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Classification and prediction of hypoglycemia in diabetic patients using machine learning techniques

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***Abstract*---**Type 1 diabetics can lower their risk of microvascular and macrovascular problems by carefully regulating their blood glucose levels. The downside is that these measures are incredibly challenging because of the wide diversity across individuals, as well as other factors that affect glycemic management. Keeping glucose levels under control is difficult due to the possibility of severe hypoglycemia in patients receiving intensive insulin therapy. In people with diabetes, hypoglycemia is a common complication, which has a negative impact on overall health and well-being. Improving patient safety by anticipating unfavourable glycemic events has become a practical approach to enhanced patient safety using machine learning decision assistance. This paper suggests the use of three machine learning techniques to solve the problem of diabetic safety: (1) Random Forest for continuous glucose predictions, (2) support vector machines for postprandial period predictions, and (3)artificial neural networks for overnight hypoglycemic predictions. It has the two different categorization and prediction capabilities already established. A major system feature is the overall reduction in bouts of hypoglycemia, which results in an increase in patient safety and provides better confidence in treatment decisions.

***Keywords*---**hypoglycaemia, microvascular, macrovascular consequences, artificial neural networks.

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Introduction

People with diabetes have to have ongoing medical care and work with a diabetic self-management programme to keep their condition under control and prevent serious complications from arising. Diabetes has reached pandemic proportions due to its occurrence in all communities. Approximately 220 million individuals are diabetic, and 70% of them live in low- and middle-income nations. Over the next two decades, the number of individuals living with diabetes worldwide is expected to rise to 365 million, nearly tripling from 2000's figure. According to epidemiological research, global prevalence will continue to rise unless effective preventive methods are implemented.

Many published data for national estimates of type 2 diabetes prevalence are unused in the Middle East. an Iranian study revealed a frequency of 7.7% among those who are between the ages of 15 and 65. The disease places a significant strain on health care systems due to the problems that result from diabetes. An analysis in our country revealed that the burden of diabetes and its sequelae (disability-adjusted life years, or DALYs) amounts to around three hundred sixty-four thousand years. All of these details underline the need of ensuring that this disease and its consequences be prevented in Iran.

Despite the current development in therapies and technology, many people with diabetes continue to suffer from low blood sugar levels which further slow down treatment intensification and the accomplishment of specific glycemic goals. Determining an individualised treatment plan for diabetes for people at risk for severe hypoglycemia is crucial in helping to prevent excessive therapy. Hypoglycemia, or low blood sugar, was reported 235,000 times at U.S. emergency rooms in 2016, according to the CDC. A history of hypoglycemia (low blood sugar) is associated with a higher than normal risk of cardiovascular disease and death from any cause. When formulating a patient-centered treatment plan, these organisations' current recommendations emphasise the need of minimising hypoglycaemia risk.

Hypoglycemia in diabetes

With diabetes, hypoglycemia is common, as insulin excess and insufficient physiological protections against a drop in blood glucose levels interact. Pharmacokinetic concerns such as the use of various insulin preparations and secretagogues in diabetes treatment, as well as dietary habits, physical activity, pharmaceutical interactions, and altered insulin sensitivity can all result in an excess of insulin being produced. Pathophysiology undermines the body's natural defences against declining plasma glucose concentrations in both type 1 and advanced type 2 diabetes. Endogenous insulin deficiency causes plasma glucose levels to fall because all three of the body's defences against lowering glucose levels are compromised. When insulin levels remain the same, glucagon levels remain unchanged, and when epinephrine levels increase, the change is generally less significant. It is caused by the absence of insulin and glucagon reactions, resulting in an attenuated epinephrine response. It is also known as autonomic neuropathy when the patient loses the warning signals that once allowed them to detect developing hypoglycemia and take corrective action. Because of recent iatrogenic hypoglycemia, it is now known that an absent sympathoadrenal response to increasing hypoglycemia develops progressively over time and over time. Diabetic Type 1 and Advanced Type 2 Patients With Hypoglycemia-Associated Autonomic Failure This leads to repeated hypoglycemia because of the patient's unawareness of their hypoglycemia and the insufficient counter-regulatory response to hypoglycemia. Hypoglycemia and exercise- and sleep-related autonomic dysfunction are part of that idea these days. Because the majority of patients who are unaware of their hypoglycemia can help themselves, it's reversible, and epinephrine-deficient glucose counter regulation can be significantly improved by only 2 to 3 weeks of strict avoidance of iatrogenic hypoglycemia. It's also worth noting that the sympathoadrenal system's responses to future hypoglycemia are substantially less when plasma glucose levels are above 70 mg/dl (3.9 mmol/l).

Hypoglycemia signs and symptoms

In cases of mild hypoglycemia, the symptoms and indications can be absent or they might only be minor. However, in cases of more severe hypoglycemia, symptoms and signs might become much more noticeable. The majority of symptoms are grouped into two broad categories: neuroglycopenic or autonomic. The list of common autonomic symptoms includes symptoms that are linked to adrenaline (epinephrine-mediated) and symptoms that are linked to acetylcholine (acetylcholine-mediated). A common feature of both cholinergic and adrenergic symptoms is trembling, whereas palpitations, rapid heartbeat, and an increased heart rate are other examples of adrenergic symptoms. Beta-adrenergic blockers may diminish the symptoms of hypoglycemia, and patients on these medications should be informed about which symptoms they should watch for (i.e., neuroglycopenic and cholinergic symptoms). Importantly, the level of diabetes therapy has a considerable impact on the patient's blood glucose threshold for developing hypoglycemic symptoms. Patients with high blood glucose levels have a higher threshold for hypoglycemia, but those with recurrent episodes of hypoglycemia have a lower threshold. The symptoms of neuroglycopenic toxicity may include dizziness, weakness, drowsiness, hallucinations, confusion, seizures, and even coma in extreme cases.

Symptoms of hypoglycemia are very serious and can result in kidney and brain damage if left untreated. As a result of the duration and intensity of hypoglycemia, there is a wide range of symptoms, ranging from abnormalities in autonomic functioning to decreased cognitive ability to seizures to coma. Neurologic damage, trauma, cardiovascular events, and mortality are the problems associated with short and long term effects. Untreated severe hypoglycemia causes a major economic and personal hardship, which in turn reduces the burden of diabetes by reducing the number of complications that occur due to hypoglycemia. As a serious medical emergency, hypoglycemia must be detected and treated quickly to help prevent brain and organ damage. Diagnosing hypoglycemia in patients ranges from mild symptoms like light headedness and fatigue to more severe symptoms like tachycardia and altered mental status to seizures or coma. Neurologic impairment, trauma, cardiovascular incidents, and mortality are among long-term effects. Severe untreated hypoglycemia causes a major cost both economically and personally, hence it is critical to identify and prevent hypoglycemia in order to lessen the burden of diabetes.

Treatment associated hypoglycemia

Among those who have been found to be at greater risk of treatment-associated hypoglycemia are individuals using insulin and/or insulin secret gouges, people with impaired renal or hepatic function, older patients, people with diabetes for a longer period of time, people with cognitive impairment, people who are unaware of hypoglycemia, those who are using alcohol, people who take multiple medications, and people who have a physical or cognitive disability. Individualized treatment goals should take into consideration the following factors, which are recommended by the ADA. Individualized treatment strategies for diabetic patients who meet at least one of these criteria should take into consideration the risk of intensified therapy over the potential benefits.

Prevention strategies

Preventing patients from being hypoglycaemic is essential to managing diabetes. Hypoglycemia is a big issue that needs to be considered throughout any attempt to prevent it. Read on to learn about things you can do to lower your risk of hypoglycemia, including using medication, sticking to a balanced diet, and increasing your physical activity.

Medication-Related Considerations

Patients who are insulin- or insulin secretagogue-managed have the highest chance of suffering hypoglycemia. When background insulin and/or insulin secretagogues are used with glucose-lowering medication, the risk of hypoglycaemia is increases. Patients with severe or recurrent hypoglycemia require a critical assessment of the appropriateness of long-term usage of high-risk drugs.

Dietary Considerations

Fasting or postponing meals increases the risk of hypoglycemia, thus insulin- and insulin secretagogue-treated patients should be aware of this. Alcohol use can raise the risk of hypoglycemia in patients who are taking insulin or insulin secretagogues, so they should be warned about this. The following are important issues related to drinking and hypoglycemia:

- Moderate alcohol consumption is recommended for women who drink one drink per day and for males who drink two drinks per day.
- Alcohol consumption with food in the evening will help to lower the risk of nocturnal hypoglycemia.
- Identify and manage hypoglycemia as early as possible after drinking alcohol by increasing the frequency of glucose monitoring.
- Alcohol-induced hypoglycemia may take a long time to manifest, especially when there has been substantial consumption of alcohol before to the hypoglycaemic event.

- Alcohol might help decrease the signs and symptoms of hypoglycemia.

Physical Activity

Patients with diabetes should be encouraged to engage in physical activity because of the multiple health benefits it provides.However, physical activity can increase the risk of hypoglycemia in individuals who are at risk for this condition, and thus they should be carefully monitored and personalised strategies to combat hypoglycemia should be developed. A person's glucose levels respond differently to different types of physical activity, as well as to food and medication administration, as well as to different amounts of time spent exercising. People with diabetes who have pre-exercise blood glucose levels of less than 90 mg/dL should eat more carbohydrates before engaging in physical activity, and those who use insulin should reduce the mealtime insulin dose and/or the basal insulin dose while exercising.

Glucose Monitoring

For the detection and avoidance of hypoglycemia, finger-stick glucose measurements and a glucose metre or a continuous glucose monitor (CGM) are needed. People with rigorous insulin regimens and those who are unaware of low blood sugar levels can benefit from CGMs. A possible concern to patients at risk for hypoglycemia is that they may make serious errors due to misjudging their blood glucose levels, and this could lead to accidental injury or death.

Classification of hypoglycemia

The following are the different types of hypoglycemia

Severe hypoglycemia

A situation in which glucose, glucagons, or other resuscitative measures must be actively administered by another person. In cases where seizures or coma are triggered by this neuroglycopenia, these occurrences may be related. For such an occurrence, neurological recovery that is regarded proof of restoration of plasma glucose to normal levels is adequate evidence.

Documented symptomatic hypoglycemia

At blood glucose level of less than 70 mg/dl (3.9 mmol/l), you could experience palpitations, tingling, anxiety, worry, and disorientation.

Asymptomatic hypoglycemia

A glucose level of 70 mg/dl (3.9mmol/l) is considered normal if no typical hypoglycaemic symptoms are present. Because antecedent plasma glucose concentrations of 70 mg/dl (3.9mmol/l) in adults without diabetes significantly reduce sympathoadrenal responses to future hypoglycemia, these findings set the top limit for people with diabetes who are not pregnant or breastfeeding.

Probable symptomatic hypoglycemia

An instance in which hypoglycemia occurs without the measurement of a plasma glucose concentration (but in which a plasma glucose concentration of <70 mg/dl [3.9 mmol/l] is probably the cause). Hypoglycemia must be distinguished from circumstances when a patient has chosen to treat their symptoms with oral carbohydrate without having their blood glucose level examined when diagnosing "probable" hypoglycemia. A contemporaneous plasma glucose measurement should not be used to verify self-reported episodes of hypoglycemia in clinical studies testing medicines. These episodes should be recorded in clinical studies as important study outcomes, but not as the primary outcome measures.

Relative hypoglycemia

One or more symptoms of hypoglycemia occur in a diabetic, although their blood glucose levels are higher than 70 mg/dl (3.9 mmol/l), indicating a hypoglycemic episode. Hypoglycemia symptoms can emerge in patients who have poor glucose control when blood glucose levels fall to 70 mg/dl (3.9mmol/L). Yet despite the fact that these episodes are distressing for the patient and may impair their sense of well-being and their ability to achieve optimal glycemic control, they are unlikely to have a negative impact and should be reported in clinical trials assessing new treatments because of this.

According to the ADA, hypoglycemia is divided into three levels:

- To be diagnosed with the first level of hypoglycemia, your blood glucose level must be between 54 mg/dL and 70 mg/dL.
- If your blood glucose level is less than 54 mg/dL, you are on level 2.
- Severe hypoglycemia incidents marked by alterations in mental and/or physical functioning, in which the individual need support for resolution is referred to as level 3.

This classification does a good job of describing the range of severity for hypoglycemia events; however any blood glucose level under 70 mg/dL is defined as being clinically significant. Based on this, any blood glucose number under 70 mg/dL can be considered hypoglycemia. In accordance with current recommendations, patients with diabetes should be queried about symptomatic and asymptomatic hypoglycemia at each clinical encounter.

People with type 1diabetes must deal with the lifelong difficulty of keeping their BG levels within a safe range, while at the same time avoiding hyperglycemia while also avoiding hypoglycemia. Decreasing blood glucose control, on the other hand, raises the risk of hypoglycemia. Significant intra- and inter-day glucose variability makes it difficult to maintain appropriate insulin therapy for glycemic control. Patients and doctors struggle to manage blood glucose levels within normal limits when dealing with issues including meals, physical exercise, menstruation, illness, and stress.

In recent years, numerous new strategies for improving patient safety have been developed. CGM systems provide patients with real-time measurements of BG levels, allowing them to take immediate action. Insulin infusion was discontinued if BG levels were between a certain thresholds. Next-generation of this system used future BG readings to anticipate hypoglycemia and then suspended insulin supply ahead of time. Artificial pancreas has now been commercialised for the first time. This new approach makes use of a closed-loop system that constantly modifies insulin delivery based on CGM measurements.

Machine Learning Techniques for Hypoglycaemia Prediction

Machine learning techniques are used to provide predictive modelling for innumerable applications and requirements. Machine learning approaches can be categorised as 'general purpose' and 'universal' according on the specific task at hand. According to the needs, facts and focus of the problem several solutions will be appropriate. A proposed research approach is based on machine learning techniques that are intended to increase patient safety in the management of diabetes.

Predictive modelling sometimes necessitates extensive pre-processing steps, which calls for the use of machine learning algorithms. To begin, an exploratory analysis was performed on the experimental datasets that contained information from MDI or CSII-CGM therapy and data from a fitness tracker band. In spite of the fact that the preceding study covers the fundamentals of data categories and distribution, number of observations, and correlations, more data structures are accessible and those data structures may be utilised to modify data. The Exploratory Data Analysis was performed and the findings were : Median blood glucose level for hypoglycemic is slightly higher for non hypoglycemic population, The standard deviation is slightly higher for the hypoglycemic population, tight control may be one of the reasons for hypoglycemia, hypoglycemic population takes more insulin shots per day, NPH insulin users have slightly higher chances of experiencing hypoglycemia, during the afternoon 12noon and 6pm, the most hypoglycemic events happen. The following sections go into detail on the various methodologies employed.

Table 1: Summary of algorithms, Database used and Objectives

Objective	Time Window	Methodology	Database
Continuous Prediction	1h	Random Forest	1
Postprandial Prediction	4h	Support Vector Classifier	2
Nocturnal Prediction	6h	Artificial Neural Network	3

Random Forest for continuous prediction

A random forest model was developed for the use of type 1 diabetics physicians and other medical professionals who treat type 1 diabetics to predict a patient's risk of hypoglycemia using machine learning models. The tool analyzes a patient's daily blood glucose levels and day to day activities to predict whether a patient is at risk of experiencing severe hypoglycemia. The model uses the UCI machine learning repository for dataset. A model was created using this dataset to acheive the goal. A three fold cross validation was performed on 60/40 train test split to test the accuracy of the model. Python's machine learning libraries like numpy, pandas, matplotlib, seaborn and scikit-learn used for implementation. The multivariate time series dataset used contains blood glucose logs with the associated events of seventy patients for at least three weeks.

The dataset contains the features: Date - Date of the blood glucose level measurement, Time - Time of the blood glucose level measurement, Code - A number that represents the activity during the blood glucose level measurement . Example: after excersise, before breakfast, before snack, etc., Blood Glucose level – The level which is obtained during the measurement. A random forest model was created using the features : Irregular diet, Median blood glucose level, Number of NPH insulin shots per day, Number of readings per day, Number of snack times per day.

Support vector classifier for postprandial risk assessment

By anticipating low blood sugar after eating, doctors may better manage a patient's postprandial insulin needs, which helps keep blood sugar levels stable and lower the risk of hypoglycemia. Postprandial hypoglycemia prediction architecture is presented in this paper, allowing insulin pump and MDI users to re-estimate their bolus amounts. Predecessors have only targeted night time hypoglycemia and predictive horizons of 30–45 minutes. Hypoglycaemia was predicted within around 240 minutes after a meal for the individuals because their diet was reasonably consistent.

Postprandial risk assessment can be done by administering a class prediction to the subjects after they have eaten. An SVC employing relevant features taken from the available inputs can identify this class. There are several applications for supervised learning, including as classification and regression. Retrospective data were used to collect an initial set of characteristics. The following features were chosen for postprandial hypoglycemia:

- Glucose range (GR)
  $$GR = abs(BG[k-12] - BG[k]) \quad (1)$$
- BG[k]: The CGM value at mealtime k.
- Glucose ROC: The change in CGM values over the last 30 minutes is shown by this number.
- Prediction Basal: In the following 4 hours, the basal insulin will be added up.
- Carbohydrate: Gms of carbohydrate per serving of the projected meal
- Mean glucose: The hourly average of CGM values.
- Previous basal: The last two hours' worth of basal insulin added together.
- AUC: The area under the curve was determined if the CGM values fell below 70mg/dL in the previous hour.
- Bolus: bolus insulin cumulative dose up to one hour after injection.

The scenario of each patient was put through several iterations in order to evaluate it for personalization. After feature extraction and target labelling, a grid search and 5- fold cross-validation were used to fine-tune the SVC hyper-parameters. Cross-validation had deleted the final 20 percent of the training data, so we had to rely on that.

ANNs to predict nocturnal hypoglycaemia

A danger to someone with T1D management is the risk of having a hypoglycemic incident throughout the night. During this time, patients will be asleep, which means they may not be able to recognise any fluctuations in their glucose levels and, as a result, they have a very high risk of severe hypoglycemia. This is a complicated hormonal system that warns patients when their levels are decreasing. Even yet, patients with diminished awareness of hypoglycemia cannot identify declining glucose levels and hence delay treatment in order to afford themselves a higher chance of suffering from a severe hypoglycemic episode.

The nocturnal hypoglycemia prediction is a module based on artificial neural networks. The module's objective is to alert patients about the risk of hypoglycemia during the hours leading up to bedtime. The system keeps track of when patients set their alarms, so it can tell whether there's a significant risk of hypoglycemia in the six hours after that. With this new information, patients can plan ahead and, as a result, avoid hypoglycemia by reducing basal insulin delivery rates and/or eating a snack before going to bed rather than blousing to boost glucose levels.

Data on blood glucose, insulin, meals, and physical activity were used to provide input for glucose characteristics from previous data on the timing of patients' sleep announcements (sleep announcement).A wake-up call to sleep CGM value, hourly average of CGM readings in the 30 minutes prior to sleep announcement, and the rate of change (ROC) of CGM readings in the 6 hours prior to sleep announcement for the previous 30 minutes When sleep announcements were made, the ANN was also fed data from the IOB, AOB, and Ra meal consumption measures. Classes were assigned following a six-hour time block following an announcement about sleep. If you experience hypoglycemia of either the first or second degree, you will be treated at the lowest level. It was given the designation of Class 0 alone. Each patient received personalised models. The search for the ideal input features for each patient was exhaustive. The adaptive synthetic sampling (ADA SYN) approach was used to distribute the dataset's classes equally while training it. In the complete dataset, cross-validation was done with a dataset of five times the size to estimate accuracy. In order to limit the influence of sample selection bias, a split was performed a hundred times in each repetition. Averaging the findings across 100 runs allowed for individualised results.

Databases

Each database was utilised to analyse the different methods on their own. Several criteria were used in order to differentiate between normal and low blood sugar. Whenever three consecutive BG readings (15 minutes) are discovered above or below their respective levels, there is an increased risk of an unfavourable glycemic episode.

Database1: It was discovered that retrospective data from UCI Machine Learning Repository of 70 T1D patients had been obtained.
Database2: T1D patient decision-making models were used to simulate an entire cohort of 100 patients utilising the UVA/Padova simulator.
Database3. This data set includes six adult T1D patients that were followed for an eight-week period.

Assessment metrics

The techniques were tested one at a time. This is a combined presentation of the data utilising sensitivity, specificity, and accuracy.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

Proposed System for Prediction

The fig 1 illustrates the design of the system for predicting hypoglycemia. It is organised into four subsystems: first, continuous predictions on the order of hours to days; second, postprandial predictions; third, predictions related to nocturnal hypoglycemia. Another key benefit of an integrated system that employs the modules discussed above is to increase patient safety by employing classification and regression algorithms to forecast possible medical errors. It's beneficial since alarms require only a forecast of a class and an activation, but remedial measures should be conducted if a continuous prediction can be established. It is also possible to modify the length of time a prediction horizon is active in order to meet a patient's specific needs and habits. The regression job can be performed with the shortest prediction horizon in our suggestion. To make these treatment judgments, the continuous value needs to be as trustworthy as feasible, with a forecast horizon of at least one hour.

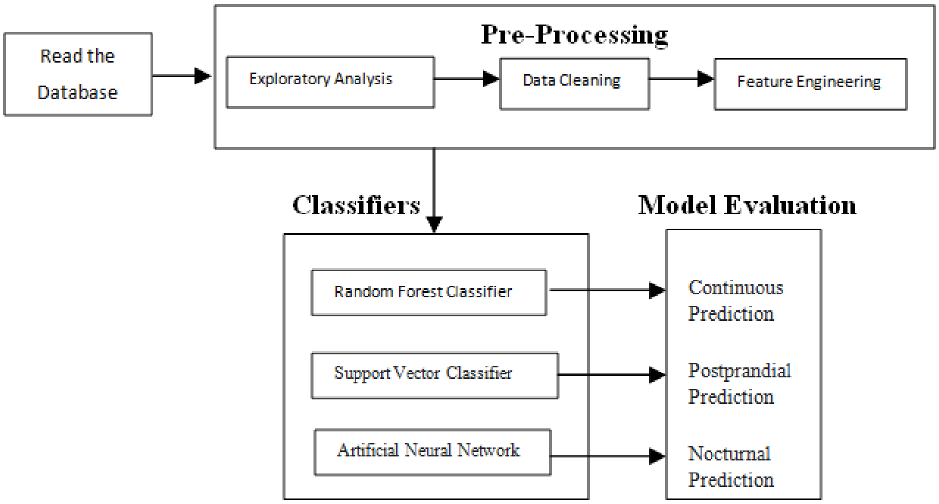

Fig 1: Proposed system

Module using Databases 1, 2, and 3 which is capable of providing continuous BG predictions, is reliable. When dinner is announced, the postprandial module can forecast for four hours. This unit can warn the patient of an oncoming hypoglycemic incident, which is displayed as a labelled output. Despite the predictive technology continuing to give predictions every few seconds, it tends to underestimate the occurrences of hypoglycemic events, since the majority of training data samples show instances of normal glycemic excursions. The postprandial module, with a different forecast, provides a more sensitive reading to avoid an imminent missing event. This night-time prediction module and the continuous prediction module work in tandem. This whole prediction horizon goes over a 6-hour period, which means it benefits the patient in the overnight period. This would free patients from needing to wake up at night due to a machine-triggered alarm, leading to better overall sleep. Before bedtime, patients would be recommended to have a snack. Patients would not ingest excessive carbohydrates without the requirement of doing so.

Results

Mid-term continuous prediction

The dataset was divided into 60/40 train test split. The model was able to predict with a maximum of 82% accuracy. The algorithms were developed based on three machine learning models with a unique data-driven feature set: a random forest (RF), Decision Tree and K-nearest neighbour.. As a result, RF is better in predicting continuous prediction with the high level of predictability.

Confusion matrix

Table 2: Population outcome for continuous prediction module to predict hypoglycamia

Classifiers	Train Accuracy	Test Accuracy
RFC	96%	82%
Decision Tree	82%	60%
KNN	73%	60%

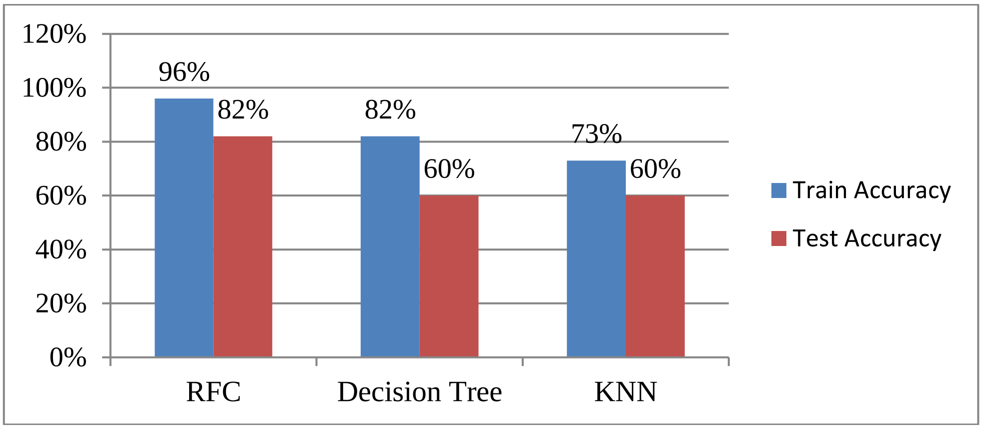

Fig 2: Performance Evaluation

Postprandial risk assessment

We use retrospective CGM datasets of 100 people who had experienced at least one hypoglycaemia alert value during a three-day CGM session. a support vector machine using a linear function or a radial basis function, With 5-fold cross-subject validation, the performance of model was calculated to compare and contrast their individual performance. Level 1 hypoglycaemia has a sensitivity and specificity of 68% and 81%, while Level 2 hypoglycaemia has sensitivity and specificity of 74% and 80%. These findings were derived for the postprandial time, in which the data was collected over the course of 4 hours after the meal was consumed, and using a one-class classifier.

Table 3: Population outcomes of each patient for hypoglycaemia level 1 and level 2

Classifier Performance Metric		Mean (%)	Min (%)	Max (%)
Level 1	Sensitivity	68	41	81
	Specificity	81	73	96
Level 2	Sensitivity	74	61	84
	Specificity	80	61	97

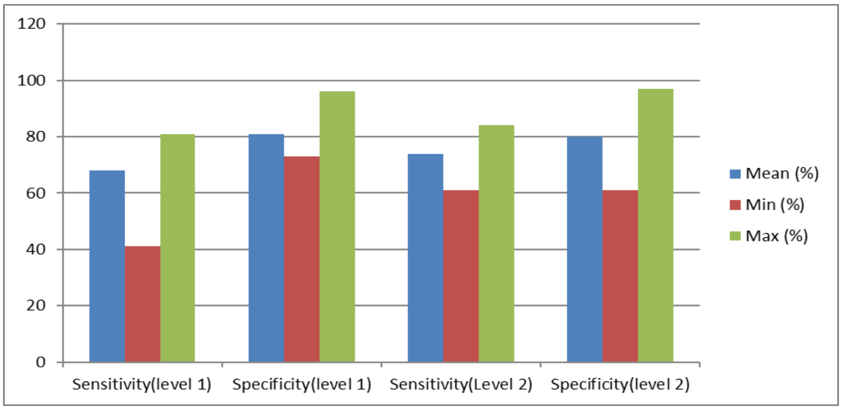

Fig 3: Population outcomes of each patient for hypoglycaemia level 1 and level 2

Nocturnal hypoglycaemic events

Database 3 was selected to evaluate the ANN's capacity to predict nocturnal hypoglycemic occurrences. The only database that collects data on physical activity and sleep status is the one used in this study. The data provided in Table 5 include all the individuals in the cohort.

Table 5: Population outcomes for nocturnal hypoglycaemia predictor module

Performance Metrics	Mean(%)	Min(%)	Max(%)
Sensitivity	43.9	15	67.4
Specificity	84.9	81.9	96.8
Accuracy	81.1	71	93.8

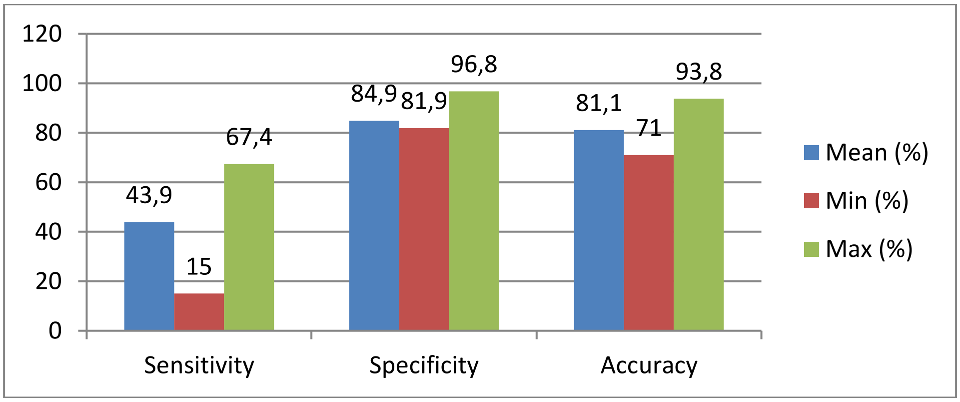

Fig 4: Population outcomes for nocturnal hypoglycaemia predictor module

Conclusion

An innovative approach for predicting hypoglycemic incidents in individuals with type 1 diabetes has been unveiled. Machine learning approaches were used to diagnose patients with different illnesses, forecast blood glucose levels, and determine the probability of nocturnal hypoglycemia and postprandial glucose levels. While the systems did what they were designed to do, they were assessed solely with regards to CSII therapy data. This is true, but the methods may easily be applied to MDI.Increased robustness is provided for the proposed system through models with multiple prediction algorithms functioning in tandem. Each predictive system has a better chance of succeeding when the surrounding conditions are favourable. When different models are combined, it is more likely that significant occurrences that may have been overlooked by a single subsystem of a prediction system would be foreseen. Integrated and resilient systems for the avoidance of hypoglycemic incidents will be possible through the use of multiple customised prediction models that are simultaneously in operation.

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