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A Survey on Personalization of Diabetes Treatment using Artificial Intelligence Techniques

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Abstract

Diabetes mellitus is a disease caused by uncontrolled diabetes that can lead to multiple organ failure in patients. Fortunately, recent advancements in artificial intelligence have made it possible to diagnose and detect diabetic disease early on. Numerous articles are currently being published on the use of artificial intelligence and machine learning techniques for automated detection, diagnosis, and personalized treatment and management of diabetes. This survey examines technologies for personalized diabetes treatment from five distinct perspectives: blood glucose prediction, glycemic variability detection, hyperglycemia detection, insulin controller therapy, and pharmacogenetics. The treatment of diabetes is dependent on various medical, demographic, and lifestyle factors, including diabetes type, age, body weight, duration of diabetes, comorbidities, blood sugar, physical activity, and diet. Artificial intelligence is regarded as a valuable technology to aid in diabetes treatment. This survey offers a comprehensive overview of techniques for diabetes detection and personalized treatment, which may prove beneficial to the scientific community focused on automatic diabetes detection and personalized treatment.

This survey furnishes a comprehensive outline of techniques for the detection of diabetes and personalized treatment, which can prove immensely beneficial to the scientific community working on automatic diabetes detection and personalized treatment.

Keywords: Diabetes mellitus, personalized treatment, Artificial intelligence.

1. Introduction

Diabetes is a perilous global disease that significantly impacts individual patients and has financial implications for national healthcare systems. It is projected that the number of diabetes cases will rise to 592 million by 2035, with an estimated 175 million individuals with diabetes remaining undiagnosed [2]. In the United States alone, the total estimated cost of diabetes was $174 billion in 2007 [3].

Diabetes is a chronic disease of the metabolic system that causes high blood sugar levels. Diabetes can be broadly classified into two categories. Type 1 diabetes (T1DM) occurs in children, adolescents, and young adults and is caused by the loss of beta cells responsible for storing and releasing insulin. Type 2 diabetes mellitus (T2DM), on the other hand, is mainly observed in obese older adults and is characterized by insulin resistance and progressive defects in insulin secretion. [4].

Both conditions require ongoing medical care to minimize the risk of long-term complications such as diabetic foot ulcers, cardiovascular disease, or stroke [5]. Only T1 diabetes can be treated with insulin, whereas patients with T2 diabetes have several options [4]. To minimize the risk of long-term complications such as diabetic foot syndrome, cardiovascular diseases, or stroke, continuous medical care is necessary for both conditions [5]. Only insulin can be used to treat type 1 diabetes, whereas patients with type 2 diabetes have access to a broad range of treatment options [4]. Type 2 diabetes demands active engagement and can be quite challenging for patients. Furthermore, the consequences of non-adherence may not be immediately apparent. Long-term complications such as diabetic foot syndrome or retinopathy take years to develop [6].

Artificial intelligence (AI) allows for the continuous and remote monitoring of patient symptoms and biomarkers in a simple manner. The application of AI is expected to revolutionize diabetes care by shifting away from conventional management approaches towards establishing precision care that is data-driven and targeted [47].

The objective of this survey is mentioned the improvement of treatment for each diabetes patient based on the patient characteristics by using artificial intelligence techniques.

2. Diabetes Disease

The fundamental principle underlying diabetes is the conversion of food into energy by the body. After food consumption, the body transforms it into glucose, an energy source that is carried through the blood. The transfer of glucose from the blood to the cells where it can be utilized for energy is facilitated by insulin, a hormone produced by the pancreas [7].

When Diabetic don't take their treatment, their body may not produce insulin as it should, leading to a build-up of glucose in the body. This condition, known as high blood sugar, can result in severe and potentially life-threatening health problems. The development of diabetes varies in each patient based on its underlying cause [8].

2.1 Type-I diabetes

Type 1 diabetes is an autoimmune condition where the body generates antibodies that attack the pancreas, obstructing its ability to produce insulin. [9]. Type 1 diabetes can occur due to genetic factors. Individuals with type 1 diabetes are at an elevated risk of heart failure and stroke.

2.2 Type-II diabetes

Type 2 diabetes occurs when the pancreas produces some insulin, but not enough, or the body is unable to utilize it effectively. Although type 2 diabetes is typically less severe than type 1, it can still lead to various health issues, particularly in the small blood vessels of the eyes, nerves, and kidneys. It is noteworthy that around 90% of all diabetes patients have type 2 diabetes [10].

3. Personalization of Diabetes Therapy Using AI

Artificial Intelligence (AI) and Machine Learning (ML) are research techniques that enable computers to learn from data. Machine learning is a subset of AI, and its objective is to develop automated processes in computer systems that can learn from experiences and make predictions. Meanwhile, artificial intelligence aims to create intelligent agents that can deliver solutions based on various machine learning techniques. [11].

Rapid developments in AI aim to real-time health data accessible for Diabetes treatment [12]

Personalization Treatment Therapy for diabetes used in the following sectors:

3.1 Patient self-management

Physical activity has an impact on a patient's insulin and blood glucose levels. Therefore, in a diabetes treatment plan, it is crucial to prioritize physical activity for its health benefits. Patients with type-2 diabetes are often asked to get a self-report of their physical activity according to their treatment plan through surveys. On the other hand, in the case of type 1 diabetes patients, physical activity is considered significant in insulin calculation using calculators. The insulin dosage varies among diabetes patients and depends on the duration of physical activity. [13]

Examples of Applications of diabetes assistant for self-management:

1- According to Maharjan (2019), an AI-powered voice virtual assistant system was developed to assist Native American diabetes patients in tracking their food intake and improving their health and nutritional knowledge on a daily basis [14].

2- Czmil et al. (2019) proposed a system for diagnosing type-1 diabetes in children’s physical activity levels. Disease monitoring is achieved through tracking the weekly step counts and minutes of strong physical activity. The study demonstrated that type 1 diabetes can be identified through the evaluation of physical movement, providing positive evidence for this method of diagnosis. [15].

3- Vaskovsky and Chvanova (2019) proposed a personalized food recommendation system called Ramus was suggested, which suggests appropriate food choices for diabetic patients based on their taste preferences. The system is trained using data that contains diverse food impacts on patients to provide tailored recommendations. [16].

4- Olatunji, Bolanle, Asegunoluwa, Tobore, Zedong and Lei proposed a new approach which high involves combining multiple variants of adaptive neuro-fuzzy inference systems with multiple modalities to create a hybrid system. The implementation of the MANFIS and diet recommendation models of the affective system. Additionally, it provides some experimental information regarding the diet recommender system, including details about the diagnosis model and dataset used for training and validation, which were developed specifically for this study. Furthermore, the food database used for diet recommendations was updated and obtained [49].

3.2 Personalized Medicine in Diabetes

Personalized medicine in diabetes refers to tailoring treatment strategies to the specific characteristics of each individual patient to achieve the most effective outcomes. Clinical laboratory findings, gene sequences, and other molecular markers are among the data that can guide personalized decisions on diabetes care. With the significant advancements in characterizing human gene sequences, there is a growing interest in using individual molecular biomarkers to inform patient-specific management of diabetes. AI advancements in genetics, genomics, proteomics, and metabolomics have made it possible to analyse thousands of genes, proteins, and metabolites, providing new opportunities for identifying genetic factors and gene products associated with different diabetes subtypes. [17].

An Example: Sang, Jongyoul, Su, Seungyeon, Jeonghoon proposed a new diabetes treatment recommendation system, which incorporates the principles of contextual bandits and reinforcement learning, has been suggested. The model was developed using electronic health records obtained from a South Korean database that is updated annually with a million patient records [50].

4. Diabetes Personalized treatment methodologies:

Personalized treatment for diabetes is dependent on a range of medical, demographic, and lifestyle data, including diabetes type, age, weight, diabetes duration, blood glucose levels, and physical activity. Artificial intelligence (AI) is a useful technology that can assist in diabetes therapy. The following are five AI approaches that can aid in diabetes therapy:

4.1 Blood glucose prediction:

Data-driven techniques that are related to blood glucose utilize the collection of data and uncover the information hidden in the data to predict future levels of blood glucose [18]. Unlike systems that imitate the human physiology of the glucose-insulin regulatory system, data-driven glucose prediction does not necessitate knowledge of diabetes physiology. These methods mainly rely on gathered data and extract concealed information from it to forecast future blood glucose levels [41].

4.2 Hyperglycemia detection

Blood glucose prediction can be considered a regression problem that is related to machine learning (ML) techniques. Detecting cases of hypo or hyperglycemia can be seen as a classification issue, where the model must identify whether a hypo or hyperglycemic episode is likely to happen based on a specific input dataset. [19]. According to Sudharsan [42], even with sparse blood glucose readings taken once or twice daily through self-monitoring (SMBG), hypoglycemic and hyperglycemic events in patients with type 2 diabetes can be accurately detected. The model was trained on approximately 10 weeks of data, and the prediction of hypoglycemic events within the next 24 hours achieved 92% sensitivity and 70% specificity. By incorporating drug information from the past few days, specificity increased reach to 90%, Although the prediction range was limited to the period during which hypoglycemia occurred.

4.3 Glycaemic variability detection:

Glycaemic variability is characterized by fluctuations in blood glucose levels and serves as an indicator of inadequate diabetes management, as it increases the risk of hypo- and hyperglycemia [20]. Marin et al. [43] utilized multilayer perceptrons (MPs) and support vector regression (SVR) algorithms to classify the consensus indicator of perceived glycaemic variability (CPGV) into four classes of CV (low, borderline, high, very high) based on 250 24-hour continuous glucose monitoring (CGM) maps. The CPGV metric achieved 90.1% accuracy, 97.0% sensitivity, and 74.1% specificity through manual scoring using 10-fold cross-validation. SVR outperformed MPs, and this metric outperformed other metrics such as MAGE or SD.

Hua, Ilya and Wei utilized a framework for personalized RL (Reinforcement Learning) in the context of type 2 diabetes resulted in significant improvements in glycemia, blood pressure, and CVD risk outcomes, while also demonstrating a high level of agreement with the prescriptions provided by clinicians [48].

4.4 Insulin controller therapy:

Machine learning can be employed to control blood glucose levels, as it is a model-free approach that does not necessitate a mathematical model of glucose-insulin interaction [21]. Zita [44] utilized two distinct artificial neural network (ANN) models, namely the multilayer feedforward neural network (LM-NN) and polynomial network (PN), as controllers for insulin dose titration. The simulations were conducted using a dataset of 30,000 blood glucose samples from 70 different patients, with LM-NN outperforming PN. The authors suggest that LM-NN has the potential to serve as a model-free insulin controller.

4.5 Pharmacogenetics:

Pharmacogenetics provides an opportunity to introduce personalized medicine in the field of type 2 diabetes. Personalized medicine is already being practiced in certain types of monogenic diabetes.

With significant advancements made in recent decades, the application of "personalized diabetology" in T2DM is expected to become more prevalent in the coming years. Advancements in genetic engineering, candidate gene studies, large-scale genotyping surveys, and genome-wide association studies (GWAS) have yielded promising results that could result in changes in clinical practice. Pharmacogenetic research has started to realize the potential of personalized diabetes treatment for certain monogenic forms. Furthermore, in the field of "miRNA pharmacogenomics," which explores polymorphisms in miRNA-regulated pathways and their association with drug response, is also valuable for personalized medicine. [22].

Table 1

Table (1) Review of AI systems which made by the researchers in field of Diabetes.

Reference	AI System	Technique
Maharjan (2019) [23]	Recommendation system for food	Forward Chaining and Backward Chaining
Czmil (2019) [24]	Records the step numbers. Accelerometers	Random Forest
Al-Taee (2016) [25]	Intelligent system: Management of Diabetes in children.	Capillary network

Reference	AI System	Technique
Neerincx (2019) [26]	Intelligent Assistant for a healthy Lifestyle	Hybrid AI approach
Mall (2017) [27]	Diet Monitoring	Medical sensors for Blood Glucose monitoring
Steinert (2017)[28]	Self-monitoring smartphone App	The system was trained using patients' recorded health data, such as blood sugar levels and weight, over a period of three months.
Zhang (2019)[29]	Automated insulin-releasing agent	Use statistical analysis techniques of diabetes data.

5. AI techniques in the field of Diabetes

The data available for diabetes diagnosis and treatment offers an excellent opportunity to integrate artificial intelligence and machine learning techniques, leading to better outcomes and innovative approaches. Many studies related to diabetes management have employed various machine learning algorithms. Moreover, several smart assistants for diabetes have been developed using artificial intelligence techniques. This section provides an overview of the machine learning algorithms used in these primary studies. Generally, researchers have mainly used ten different ML algorithms for primary research focused on DM detection, diagnosis, and classification.

The following subsections will highlight some of the significant algorithms that researchers have utilized.

5.1 K-nearest neighbour Algorithm

The KNN algorithm operates on the assumption that similar diabetes-related data points are located near each other. Firstly, the classifier is loaded with diabetes training and test data. The number of neighbours is then determined by selecting a value for K through investigation. For each diabetes test data point, the distance from each training data point is calculated and stored in ascending order. The top K entries are then selected, and the test data point is classified based on the majority of categories present in the selected points.

In 2020, Ali utilized various KNN algorithms to detect and categorize diabetes by creating a database according to the guidelines of the American Diabetes Association. The learner classifier method was implemented using 4900 samples for training and 100 for testing. The findings indicate that fine, medium, weighted, and cubic KNN models had better accuracy compared to the coarse and cosine methods. Based on the classification accuracy of the samples, the refined KNN algorithms were deemed the most effective. [30].

5.2 Naïve Bayes Algorithm

Ontology and machine learning techniques were utilized to observe the risk levels of patients with diabetes [31]. The Naïve Bayes algorithm was used to make decisions based on medical records and determine the possible risk level. The proposed algorithm was tested against various parameters, such as confusion matrix, precision points, and mean, and it is believed that the study provided a higher level of accuracy than the current study.

5.3 Support Vector Machine Algorithm

Qomariah et al. (2019) put forth a technique for the extraction of feature and diabetic classification retinopathy (DR) using the algorithm of support vector machines. The authors employed a top-level function of the final fully connected layer, highlighting the transfer learning aspect from a convolutional neural network (CNN), as an input function for SVM-based classification. The effectiveness of the proposed approach was evaluated using 70 and 77 retinal images from Base 13 and Base 12 of the Messidor database. The test results indicated that the maximum accuracy achieved for Base 13 and Base 12 was 95.24% and 95.83%, respectively [32].

5.4 Decision Trees Algorithm|

Al-Zebari and Sengur (2019) proposed a method for the early diagnosis of type 2 diabetes to facilitate appropriate drug therapy. The study utilized of PIDD dataset; this data is available at the UCI Machine Learning Repository website. The evaluation employed decision trees, including thick tree (CT), medium tree (MT), and thin tree (FT), the most pitches are assigned 4, 20, and 100, respectively. For the decision tree method, CT provided an accuracy score of 75.3%, which is the best among all decision tree methods [33].

5.5 Random Forest

Random Forest is a highly efficient machine learning algorithm used for classification. It generates forests by utilizing decision trees, and generally, the more trees in the forest, the better the predictions. Each tree provides a recognition vote to define new models based on features, and the tree labels store the model. In a 2019 study, Prabhu et al. proposed an adaptive decision tree approach for detecting and diagnosing mild retinopathy, a key characteristic of diabetes. The method involves separating the optic disc from the fundus image, followed by the extraction of exudate and various properties associated with it. Signature-based diagnosis is then performed to identify the different stages of the disease. The Random Forest algorithm is utilized to evaluate accuracy, specificity, and sensitivity at each classification point. The results show that for classes 1, 2, and 3, the accuracy achieved using Random Forest is 100%, 85.71%, and 87.5%, respectively. [34].

Table 2

Table (1) Machine Learning classifiers in of Diabetes Review.

Reference	Domain of use	ML Classifier	Performance
Xu and Wang (2019) [35]	A Risk Prediction for Type-II Diabetes	XGBoost	93.75% Accuracy
Wang and Liu (2017) [36]	Identifying diabetes biomarkers through gene Coexpression networks.	Support Vector Machine	under the ROC equal to 96%
Dai (2018) [37]	Blood Glucose detection	PSO-ANN	RMSE=0.69
Aiello (2018) [38]	Meal Classification in Type-I Diabetes	KNN	RMSE=36.15
Hao (2019) [39]	Type-II DM monitoring	Support Vector Machine with polynomial kernel	Accuracy=96.3%
Ling (2016) [40]	Hyperglycemia detection	Linear multiple regression, multiple regression fuzzy inference system, Particle swarm optimization	78% Sensitivity

6. Challenges

The focus of the challenges surrounding therapy personalization lies in technical implementation rather than medical issues. Some of the primary challenges are highlighted below:

Challenge 1: The human insulin system is complex, and AI is still a field of research. Depending solely on this technology for personalized treatment without consulting diabetes doctors and specialists may lead to various issues.

Challenge 2: Treating diabetes is a multifaceted process that can differ greatly from patient to patient. The effectiveness of treatment is influenced by numerous factors, including physical activity levels and overall health status, which can impact the specific approach taken. While insulin is a common treatment option for patients with type 1 diabetes, there are a multitude of treatment options available for those with type 2 diabetes. Given the various factors that affect treatment options, it can be challenging to optimize personalized therapy.

Challenge 3: There are numerous smartphone apps that can assist in calculating insulin doses, but it is important for patients to avoid using unauthorized medical software as it may lead to unsafe insulin dosages. [45].

Challenge 4: Patient engagement is crucial for achieving personalized diabetes therapy. This involves regular documentation of important factors such as blood glucose levels, diet, physical activity, and health status, as well as adherence to treatment objectives. [46]. However, for elderly, inexperienced, or unmotivated patients, this can quickly become overwhelming. Unfortunately, the majority of patients with type 2 diabetes fall into this category. The primary obstacle is to create treatment aids that are minimally intrusive and interactive, in order to assist patients in managing their condition without adding to their burden.

Challenge 5: The prediction of blood glucose values by machine learning algorithms is dependent on the quality of available data. Hypoglycemia is an adverse event, and data on this critical situation may be scarce. Therefore, predictive results for this safety-critical situation may be unsatisfactory.

7. Conclusion

This survey provided a study of AI techniques for personalized treatment of diabetes. A total of 46 studies were selected for this survey. The survey discussed five different methodologies for diabetes personalized treatment, including blood glucose prediction, glycemic variability detection, hyperglycemia detection, insulin controller therapy, and pharmacogenetics. Additionally, the survey covered machine learning classification and diagnostic algorithms for diabetes data and AI-based intelligent systems for patients with diabetes. The challenges associated with applying AI in the field of personalized diabetes treatment were also mentioned.

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