose level readings and tests for glycosylated hemoglobin. In the realm of managing diabetes, many AI-based methods have found use. The subsequent section contains a few of the most crucial methods. A variability of machine learning methods has been utilized for the development of digital support systems for the medical management of diabetes. Random forests, Support vector machines, artificial neural networks, decision trees, naive Bayes, classification, k-nearest neighbors and regression trees are few of the techniques that are used in these processes [2]. The automation of the evaluation of blood glucose variations has been accomplished successfully using machine learning. The use of machine learning principles extends to a wide range of areas, which includes principal component analysis, feature selection techniques (such as Fisher discriminant ratio, logistic regression, mutual information, and random forest), quadratic discriminant analysis, Naive Bayes, outlier removal techniques, and the use of classifiers (such as linear discriminant analysis, cross-validation protocols, Gaussian process classification, and support vector). These ideas and methods are essential for properly determining the risk for developing diabetes and for identifying both those who already have the disease and control groups. By considering genetic and metabolic characteristics, machine learning programs could recognize those who have a high risk of developing diabetes. To review the study, we consider the following most recently used techniques.

5.1 Support Vector Machine:

Support Vector Machine (SVM) can be applied for predicting diabetes mellitus amongst other classification challenges. When dealing with binary problems with classification, such as identifying patients as diabetic or non-diabetic based on a set of traits or aspects, SVMs are especially helpful [46]. A series of fundamental processes, encompassing Data Collection, Data Preprocessing, Feature Selection, Model Selection, Model Training, Model Evaluation, Hyperparameter Tuning, and Finally, Model Deployment, were found by the SVM evaluation of this study. Table 1. Provides the research review summary for diabetic mellitus using Support Vector Machine.

Table 1. Exploring Support Vector Machine for Diabetic Mellitus

Sr. No.	Year	Author(s)	Focus of the Paper	Key points in the Coverage	Data Set	Techniques Used	Parameter Analyzed	Future Research
1	2019	Lukmanto et.al. [47]	Fuzzy Support Vector Machine for early detection of DM	SVM, Fuzzy, Feature Selection	Pima Indian Diabetes Dataset [48]	Fuzzy logic, SVM,	Plasma Glucose, Body Mass Index, Pregnancy count, Age, blood pressure	Genetic Algorithm and Clustering technique should be applied to enhance accuracy
2	2022	Patil et.al. [49]	Early identification of type 2 DM using a updated mayfly-SVM	Type 2 DM, SVM, MayFly Algorithm, Optimization	Collected from Local Hospital and PIMA [48]	SVM, MayFly Algorithm	Plasma concentration, Pregnancy count, Skin thickness, Body Mass Index, oral glucose test, age, serum insulin test	Health Suggestions system need to develop for high-risk patient.
3	2013	Kumari et.al. [50]	Diabetic Disease classification using SVM	Support Vector Machine	Pima Indian Diabetes Dataset [48]	Support Vector Machine	Plasma concentration, Pregnancy count, Skin thickness, Body Mass Index, oral glucose test, age, serum insulin test	Feature subset selection procedure is required to improve classification
4	2021	Ramadhan et. al.[51]	Type 2 DM detection using ADASYN-SVM and SMOTE-SVM technique	Diabetes type 2, ADASYN and SMOTE-SVM, classification, Random Forest	Karya Medika Dataset	ADASYN-SVM and SMOTE-SVM	Systolic and Diastolic Blood Pressure, Height, Weight, Age	Balanced data should be applied for pre-processing
5	2020	Devi et.al. [52]	Diabetic diagnosis's using SVM and farthest first algorithm	IQR, Data Mining, diabetes, SMO,	Pima Indian Diabetes Dataset [48]	SVM, IQR, SMO, Farthest First clustering, Kappa Statistics	Plasma concentration, Pregnancy count, Skin thickness, Body Mass Index, oral glucose test,	-

							age, serum insulin test	
6	2020	Viloria et al. [53]	Prediction of Diabetic Diagnosis using SVM	Medical Computing, Medical Diagnosis, Support Vector Machine	Public Hospital in Colombia & Pima Indian Dataset.	SVM, dYG Classifier	Body mass index (BMI), Blood glucose, age, concentration (CG), prior medical diagnosis of DM	Need to improve accuracy and predictability using genetic and practical swarma algorithm.
7	2023							

When utilizing Support Vector Machine for data classification in data mining, two categories can be made: non-linear and linear. SVM is applied in the above process to transform the training data via data mining into a higher-dimensional space via non-linear mapping [54] . After this transformation, the most optimal linear separating hyperplane will be sought after. SVM's primary objective is to partition the data mining data space by identifying various classes, whether using non-linear or linear techniques. As a result, within the SVM classifier, readily apparent margins between various classifiers are formed, which are then used to improve the efficiency of both the training and testing methods.

5.2 Neural Network:

To create personalized remedies, neural networks, that connect and analyze many data sources, are necessary. In the domain of diabetes diagnosis, the use of neural networks has been applied extensively and with great success. To comprehensively study how many factors affect glycemic indices in this setting, sophisticated algorithms have been developed.

Table 2. Exploring Neural Network for Diabetic Mellitus

Sr. No .	Year	Author(s)	Focus of the Paper	Key points in the Coverage	Data Set	Techniques Used	Parameter Analyzed	Future Research
1	2018	Ali et. al. [55]	Application of artificial neural network (ANN) techniques for continuous prediction of glucose levels in individuals with Type 1 diabetes.	Type 1 diabetes, CGM, forecasting using time series, Horizon prediction,	Self-developed (Derived from 12 Patients)	ANN, SVR, AR, ELM	Blood glucose, Abalone, Ozone, Servo, Housing	Large amount of patient data required with long period.
2	2017	Erkaymaz et.al. [56]	Diabetes diagnosis by using feedforward network.	Newman–Watts model, Watts–Strogatz model, feedforward network, small-world network	Pima Indian Diabetes Dataset [23]	Newman-Watts and Strongatz FFNN, Conventional FFANN,	blood pressure, Plasma glucose concentration, BMI, age,skin thickness, insulin and pedigree function	Result analysis should be compared with other intelligent algorithms like local heuristic search, Levenberg-

								Marquardt etc.
3	2019	Srivastava et.al. [57]	Prediction of diabetic using ANN	Classification, machine learning, ANN, diabetes	Pima Indian Diabetes Dataset [23]	NumPy Package, ANN, RMSE and ROC Model,	blood pressure, Plasma glucose concentration, BMI, age,skin thickness, insulin and pedigree function	Comparative study with other machine learning techniques is required.
4	2018	Goyal et. al. [58]	Diabetic foot ulcer classification using conventual neural network.	DFunet, Convential Neural network, deep learning, foot ulcers	Collected from the Lancashire Teaching Hospital [292 images], Normal Healthy Class [105 images]	CNN, Proposed DFuNet, Zero center technique for preprocessing,	Local binary pattern, Histogram oriented gradients,	Reducing the number of layers and neurons in the fully connected (FC) layer is essential to enhance classification performance.
5	2018	Alade et. al. [59]	Diagnosis of Diabetic Mellitus using Neural Network based expert system	Expert system, back-propagation, Neural Network, Type 1 and Type 2 diabetic	Pima Indian Diabetes Dataset [23]	4-Layer Neural Network, back-propagation, Bayesian Regulation algorithm, BR algorithm	Triceps Skin Thickness, age, Insulin, blood pressure, Plasma glucose concentration, BMI, skin thickness, insulin, and pedigree function	System needs to convert into mobile platform for ease of use.
6	2017	Sejadinovic et. al. [60]	Classification of type2 diabetics and pre-diabetics using ANN	Fasting plasma glucose, ANN, Pattern recognition, HbA1c	Healthcare institutions in Bosnia and Herzegovina Prediabetics (81 samples), T2D (127 Samples), healthy patients (102 Samples)	Artificial Neural Network	HbA1C blood tests and fasting plasma glucose (FPG)	Using this research technique hardware-based device development is required for rapid analysis of diabetic patients.
7	2020	Kumar P et.al. [61]	DM2 prediction using deep	Deep learning, classification	Pima Indian Diabetes	Deep Neural Network classifier	Triceps Skin Thickness, age, Insulin,	Computational time should be reduced

			neural network	, feature selection	Dataset [23]		Blood Pressure, Body Mass Index, Diabetes Pedigree Function, and age	using genetic algorithms or particle swarm optimization techniques.

Diabetes stands out as one of the most widespread diseases globally. Regardless of the type of diabetes, predicting the disease in its early stages poses an ongoing challenge for doctors, healthcare providers, and scientists. This challenge is particularly pronounced in developing and underdeveloped nations due to a lack of education. Early diagnosis and appropriate treatment are crucial for saving lives by avoiding unforeseen complications associated with diabetes. All illnesses may be reliably diagnosed and predicted using deep neural network-based models. Neural network-based techniques consist artificial neural networks, conventual neural and deep neural networks with various numbers of layers. Neural network-based techniques are used for prediction and analysis of various type 1 and type 2 diabetic mellitus with expertise.

5.3 Decision Tree

The decision tree is a machine learning technique utilized for both regression and classification. It serves as an approach in machine learning that can be utilized for tasks involving both classification and regression. Decision trees can be utilized for several purposes when it comes to diabetes, including diagnosis, risk evaluation, and medication recommendation. Decision tree is used for building the diagnostics model using various features like BMI, blood pressure and glucose, family history, age, and blood glucose level etc. In the case of diabetic risk assessment, the decision tree analyzes the data based on persons diet, physical activity and considering other health matrices to predict the diabetes future. This is very important to avoid the future risk and early detection of diabetes, based on the previous history decision tree gives the recommendation for the treatment. Table 3 below provides a summary of the study review conducted using the decision tree algorithm.

Table 3. Exploring Decision Tree for Diabetic Mellitus

Sr. No.	Year	Author(s)	Focus of the Paper	Key points in the Coverage	Data Set	Techniques Used	Parameter Analyzed	Research Gap
1	2016	Yuvarani et. al. [62]	Decision tree model analysis for diabetics	Classification, J48, C4.5, FB trees, diabetics	Pima Indian Diabetes Dataset [23]	Genetic J48 decision tree, Least Absolute Deviation [LAD], NB [Navies Bayes]	Triceps Skin Thickness, age, Insulin, blood pressure, Plasma glucose concentration, BMI, skin thickness, insulin, and pedigree function	Clinical testing is required with predicted data analysis to verify the result.
2	2020	Pei et. al. [63]	Diabetic prediction of adult China's people using J48 decision tree	Decision tree, J48 algorithm, diabetics risk factor	Shengjing Hospital (China Medical University) [3454 Samples]	J48 algorithm,	Gender, age, marital status, annual income, and education level, BMI, stroke, sleeping time, physical	-

							activity, stress, smoking etc.	
3	2017	Sayadi et.al. [64]	Prediction of Type2 diabetic mellitus using modelling of decision tree	T2DM, Screening Test,	Healthy Heart House of Shiraz, Iran	Decision tree technique and J48 algorithm, Receiver Operator Characteristic (ROC) curve, Area Under Curve (AUC)	Body Mass Index (BMI), Age, gender, Body Mass Index (BMI), family history of diabetes, and systolic and diastolic blood pressure	Early diagnosis is of screening test is required. To check the robustness study, need to be implemented on public health programs.
4	2016	Varma et.al. [65]	Utilizing Intelligent Computational Techniques for Efficient Diagnosis of Diabetic Patients: A Study on PCA and Modified Fuzzy SLIQ Decision Tree.	Knowledge Inference System, Fuzzy decision tree, fuzzification, , GINI index, SLIQ	Pima Indian Diabetes Dataset [23]	PCA, Fuzzy SLIQ decision tree, Standard deviation, Confirmatory Factor Analysis	Gender, age, marital status, annual income, and education level, BMI, stroke, sleeping time, physical activity, stress, smoking etc.	To improve the accuracy in result selection of appropriate fuzzy membership function is required. Comparison using other membership function is required.
5	2020	Posonia et. al. [66]	Diabetic prediction using machine learning based J48 decision tree.	Machine Learning, diabetic prediction, J48 decision tree,	Pima Indian Diabetes Dataset [23]	J48 decision tree,	Gender, age, marital status, annual income, and education level, BMI, stroke, sleeping time, physical activity, stress, smoking etc.	Need to develop web-based application for better utilization of diabetic prediction.
6	2022	Seto et. al. [42]	Comparative analysis of gradient boosting decision tree and logistic regression in the case of diabetic prediction.	Diabetic prediction, Light GBM Decision tree, Logistic regression	Kokuho-database (KDB), (Japan)	Logistic Regression, LightGBM, (Gradient Boosting Machine)	MBI, SBP, TG, HDL-C, LDL-C, ALT, HbA1c, age, anti DLP, UP, MH of Stroke.	Comparative study with other machine learning models is required.

The above literature study shows the various decision tree techniques are available to predict diabetics. J48 decision tree is mostly used for diabetic prediction using decision tree algorithms. Along with decision tree SVM, Navie Bayes, logistic regression, fuzzy decision tree, least absolute deviation techniques are used for the diabetic prediction. Study successfully showed that decision tree algorithms are better to predict diabetics.

5.4 Random Forest

Random Forest is a machine learning technique mostly used to predict diabetic mellitus. It assesses a person's chance of getting diabetes based on a collection of pertinent attributes using an ensemble of decision trees. This method sheds light on feature significance and robustness. To use it efficiently, one needs to collect and arrange the data, select the most crucial features, split the dataset into training and testing sets, assess the accuracy and precision of the model using metrics, optimize the hyperparameters for optimal outcomes, and recognize the significance of the features. It's important to think about ethical issues when working with medical professionals while employing Random Forest to arrive at diagnoses. The research review on the use of the decision tree algorithm in diabetes mellitus is outlined in the table below.

Table 4. Exploring Random Forest for Diabetic Mellitus

Sr. No.	Year	Author(s)	Focus of the Paper	Key points in the Coverage	Data Set	Techniques Used	Parameter Analyzed	Future Research
1	2019	K.Kumar et.al. [67]	Prediction of diabetic using optimized random forest algorithms.	Random forest, machine learning, diabetics prediction, multi-class decomposition	Repository of the University of California at Irvine	Random forest, Genetic Algorithms, fitness computation,	kvalues, ntrees, and mtry,	Need to develop hybrid genetic algorithm to improve accuracy.
2	2015	Butwal et. al.[68]	Diabetic mellitus diagnosis using random forest classifier	Medical data mining, Random Forest classifier	Pima Indians Diabetes Database [22]	Random Forest Classifier along with decision tree	Pregnancy count, Plasma glucose Concentration, diastolic blood pressure, Triceps skin fold thickness, 2-Hour serum insulin, BMI, Diabetes pedigree function, Age, class variable (0 or 1)	Hybrid classification is required to improve the accuracy
3	2017	Xu et.al. [69]	Type-II diabetic prediction using random forest.	Type-II diabetic, random forest, Prediction Model	Pima Indians Diabetes Database [22]	Random Forest, K-Means, Adaboost, Navies Bayes, ID3	Pregnancy count, Plasma glucose Concentration, diastolic blood pressure, Triceps skin fold thickness, 2-Hour serum insulin, BMI, Diabetes	Impact of other parameters like illness should be required to consider during diabetic prediction.

							pedigree function, Age, class variable (0 or 1)	
4	2021	Wang et. al. [70]	Combined Random Forest classifier for diabetic mellitus classification	Random Forest, Type-2 diabetic Mellitus, classification	Self-Developed using questionnaire developed by CDC (Chinese Center for Disease Control and Prevention)	Random Forest, Logistic Regression, GBDT, SVM	Gender, Age Vegetable intake level, Meat, Heart rate, BMI, Smoking, Drinking, Hypertension	To save the coasting about data collection AI based model is required to develop.
5	2014	Sabarih et. al. [71]	Classification and Regression Tree (CART), Random Forest based techniques for early detection of type 2 diabetic	Early detection of diabetics, CART, Random Forest,	Public Health Center, Banjarnegara, Indonesia	CART, Random Forest	Gender, Age, BMI, Sistole, Diastole, Heredity, Dignosis	Number of trees should be increased to enhance the result accuracy.

5.5 Case-Based Reasoning (CBR) Techniques

In the arena of diabetes treatment, CBR, a well-known AI technique, is often used to address novel challenges by drawing from previous encounters with comparable circumstances. The 4 Diabetes Support System, which is employed in the treatment of diabetes, is a prime instance of CBR in action. The main goal of this system is to streamline the identification of blood glucose control issues, provide recommendations for addressing these issues, and document both successful and unsuccessful alternatives tailored to each patient. Within the framework of diabetes management, CBR has also been critical in optimizing and adapting insulin dosage for a range of meal configurations. Table 5 provides a review on diabetic mellitus using CBR technique.

Table 5. Exploring Case Based Reasoning for Diabetic Mellitus

Sr. No.	**Year**	**Author(s)**	**Focus of the Paper**	**Key points in the Coverage**	**Data Set**	**Techniques Used**	**Parameter Analyzed**	**Future Research**
1	2017	Brown et.al. [72]	Insulin Decision support System for type 1 DM using CBR	Knowledge based system, Feature Selection, Case-based reasoning, Feature selection	Case based Data Set (Self-Created using C 4.5)	Chi-Squared, Information Gain, one rule, Gain ratio, RELIEF-F, Symmetrical Uncertainty	Pre-prandial blood glucose, Target blood glucose, Insulin sensitivity factor, Carbohydrate intake, Carbohydrate-to-insulin ratio, Insulin-	Examining and assessing performance of the various algorithms in this domain is required.

							on-board, Exercise	
2	2017	Benamina et. al. [73]	CBR and Fuzzy based diabetic diagnosis	Case Based reasoning, case retrieval and Classification, Fuzzy decision tree, diabetic applications	Pima Indians Diabetes Database [22]	CBR and Fuzzy Logic	Pregnancy count, Plasma glucose Concentration, 2-Hour serum insulin, BMI, diastolic blood pressure, Triceps skin fold thickness, Diabetes pedigree function, Age, class variable (0 or 1)	More study is required to improve FDT4CR based strategy for accommodating several stages of CBR life cycle with optimizing complexity and response time.
3	2013	Jha et al. [74]	Diabetic detection and Care using CBR	CBR, Diabetic care and detection	Case based Data Set (Self-Created)	CBR, SVR and Baseline performance techniques.	Age, Sex, family History, Physical activity, frequent urination, Fatty and Junk Food, Stress level, Ailment	More research work/study is required to develop same system to take care of the other disease care.
4	2016	Sappagh et. al. [75]	Developing a Decision Support System for Diabetic Management through Case-Based Reasoning.	Case-Based Reasoning, Fuzzy ontology, Medical Ontology,	Auto Lab of Mansoura institution, Mansoura University, Diagnostic biochemical lab, Mansoura, Egypt.	Machine Learning Models with 1 to 10-fold (SVM, k-NN, NB, ANN), Conventional CBR, Proposed Fuzzy KI-CBR system	Demographic, Lab Test, Symptoms, Kidney function test, Urine Analysis, Leaver Function Test,	Research needed to integrate CBR with EHR for improved CDSS

In this manner Case-Based Reasoning (CBR) is applied for Diabetes Mellitus which involves utilizing past cases and their outcomes to guide decision-making for current patients. In the context of CBR, it measures a patient's situation by comparing it to similar historical cases with factors like blood glucose levels, lifestyle, and treatment responses. The CBR technique modernizes to improve the decision-making process, improving patient care in the context of a complex medical condition like diabetes mellitus. Thus, based on the review study CBR approach work more effective for individual diabetic management, contributing to better overall health outcomes for diabetic patients.

5.6 Review on Most Commonly used Diabetic Mellitus datasets:

Several data sets are often implemented in research on diabetes mellitus. For creating and evaluating machine learning and data analysis models, these datasets are valuable. Perhaps the datasets that are most frequently employed are listed in the table 6.

Table 6. Summary of most used datasets in Diabetic Mellitus

Sr.NO.	Dataset Name	Description	Parameters	URL	References
1	Pima Indian Diabetic Database	The dataset, initially formed by the National Institute of Diabetes and Digestive and Kidney Diseases, aims to assess the likelihood of diabetes using diagnostic parameters	Pregnancies, BMI, glucose concentration, Blood Pressure, Skin Thickness, insulin, Diabetic pedigree function, age, outcome (class variable 0 and 1)	https://archive.ics.uci.edu/dataset/34/diabetes	[50], [56], [57], [59], [62], [65], [66], [68], [69], [73],[76],[77], [78]
2	MESSIDOR Diabetic Dataset	- Consist of 12 hundred retinopathy based numerical color images. -It consists healthy retinas, glaucoma images and diabetic retinopathy -Images having 1440*960, 2240*1488 or 2304*1536 pixels. [79]	Five Grades (0 to 4) G 0: No DR G 1: Mild Non-proliferative Retinopathy G 2: Moderate Non-proliferative Retinopathy G 3: Severe Non-proliferative Retinopathy G 4: Proliferate Retinopathy (Grade 1 to 4 treated as positive whereas Garde 0 treated as Negative)	https://www.adcis.net/en/third-party/messidor/	[80], [81],[82], [83], [84]
3	Kaggle diabetic dataset	-Images that have a right- or left-tagged patient ID are mentioned. - 35,126 images with tags are provided. end-stage, severe, moderate, and mild. Sets of color photographs with widths and heights between the low thousands and the low hundreds make up the datasets.	0: No DR 1 - Mild 2 - Moderate 3 - Severe 4 - Proliferative DR	https://www.kaggle.com/c/diabetic-retinopathydetection/data	[85], [86], [87]
4	NHANES (National Health and Nutrition Examinati	-5000 US people/samples are available with clinical test and physical examination result. -	-demographic and socio-economic data, dietary, physical, medical, and	https://www.cdc.gov/nchs/nhanes/	[88]–[90]

	on) dataset		physiological measurements		
5	Stare Dataset	-Stare is known as STructured Analysis of the Retina	Data in the form of images	https://cecas.clemson.edu/~ahoover/stare/	[91]–[93]
6	Kokuho-database (KDB), (Japan)	The Kokuho Database encompasses monthly health insurance statements for NHI and LSEMCS, including results of annual health checkups and daily care-service data from LTCI. All data are connected through the Kokuho Database identifier (KDBID), covering annual health checkups and day-by-day care-service details	MBI, SBP, TG, HDL-C, LDL-C, ALT, HbA1c, age, anti DLP, UP, MH of Stroke.	https://www.jstage.jst.go.jp/article/jea/advpub/0/advpub_JE20200480/_article/-char/en	[94], [95]
7	IDRiD Dataset	-This dataset contains grading of Diabetic retinopathy -This dataset created from real clinical exams -Sample size is about 516 with DR images which are in the form of JPEG.	G0 - No DR G1 - Mild G2 - Moderate G3 - Severe G4 - Proliferative DR	https://idrid.grand-challenge.org/	[96]–[98]

In addition to these diabetic datasets, several other datasets are available for research purposes, including the Indian Diabetes dataset, the Diabetes Data Set from the UCI Machine Learning Repository, the National Health and Nutrition Examination Survey (NHANES) datasets, and a few other datasets that the author created in order to apply AI to a particular diabetic mellitus domain [30], [70], [47], [49], [75]. These databases provide information on diabetes outcomes, clinical measures, and patient demographics. These datasets may be used by researchers to look for trends, create prediction models based on machine learning, and analyze the variables affecting the prevalence and treatment of diabetes. These databases are essential for expanding our knowledge of diabetes, its risk factors, and possible treatments. This information will eventually lead to better medical care and treatment plans.

6. Artificial Intelligence in Diabetic Mellitus: Limitation and Challenges

Artificial intelligence (AI) powers an excellent role in the management of diabetic mellitus, yet throughout this study in this domain, it is found several limitations and challenges. Data Privacy, data security, data quality and quantity, patient acceptance, complexity of diabetics, clinical validation and interoperability, ethical consideration, data imbalance, long term monitoring, addressing algorithm bias, collecting high quality data for training, and testing of AI models are some of the primary challenges in this domain. Also compiling and validating the result of AI based model with clinical validation is a complex task. Here are the some of the summarized challenges and limitations found in this domain [4], [99], [100]. Applications of AI in the research arena of diabetes depend on large datasets. It might be challenging to obtain high-quality data, specifically longitudinal patient records. Incomplete or incorrect information might inject biases into the models, which will lead to faulty projections. In diabetic mellitus, achieving interoperability poses a formidable challenge due to the dispersed nature of healthcare data across multiple platforms and formats. The integration and streamlining of data from diverse sources for AI research can be particularly challenging. Another critical aspect pertains to data privacy in this context. Safeguarding patient data is of paramount importance, considering the sensitivity of patient records when AI is employed for study and treatment. Ensuring patient privacy while utilizing AI poses both ethical and technological challenges. Conducting clinical validation within clinical environments is essential to thoroughly assess the reliability, effectiveness, and safety of AI models applied in diabetes studies for patient care. The intricate nature of diabetes, characterized by various types and numerous contributing factors, adds complexity to the development of AI models capable of adequately addressing this diversity. The ethical dimension of integrating AI into diabetes research emphasizes the importance of ensuring that AI-driven recommendations align with the values and preferences of the individual undergoing treatment. Furthermore, the development and upkeep of AI systems in the healthcare industry necessitates substantial resources, including computing infrastructure, data storage, and specialized personnel. This presents challenges, particularly for smaller healthcare institutions and researchers who may encounter limitations in these areas.

To enhance the skilled deployments of artificial intelligence in the domain of diabetic mellitus research and clinical practices it is required to addressing overcoming limitations and challenges. For the successful execution of artificial intelligence in the domain of diabetic treatment and management, individuals need to give the careful responsiveness in legal consideration, patient security and data quality.

7. Future Directions

Artificial Intelligence is a user-friendly technology which is mostly used to predict and analyze diabetic mellitus. The development of AI algorithms that account for genetic characteristics, environmental influences, and individual patient profiles can enhance the precision of medical interventions for effectively managing symptoms associated with diabetes. Second, wearable technology and continuous glucose monitoring may be used to create more intricate and associated real-time tracking and feedback systems. AI may also improve preventative actions and help with the early detection of issues. Collaboration between AI developers and healthcare professionals will be necessary to deal with concerns regarding algorithm transparency and information confidentiality. By seizing the opportunities for the future, we can control diabetes mellitus in a way that is more beneficial, patient-centered, and data-driven.

8. Discussion

In the context of this research paper's discussion, Diabetes Mellitus, commonly known as diabetes, emerges as a chronic metabolic disorder characterized by elevated blood glucose levels, resulting from either insufficient insulin production or ineffective utilization of insulin by the body [5]. Through an extensive review of the existing literature, the study addresses the classification of AI applications in diabetic management, identifies gaps and challenges, and provides insights into future directions and recommendations. The theoretical framework employed in this research, encompassing AI, machine learning, and deep learning, aligns with the fundamental concepts, precepts, and models that constitute the basis of these fields [7], [8]. The research methodology involved the collection of relevant articles focusing on machine learning and diabetes mellitus for a comprehensive examination. The scholarly paper includes an extensive examination of articles covering diverse topics, including Diabetes Mellitus, Machine Learning, Artificial Intelligence, Neural Networks, and Case-Based Reasoning (CBR). Most of these articles are sourced from esteemed journals and publications, such as Springer Nature, Science Direct, and IEEE. Notably, the study covers a spectrum of diabetes types, including Prediabetes [22] [26], Type 1, Type 2, and gestational diabetes, collectively constituting a significant global health concern [24], [25]. Diabetes manifests through diverse symptoms, including unexpected weight loss, increased thirst, frequent urination, fatigue, weakness, recurrent infections, tingling or numbness in the limbs (neuropathy), and poor wound healing [32]. The paper also emphasizes the severe long-term complications associated with diabetes, such as heart disease, stroke, kidney failure, neuropathy, retinopathy (eye damage), and circulatory issues that may necessitate amputations [33].

Artificial intelligence (AI) assumes a pivotal role in healthcare, particularly in the evaluation of diverse datasets that encompass genetic information, lifestyle factors, and electronic health records (EHRs)[4]. Leveraging this wealth of data, AI demonstrates the capability to tailor patient treatments by considering individual health profiles, lifestyles, and responses to therapeutic interventions. This personalization extends to considerations such as medication dosage, timing, and selection [41]. In the realm of diabetes management, a plethora of machine learning methods have been employed in the development of digital support systems. These techniques include support vector machines [47], [49], [50], [51], [52], [53], artificial neural networks [55][56][57][58][59][60][61], CBR-Based reasoning [72][73][74][75], decision trees [62][63][64][65][66][42], random forests [67][68][69][70][71], classification and regression trees, as well as naive Bayes [62] and k-nearest neighbors. These diverse approaches contribute to advancing the efficacy and personalization of diabetes management processes [2]. In this domain of diabetes mellitus research, numerous datasets are crucial for the creation and evaluation of machine learning and data analysis models. Among the commonly utilized datasets are the Pima Indian Diabetic Database [50], [56], [57],

[59], [62], [65], [66], [68], [69], [73],[76],[77], [78], MESSIDOR Diabetic Dataset [80], [81],[82], [83], [84], Kaggle diabetic dataset [85], [86], [87], NHANES (National Health and Nutrition Examination) dataset [88]–[90], Stare Dataset [91]–[93], Kokuho-database (KDB), (Japan) [94], [95], and IDRiD Dataset [96]-[98]. These datasets are widely employed for research purposes. In addition to the diabetic datasets, a variety of other datasets serve research objectives, including the Indian Diabetes dataset, the Diabetes Data Set from the UCI Machine Learning Repository, the National Health, and Nutrition Examination Survey (NHANES) datasets, and several datasets created by the author for the specific application of AI in the diabetic mellitus domain [30], [70], [47], [49], [75]. The research paper explores the promising future scope and opportunities in Artificial Intelligence, advocating the application of Genetic Algorithm and Clustering techniques to enhance accuracy [47]. Additionally, it emphasizes the necessity for developing a Health Suggestions system tailored for high-risk patients [49]. The paper proposes a comparative study involving various machine learning techniques [56], advocates for the development of a mobile application-based healthcare system [59], and suggests research focused on reducing computational time [61]. Furthermore, the study delves into clinical testing for predictive data [62], the selection of appropriate fuzzy membership functions [65], the creation of a web-based application system using AI [66], and the exploration of a Hybrid genetic algorithm to improve accuracy [67]. The study also focuses on cost-saving mechanisms in data collection strategies [70] with proposes developments in the strategy of FDT4CR to improve the overall accuracy [73].

9. Conclusion

The transformative capabilities of artificial intelligence in healthcare are underscored by an examination of AI-driven insights into Diabetes Mellitus. Positive outcomes have been observed across various AI applications, encompassing predictive modeling and personalized therapeutic recommendations. These technological advancements offer potential advantages such as early detection, improved disease management, and more tailored patient care. However, there is a persistent demand for algorithm transparency, data privacy, and the availability of high-quality, expansive datasets. The judicious utilization of AI in practical settings requires careful consideration. In summary, artificial intelligence (AI) holds the promise of reshaping the treatment landscape for individuals with diabetes, necessitating collaboration among government agencies, healthcare providers, and AI developers. Overcoming challenges related to algorithm transparency, data privacy, and dataset quality is crucial for unlocking AI's potential to enhance patient outcomes and the overall management of this lifelong condition in the field of diabetes mellitus.

References

[1] D. V. Gunasekeran, D. S. Ting, G. S. Tan, and T. Y. Wong, “Artificial intelligence for diabetic retinopathy screening, prediction and management,” Curr. Opin. Ophthalmol., vol. 31, no. 5, pp. 357–365, 2020.

[2] J. Chaki, S. Thillai Ganesh, S. K. Cidham, and S. Ananda Theertan, “Machine learning and artificial intelligence based Diabetes Mellitus detection and self-management: A systematic review,” J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 6, Part B, pp. 3204–3225, Jun. 2022, doi: 10.1016/j.jksuci.2020.06.013.

[3] S. Binhowemel, M. Alfakhri, K. AlReshaid, and A. Alyani, “Role of Artificial Intelligence in Diabetes Research Diagnosis and Prognosis: A Narrative Review,” J. Health Inform. Dev. Ctries., vol. 17, no. 02, 2023.

[4] S. Ellahham, “Artificial Intelligence: The Future for Diabetes Care,” Am. J. Med., vol. 133, no. 8, pp. 895–900, Aug. 2020, doi: 10.1016/j.amjmed.2020.03.033.

[5] A. B. Chausmer, “Zinc, Insulin and Diabetes,” J. Am. Coll. Nutr., vol. 17, no. 2, pp. 109–115, Apr. 1998, doi: 10.1080/07315724.1998.10718735.

[6] R. D. Sriram and S. S. K. Reddy, “Artificial intelligence and digital tools: future of diabetes care,” Clin. Geriatr. Med., vol. 36, no. 3, pp. 513–525, 2020.

[7] T. Zhu, K. Li, P. Herrero, and P. Georgiou, “Deep Learning for Diabetes: A Systematic Review,” IEEE J. Biomed. Health Inform., vol. 25, no. 7, pp. 2744–2757, Jul. 2021, doi: 10.1109/JBHI.2020.3040225.

[8] R. Haneef et al., “Use of artificial intelligence for public health surveillance: a case study to develop a machine Learning-algorithm to estimate the incidence of diabetes mellitus in France,” Arch. Public Health, vol. 79, no. 1, p. 168, Sep. 2021, doi: 10.1186/s13690-021-00687-0.

[9] R.-X. Ding et al., “Large-Scale decision-making: Characterization, taxonomy, challenges and future directions from an Artificial Intelligence and applications perspective,” Inf. Fusion, vol. 59, pp. 84–102, Jul. 2020, doi: 10.1016/j.inffus.2020.01.006.

[10] M. Garnelo and M. Shanahan, “Reconciling deep learning with symbolic artificial intelligence:

representing objects and relations," Curr. Opin. Behav. Sci., vol. 29, pp. 17–23, Oct. 2019, doi: 10.1016/j.cobeha.2018.12.010.

[11] B. Mondal, "Artificial Intelligence: State of the Art," in Recent Trends and Advances in Artificial Intelligence and Internet of Things, V. E. Balas, R. Kumar, and R. Srivastava, Eds., in Intelligent Systems Reference Library. , Cham: Springer International Publishing, 2020, pp. 389–425. doi: 10.1007/978-3-030-32644-9_32.

[12] F. K. Došilović, M. Brčić, and N. Hlupić, "Explainable artificial intelligence: A survey," in 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), May 2018, pp. 0210–0215. doi: 10.23919/MIPRO.2018.8400040.

[13] I. El Naqa and M. J. Murphy, "What Is Machine Learning?," in Machine Learning in Radiation Oncology: Theory and Applications, I. El Naqa, R. Li, and M. J. Murphy, Eds., Cham: Springer International Publishing, 2015, pp. 3–11. doi: 10.1007/978-3-319-18305-3_1.

[14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, Art. no. 7553, May 2015, doi: 10.1038/nature14539.

[15] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: review, opportunities and challenges," Brief. Bioinform., vol. 19, no. 6, pp. 1236–1246, Nov. 2018, doi: 10.1093/bib/bbx044.

[16] A. Miglani and N. Kumar, "Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions, and challenges," Veh. Commun., vol. 20, p. 100184, Dec. 2019, doi: 10.1016/j.vehcom.2019.100184.

[17] J. Huang, J. Chai, and S. Cho, "Deep learning in finance and banking: A literature review and classification," Front. Bus. Res. China, vol. 14, no. 1, p. 13, Jun. 2020, doi: 10.1186/s11782-020-00082-6.

[18] I. H. Sarker, "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," SN Comput. Sci., vol. 2, no. 6, p. 420, Aug. 2021, doi: 10.1007/s42979-021-00815-1.

[19] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," Electron. Mark., vol. 31, no. 3, pp. 685–695, Sep. 2021, doi: 10.1007/s12525-021-00475-2.

[20] I. Bose and R. K. Mahapatra, "Business data mining — a machine learning perspective," Inf. Manage., vol. 39, no. 3, pp. 211–225, Dec. 2001, doi: 10.1016/S0378-7206(01)00091-X.

[21] I. H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," SN Comput. Sci., vol. 2, no. 3, p. 160, Mar. 2021, doi: 10.1007/s42979-021-00592-x.

[22] A. M. Egan and S. F. Dinneen, "What is diabetes?," Medicine (Baltimore), vol. 47, no. 1, pp. 1–4, Jan. 2019, doi: 10.1016/j.mpmed.2018.10.002.

[23] N. G. Forouhi and N. J. Wareham, "Epidemiology of diabetes," Medicine (Baltimore), vol. 38, no. 11, pp. 602–606, Nov. 2010, doi: 10.1016/j.mpmed.2010.08.007.

[24] A. Nouwen et al., "Type 2 diabetes mellitus as a risk factor for the onset of depression: a systematic review and meta-analysis," Diabetologia, vol. 53, no. 12, pp. 2480–2486, Dec. 2010, doi: 10.1007/s00125-010-1874-x.

[25] R. A. DeFronzo et al., "Type 2 diabetes mellitus," Nat. Rev. Dis. Primer, vol. 1, no. 1, Art. no. 1, Jul. 2015, doi: 10.1038/nrdp.2015.19.

[26] N. Bansal, "Prediabetes diagnosis and treatment: A review," World J. Diabetes, vol. 6, no. 2, pp. 296–303, Mar. 2015, doi: 10.4239/wjd.v6.i2.296.

[27] E. M. Venditti and M. K. Kramer, "Necessary Components for Lifestyle Modification Interventions to Reduce Diabetes Risk," Curr. Diab. Rep., vol. 12, no. 2, pp. 138–146, Apr. 2012, doi: 10.1007/s11892-012-0256-9.

[28] M. Cardona-Morrell, L. Rychetnik, S. L. Morrell, P. T. Espinel, and A. Bauman, "Reduction of diabetes risk in routine clinical practice: are physical activity and nutrition interventions feasible and are the outcomes from reference trials replicable? A systematic review and meta-analysis," BMC Public Health, vol. 10, no. 1, p. 653, Dec. 2010, doi: 10.1186/1471-2458-10-653.

[29] A. Katsarou et al., "Type 1 diabetes mellitus," Nat. Rev. Dis. Primer, vol. 3, p. 17016, Mar. 2017, doi: 10.1038/nrdp.2017.16.

[30] H. D. McIntyre, P. Catalano, C. Zhang, G. Desoye, E. R. Mathiesen, and P. Damm, "Gestational diabetes mellitus," Nat. Rev. Dis. Primer, vol. 5, no. 1, Art. no. 1, Jul. 2019, doi: 10.1038/s41572-019-0098-8.

[31] CDC, "Gestational Diabetes and Pregnancy | CDC," Centers for Disease Control and Prevention. Accessed: Sep. 10, 2023. [Online]. Available:

https://www.cdc.gov/pregnancy/diabetes-gestational.html

[32] T. Drivsholm, N. de Fine Olivarius, A. B. S. Nielsen, and V. Siersma, “Symptoms, signs and complications in newly diagnosed type 2 diabetic patients, and their relationship to glycaemia, blood pressure and weight,” Diabetologia, vol. 48, no. 2, pp. 210–214, Feb. 2005, doi: 10.1007/s00125-004-1625-y.

[33] D. Tomic, J. E. Shaw, and D. J. Magliano, “The burden and risks of emerging complications of diabetes mellitus,” Nat. Rev. Endocrinol., vol. 18, no. 9, Art. no. 9, Sep. 2022, doi: 10.1038/s41574-022-00690-7.

[34] D. M. Nathan, “Long-Term Complications of Diabetes Mellitus,” N. Engl. J. Med., vol. 328, no. 23, pp. 1676–1685, Jun. 1993, doi: 10.1056/NEJM199306103282306.

[35] A. L. Wicaksana, N. S. Hertanti, A. Ferdiana, and R. B. Pramono, “Diabetes management and specific considerations for patients with diabetes during coronavirus diseases pandemic: A scoping review,” Diabetes Metab. Syndr. Clin. Res. Rev., vol. 14, no. 5, pp. 1109–1120, Sep. 2020, doi: 10.1016/j.dsx.2020.06.070.

[36] S. Secinaro, D. Calandra, A. Secinaro, V. Muthurangu, and P. Biancone, “The role of artificial intelligence in healthcare: a structured literature review,” BMC Med. Inform. Decis. Mak., vol. 21, no. 1, p. 125, Apr. 2021, doi: 10.1186/s12911-021-01488-9.

[37] D. Ben-Israel et al., “The impact of machine learning on patient care: A systematic review,” Artif. Intell. Med., vol. 103, p. 101785, Mar. 2020, doi: 10.1016/j.artmed.2019.101785.

[38] K. Zhang and A. B. Aslan, “AI technologies for education: Recent research & future directions,” Comput. Educ. Artif. Intell., vol. 2, p. 100025, Jan. 2021, doi: 10.1016/j.caeai.2021.100025.

[39] A. Nomura, M. Noguchi, M. Kometani, K. Furukawa, and T. Yoneda, “Artificial Intelligence in Current Diabetes Management and Prediction,” Curr. Diab. Rep., vol. 21, no. 12, p. 61, Dec. 2021, doi: 10.1007/s11892-021-01423-2.

[40] A. Czyzewski, F. Krawiec, D. Brzezinski, P. J. Porebski, and W. Minor, “Detecting anomalies in X-ray diffraction images using convolutional neural networks,” Expert Syst. Appl., vol. 174, p. 114740, 2021.

[41] P. Manickam et al., “Artificial intelligence (AI) and internet of medical things (IoMT) assisted biomedical systems for intelligent healthcare,” Biosensors, vol. 12, no. 8, p. 562, 2022.

[42] D. M. M. Pacis, E. D. Subido, and N. T. Bugtai, “Trends in telemedicine utilizing artificial intelligence,” in AIP conference proceedings, AIP Publishing, 2018.

[43] A. K. Dwivedi, “Analysis of computational intelligence techniques for diabetes mellitus prediction,” Neural Comput. Appl., vol. 30, pp. 3837–3845, 2018.

[44] T. Miyazawa et al., “Artificial intelligence in food science and nutrition: a narrative review,” Nutr. Rev., vol. 80, no. 12, pp. 2288–2300, 2022.

[45] A. Bohlmann, J. Mostafa, and M. Kumar, “Machine learning and medication adherence: scoping review,” JMIRx Med, vol. 2, no. 4, p. e26993, 2021.

[46] S. G. Rabiha, A. Wibowo, Lukas, and Y. Heryadi, “Diabetes Classification Using Support Vector Machine : Binary Classification Model,” in 2021 4th International Conference on Information and Communications Technology (ICOIACT), Aug. 2021, pp. 280–284. doi: 10.1109/ICOIACT53268.2021.9563994.

[47] R. B. Lukmanto, A. Nugroho, and H. Akbar, “Early detection of diabetes mellitus using feature selection and fuzzy support vector machine,” Procedia Comput. Sci., vol. 157, pp. 46–54, 2019.

[48] “Pima Indians Diabetes Database.” Accessed: Sep. 22, 2023. [Online]. Available: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database

[49] R. Patil, S. Tamane, S. A. Rawandale, and K. Patil, “A modified mayfly-SVM approach for early detection of type 2 diabetes mellitus,” Int J Electr Comput Eng, vol. 12, no. 1, pp. 524–533, 2022.

[50] V. A. Kumari and R. Chitra, “Classification of diabetes disease using support vector machine,” Int. J. Eng. Res. Appl., vol. 3, no. 2, pp. 1797–1801, 2013.

[51] [51] N. G. Ramadhan, “Comparative Analysis of ADASYN-SVM and SMOTE-SVM Methods on the Detection of Type 2 Diabetes Mellitus,” Sci J Inform., vol. 8, no. 2, pp. 276–282, 2021.

[52] R. D. H. Devi, A. Bai, and N. Nagarajan, “A novel hybrid approach for diagnosing diabetes mellitus using farthest first and support vector machine algorithms,” Obes. Med., vol. 17, p. 100152, 2020.

[53] A. Viloria, Y. Herazo-Beltran, D. Cabrera, and O. B. Pineda, “Diabetes Diagnostic Prediction Using Vector Support Machines,” Procedia Comput. Sci., vol. 170, pp. 376–381, Jan. 2020, doi: 10.1016/j.procs.2020.03.065.

[54] P. Sah and K. Sarma, “Bloodless Technique to Detect Diabetes using Soft Computational Tool,” 2015, pp. 139–158. doi: 10.4018/978-1-4666-8493-5.ch006.

[55] J. B. Ali, T. Hamdi, N. Fnaiech, V. Di Costanzo, F. Fnaiech, and J.-M. Ginoux, “Continuous blood glucose level prediction of type 1 diabetes based on artificial neural network,” Biocybern. Biomed. Eng., vol. 38, no. 4, pp. 828–840, 2018.

[56] O. Erkaymaz, M. Ozer, and M. Perc, “Performance of small-world feedforward neural networks for the diagnosis of diabetes,” Appl. Math. Comput., vol. 311, pp. 22–28, Oct. 2017, doi: 10.1016/j.amc.2017.05.010.

[57] S. Srivastava, L. Sharma, V. Sharma, A. Kumar, and H. Darbari, “Prediction of Diabetes Using Artificial Neural Network Approach,” in Engineering Vibration, Communication and Information Processing, vol. 478, K. Ray, S. N. Sharan, S. Rawat, S. K. Jain, S. Srivastava, and A. Bandyopadhyay, Eds., in Lecture Notes in Electrical Engineering, vol. 478. , Singapore: Springer Singapore, 2019, pp. 679–687. doi: 10.1007/978-981-13-1642-5_59.

[58] M. Goyal, N. D. Reeves, A. K. Davison, S. Rajbhandari, J. Spragg, and M. H. Yap, “Dfunet: Convolutional neural networks for diabetic foot ulcer classification,” IEEE Trans. Emerg. Top. Comput. Intell., vol. 4, no. 5, pp. 728–739, 2018.

[59] O. M. Alade, O. Y. Sowunmi, S. Misra, R. Maskeliūnas, and R. Damaševičius, “A Neural Network Based Expert System for the Diagnosis of Diabetes Mellitus,” in Information Technology Science, vol. 724, T. Antipova and Á. Rocha, Eds., in Advances in Intelligent Systems and Computing, vol. 724. , Cham: Springer International Publishing, 2018, pp. 14–22. doi: 10.1007/978-3-319-74980-8_2.

[60] D. Sejdinović et al., “CLASSIFICATION OF PREDIABETES AND TYPE 2 DIABETES USING ARTIFICIAL NEURAL NETWORK,” in CMBEBIH 2017, vol. 62, A. Badnjevic, Ed., in IFMBE Proceedings, vol. 62. , Singapore: Springer Singapore, 2017, pp. 685–689. doi: 10.1007/978-981-10-4166-2_103.

[61] B. M. K. P, S. P. R, N. R k, and A. K, “Type 2: Diabetes mellitus prediction using Deep Neural Networks classifier,” Int. J. Cogn. Comput. Eng., vol. 1, pp. 55–61, Jun. 2020, doi: 10.1016/j.ijcce.2020.10.002.

[62] S. Yuvarani and R. Selvarani, “An analysis of decision tree models for diabetes,” Int Res J Eng Technol, vol. 3, no. 11, pp. 680–684, 2016.

[63] D. Pei, T. Yang, and C. Zhang, “Estimation of Diabetes in a High-Risk Adult Chinese Population Using J48 Decision Tree Model,” Diabetes Metab. Syndr. Obes. Targets Ther., vol. Volume 13, pp. 4621–4630, Nov. 2020, doi: 10.2147/DMSO.S279329.

[64] M. Sayadi, M. J. Zibaeenezhad, and S. M. T. Ayatollahi, “Simple prediction of type 2 diabetes mellitus via decision tree modeling,” Int. Cardiovasc. Res. J., vol. 11, no. 2, 2017, Accessed: Oct. 01, 2023. [Online]. Available: https://brieflands.com/articles/ircrj-10657.html

[65] V. S. R. P. V. Kamadi, A. R. Allam, S. M. Thummala, and V. N. R. P., “A computational intelligence technique for the effective diagnosis of diabetic patients using principal component analysis (PCA) and modified fuzzy SLIQ decision tree approach,” Appl. Soft Comput., vol. 49, pp. 137–145, Dec. 2016, doi: 10.1016/j.asoc.2016.05.010.

[66] A. M. Posonia, S. Vigneshwari, and D. J. Rani, “Machine Learning based Diabetes Prediction using Decision Tree J48,” in 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Dec. 2020, pp. 498–502. doi: 10.1109/ICISS49785.2020.9316001.

[67] N. Komal Kumar, D. Vigneswari, M. Vamsi Krishna, and G. V. Phanindra Reddy, “An Optimized Random Forest Classifier for Diabetes Mellitus,” in Emerging Technologies in Data Mining and Information Security, vol. 813, A. Abraham, P. Dutta, J. K. Mandal, A. Bhattacharya, and S. Dutta, Eds., in Advances in Intelligent Systems and Computing, vol. 813. , Singapore: Springer Singapore, 2019, pp. 765–773. doi: 10.1007/978-981-13-1498-8_67.

[68] M. Butwall and S. Kumar, “A data mining approach for the diagnosis of diabetes mellitus using random forest classifier,” Int. J. Comput. Appl., vol. 120, no. 8, 2015, Accessed: Oct. 17, 2023. [Online]. Available: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=2fb4e7168b1bfaac80e15a82695d36f0bf4f36be

[69] W. Xu, J. Zhang, Q. Zhang, and X. Wei, “Risk prediction of type II diabetes based on random forest model,” in 2017 Third International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB), Feb. 2017, pp. 382–386. doi: 10.1109/AEEICB.2017.7972337.

[70] X. Wang et al., “Exploratory study on classification of diabetes mellitus through a combined Random Forest Classifier,” BMC Med. Inform. Decis. Mak., vol. 21, no. 1, p. 105, Mar. 2021, doi: 10.1186/s12911-021-01471-4.

[71] [71] M. T. Mira Kania Sabariah, S. T. Aini Hanifa, and M. T. Siti Sa’adah, “Early detection of type II Diabetes Mellitus with random forest and classification and regression tree (CART),” in 2014 International Conference of Advanced Informatics: Concept, Theory and Application (ICAICTA), Aug. 2014, pp. 238–242. doi: 10.1109/ICAICTA.2014.7005947.

[72] D. Brown, A. Aldea, R. Harrison, C. Martin, and I. Bayley, “Temporal case-based reasoning for type 1 diabetes mellitus bolus insulin decision support,” Artif. Intell. Med., vol. 85, pp. 28–42, Apr. 2018, doi: 10.1016/j.artmed.2017.09.007.

[73] B. Atmani, M. Benamina, and S. Benbelkacem, “Diabetes Diagnosis by Case-Based Reasoning and Fuzzy Logic,” Int. J. Interact. Multimed. Artif. Intell., vol. 5, no. Regular Issue, pp. 72–80, 2018.

[74] M. K. Jha, D. Pakhira, and B. Chakraborty, “Diabetes detection and care applying CBR techniques,” IJSCE, vol. 6, no. 2, pp. 132–137, 2013.

[75] S. El-Sappagh and M. Elmogy, “A Decision Support System for Diabetes Mellitus Management,” Diabetes Case Rep., vol. 1, pp. 1–13, Feb. 2016, doi: 10.4172/2572-5629.1000102.

[76] S. Lekkas and L. Mikhailov, “Evolving fuzzy medical diagnosis of Pima Indians diabetes and of dermatological diseases,” Artif. Intell. Med., vol. 50, no. 2, pp. 117–126, Oct. 2010, doi: 10.1016/j.artmed.2010.05.007.

[77] H. Naz and S. Ahuja, “Deep learning approach for diabetes prediction using PIMA Indian dataset,” J. Diabetes Metab. Disord., vol. 19, no. 1, pp. 391–403, Jun. 2020, doi: 10.1007/s40200-020-00520-5.

[78] M. Chen, J. Yang, J. Zhou, Y. Hao, J. Zhang, and C.-H. Youn, “5G-Smart Diabetes: Toward Personalized Diabetes Diagnosis with Healthcare Big Data Clouds,” IEEE Commun. Mag., vol. 56, no. 4, pp. 16–23, Apr. 2018, doi: 10.1109/MCOM.2018.1700788.

[79] G. P. MAFFRE Gervais GAUTHIER, Bruno LAY, Julien ROGER, Damien ELIE, Mélanie FOLTETE, Arthur DONJON, Hugo, “Messidor,” ADCIS. Accessed: Oct. 24, 2023. [Online]. Available: https://www.adcis.net/en/third-party/messidor/

[80] A. Erciyas and N. Barışçı, “An Effective Method for Detecting and Classifying Diabetic Retinopathy Lesions Based on Deep Learning,” Comput. Math. Methods Med., vol. 2021, p. e9928899, May 2021, doi: 10.1155/2021/9928899.

[81] “Improved and robust deep learning agent for preliminary detection of diabetic retinopathy using public datasets,” Intell.-Based Med., vol. 3–4, p. 100022, Dec. 2020, doi: 10.1016/j.ibmed.2020.100022.

[82] E. AbdelMaksoud, S. Barakat, and M. Elmogy, “A computer-aided diagnosis system for detecting various diabetic retinopathy grades based on a hybrid deep learning technique,” Med. Biol. Eng. Comput., vol. 60, no. 7, pp. 2015–2038, Jul. 2022, doi: 10.1007/s11517-022-02564-6.

[83] P. Costa and A. Campilho, “Convolutional bag of words for diabetic retinopathy detection from eye fundus images,” IPSJ Trans. Comput. Vis. Appl., vol. 9, no. 1, p. 10, Mar. 2017, doi: 10.1186/s41074-017-0023-6.

[84] W. L. Alyoubi, M. F. Abulkhair, and W. M. Shalash, “Diabetic Retinopathy Fundus Image Classification and Lesions Localization System Using Deep Learning,” Sensors, vol. 21, no. 11, p. 3704, May 2021, doi: 10.3390/s21113704.

[85] M. Arora and M. Pandey, “Deep Neural Network for Diabetic Retinopathy Detection,” in 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Feb. 2019, pp. 189–193. doi: 10.1109/COMITCon.2019.8862217.

[86] F. Arcadu et al., “Deep Learning Predicts OCT Measures of Diabetic Macular Thickening From Color Fundus Photographs,” Invest. Ophthalmol. Vis. Sci., vol. 60, no. 4, pp. 852–857, Mar. 2019, doi: 10.1167/iovs.18-25634.

[87] D. S. Sisodia, S. Nair, and P. Khobragade, “Diabetic Retinal Fundus Images: Preprocessing and Feature Extraction for Early Detection of Diabetic Retinopathy,” Biomed. Pharmacol. J., vol. 10, no. 2, pp. 615–626, Jun. 2017.

[88] A. Dinh, S. Miertschin, A. Young, and S. D. Mohanty, “A data-driven approach to predicting diabetes and cardiovascular disease with machine learning,” BMC Med. Inform. Decis. Mak., vol. 19, no. 1, p. 211, Nov. 2019, doi: 10.1186/s12911-019-0918-5.

[89] A. Whaley-Connell et al., “Diabetes mellitus and CKD awareness: the kidney early evaluation program (KEEP) and national health and nutrition examination survey (NHANES),” Am. J. Kidney Dis., vol. 53, no. 4, pp. S11–S21, 2009.

[90] P. Muntner, J. He, J. Chen, V. Fonseca, and P. K. Whelton, “Prevalence of non-traditional cardiovascular disease risk factors among persons with impaired fasting glucose, impaired glucose tolerance, diabetes, and the metabolic syndrome: analysis of the Third National Health and Nutrition Examination Survey (NHANES III),” Ann. Epidemiol., vol. 14, no. 9, pp. 686–695, Oct. 2004, doi: 10.1016/j.annepidem.2004.01.002.

[91] S. Karthikeyan, K. P. Sanjay, R. J. Madhusudan, S. K. Sundaramoorthy, and P. K. Namboori, “Detection of multi-class retinal diseases using artificial intelligence: an expeditious learning using deep CNN with minimal data,” Biomed. Pharmacol. J., vol. 12, no. 3, p. 1577, 2019.

[92] P. S. Chandakkar, R. Venkatesan, and B. Li, “MIRank-KNN: multiple-instance retrieval of clinically relevant diabetic retinopathy images,” J. Med. Imaging, vol. 4, no. 3, pp. 034003–034003, 2017.

[93] D. B. Mule, S. S. Chowhan, and D. R. Somwanshi, “Detection and Classfication of Non-proliferative Diabetic Retinopathy Using Retinal Images,” in Recent Trends in Image Processing and Pattern Recognition, vol. 1036, K. C. Santosh and R. S. Hegadi, Eds., in Communications in Computer and Information Science, vol. 1036. , Singapore: Springer Singapore, 2019, pp. 312–320. doi: 10.1007/978-981-13-9184-2_28.

[94] K. Shimada et al., “Real-World Evidence of the Incidence of and Risk Factors for Type 1 Diabetes Mellitus and Hypothyroidism as Immune-Related Adverse Events Associated With Programmed Cell Death-1 Inhibitors,” Endocr. Pract., vol. 27, no. 6, pp. 586–593, Jun. 2021, doi: 10.1016/j.eprac.2020.12.009.

[95] A. Christiaens, S. Henrard, A. J. Sinclair, F. Tubach, D. Bonnet-Zamponi, and L. Zerah, “Deprescribing Glucose-Lowering Therapy in Older Adults with Diabetes: A Systematic Review of Recommendations,” J. Am. Med. Dir. Assoc., vol. 24, no. 3, pp. 400–402, Mar. 2023, doi: 10.1016/j.jamda.2022.12.018.

[96] P. Porwal et al., “Idrid: Diabetic retinopathy–segmentation and grading challenge,” Med. Image Anal., vol. 59, p. 101561, 2020.

[97] P. Porwal et al., “Indian diabetic retinopathy image dataset (IDRiD): a database for diabetic retinopathy screening research,” Data, vol. 3, no. 3, p. 25, 2018.

[98] M. Kalpana Devi and M. Mary Shanthi Rani, “Classification of Diabetic Retinopathy Using Ensemble of Machine Learning Classifiers with IDRiD Dataset,” in Evolutionary Computing and Mobile Sustainable Networks, vol. 116, V. Suma, X. Fernando, K.-L. Du, and H. Wang, Eds., in Lecture Notes on Data Engineering and Communications Technologies, vol. 116. , Singapore: Springer Singapore, 2022, pp. 291–303. doi: 10.1007/978-981-16-9605-3_20.

[99] J.-H. Wu, T. A. Liu, W.-T. Hsu, J. H.-C. Ho, and C.-C. Lee, “Performance and limitation of machine learning algorithms for diabetic retinopathy screening: meta-analysis,” J. Med. Internet Res., vol. 23, no. 7, p. e23863, 2021.

[100] A. Behera, “Use of artificial intelligence for management and identification of complications in diabetes,” Clin. Diabetol., vol. 10, no. 2, pp. 221–225, 2021.