Artificial Intelligence and Machine Learning for Diabetes Decision Support

Josep Vehi, Omer Mujahid, and Ivan Contreras

Abstract Artificially intelligent decision support systems are proving instrumental in the quest of enabling diabetes patients to lead a normal life. These systems provide suggestions to the patients to enhance their judgments regarding their glycemic profile. A variant of such systems, the clinical decision support systems, helps clinicians and healthcare professionals make clinical decisions. For a diabetes patient, it is imperative to keep their blood glucose level inside a lower bound of 70 mg/dL and an upper bound of 140 mg/dL. This range is known as the normoglycemic range. Such systems aim to utilize artificial intelligence and machine learning techniques to estimate relationships between patient-related data and the glycemic outcomes and then propose preventive/protective measures to keep the glycemic profile of the patient in the specified range. Apart from tracking and correcting the glycemic profile of a diabetes patient, the decision support systems are also responsible for detecting/predicting adverse glycemic events like hypoglycemia and suggest proactive measures to be taken by the patient so that adversity is avoided. The recommendations given by such systems to patients with diabetes may consist of information about meal intake in the form of carbohydrates, insulin delivery, medicine/drug consumption and other lifestyle-related advice such as physical activity and sleep routine, etc. On the other hand, the clinical decision support systems aid healthcare professionals in diagnosing diabetes and its comorbidities. Such systems may also assist the doctors by issuing prognosis of the illness as well as help them in drug prescriptions. This chapter discusses the latest trends in artificial intelligence and machine learning-based decision support in diabetes healthcare. Moreover, it also weighs up the challenges designers face in this domain. This chapter could be a thorough guide to the researchers planning to work in diabetes decision support.

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1 Introduction

Patients with type 1 diabetes have to make about 180 diabetes-related decisions per day [1]. For a person that aspires to a normal life, diabetes could prove to be a constant struggle. From decisions regarding physical activities to choices concerning meals, a person with diabetes has to consider it all to avoid adversity. Accurate insulin dose measurements, carbohydrate intake calculations, and physical activity monitoring based on real-time blood glucose values are all parts of the decision-making process that a diabetes patient goes through every day. A large number of decisions and the greater complexity of some of these decisions make the lives of people with diabetes very difficult. For this reason, a tool that could assist this decision-making process is imperative.

Moreover, diabetes patients are at a higher risk of other comorbidities [2]. Diabetic foot, diabetes retinopathy, ketoacidosis, and neuropathy are complications arising from diabetes. A tool that could provide an early diagnosis of such complications may prove life-changing for the patients. In technical terms, one such tool that performs all the tasks mentioned above and assists diabetes patients in improving their decision-making capability is known as a decision support system (DSS). A DSS aids patients of a specific disease in decision making and provides other services such as early detection of complications and predictions of adverse events. A diabetes DSS has to assist patients in managing their medications such as insulin adjustments recommendations, warning about adverse glycemic events such as hypoglycemia and hyperglycemia, carbohydrates counting, behavioral and lifestyle adjustments, and data visualization/interpretation [3]. Moreover, a good diabetes DSS must educate the patients about their disease and provide personalized solutions.

Artificial intelligence (AI) and machine learning (ML) are set to restructure diabetes healthcare in several ways [4]. Data-driven approaches are proving to be more efficient with increased available data and computational power. ML and Neural Networks (NNs) based prediction and classification techniques are now accurate enough to integrate into a DSS [5]. Improvement in AI/ML techniques and advances in glucose sensor technology have made the realization of efficient DSS possible [6, 7]. Glucose sensor technology has made collecting a large amount of blood glucose data possible [8, 9]. A DSS based on data-driven approaches improves the knowledge-based DSS of the past that only worked on rule-based reasoning or case-based reasoning techniques in terms of output accuracy and design flexibility [10]. A diabetes DSS could be classified into a patient DSS and a clinical DSS (CDSS). As the name suggests, a patient DSS assists diabetes patients while a clinical DSS assists healthcare professionals. A patient DSS could be embedded inside a smart device that a diabetic patient can carry at all times. The most suitable device to host a patient DSS is a smartphone. Since most of the patients carry a smartphone device virtually, the DSS can monitor the patient's health efficiently.

On the other hand, a CDSS is usually deployed in the doctor's workplace PC. Figure 1 shows a general overview of the chapter. The left section represents the needs/requirements of a patient DSS, while the right section portrays what a good CDSS be constituted of. The center section represents the ML/AI techniques used to design both sets of DSS. This chapter discusses the cutting-edge technologies and trends in the field of AI/ML-based DSS for diabetes. The chapter unfolds by first discussing the needs/requirements of diabetes patients and what they expect from a

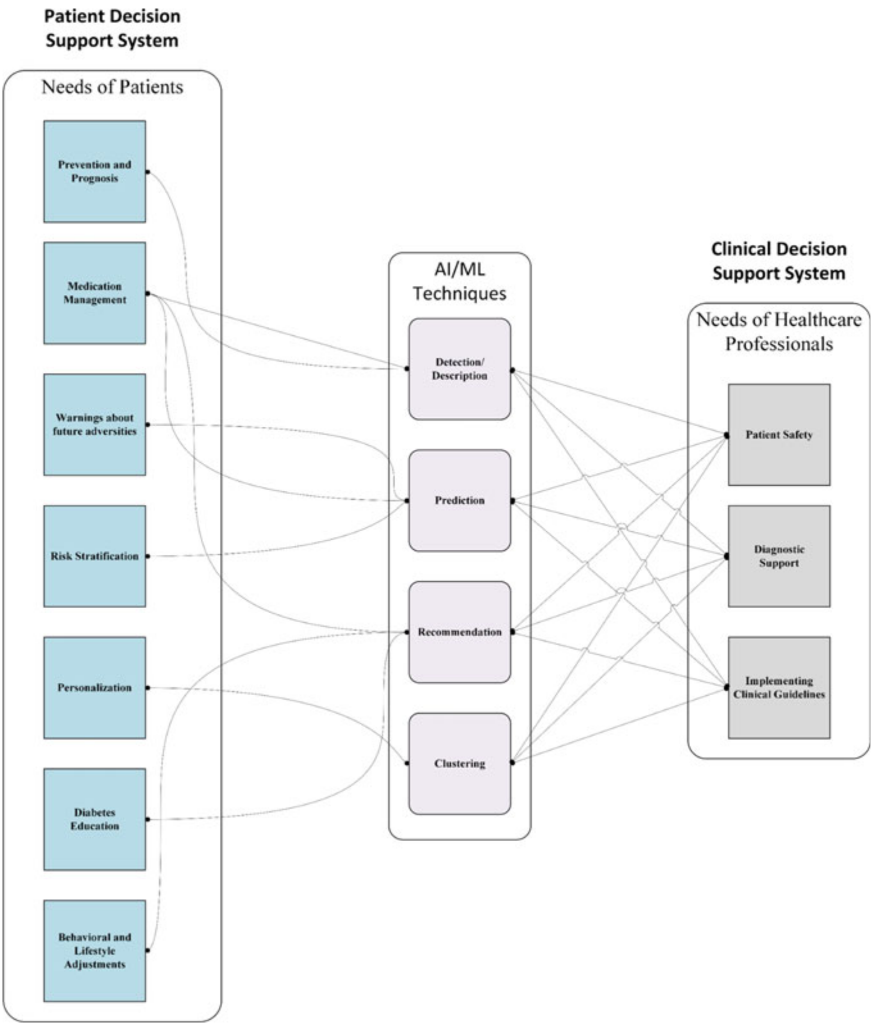

Fig. 1 A high-level graphical representation of AI/ML-based DSS

DSS of this type. Next, a brief description of a diabetes clinical DSS is given and how it can make the lives of diabetes healthcare workers easy. After that, AI and ML-based approaches for a diabetes DSS are discussed. The chapter then provides an account of the challenges faced by the designers of such DSS' before concluding in the follow-up section.

2 Needs of the Patients

A diabetes DSS has to fulfill the patients' needs to be classified as a capable aiding system. Along with the ease of use, a diabetes DSS has to be responsive, interactive, and trustworthy. Other than that, a DSS should fulfill the following needs of a diabetes patient.

2.1 Prevention and Prognosis

A diabetes DSS must be able to perform a prognosis. Prognosis is predicting the course of an illness after it has happened. It is understood that diabetes can result in many other complications in the body. Diabetes patients must keep track of their disease and the overall health of their bodies. A DSS aims to keep the glycemic profile of a diabetes patient in the normal range. This is done by regulating the BG levels with the help of insulin delivery, carbohydrates intake, and physical activity. The more a diabetic patient stays outside of the normoglycemic range, the greater are their chances of developing diabetic comorbidities. A diabetes DSS can help patients keep track of their glycemic profile and provide insight into the severity of diabetes they suffer from, the chances of creating other complications, and the actions required to avoid such complications [11].

2.2 Medication Management

Medication management is one of the most important traits for a DSS. In a disease like diabetes, where the course of medication is not fixed but varies according to the patient's glycemic profile and physiological characteristics, having a DSS that can help the patient manage their medications is essential. Diabetes patients are often dependent on medicines like insulin. The delivery of insulin to the bloodstream is timely and in the correct measured quantity. Moreover, several types of insulin are injected based on time of the day, the quantity of carbohydrates intake and the intensity of physical activity, etc. For a diabetes patient, it is a cumbersome task to calculate the right amount of the right type of insulin throughout the day [12]. However, it is important to mention that not all diabetes patients are insulin-dependent. Most type2 diabetes or prediabetes patients use drugs other than insulin, such as Alpha-glucosidase inhibitors and Biguanides, to manage their BG. A DSS may prove vital in such a scenario where the medication management is done by the automated system and suggested to the patient.

2.3 Warning About Future Adversities

Diabetes patients live in constant fear of adverse glycemic events. Hypoglycemia and hyperglycemia are decrease and increase of BG above critical levels, respectively. Both of these conditions come with their complications and harms. Being the more threatening of the two, Hypoglycemia is also the more feared among diabetes patients [13]. A DSS must predict and inform the patient beforehand about the occurrence of any such event. Such predictions result in peace of mind for diabetes patients and prevent the patients from going into the jaws of calamity. For instance, hypoglycemia can cause loss of cognitive ability, hearing, and in extreme cases, death. Normally when a patient recognizes a hypoglycemic episode, it is too late. A patient needs to anticipate the occurrence of hypoglycemia in advance to avoid its event [14, 15]. A DSS with the mechanism of hypoglycemia prediction may prove crucial for the patients.

2.4 Risk Stratification

Risk stratification means measuring or quantifying the risk of occurrence of an adverse event. Furthermore, it might also mean assessing the prospect of how fatal an adverse event is after it has happened [16]. A DSS with the functionality for risk stratification may prove useful for patients by informing them about the danger of an event with the predicted percentage values. A patient's DSS may be used to predict comorbidities or any sort of organ failure that can occur due to diabetes. An AI/ML-based DSS takes its cues from the data it is trained on, and learning from patterns in the data can output the risk associated with a comorbidity or organ failure. Risk stratification makes the accurate delivery of medication doses possible and contributes to the mental peace of diabetes patients [17]. When patients can observe the quantified risk related to comorbidities caused by diabetes on the user interface of their DSS, they may manage their disease better and escape the stress of uncertainty.

2.5 Personalization

Personalization in medicine means customizing treatments for patients according to their individual needs [18]. Like every individual patient has unique physiological dynamics, there is a need for special treatments to cure any illness. In diabetes, each patient may be treated individually by assessing specific information such as the insulin tolerance, glycemic variability, age of patient and body-mass index, etc. Personalization helps minimize the risk of diabetic comorbidities and increases the efficiency of the treatment [19]. It also saves a lot of money wasted otherwise in treating a patient with the conventional hit and trial method. A personalized DSS may help patients overcome diabetes more effectively and increase patient trust in such systems.

2.6 Diabetes Education

The most important thing for a diabetes patient is to understand their disease and, even more so, to grasp the idea of their personalized variant of the disease [20]. People with diabetes must first understand the basics of diabetes and how it may be managed. Secondly, they must learn how to use diabetes devices like glucometers, CGMs, insulin pumps etc. They must also develop problem-solving strategies while facing adversity. A DSS can educate diabetes patients and help them manage their disease.

The lack of diabetes literacy and numeracy is linked with various studies' below par diabetes outcomes [21, 22]. Lower diabetes literacy and numeracy results in poor glycemic control, less time in range and weaker knowledge of the disease itself. The lack of a diabetes patient's literacy or numeracy is not always evidently obvious. For this particular reason, a DSS that could educate diabetes patients becomes vital.

2.7 Behavioral and Life Style Adjustments

A diabetes DSS can induce behavioral changes and lifestyle adjustments in diabetes patients. Diabetes is one of those diseases where lifestyle adjustments make a huge difference to a patient's health [23]. A weight loss of 5–6% of the total body weight and 150 min of moderate-intensity physical activity per week is recommended for most diabetes patients [24]. A DSS may guide the patients about their eating habits, physical activities, sleep patterns, and other things like alcohol consumption and stress management, etc.

3 Clinical DSS: Demands of Healthcare Professionals

A diabetes CDSS is a type of DSS meant to assist healthcare workers, doctors, and clinicians in the quest to treat diabetes patients. Such a DSS improves the making ability of professionals while treating a diabetes patient by providing important suggestions and showing a broader picture to the clinicians by depicting multiple outcomes to a scenario. Like the diabetes DSS meant for the patients, the CDSS can also be a knowledge-based system or based on data-driven approaches. A CDSS can cover various areas of the healthcare system and assist healthcare workers in multiple forms [25]. Some of the tasks that a diabetes CDSS can perform are presented below.

3.1 Patient Safety

Improved patient safety is one of the prime goals of any CDSS. In diabetes, medication errors are common and can be reduced with the help of a CDSS. According to a study, approximately 65% of inpatients are exposed to one or more types of harmful drug combinations [26]. Along with assistance in medication management, CDSS also helps the healthcare workers in other areas. A CDSS installed in a hospital ICU ward significantly reduced the hypoglycemia cases by alerting the nurses about the occurrence of a hypoglycemia episode [27].

3.2 Diagnostic Support

Diabetes CDSS can provide diagnostic support to clinicians while treating diabetes patients. In diabetes healthcare, such CDSS may assist the healthcare professional in identifying the development and diagnosis of diabetes and the diagnosis of other diabetic comorbidities. Diagnostic errors are real in primary care and are termed a high-priority problem by the world health organization (WHO) [28]. AI/ML-based diagnostic tools may pave the way towards accurate diagnosis and ease the burden of the existing healthcare system.

3.3 Implementing Clinical Guidelines

Studies show that clinical guidelines have adhered to more with the help of CDSS [29]. It has been seen that because of low clinician adherence, new clinical guidelines have been very hard to implement. The experts do not automatically adopt new clinical policies, opposing the general belief. CDSS can also notify clinicians about the patients that haven’t complied with a specific management plan and could also aid the professionals to reach out to such patients.

4 What Can AI and ML Offer?

AI is a vague term and can be defined as a collection of algorithms that enable a certain computer processor to make decisions that imitate the human decision-making process [30]. Though AI is incapable of replicating the intuitive ability of the human mind, the aim of comparison with the human mind is only to specify the goal of achieving optimal solutions just like a normal human mind would strive for. In the following section, we will talk about how ML/AI-based techniques help design a DSS that could fulfill all the needs of diabetes patients and healthcare workers.

4.1 Detection/Description

Detection in ML terms refers to identifying an event in a time series data. It may also be referred to as a description. ML detection could identify unusual glycemic events in BG time-series data [31]. Identifying these events could prove to be helpful in a DSS when the aim is prevention or prognosis of an adverse event. The description of an adverse event using ML could be performed by using labeled time series data. This data could contain a BG time series, an insulin time series, and a time series that specifies meal intakes in the form of carbohydrates. By learning from this past labeled data, the ML algorithm could then identify patterns in the data that correspond to the occurrence of unique events and, on the occurrence of any such marks in the future, notify the patient about their circumstance. Detection could be performed by using several ML/AI techniques. It could be taken as both regression or a classification problem. As a regression problem, the ML algorithm tries to map the input–output relations with the help of a mathematical function. After obtaining the function, it computes unknown outputs for known inputs. So, for instance, if the known result is the past BG value, insulin value, and carbohydrate value, the unknown output will be the current BG value. The calculated BG value could then be used to inform the patient about any abnormality. The ML algorithm tries to draw a line between two or more labeled classes in a classification scenario. A new sample falling in any of these classes is a part of that class group. Adverse events, hence, could be mapped with the data as classes of data.

4.2 Prediction

Prediction means estimating future values in a time series data. For prediction, it is necessary that the estimated value is somewhere in the future and not in the present. This is the prime difference that distinguishes prediction from detection. Though prediction could be performed on any data, it is most commonly associated with time-series data. This is because timestamps related to time-series data act as an extra feature in determining the output and result in more accurate predictions. ML-based prediction can prove vital in a DSS that warns the patient about an adverse glycemic event in the future. In case of hypoglycemia, a warning before the future occurrence of a hypoglycemic event may prove to be lifesaving [32]. Prediction too may both be treated as a regression or classification problem.

4.3 Recommendation

AI-based recommender systems have found their application in many areas of life. In diabetes healthcare, AI-based diabetes recommender systems may recommend medication doses, lifestyle choices, and meal portions to the patients. Recommender systems use various AI-based techniques, including ML and deep learning (DL), to perform recommendations. It is important to understand that the recommender system could be standalone or aid the other systems mentioned above in a DSS. In the case of a standalone recommender system, the DSS will only give away recommendations to the patients. It will not appraise the patient about the possibility of an adverse event in the future or the level of threat they face from a particular adverse event. A scenario where the recommender system collaborates with other systems gives recommendations after a prediction or detection is performed. Such DSS' are not mere recommendation DSS but can also act as a warning or educatory systems.

4.4 Clustering

The division of data points into groups of similar characteristics is called clustering. Clustering, though a famous machine learning technique, can prove vital in personalizing a DSS for a particular patient [33]. Personalization means tailoring a system to fulfill the demands of personalized treatment for individual patients in the best possible way [34]. A customized system might not work with the same efficiency for a person it is not designed for. This logic might become almost impossible to have a customized DSS for each patient separately. We, however, can use clustering to group patients with the same characteristics together and then design a DSS that could fulfill the needs of that particular group of people.

5 Challenges for the Designers

AI-based methodologies come with their own set of limitations. Most AI-based techniques are data-driven and can enhance performance only when a sufficient amount of good quality data is available. Good quality data in a data-driven setup essentially means data that is consistent, free of noise, and available in large quantities. The problem arises when there is a lack of such data. This directly affects the performance of a data-driven algorithm, whether an ML model or a neural network. There is always a scarcity of good-quality clinical data in healthcare applications—the reason for this is the natural and technical constraints involved in clinical data collection.

ML designers also face many non-technical obstacles while deploying models for clinical DSS. Coming up with safety protocols that can ensure patients' safety is complicated. Legal issues involving data privacy and moral dilemmas are always challenging for AI/ML designers. In a scenario where good quality data is already scarce for AI/ML designers to work with, privacy-related laws make it even harder for them to experiment freely. Another issue that poses a challenge for the designers is gaining user's trust. Since there is a lack of transparency about AI/ML models; the users often find it hard to trust the results of an AI/ML-based DSS. It is known that AI-based models are virtual black boxes with certain inputs and outputs. What happens inside these black boxes is often hidden from a user's eyes. In a DSS that uses neural networks, the trust issue is even greater since it is almost impossible to comprehend the computational structure of a neural network. This leads to a lack of trust among the patients and causes significant problems for the designers. Furthermore, the inability of users to understand extremely specific terminologies of AI/ML also creates problems for the designers. The designers then look for languages that are more common to a layman to be used in the DSS.

6 Conclusion

Decision support in diabetes holds great importance because of the huge number of decisions a diabetes patient has to make every day. AI/ML-based diabetes DSS can transform the entire structure of the diabetes healthcare system. Such DSS' are user-friendly, flexible, and can be customized according to patients' needs. Healthcare professionals can also benefit from these technologies by using CDSS. CDSS are variants of DSS designed to assist clinicians and healthcare workers. Different AI techniques such as description, prediction, clustering, and recommendation integrate various methodologies inside such DSS. These DSS could be deployed using smartphone devices and integrated with CGM sensors for continuous decision support. In the case of CDSS, patient's electronic health records and secure messages could be used to analyze patterns in the patient's data and assist healthcare workers by providing them decision support. Though there are challenges for the designers in the shape of unavailability of high-quality data, privacy laws and user trust issues, the future of AI/ML-based DSS is bright. Designers should strive for faster and more accurate models, better and friendlier user interfaces, and more flexible DSS to gain patients' trust and help ease the burden of the current healthcare system.

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