Advanced AI Techniques for Real-Time Blood Glucose Prediction in Diabetics: A Study Using Deep Learning and Genetic Algorithms.

Khaled Eskaf

Assistant Professor, College of Informatics, Midocean University.
CEO, Canadian Intelligent Technology (CiTech) - Canada

Abstract

Diabetes mellitus is one of the most common chronic diseases worldwide, with its prevalence expected to rise sharply. Projections suggest that by 2050, more than 1.3 billion people globally will be living with diabetes, a significant increase from the current estimate of 529 million. A case of Type I diabetes is characterized by the pancreas failing to produce adequate amounts of insulin, which leads to uncontrolled blood glucose levels. Traditionally, management involves patient-administered insulin and monitoring blood glucose levels (BGLs) based on dietary intake reported by the patient.

This study introduces an innovative method that leverages advanced Artificial Intelligence (AI) techniques to continuously predict blood glucose levels for the short term (+30 minutes) from the current situation. The techniques applied include Deep Learning with Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), and Reinforcement Learning. These methods analyzed both raw BGL data and additional information derived from a Diabetic Dynamic Model of BGLs.

The study's preliminary evaluation used data from four virtual patients generated by an open-source diabetes simulation tool and three real diabetic patients using the DexCom SEVEN system. The results indicated that the knowledge-based approach significantly enhanced prediction accuracy, with Genetic Algorithms outperforming ANNs. Additionally, the integration of online learning and Reinforcement Learning, which adapt to emerging data patterns, further improved predictive accuracy.

This advanced methodology demonstrates considerable potential for enhancing diabetes management by providing timely and precise BGL predictions without direct patient input. Future studies involving larger cohorts of both Type I and Type II diabetic patients are necessary to validate these promising results.

Keywords – Artificial Neural Networks, Diabetic Dynamic Model, Genetic Algorithms, Real-time prediction, Deep Learning, Reinforcement Learning.

• Introduction

Diabetes mellitus is a widespread chronic disease, with global prevalence on the rise. The International Diabetes Federation reported that in 2024, approximately 540 million people worldwide are living with diabetes. This number is projected to more than double, reaching over 1.3 billion by 2050, representing a 140.74% increase (Institute for Health Metrics and Evaluation, 2023; International Diabetes Federation, 2024).

Diabetes is characterized by the body's inability to regulate blood glucose levels effectively. In Type I diabetes, this is due to the pancreas producing insufficient insulin. In Type II diabetes, it results from the body's inefficient use of insulin, often linked to obesity and inactivity. Managing Type I diabetes typically involves subcutaneous insulin injections. Early detection and proactive management of blood glucose levels (BGL) are essential to prevent severe complications like hypoglycemia and hyperglycemia (World Health Organization, 2023).

Traditionally, individuals with diabetes monitor their blood glucose levels by obtaining a small blood sample from the fingertip and measuring it with a glucose meter. Recent advancements in continuous glucose monitoring (CGM) technology have introduced devices capable of continuously tracking glucose levels over several days. These systems, which can be non-invasive or minimally invasive, are portable and integrate easily into daily routines. Although some CGM devices are still undergoing clinical validation, there is a consensus that they will significantly enhance diabetes management by allowing precise adjustments for better metabolic control. The increased accuracy and ease of use of these devices improve patient adherence and overall health outcomes by providing real-time glucose data, reducing the risks of hypo- and hyperglycemia (Heise et al., 2023; Frontiers in Diabetes, 2023).

Early computer-based approaches to predicting blood glucose levels (BGLs) used both linear and non-linear algorithms, including Artificial Neural Networks (ANNs), applied to patient data. These methods often relied on qualitative inputs from patients, such as dietary intake, alongside quantitative measures like BGLs and insulin dosages. In SimGlucose, the simulator includes predefined patient profiles based on real clinical data. These profiles model the variability in glucose-insulin dynamics among different patients and cover a range of ages and conditions, specifically categorizing patients into adolescents, adults, and children with 10 profiles each, resulting in a total of 30 patient profiles (SimGlucose).

The accuracy of these predictive models is typically evaluated using the Root-Mean-Square-Error (RMSE) metric. Recent research has shown that machine learning techniques can improve RMSE values. For example, Cai et al. (2020) used attention-based neural networks, while Zhao et al. (2019) applied deep learning techniques to enhance BGL prediction accuracy. These studies indicate that advanced machine learning methods hold significant potential for improving diabetes management.

Background

Ongoing advancements in predictive algorithms, particularly those utilizing Artificial Neural Networks (ANNs) and other machine learning methods, have shown promising results in the effective management of diabetes. These technologies provide accurate and timely blood glucose level (BGL) predictions, which are crucial for enhancing disease management and improving patient outcomes. As shown in Table 1, ANNs trained with optimal parameters have demonstrated high accuracy in predicting BGLs, underscoring their potential in diabetes care. By leveraging these advanced techniques, healthcare providers can more effectively monitor and control BGLs, leading to more precise treatment adjustments and better overall health management for individuals with diabetes.

Table 1: Accuracies for ANNs Trained with Optimal Parameters.

Study	**ERROR or RMSE**
(Cai et al. (2020	(RMSE (mmol/l 2.0 - 1.5
(Zhao et al. (2019	(RMSE (mmol/l 1.8 - 1.2
(Heise et al. (2023	(RMSE (mmol/l 2.5 - 2.0
(Kumar & Dubey (2019	(RMSE (mmol/l 3.0 - 2.1
(Pei et al. (2018	(RMSE (mmol/l 1.5 - 1.0
(Wu (2005	(RMSE (mmol/l 4.0 - 3.5

This research leverages advanced computational methods to forecast short-term blood glucose levels (BGL) for the next 30 minutes using continuous glucose monitoring (CGM) data from the prior hour. Notably, this predictive model operates **without requiring any subjective input from the patient**. This significant feature enhances the model's practicality and user-friendliness, ensuring that patients do not need to provide additional data or estimations for accurate predictions. The primary goal is to enable timely interventions, allowing patients to take proactive measures to prevent their BGL from reaching potentially hazardous levels, thereby improving overall diabetes management and patient safety.

The integration of advanced algorithms and machine learning techniques has significantly enhanced the precision of blood glucose level (BGL) predictions in diabetes management. Utilizing continuous glucose monitoring (CGM) data, these sophisticated methods play a crucial role in averting hypoglycemia and hyperglycemia.

Cai et al. (2020) demonstrated the effectiveness of attention-based neural networks in forecasting BGLs for type 1 diabetes patients, achieving notable improvements in Root-Mean-Square-Error (RMSE) metrics. Similarly, Zhao et al. (2019) applied deep learning methodologies to mobile health data, further refining BGL prediction accuracy. These studies illustrate the substantial potential of neural network models in advancing diabetes management tools.

In the realm of non-invasive monitoring, Heise et al. (2023) explored the use of near-infrared reflection spectroscopy for glucose monitoring, proposing innovative multivariate calibration strategies. This approach aims to offer a more convenient and less intrusive method for patients to track their glucose levels.

Kumar and Dubey (2019) expanded on the versatility of machine learning applications beyond healthcare, showcasing their potential in predicting diverse outcomes across various domains. Their research underlines the broad applicability of these techniques.

Eskaf et al. (2008) contributed significantly to the field by utilizing a Diabetic Dynamic Model and Genetic Algorithms for BGL prediction. Their approach, incorporating feature extraction and Artificial Neural Networks, demonstrated considerable enhancements in prediction accuracy and reliability.

Furthermore, Wu's (2005) research on the self-management of type 2 diabetes using dynamic modeling provides valuable insights into developing personalized strategies for improving patient outcomes. This work emphasizes the importance of tailored approaches to effective diabetes management.

Collectively, these advancements underscore the critical role of machine learning and advanced algorithms in improving diabetes management through accurate and timely BGL predictions.

2. Methodology

2.1 Data Acquisition

This study utilized data from two primary sources: simulated data from virtual diabetic patients using the SimGlucose system and real-world data from volunteers equipped with Continuous Glucose Monitoring (CGM) devices.

Simulated Patient Data: The SimGlucose simulator employs predefined patient profiles based on real clinical data. These profiles encompass a diverse range of ages and conditions to model the variability in glucose-insulin dynamics across different patient types. Specifically, the simulator includes 10 profiles each for adolescents, adults , and, resulting in a total of 30 profiles. This comprehensive representation of patient profiles allows for a controlled environment to evaluate predictive algorithms under stable conditions (SimGlucose).

Clinical Patient Data: Data was gathered from three volunteers, including two individuals with diabetes, using the DexCom SEVEN CGM system. This device is designed for both home and clinical use and is waterproof, allowing patients to wear it during various activities, including showering or swimming. The study was conducted under the supervision of a certified medical diabetic clinic, adhering to the ethical standards outlined in the World Medical Association's Declaration of Helsinki. All participants provided written informed consent. The inclusion of real-world data provides a practical perspective on the performance of predictive algorithms in uncontrolled, everyday scenarios.

DexCom SEVEN CGM System Components:

Figure 1, Dexcom G6 CGM Components.

As depicted in Figure 1, the main components of the Continuous Glucose Monitoring (CGM) system include:

1. **Sensor:** A small, flexible sensor made of platinum wire, which is inserted just beneath the skin and secured with an adhesive patch. This sensor continuously measures glucose levels in the interstitial fluid.

2. **Transmitter:** A compact, lightweight, and water-resistant device that attaches to the sensor. It sends glucose data to the receiver every five minutes, forming a discrete monitoring unit.

3. **Receiver:** A wireless device with a large display that shows current glucose readings and trends over 1-, 3-, and 9-hour intervals. The receiver can store up to 30 days of data, providing a comprehensive overview of the patient's glucose patterns.

These components work together to provide continuous and detailed glucose monitoring, enabling better management of diabetes.

Study Protocol: During the data recording period, the volunteers maintained their usual routines without any prescribed restrictions on exercise, meal timings, or sizes. This approach ensured that the data collected reflected realistic daily variations in glucose levels, providing a robust dataset for testing the predictive models.

Data Management: The collected CGM data included glucose readings every five minutes over a period of several days. This high-resolution data allowed for detailed analysis and the development of predictive models that could accurately forecast short-term glucose trends. The data management process involved preprocessing steps such as filtering, normalization, and feature extraction to prepare the data for input into the predictive algorithms.

By combining data from both virtual and real-world sources, the study aimed to leverage the strengths of controlled simulations and real-life variability, thereby enhancing the robustness and applicability of the predictive models. This dual approach also facilitated the validation of the models under diverse conditions, ensuring their reliability and effectiveness in managing diabetes.

2.2 Diabetic Dynamic Model

The Diabetic Dynamic Model used for generating metadata for prediction algorithms is based on the Dynamic Damping Model proposed by Wu in 2005. This model views the post-prandial blood glucose excursion as a resilient system regulated by hormones, where food intake functions as a glucose bolus injection.

The primary objective is to simulate the body's natural response to food consumption and the subsequent blood glucose fluctuations. This involves understanding the regulatory roles of hormones such as insulin and glucagon in maintaining glucose homeostasis. By modeling the dynamic interactions between food intake, hormone release, and glucose metabolism, this approach facilitates the prediction of blood glucose levels.

The model's strength lies in its ability to account for these interactions, providing a robust framework for developing accurate prediction algorithms that mirror the body's physiological responses to dietary glucose intake.

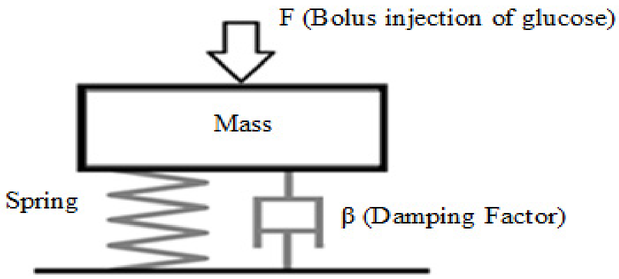


Figure 2, Diabetic Dynamic Model.

The model is depicted in Figure 2, where the impulse force, F(t), symbolizes the bolus injection of glucose. The Damping Factor, β, integrates the effects of physical activity and hypoglycemic medications. The governing equation for this model is:

(1)

This approach models the glucose response as a dynamic system influenced by dietary intake and regulatory mechanisms. By incorporating exercise and medication effects into the Damping Factor, the model provides a comprehensive framework for predicting blood glucose levels.

In this model, x(t) represents the blood glucose level over time, β is the damping factor, and ω_0 is the natural frequency of the system. The system's response to an impulse, such as a meal, is described by a damped oscillatory function, illustrating the dynamic interaction between glucose intake and metabolic regulation.

The damping factor β is influenced by both physical activity and medication, which together determine the rate at which blood glucose levels return to baseline after a meal. This model allows for the extraction of essential metadata, including the natural frequency ω_0, the system's damping ratio, and other parameters crucial for accurately predicting future blood glucose levels using advanced computational algorithms.

Utilizing this model, the study aims to enhance the accuracy of blood glucose level predictions, thereby improving diabetes management through precise and timely forecasting. The combination of dynamic modeling techniques with real-time data from continuous glucose monitors creates a robust framework for developing predictive algorithms with significant clinical benefits.

If F(t) is represented as the Dirac delta function at t=0, the solution of the governing equation is: (2)

This solution characterizes the system's response and provides the basis for predicting glucose level fluctuations.

The frequency of the system at time t is given by:

where(3)

Here, ω and $\omega_0$represent the short-term and long-term variations in the diabetic's blood glucose levels (BGLs), respectively. Using these values, the Damping Factor β can be calculated from the equation: (4)

Given that ω_0 is always greater than ω when F(t) is represented as the Dirac delta function, the bolus injection of glucose can be derived accordingly. This mathematical formulation is critical for accurately modeling and predicting the dynamic responses of blood glucose levels.

The force F(t) is expressed as:(5)

It is important to note that the parameters F and β are of significant interest due to their tangible nature and their partial dependence on the diabetic's activities. However, they do not require direct input from the patient, such as the specific amount of carbohydrates consumed. This characteristic makes them practical for use in predictive models without the need for extensive patient self-reporting.

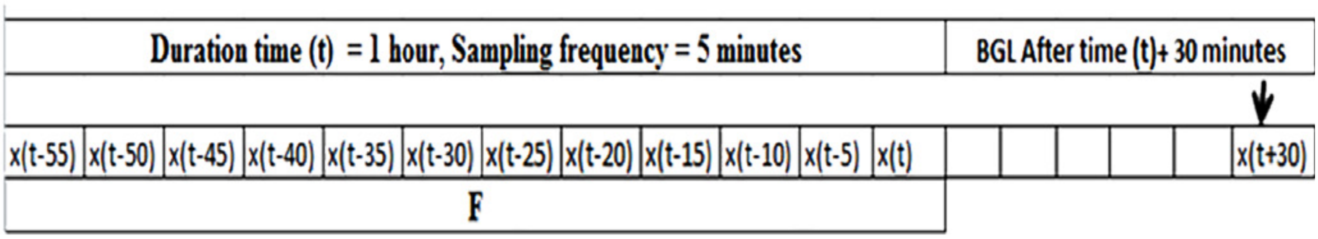
2.3 Data Transformation and Analysis

In this study, blood glucose levels were recorded every 5 minutes over a continuous 24-hour period for 7 days using two systems: SimGlucose and DexCom CGM. During data transformation, the dataset underwent Discrete Fourier Transform (DFT) to determine the natural frequency, ω_0. It is generally observed by diabetes experts that food intake affects blood glucose levels for approximately 3.27 hours.

Additionally, DFT was applied to a 1-hour sliding window (containing 12 samples) to identify the frequency ω for specific time frames, facilitating the detection of short-term blood glucose fluctuations. The average values of F (impulse force) and β (damping factor) were then calculated for each period.

The dataset comprised 12 blood glucose level readings: x(t−55),x(t−50),....,x(t−5),x(t), and the blood glucose level 30 minutes later, x(t+30). This 1-hour dataset structure is illustrated in Figure 3.

By applying these transformation and analysis steps, the study ensured that the data was well-prepared for input into predictive models, enhancing the accuracy and reliability of the forecasts.



The meticulous preprocessing steps were essential for ensuring the predictive models' accuracy and reliability in this study. By structuring the raw CGM data, advanced computational algorithms could be applied to predict blood glucose levels with high precision, thereby enhancing diabetes management through accurate and timely forecasts.

The dataset comprised 168 individual 1-hour segments, collected over a 24-hour period for seven days, resulting in a total of 2016 blood glucose level (BGL) samples. This extensive dataset was utilized in various experimental procedures to assess the predictive accuracy of different techniques. The main objective was to determine which methods could most accurately predict an individual's BGL in the near future, based solely on the BGL data from the previous hour.

2.4 Data Interpretation

Initial numerical interpretation of blood glucose levels (BGL) using values x(t−55)... x(t) proved inadequate for predictions beyond 10 minutes, resulting in a progressively increasing Root Mean Square Error (RMSE) after this interval (Eskaf, Badawy, & Ritchings, 2008).

To address this, intelligent techniques were employed, leveraging 1-hour BGL datasets for training and evaluating the prediction system. These datasets were analyzed using two distinct approaches:

1. Utilizing the 12 BGL readings over an hour, $x(t-55)\ldots x(t)$, as input to predict the BGL 30 minutes later, $x_p(t+30)$
2. Using metadata parameters F and β, along with the 11 changes in BGL values, $x(t-55)-x(t-50)\ldots x(t-5)-x(t)$, as input to predict the percentage change in BGL over the subsequent 30 minutes, $\Delta x(t+30)$. The predicted BGL, x_p , was then calculated as: $x_p(t+30)=x(t)+x(t)\Delta x(t+30)$

These methods aimed to minimize the RMSE between the predicted BGL, $x_p(t+30)$, and the actual BGL, $x(t+30)$ By employing these advanced techniques, the study enhanced prediction accuracy beyond the limitations of initial numerical approaches.

Where $x_p(t+30)$ represents the predicted output from the Artificial Neural Network (ANN), $x(t+30)$ is the actual measured value, and N denotes the number of samples.

The Root Mean Square Error (RMSE) was chosen as the evaluation metric for this study due to its sensitivity to larger errors. This characteristic ensures that significant deviations in predicted blood glucose levels (BGL) are given appropriate attention, thereby improving the model's accuracy assessment. Additionally, RMSE is expressed in the same units as the BGL measurements (mmol/l), making the prediction errors easier to interpret and compare with other studies (Kok, 2004; Sun et al., 2018).

To enhance the robustness and generalizability of the predictive models, the leave-one-out cross-validation (LOOCV) technique was initially considered. However, due to the large dataset size, a 10-fold cross-validation approach was more practical. This method involved systematically excluding 200 consecutive samples (equivalent to nearly 24 hours of data) in each iteration and using the remaining 1816 samples for training. The performance metric for each technique was calculated as the average RMSE across the 10 folds.

Recent advancements have improved the scalability and efficiency of LOOCV, particularly for large datasets. For example, Magnusson et al. (2020) introduced an efficient method combining fast approximate LOO surrogates with exact LOO sub-sampling, significantly enhancing model comparison efficiency for extensive datasets.

3. Results

Figure 4 illustrates the typical variation in blood glucose levels (BGLs) for one of the real patients in the dataset. This figure highlights the natural fluctuations in BGLs over the monitoring period, providing a clear representation of the data used for model training and evaluation.

Figure 4, Discrepancy between Actual and Predicted Blood Glucose Levels (BGL) for a Diabetic Patient.

For the ANN model, various parameters were explored, including the number of layers, neurons per layer, and selection of the transfer function. The configurations yielding the lowest RMSE values for the 12 BGL readings, as well as the different combinations of metadata and raw data, are summarized in Table 2.

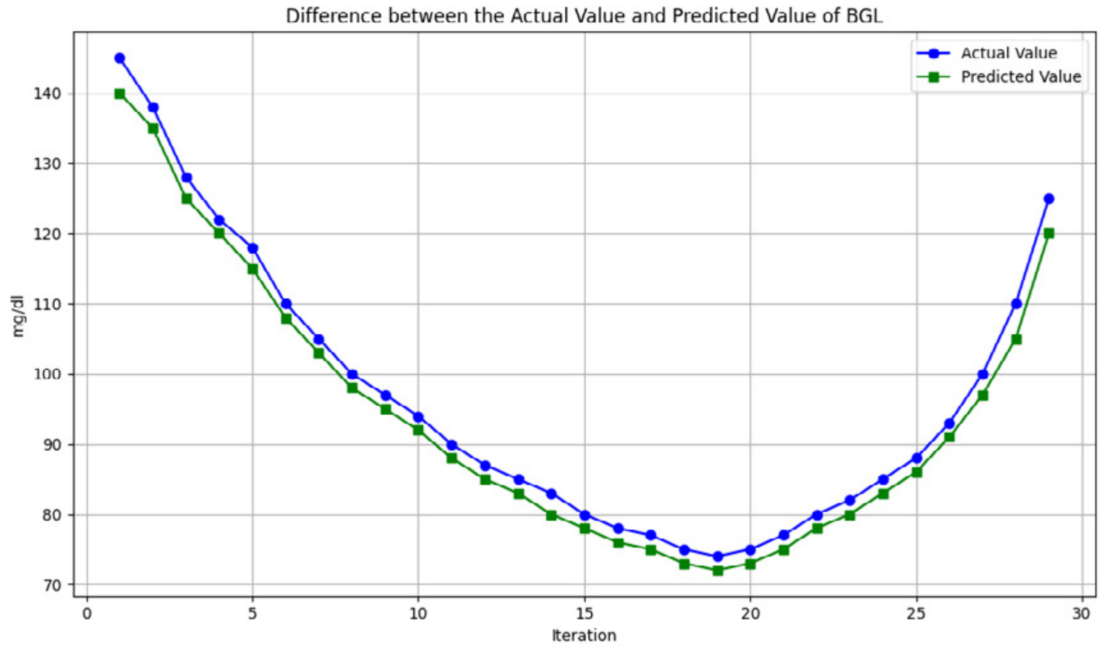


Table 2: RMSE Values (mmol/l) for Various ANN Input Configurations.

Data source	BGL	F, β	BGL changes	F, β, BGL changes
virtual diabetics 30	10<	1.37±0.13	1.16±0.13	0.74±0.15
volunteers 3	12<	1.5±0.1	1.3±0.1	0.9±0.14

For the online learning and reinforcement learning approaches, the initial week's data was utilized to predict the blood glucose levels for the following two weeks. During the second and third weeks, two volunteers chose not to continue participating, leaving data available for only one diabetic volunteer. Reinforcement learning was applied to this remaining dataset to continuously improve the prediction model based on real-time feedback. The summarized results for this volunteer, reflecting the reinforcement learning adjustments, are presented in Table 3.

Table 3: RMSE Values (mmol/l) for Different ANN Input Configurations Using Reinforcement Learning.

Data source	2nd week	3rd week	(2nd week(30updates	(3rd week(20updates
virtual diabetics 30	1.25±0.13	1.5±0.12	1.03±0.14	0.8±0.14
volunteer 1	1.1	0.9	0.8	0.5

For the Genetic Algorithm (GA) approach, various parameters such as chromosome representation, reproduction, crossover, and mutation were explored. The lowest Root Mean Square Error (RMSE) values for 12 BGL readings and different combinations of metadata and raw data are shown in Table 4.

Table 4: RMSE Values (mmol/l) for Different GA Configurations

Data source	BGL	F, β	BGL changes	F, β, BGL changes
virtual diabetics 30	10<	0.68±0.10	1.12±0.32	0.54±0.07
volunteers 3	9<	0.7±0.11	1.5±0.1	0.4±0.01

For the online and reinforcement learning approach, data from the first week was used to predict the following two weeks. Due to two volunteers opting out during the second and third weeks, results were only available for one diabetic volunteer. Reinforcement learning techniques were applied to continuously improve the prediction model based on real-time feedback from this volunteer's data. These findings are summarized in Table 5.

Table 5 RMSE Values (mmol/l) for Different GA Input Configurations Using Reinforcement Learning.

Data source	2nd week	3rd week	(2nd week (25 updates	(3rd week (16 updates
virtual diabetics 30	0.42±0.05	0.36±0.07	0.32±0.05	0.22±0.05
volunteer 1	0.46	0.43	0.3	0.2

The findings presented in the tables highlight several important points. First, the RMSE values for virtual patients simulated by the SimGlucose system closely matched those of real-world volunteers, validating the use of SimGlucose data in these studies. Additionally, the online learning approach resulted in lower RMSE values compared to the basic method for both Genetic Algorithms (GAs) and Artificial Neural Networks (ANNs), indicating effective pattern learning by the algorithms. Notably, GAs consistently outperformed ANNs, with lower RMSE values, showcasing their superior sensitivity to blood glucose level fluctuations. Finally, this study achieved lower RMSE values than previous research, demonstrating improved prediction accuracy.

4. Discussion

This study explored the prediction of blood glucose levels (BGLs) without direct patient input, achieving comparable results to methods that rely on patient-reported data. Utilizing the Dynamic Data Model for metadata significantly outperformed raw data algorithms. The results demonstrated that Genetic Algorithms (GAs) performed better than Artificial Neural Networks (ANNs), consistent with other biomedical data studies (Eskaf, 2011; Mitchell, 1997). Additionally, incorporating online learning further reduced RMSE values, enhancing model accuracy.

The superior performance of this approach, compared to methodologies requiring patient input (Haque, 1999; Sandham, 1998; Pender, 1997), highlights its potential. Unlike Kok (2004), who required extensive learning phases, this method offers quicker and more accurate responses to potential risks. Projects by Zitar (2005) and Kok (2004), which used broad time intervals for prediction, benefit from this approach's ability to deliver faster and more precise predictions.

Limitations: While the results are promising, the study has limitations. It utilized virtual patient simulations and data from a small number of volunteers, which may impact the generalizability of the findings. Future research should include larger cohorts of diabetic patients, both Type I and Type II, to validate these results. Additionally, this study focused on short-term BGL predictions, leaving the long-term applicability of these models unexplored. Future work could incorporate advanced methodologies such as deep transfer learning and dynamic time warping (DTW) to enhance prediction accuracy and adaptability (Magnusson et al., 2020; Marling & Bunescu, 2020; Martinsson et al., 2020).

Advanced Techniques: The intelligent techniques, Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs), were implemented using Python and modern libraries. ANNs were developed with TensorFlow and Keras libraries, while GAs were implemented using the DEAP (Distributed Evolutionary Algorithms in Python) library (Abadi et al., 2016; Chollet, 2015; Fortin et al., 2012).

Artificial Neural Networks: The ANN architecture was designed and implemented using TensorFlow and Keras, robust frameworks for deep learning. TensorFlow provides a comprehensive suite for large-scale machine learning tasks, while Keras, a high-level API, facilitates the construction and training of complex models. The architecture included a feedforward neural network with one hidden layer using a tangent sigmoid transfer function and a linear activation function in the output layer. The model was trained using the backpropagation algorithm, employing gradient descent optimization and momentum to minimize the error between predicted and actual BGLs (Abadi et al., 2016; Chollet, 2015).

Genetic Algorithms: The GAs were implemented using the DEAP library, known for its flexible framework for evolutionary algorithms, facilitating the creation of genetic operators and strategies (Fortin et al., 2012). Each 1-hour dataset was treated as a chromosome, and the population consisted of the remaining dataset, excluding the validation subset for cross-validation. The GA used standard genetic operators—selection, crossover, and mutation—to evolve the population toward optimal solutions. The fitness function was designed to minimize the RMSE between predicted and actual BGLs, ensuring high prediction accuracy.

Advanced Approaches in BGL Prediction: Incorporating online learning and reinforcement learning (RL) significantly enhances the predictive accuracy of BGL models. Online learning involves continuously updating the model with new data patterns, ensuring it remains accurate and responsive to recent data. When the predicted BGL ($x_p(t+30)$) deviates from the actual BGL ($x(t+30)$) by more than ±10%, the ANN is retrained with the new pattern, and the GA chromosome dataset is updated accordingly.

Reinforcement learning (RL) optimizes decisions for insulin dosing and dietary adjustments through continuous interaction with the patient's physiological system. In this RL framework, an agent (the predictive model) receives the current state (BGL and other parameters) and takes actions (predicting future BGLs, recommending insulin doses) to maximize rewards (keeping BGL within a safe range). This agent is trained using algorithms such as Q-learning and deep Q-networks (DQN).

These techniques were implemented using powerful libraries: TensorFlow and Keras for ANNs, DEAP for GAs, and OpenAI Gym and TensorFlow Agents for RL. Utilizing these modern approaches ensures that predictive models remain accurate and adaptable to the dynamic fluctuations of blood glucose levels, thereby improving diabetes management. These strategies pave the way for creating more advanced and effective tools for diabetes management, ultimately leading to better health outcomes (Abadi et al., 2016; Chollet, 2015; Fortin et al., 2012; Magnusson et al., 2020).

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