ARTIFICIAL INTELLIGENCE IN DIABETES RISK FACTOR PREDICTION AND MANAGEMENT

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ABSTRACT

Diabetes mellitus, particularly Type 1 and Type 2, presents significant long-term health challenges, including complications such as diabetic peripheral neuropathy, nephropathy, retinopathy, and cardiovascular diseases. Effective management of diabetes, particularly in relation to insulin titration, is critical to minimizing these complications. This article explores various innovative approaches to diabetes management using artificial intelligence and machine learning. AI-based tools, such as Voice-Based Artificial Intelligence for basal insulin titration and continuous glucose monitoring systems, are increasingly integrated into diabetes care. These technologies aim to optimize insulin delivery, predict complications, and improve patient outcomes by using real-time data analysis. Additionally, AI-powered systems like automated insulin delivery and decision support tools such as the Advanced Bolus Calculator for Type 1 Diabetes are being developed to provide more personalized, adaptive management strategies for diabetes. The article also highlights emerging diagnostic methods, such as AI-enhanced imaging for diabetic retinopathy and predictive models for diabetic kidney disease, underscoring the potential of AI in predicting, monitoring, and managing diabetes-related complications. Through these advances, AI has the potential to revolutionize diabetes care by reducing the burden of

disease management, enhancing clinical decision-making, and improving patient quality of life.

Keywords: Diabetes mellitus, Artificial intelligence, AI-based tools

Introduction

One of the most prevalent long-term effects of diabetes is diabetic peripheral neuropathy, which weakens the muscles and damages the nerves. In type I diabetes mellitus, a chronic autoimmune illness, the beta cells in the pancreas are destroyed by T cells [1]. High blood glucose levels are a defining feature of a diverse set of disorders known as diabetes mellitus [2].

When the pancreas is unable to create enough insulin or the cells are unable to use the insulin that is produced efficiently, blood glucose levels rise because the glucose cannot be metabolized in the cells. There are three types of diabetes: Type 1 diabetes is characterized by the pancreas's inability to produce insulin; type 2 diabetes is characterized by body cells' resistance to the action of insulin, which causes the production of insulin to gradually decline over time; and gestational diabetes, which develops during pregnancy and can result in complications during pregnancy and at birth, as well as an increased risk of type 2 diabetes in the mother and obesity in the offspring.

Numerous organ issues result from uncontrolled diabetes. Amputations of lower limbs, heart attacks, strokes, and loss of vision and renal function are all consequences of damage to both major and small blood arteries and nerves. Diabetes shortens life expectancy and creates impairment. Compared to their contemporaries without diabetes, persons with diabetes have a two to three times increased risk of cardiovascular disease [3].

Although diabetes was responsible for about 5.0 million deaths in 2015, managing the condition and its consequences accounted for more than 12% of global health spending that year [4]. Patients with type 1 or type 2 diabetes frequently experience diabetes complications, which can contribute significantly to morbidity and mortality. The two main categories of diabetes's chronic consequences are microvascular and macrovascular, with the former being far more common than the latter [5]. Neuropathy, nephropathy, and retinopathy are examples of microvascular problems, whereas peripheral artery disease (PAD), cardiovascular disease, and stroke are examples of macrovascular issues. One of the main causes of lower limb amputation is diabetic foot syndrome, which is characterized as the presence of foot ulcers linked to neuropathy, PAD, and infection [6]. Lastly, dental disease, decreased resistance to infections, and delivery problems in women with gestational diabetes are examples of other complications of diabetes that do not fall under the two previously described categories [5]. A condition known as diabetes mellitus occurs when blood glucose levels are consistently elevated above the usual range. It happens when there is insufficient insulin, whether or not there are other variables that interfere with insulin's activity. The effect of inadequate insulin activity is hyperglycemia [7].

Risk Factor Prediction

A remote (decentralized), randomized, open-label, parallel-group clinical study examining a novel VBAI application for basal insulin titration in comparison to standard of care was called the Managing Insulin with Voice AI (MIVA) experiment.
For this experiment, we created bespoke speech AI software using Alexa, an Amazon conversational AI platform that complies with the Health Insurance Portability and Accountability [8] Amazon was not involved in this study; the research team developed all of the software on their own, without any sponsorship. An Amazon smart speaker was used to implement the VBAI. Voice commands and brief chats were used for all participant interactions. The purpose of the VBAI was to help the individual titrate their basal insulin at home. The American Association of Clinical Endocrinologists' and the American College of Endocrinology's titration algorithms served as the foundation for the rules-based, deterministic VBAI, which also incorporated emergency procedures for managing hypoglycemia and hyperglycemia.

An Amazon smart speaker with the customized VBAI installed was given to the participants. An insulin titration strategy was chosen by the participant's primary diabetic doctor (primary care physician, endocrinologist, or clinical pharmacist) through a customized online portal prior to activation. A starting insulin dosage, a range of target fasting blood glucose (FBG) levels, and directions for insulin titration were among the protocol components. Following protocol approval, participants were told to use the phrase "Alexa, check in with clinical trial" to check in with the VBAI every day. This statement started a dialogue during which the participant shared clinical information, including FBG readings and recent insulin use. Based on these findings, the VBAI changed insulin dosage guidelines at the conclusion of the discussions. Clinicians and the research team had real-time access to all data on our portal.

The AI system's sensitivity and specificity in detecting eyes with mtmDR or vtDR by 2-field undilated CFP in comparison to the FPRC reference standard were the main result measures. Secondary result measures included comparing sequential versus enriched enrolment populations, worst-case imputation, safety outcomes, and the AI system's image ability, sensitivity, and specificity against the reference standard using the dilate-if-needed technique. To support FDA clearance, a subset of participant's selected based on FDA-specified criteria underwent additional pre specified analyses.

Commercially available automated insulin delivery (AID) systems consist of an insulin pump, a continuous glucose monitor (CGM) which is depicted in figure 1, and a control algorithm that uses glucose sensing to automate insulin delivery [9-13]. In order to calculate meal insulin, users of commercial systems, which are hybrid systems, must estimate the amount of carbohydrates in their meals and enter this information into the AID. Carbohydrate input is not necessary for the more recent, totally automated systems that are currently in development [14]. Maintaining an ideal glucose concentration during and after exercise to prevent hypoglycemia is still a difficulty for those with type 1[15,16].

Dynamically monitoring the onset, progression, and prognosis of DKD is now feasible because to the advent and ongoing advancement of ultrasonic diagnosis technologies [17]. A quick, easy, non-invasive, and effective imaging technique is ultrasound. In addition to directly displaying the kidney's size and shape, vascular morphology, parenchymal echo, and other physiological data, it can also be used in conjunction with spectral Doppler and color imaging. It can provide information on hemodynamic parameters and dynamically monitor blood perfusion and the progressive branching of the renal artery in real time [18].

In order to screen renal image eigenvalues, decrease feature latitude, speed up classification and training, and lessen computational complexity, the artificial bee colony approach was employed. Furthermore, the artificial bee colony technique was employed to determine the ideal parameters required to support ultrasound picture classification in order to increase classification accuracy. To investigate the impact of nursing intervention on DKD patients and provide data support for future therapeutic applications, the patients with DKD following nursing intervention were evaluated [19].

For a week, participants ate three standardized liquid mixed meals (SLMM) rather than three breakfasts while wearing a CGM. From two-hour post-SLMM CGM traces, glucose characteristics were taken out, compared between groups, and applied to four supervised machine learning Ab risk status classifiers. Features were chosen using the Recursive Feature Elimination (RFE) technique; classifiers were assessed using 10-fold cross-validation, and the best classification model was chosen by calculating the receiver operating characteristic area under the curve (AUC-ROC).

A glucometer, a scale with bioelectrical impedance analysis, a sphygmomanometer, and a watch-style pedometer can all be connected via Bluetooth to the mobile health care platform Auto-Check Care (Aprilis Co., Ltd., Seoul, Korea). This enables the platform to automatically collect all of the data for integrated analysis in a single smartphone application. Additionally, AI-based food content classification in photos is now possible thanks to convolution neural networks and deep learning technologies for object detection. Food Lens (Doing Lab Co., Ltd., Seoul, Korea) is an AI-based food recognition tool that can identify several food items in a single image. With an 86.6% food categorization recognition rate, it passed the Korean Information Security Technology accreditation test in January 2018.

Figure 1: continuous glucose monitor deices for non diabetics.

Dietary and nutritional information is automatically compiled into the integrated digit al health care platform from this program once users snap pictures of many dishes rig

ht before eating.We assessed the effectiveness of the integrated digital health care plat form utilizing a AI-
based dietary management solution in adults with type 2 diabetes in order to look at th e usefulness of this strategy in a clinical environment.
We also investigated the effectiveness of this platform in conjunction with remote fee dback from medical professionals and intermittently used personal continuous glucose monitoring (CGM).

The Advanced Bolus Calculator for Type 1 Diabetes (ABC4D) is a decision assistance tool that adjusts and customizes insulin bolus dosages by utilizing the artificial intelligence method of case-based reasoning. A clinical online site and smartphone application are part of the integrated system. Our goal was to evaluate the ABC4D's (intervention) safety and effectiveness in comparison to a no adaptive bolus calculator (control) [20].

A glucometer, a scale with bioelectrical impedance analysis, a sphygmomanometer, and a watch-style pedometer can all be connected via Bluetooth to the mobile health care platform Auto-Chek Care (Aprilis Co., Ltd., Seoul, Korea). This enables the platform to automatically collect all of the data for integrated analysis in a single smartphone application. Additionally, AI-based food content classification in photos is now possible thanks to convolution neural networks and deep learning technologies for object detection [21].

According to studies, CGM devices can be used to predict the development of diabetes in children who are autoantibody positive (Ab+) and to identify early hyperglycemia in children with multiple autoantibodies [22-24]. According to Steck "CGM should be included in the ongoing monitoring of high-risk children (Ab+)," and they employed home-based CGM wear in the absence of any further metabolic testing (such as the mixed meal tolerance test [MMTT]).

Predicting Immunological Risk for Stage 1 and Stage 2 Diabetes Using a 1-Week CGM Home Test, Nocturnal Glucose Increments, and Standardized Liquid Mixed Meal Breakfasts, with Classification Enhanced by Machine Learning

METHODS FOR MANAGEMENT OF DIABETES USING ARTIFICIAL INTELLIGENCE

METHOD 1

After the search phrases were combined and examined, 1841 "hits" were found. Conjunctive operators were utilized to combine the terms "diabetes," "management," "artificial pancreas," and "blood glucose" with the other terms. These terms were then employed as keywords to generate distinct datasets that included all references to the following phrases: “artificial intelligence” (186), “computational intelligence” (179), “machine learning” (88), “data mining” (111), “deep learning” (3), “k-means” (9), “fuzzy logic” (24), “heuristic” (10), “clustering analysis” (281), “Bayes” (19), “decision tree” (67), “random forest” (21), “pattern recognition” (31), “genetic algorithm” (43), “supervised algorithm” (14), “unsupervised algorithm” (9), “evolutionary computation” (2), “neural network” (72), “natural language processing” (34), “reinforcement learning” (6), clustering (510), and “support”

METHOD 2

The EMR utilized for this investigation and the definition of type 2 diabetes

Our hospital began using the EMR system in 2005, and by 2016, there were 858,660 EMRs. We could extract 451,584 EMR in total because there are 407,076 EMR without any clinical data. Using the following criteria, we identified 64,059 patients who had been diagnosed with type 2 diabetes: (1) The medical billing indicated that the patient had type 2 diabetes; (2) the HbA1c level was 6.5% or higher (NGSP); (3) the fasting plasma glucose level was 126 mg/dL or higher, unless in an emergency room; (4) the postprandial plasma glucose level was 200 mg/dL or higher, unless in an emergency room; and (5) anti-diabetic medication (137 medications) was prescribed. Throughout the investigation and publication process, all private and sensitive information was safeguarded and eliminated. The paper and the Supplementary Materials contain all of the data related to this investigation.

DKD staging classification in this study

Albuminuria and a decline in the estimated glomerular filtration rate (eGFR) are characteristics of diabetic nephropathy. Because hyperglycemia causes glomerular injury that result in a malfunction of the glomerulus's barrier system, micro albuminuria usually occurs before the decline in eGFR in diabetic nephropathy. However, due to medication and the aging population, the proportion of people with low eGFR who do not appear to have proteinuria has been rising recently. As a result, we have recently begun using DKD rather than diabetic nephropathy3. In this study, proteinuria was used to determine the DKD stage. Stage 5 is known as continuous ambulatory peritoneal hemodialysis or maintenance hemodialysis.

DKD predictive model

A model was created to forecast the course of DKD, one of the diabetic complications that, if worsened, may require intensive treatment, including dialysis. This model predicts whether the diabetes of DKD stage 1 patients would worsen in terms of DKD stage after 180 days based on laboratory test results and the DKD stage (one to five, Table S1) as labels. A number of aspects, such as patient profiles, the disease nomenclature, and treatment information (such as medication and treatment details), were taken from

METHOD 3

As part of routine retinal screening for DR, 311 patients with type 2 diabetes who were 18 years of age or older and receiving treatment at a tertiary care diabetes hospital in Chennai (formerly Madras) in southern India, with varying durations of diabetes, had retinal color photography (fundus photography) done at the eye department. 50 patients' retinal pictures were used in a pilot research to evaluate the sensitivity and specificity of automated DR identification with the Eye Art TM program. The findings of the pilot phase were used to determine the study's sample size. All subjects provided written informed consent, and the Madras Diabetes Research Foundation's Ethical Committee authorized the study.

After clearing out a history of dilating eye drop allergies, tropic amide eye drops were used to dilate the pupils following a preliminary eye examination. Remidio Fundus on Phone (FOP), a smartphone-based imaging tool (Remidio Innovative Solutions Pvt. Ltd, Bangalore, India), was used to take the retinal photos. It is a portable fundus camera that combines with any commercially available smartphone to take retinal photos. Its annular illumination design removes corneal reflection [4]. For fundus imaging, the FOP offers a 45° field of view. It can be mounted on any common slit lamp, or it can be used handed. The FOP camera recorded four fields in each eye: superior-temporal, inferior-temporal, disc-centered, and macula-centered. To minimize any potential bias, retinal photos were coded with an identity number and evaluated markedly for the existence and severity of DR. Two ophthalmologists (retina specialists) who were blind to the patient's name and clinical diagnosis evaluated the photos. k = 0.89 was the kappa agreement between the two ophthalmologists' grades. A third retina specialist, whose DR rating was considered final, decided any discrepancies between the two graders' retinopathy scores. The International Clinical Diabetic Retinopathy (ICDR) severity scale was used to grade the retinopathy [25]. The five stages of DR are categorized as follows using the ICDR severity scales: (1) mild non-proliferative DR (NPDR)—micro aneurysms; (2) no discernible retinopathy—no anomalies.(4) severe NPDR—one or more of the following—but less than severe NPDR Proliferative DR (PDR)—retinal neovascularization with or without vitreous/pre-retinal hemorrhage [10]; (i) more than 20 intra-retinal hemorrhages in each of the four quadrants; (ii) distinct venous beading in two or more quadrants; and (iii) a prominent intra-retinal microvascular abnormality in one or more quadrants. Severe NPDR, PDR, and/or diabetic macular oedema (DME)/clinically significant macular oedema (CSME) were considered indicators of sight-threatening DR (STDR) [26]. Each photo was rated, given a retinopathy level, and given a final diagnosis.

METHOD 4

Identification of Biomarkers and DM Prediction

Numerous factors are known to play a significant role in the onset and course of diabetes mellitus. Given the strong causal link between obesity and the establishment of diabetes mellitus, obesity is a significant risk factor, particularly in T2D [27]. Oral glucose tolerance, random blood sugar, fasting sugar, and α-glycate hemoglobin (A1C) tests are among the tests used to diagnose diabetes mellitus. There is proof that in both T1D and T2D, early diagnosis and onset prediction are essential for a) slowing the disease's progression, b) choosing the right medication, c) extending life expectancy, symptom relief, and d) the onset of associated complications [27].

Biomarkers, which include biological substances, are quantifiable indications of both health and disease states. Generally, biomarkers are a) detected in bodily fluids (blood, saliva, or urine), b) came across and so identified without reference to their etiopathogenic mechanism, and c) employed to track the burden of clinical and subclinical diseases and their response to therapy. Biomarkers may be indirect indicators of additional complications or direct indicators of the disease's progression. Numerous new biomarkers are being developed as a result of current technologies including genomics, proteomics, and metabolomics. Biomarkers for diabetes mellitus may indicate the occurrence and degree of hyperglycemia or the existence and severity of comorbidities associated with the disease [28].

Cases where a) diagnostic and predictive markers are used or new biomarkers are introduced, and b) disease prediction occurs are the two main categories into which the current section is divided. However, the purpose of this task is always to assess the predictive accuracy of the biomarkers that have been identified.

THERAPY FOR DIABETES USING ARTIFICIAL INTELLIGENCE

Rationale for ADS Technology

The basic concept of ADS for patients undergoing MDI therapy is to optimize insulin dose on a daily or weekly basis by integrating digital diabetes data, perhaps via CGM and Bluetooth-enabled smart pens, in conjunction with a computer-based dosing controller, probably on a smartphone (Fig. 1). Without requiring patients or caregivers to monitor their own data and modify their own insulin dosage, such a system would offer the advantages of digital data analysis and dosing optimization. For MDI patients, it can be thought of as a type of closed-loop control in which the control is tuned less frequently than with AP technology, which uses a 5-minute basis [29].

CBR stands for case-based reasoning

The management of diabetes makes heavy use of CBR, an AI technology that solves new issues by learning from comparable past encounters [30,31].One CBR that has been applied to diabetes treatment is the 4 Diabetes Support System. The system's objectives are to automatically identify issues with blood glucose management, suggest fixes for those issues, and keep track of the successful and unsuccessful fixes for each patient. CBR has been used to tailor and optimize insulin treatment for different diabetic meal scenarios.

Artificial neural networks

In order to connect and evaluate different data and provide individualized answers, neural networks were developed. Diabetes diagnosis is one of the many and specific uses for neural network approach [32]. To investigate the effects of different factors on glycemic indices, intelligent algorithms have been developed.

ML with Free-Living Data for Digital Health Technologies in T1D

Because the body cannot make insulin, exogenous insulin must be administered to individuals with type 1 diabetes in order to control their blood glucose levels. With the introduction of CGM devices, diabetics could now analyze the numerical and graphical data shown and check their blood glucose levels every five minutes. Insulin can be injected into the subcutaneous tissue by people with type 1 diabetes using injectors or insulin pens, or it can be infused using insulin pumps. Even though BGC regulation and insulin delivery were enhanced by these technological advancements, determining how much insulin to give remains a significant challenge for both individuals with T1D and their caregivers [33,34]. Over 100 decisions are made daily by people with T1D, which diverts them from other tasks, increases the likelihood, that they will make bad choices, and serves as a reminder of their ongoing chronic illness.

Improving Diabetes Treatment Using AI and ML

In the fields of engineering, computer science, medicine, and diabetes therapy and therapies, artificial intelligence (AI), and particularly machine learning (ML), is propelling scientific advancement. With the integration of mobile computers with ubiquitous linked sensors and medicine delivery systems, machine learning (ML) has become especially significant in producing massive data sets that may be utilized to find patterns that are pertinent to enhancing health outcomes [35].

Significant advancements in CGM, connected insulin pumps, and pens have been made in the last 20 years, but the field of machine learning has also experienced tremendous expansion and innovation during this time. The existing problems with AID and MDI treatments can be solved with the help of machine learning (ML). For instance, CGM patterns that are helpful for AID control algorithms can be found using machine learning. Additionally, by employing reinforcement learning to adapt, machine learning can be utilized to enhance the automation of insulin or other hormone distribution [36].

Gradually to each person's own physiology or to react to disruptions like physical activity. Machine learning (ML) can be used to create automated recommendation systems for decision support systems that help caregivers and diabetics on MDI therapy better control insulin dosage. Significant progress has been made in using machine learning to diabetes care.

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