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A Brief Survey on Machine Learning Techniques for Blood Glucose Prediction

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Abstract

Prognosis of blood glucose level is one of the significant roles in the effective treatment of diabetes which is a chronic metabolic disease that affects a good number of people in the world. Machine learning methods were of great interest in the recent as it is able to detect and predict the glucose level effectively based on the large range of features such as historical records, physiological indicators, and lifestyle data. It is a survey study that provides a detailed insight into the current investigation on blood glucose level forecast using machine learning methods. And the necessity of the accuracy of the prediction of blood glucose level in the diabetes care and the restrictions of the current methods. Roughly half of the machine learning methods applied to this field, similar support vector machines, random forests, regression models, decision trees and neural networks. Deep learning models are remembered with specific emphasis due to promising applications in the ability to learn time dependence and the ability to follow complex patterns in blood glucose records. Recurrent neural networks (RNNs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks are particular examples of deep learning models. The questionnaire proceeds with the recapping of the current issues as well as unresolved research inquiries in the field of machine learning-based blood glucose level detection and prediction.

Keywords: Machine Learning; Recurrent Neural Network; Convolutional Neural Network; Long Short-Term Memory; Glucose Detection; Glucose Prediction.

How to Cite This Article

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Introduction

Diabetes is a recurring chronic metabolic disorder that occurs in millions of individuals across the globe [1]. The proper management of diabetes requires taking regular control and monitoring of the blood glucose to prevent severe issues and minimize the likelihood of the long-term complications like heart disease, nerve disorders, and eye disorders [2]. Because of the dynamism characteristic of glucose metabolism, the effect of various factors including physical movement, medication, diet or carbohydrate and stress make it harder to predict the level of glucose in the blood.

The traditional monitoring tools of blood glucose measurements like intermittent fingerstick blood glucose measurements and self-reported blood glucose test results are deficient in identifying and tracking glucose values effectively. During the past years, the prediction models to predict blood glucose level are built by the means of the machine learning approaches. These models process vastly large volumes of information and identify meaningful patterns and come up with precise forecasts. This assists in the enhancement of accuracy and individualization of managing diabetes. Following are some of the benefits of machine learning structures in predicting the level of blood sugar level.

The first one is that the strategy will collect comprehensive glucose readings and contextual data of many sources: continuous glucose monitors, electronic health record, wearables, mobile applications. This is big data that will help in coming up with strong models that can address the intricate dynamics that govern the regulation of the level of blood glucose. And Second is, to enhance predictive accuracy by incorporating numerous features - such as past glucose measurements, physiological indicators, nutrition history and exercise history. Besides, the models are adaptive in nature that enables them to optimize themselves based on self-patient data and therefore will also be able to give individual predictions that will correspond to the specific glycemic response profile of a given subject.

The purpose of this assessment is to provide a short overview of recent scientific advances in regards to the applicability of machine learning approaches in predicting the level of blood glucose.. And Second is, to improve predictive precision by combining many features - including historical glucose readings, physiological signals, dietary records and activity records. Moreover, the models have adaptive properties that allow self-optimization according to the patient's own data, and which will thus also provide individual predictions that match each subject's particular glycemic response path. This assessment aims to give a brief analysis of latest scientific developments related to applicability of machine learning methods in prediction of blood glucose level. It integrated past literature, pinpoints significant methodologies applied. In this topic the literature survey inquiries about issues and prospects in creating precise and reliable prediction modes. Some of the architectures like Machine learning as well as Deep learning are discussed throughout this survey.

In addition, survey explores key areas of data processing, features extraction, and model performance with respect to blood glucose level prediction. It continues on methods for handling missing data, normalization, and choice of important features to enhance perdition performance. It also elaborates on performance metrics and validation methods for estimating the correctness of model using machine learning approach in the prognosis of blood sugar levels.

Background

it a major public health concern, as the disease not only increases the risk of serious complications but also significantly impacts the daily life and well-being of those who live with it. Diabetes is generally classified into two primary forms: Type 1 Diabetes Mellitus (T2DM) and Type 1 Diabetes Mellitus (T2DM)

Diabetes Mellitus Type 1 (T1DM)

T1DM is a form of diabetes where the immune system outbreak and abolishes the insulin-producing beta cell. It often appears in children and young adults on the other hand it can happen to any age group. Type 1 DM is accountable for 5 to 10% of total cases of diabetes [1]. The major focus of research in T1DM has been to clarify the etiological factors, enhance the means to detect the disease early in its progression, the modalities of insulin delivery and the means to prevent or mitigate the autoimmune mediation of destruction of beta cells. There are also more efforts to implement machine-learning methods into the management of T1DM, such as predicting glycemic profiles, identifying instances of hypoglycemia and hyperglycemia and reducing insulin dose. Type 1 diabetes mellitus is an autoimmune disorder, which attacks the insulin-producing beta cells. People who are afflicted with this disorder require external supply of insulin on a daily basis and they should take special care to maintain normal glycemic levels to avoid abrupt health complication. The potential uses of the shoes in diabetes are also substantial, as the current research and emerging technologies, such as machine learning, are capable of providing numerous improvements to T1DM care and clinical outcomes.

Diabetes Mellitus Type 2 (T2DM)

T2DM is one of the forms of metabolic disorders, which develops a disease where the body becomes resistant to insulin and fails to produce sufficient amounts. It is the most common subtype of diabetes which takes 90-95 of the total [1]. Although this is traditionally associated with older age groups, T2DM is becoming more common among children and adolescents especially those who are obese. The studies on T2DM are intended to comprehend the cause of the condition, enhance the early detection and diagnosis of the disease, establish therapeutics that could be effective and learn the way of the prevention of the condition. Machine learning is starting to be applied in the treatment of T2DM and can incorporate risk stratification, tool in the early diagnosis of T2DM, pharmacotherapy advice, and prediction of the glycaemic level with high precision.

T2DM is a chronic illness which involves the lifelong therapeutic intervention in order to reduce or delay the complications related to the disease like cardiovascular disease, renal failure, peripheral neuropathy and retinopathy. Education and early identification are all lifestyle modification education interventions that have been central in the control of the increasing burden of T2DM globally. It is a widespread illness with the symptoms of insulin resistance and a lack of insulin production to meet metabolic needs. It is caused by both environmental and genetic factors, and can be managed by lifestyle interventions and medication with regular monitoring. Ongoing research adopts techniques of machine learning, which is expected to improve the methods of prevention, detecting, and therapeutic strategies towards T2DM.

Significance of Accurate Blood Glucose Level Prediction

The accurate prediction of blood glucose is very important for diabetics management system the main reason of this is minimize medication dosage, treatment planning of individual patient, and prevent patient from hypoglycemia and hyperglycemia incidents as well as lifestyle modification. Specific prediction of blood glucose can help clinicians and patients in choosing the most beneficial pharmacologic treatment and insulin dosing interventions.

Early detection and prediction allows quick changes in prescription to keep glycemic values within the standard range to avoid hypoglycemic and hyperglycemic episodes.

By considering the personalized glycemic responses curves in the models used to predict them, the individual therapeutic planning becomes possible. A combination of individualized interventions with proper prognostics leads to better glucose homeostasis and reduces chances of long-term sequelae thus increasing treatment efficacy.

The accurate prediction can be used to identify in advance an impending event of hypo- or hyperglycemia and preemptive countermeasures can be implemented. This potential comes in especially handy with patients with an excessive glycemic variability.

Moreover, precise prediction is a decisive source of information on lifetime lifestyle determinants, including diet, physical exercise, psychosocial stress, and sleep quality, which shape the individual dynamics of glucose. With this information the patients would be in a position to make knowledge-based decisions regarding the practices of everyday living that would encourage self-management behaviours that assist in maintenance of glycemic level.

Traditional Approaches' Limitations

The drawbacks associated with the classical methods are that they are poor predictors that do not have as much resolution, and there is no consideration of the individual variability. Traditional technologies like self-monitoring of the blood glucose level and counting carbohydrates count on the basis of manual checks and approximations which provide a low quality of predictions of changes in future glucose and neglect the complicated interaction of the influencing factors. Such methods usually produce few data points, which are basically intermittent blood-sugar measurements, hence giving a partial solution to glucose dynamics. This deficiency may foster an unnatural interpretation of the glycemic patterns by an individual leading to reduced predictive ability. Conventional methods do not take into account the difference in the physiological and behavioral aspects of the individuals; differences in the diet physical activity, stress, and pharmacotherapy are usually ignored thus resulting in poor glucose regulation. Besides, such systems do not have the potential of providing ongoing glucose monitoring, which is essential in developing unanticipated changes or new trends. Lastly, existing treatment regimens do not apply modern decision support systems that may be helpful clinicians and patients to optimally dosing medication, insulin, and lifestyle changes.

Learning in glucose level prognosis

- Predictive Modelling: Machine learning methods analyze wide quantity of data, like past blood glucose levels, lifestyle characteristics, food information, physical activity, prescription usage, and contextual information. Machine learning methods can construct prediction models for blood glucose level prognosis by recognizing complicated patterns and relationships within this data. These models can predict future blood sugar level correctly, allowing individuals and healthcare providers to make learnt decision regarding insulin dose, prescription amendments, and lifestyle changes.
- Personalized Predictions: Machine learning helps in creating individual patient-specific predictive models that are adaptive and learn from patient-specific data. Such models generate individual forecasts for optimal glycaemic control and include demographic and clinical variables such as age, sex, body mass index, weight and previous medical history. The heterogeneity of patient needs is addressed by personalization to improve the efficiency of diabetes management.

- Real Time Monitoring and Alerts: In the area of real-time monitoring of glycaemia, the machine learning algorithms are combined with the continuous glucose monitoring (CGM) devices. By continuously observing and analyzing of incoming glucose value, these algorithms alerts indicating hypo or hyper-glycemic incidences thereby providing a vital decision support for patients and clinicians.
- Detection of Anomalies and Trends Early In: Machine - learning mechanisms identify unusual glucose curves that may be the precursors of hypo - or hyper-glycemic episodes. Early detection of such anomalies helps patient to take requirement action. Addition, the algorithms explain the contributory factors, and therefore it can be centuries to modify the behavior or the medication to maintain optimal glycemic levels.
- Integration of Multiple Data Sources: Machine-Learning approaches allows combining heterogeneous data, which includes CGM readings, electronic health record entries, data from wearable devices and self-confirmed knowledge of present way of life. Having these information combined brings a total approach of a patient's glucose dynamics and allows more accurate predictive performance.
- Decision Support Systems: With the help of study of patient data and historical patterns, barriers and decision support systems generate data-driven decisions about the insulin *needs of patients, the modification of medication regimens, lifestyle interventions, etc., leading to data-driven clinical decision making.*

Some Recent Research

Birjais et al. [3] used a dataset called the PIMA Indian Diabetes (PID) dataset in their research. This dataset includes 768 instances (individuals) and 8 features like age, body mass index, blood pressure, and glucose readings. It is available in the UCI Repository. The World Health Organisation (WHO) states that diabetes is among the prevalent long-term health issues globally, hence the researchers concentrated on diabetes diagnosis. Their goal was to create predictive algorithms that could assess whether a person was diabetic or not based on the information provided. Birjais et al. used three different methods to classify data: logistic regression, naive Bayes and gradient boosting. These methods trained on PID dataset to identify if someone has diabetes or not. Sadhu, A., and Jadli, A. [4] used a diabetic dataset from the UCI repository to conduct an experiment. There were 520 incidences and 16 traits in the dataset. Their aim was to detect diabetes at the initial phases. They tested classification on seven dissimilar approaches on the validation set, which included SVM, multilayer perceptron, k-NN, naive Bayes, decision trees, logistic regression and random forests. Based on their tests random forest gave good results with an accuracy of 98%.

Xue et al. [5] focused on early diagnosis of diabetes in their investigation, employing a dataset of 520 patients with 17 features from the UCI collection. It consists of supervised machine learning algorithms on data from diabetes patients of 16 to 90 years old, like naive Bayes, SVM classifiers, and Light GBM. SVM had the high accuracy at 96.54%, with respect to naive Bayes which having a rate of 93.27% and Light GBM having rate of 88.46%. SVM's performance gives good classification algorithm for diabetes prediction.

In a different study, Le et al. [6] used a dataset of 520 patients and 16 factors from the UCI collection to predict early-stage diabetes risk. They suggested a new technique where adaptive particle swarm optimization (ASPO) and grey wolf optimizer (GWO) are combined in order to improve the multilayer perceptron model and shrink number of input parameters required. It gives the comparison of their outcomes with existing methods. With fewer input features, the new methods, GWO-MLP and APSO-MLP, achieved high accuracy of 96% and 97%, correspondingly.

Julius et al.[7] introduced the Weka platform to analyse data from UCI repository. The dataset had 520 samples, each with various attributes. Their goal was to implement ML models to detect initial signs of patients suffering with diabetes. They used approaches like functional trees, random forest, k-NN and SVM. The result shows k-NN had highest accuracy at 98%.These finding shows that these classifiers are useful for predicting early-stage diabetes.

Shafi et al. [8] developed a model using machine learning approaches to create a model for diabetes early detection. The naive Bayes classifier shows highest accuracy at 74%, compared with the decision tree with 72% accuracy, SVM at 63% accuracy. This work shows the potential of these approaches for reliable prediction and opens up new areas for research in diabetes diagnosis and classification with missing data. Mujumdar and Vaidehi [9] proposed a diabetes prediction model that included extrinsic factors in addition to standard variables such as glucose, BMI, age, and insulin. It introduces a dataset which improve the precision of classifying diabetes along logistic regression achieving the utmost accuracy at 96%.and AdaBoost method gives accuracy at 98.8%. The suggested model's improved accuracy and precision were proven by a comparison of two distinct datasets.

Pelagie et.al [10] suggesting a Deep Neural Network (DNN) in predicting diabetes using the Pima Indians Diabetes Dataset and showing the results of 10-fold cross-validation to resume the overall 89 percent of accuracy, which reflects the ability of DNN models to find nonlinear relationships with limited clinical data. In a similar study, Huma Naz et.al.[11] provided a comparative analysis between the several classifiers, such as Artificial Neural Networks (ANN), Naive Bayes (NB), Decision Trees (DT), and a deep learning model, and found that the deep learning method had the highest predictive accuracy of 98.07% on the same dataset when compared to all traditional machine-learning models tested,A number of authors have used CNN-LSTM models to Pima Indians Diabetes dataset with great success. Kumar and Singh et.al[12] found that the CNN-LSTM model gave a 83.2% and 82.3% accurate result accuracy compared to standard classifiers (logistic regression and SVM). On the same note, Zhang et al. [13] suggested the conversion of tabular Pima data into image-like representations and the use of CNN-LSTM with conditional GANs, achieving an accuracy of 85.7, which showed that deep learning might be promising in the interaction of complex features. Ali and Hussain [14],compared deep neural networks such as CNNLSTM with random forest and decision tree and found that CNNLSTM has an overall accuracy of approximately 80 percent, which is also accompanied by the threat of overfitting the data since the dataset is relatively small. Taken together, these investigations indicate that CNN -LSTM models have the potential to increase the accuracy of diabetes prediction even on the Pima data but they also point to the necessity of larger and more diverse data to guarantee clinical relevance.

The LSTM model, an upgraded form of RNN, effectively dealt with vanishing and exploding gradients as well as long-term dependencies. Overall, these research demonstrate the utility of deep learning approaches such as CNN, LSTM, GRU in diabetes prediction. Mentioned models indicate prospective advances in diabetes research by leveraging their strengths in feature extraction, feature selection, and self-learning. Keeping eye on blood glucose levels is essential to avoid problems. Two common ways to check blood glucose are Self-Monitoring of Blood Glucose and Continuous Glucose Monitoring. While the later method offers real-time data, access to large BG datasets is limited due to privacy concerns. Studies on BG prediction, especially for T1DM, have been conducted, but T2DM data is less studied. Many research papers rely on small datasets, and publicly accessible data is rare, making further progress challenging. Table 1 shows the available CGM data sets for prediction of blood glucose level.

William P. T. M. van Doorn et al[16] proposed machine learning Models trained with CGM data using Maastricht Study dataset for Type 2 Patients predict glucose values at 15 minutes with RMSE of 0.19mmol/L and 60 minutes with RMSE of 0.59mmol/L and also compare different machine learning algorithm like ARIMA, SVR, LightGBM, Shallow MLP, Deep MLP, RNN, LSTM and find that the RMSE for RNN and LSTM is less than other prediction model hence it prove that RNN and LSTM model performs better for Type 2 glucose level prediction also.

Marling et al[17] developed OhioT1DM GCM dataset. It is a groundbreaking resource that aims to accelerate research in blood glucose level prognosis for type1 diabetes patients. By providing real patient data, including continuous glucose monitoring(CGM), insulin taken, physiological sensor for measuring physical activity, and self-reported life-event information, current dataset empowers researchers to build more accurate, effective machine and deep learning models to progress diabetes management. Initially launched in 2018 with data from six individuals, the dataset was later expanded in 2020 to include six additional participants, with each person contributing eight weeks of detailed records.

Taiyu Zhu et al[19] proposed A CNN model to forecast glucose levels of the T1DM Patients. OhioT1DM dataset is used to train the CNN algorithm which take the 4 input parameter like glucose levels, insulin intake, food intake and time span and predict glucose level for 30 min and give RMSE value 21.72±2.5.

Table 1. *Available CGM Data Sets*

Available Datasets	Type	No. of Days	No. of Patients	CGM	Food Intake	Workout	Insulin	Publication Year
Chinese Diabetics Dataset [15]	T1DM	3 to 14	12	YES	YES	NO	NO	2023
Chinese Diabetics Dataset [15]	T2DM	3 to 14	100	YES	YES	NO	NO	2023
Maastricht Study [16]	T2DM	2	851	YES	NO	YES	NO	2021
OhioT1DM [17]	T1DM	56	12	YES	YES	YES	YES	2020
OhioT1DM	T1DM	56	6	YES	YES	YES	YES	2018
D1NAMO [18]	T1DM	04	09	YES	YES	YES	YES	2018

Jonas F et al.[20] Proposed CRNN model for forecasting blood sugar levels of diabetes people of T1DM. The evaluation was performed using RMSE and MAE parameter, it gives sugar levels prediction in 30-minute horizon gives RMSE of 17.45 and for 60 min horizon gives RMSE of 33.67 mg/dl

Meng Zhang et al.[21] compared different prediction model like Multiple Linear Regression, Deep Convolutional Neural Network, Sequence-to-Sequence LSTM tested for half and one hour time limits by use of OhioT1DM dataset. The Sequence-to-Sequence LSTM approach exhibited the best performance in prognosis of glucose levels for half an hour, whereas MLR model performed greatest for forecasting glucose levels for one hour time span.

Conclusion

Finally, the survey on Blood Glucose Level Prediction Techniques indicates considerable advancements in predicting and forecasting BG levels. The traditional machine-learning models, such as logistic regression, support machine, random forests and decision trees have proved to have consistent behavior in case of structured clinical data, especially in the circumstances of thorough preprocessing of data, informed feature selection and controlled cross-validation processes. Based on these principles, more recent deep-learning models, including deep neural networks, CNN-LSTM hybrids, and existing deep-learning model architectures, achieve higher predictive accuracy by revealing complex and subtle patterns in patient data that more traditional algorithms, are not able to perceive. The ability of deep-learning systems to make personalized predictions to both type 1 and type 2 diabetes, and short-term glucose variability is further demonstrated by studies that combine specialized datasets and output of continuous glucose monitoring systems with various physiological cues. The continuous construction of the high quality, comprehensive datasets has simultaneously enhanced the model robustness and the possibility of generalization in the heterogeneous patient populations. Future studies ought to consider these models as well as other complicated deep learning arrangements, as well as exploit new sources of data, such as continuous glucose monitors and smart gadgets capable of monitoring health indicators.

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