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Prediction Of Blood Glucose Levels and Diabetes Complications Using Wearable's for Type1 Diabetics

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Abstract
Diabetes leads to early passing and impairment worldwide and affects people despite nation, age and sex. Accurate and timely prediction of blood glucose levels is important for managing diabetes, enabling proactive interventions to prevent hypo- and hyperglycemic events. Though a prediction of glucose level is a critical aspect in the real world, it helps diabetic patients manage their conditions and lowers the risk of developing health complications. This study aims to predict blood glucose values of diabetic patients using LSTM and GRU individual models on D1NAMO dataset. Forecasting of glucose level was carried out by considering diabetic patients CGM recordings additionally with their physical measurements. The comparison of these models for blood glucose forecasting under three evaluation metrics was performed. We successfully implemented our proposed approach for nine type1 diabetic patients and achieved RMSE 0.165, MAE 0.133 and 1.605 MAPE. It has been found that a single layer of GRU with a dense layer is sufficient to obtain good accuracy. Additionally, this paper includes predicting diabetes symptoms based on six glycemic diabetes ranges using SVM.

Keywords: T1DM,T 2DM,.LSTM, GRU, Diabetes Prediction, Machine Learning, Artificial Intelligence, Diabetes Complications

1. Introduction

Madhuri et al. [1] stated that, Diabetes is categorized into type1 [T1DM], type2 [T2DM] and gestational diabetes. Predicting Blood Glucose Level (BGL) is important for diabetics, especially those who rely on insulin to manage their daily condition. Deshpande et al. 2008 [2] mentioned that, Diabetes can seriously damage parts of the body including eyes, feet, kidney and heart. Shreyaswi Sathyanath, Rashmi Kundapur et al. 2022[3] highlight, Increase in Diabetes impact large financial hardship on the global healthcare organization, which directly or indirectly impacts nations' gross domestic product. Nearby 537 million peoples are diabetics. This may increase to 783 million by 2045, 541million adults are at greater threat of developing T2DM [4]. Accurate prediction can enable timely interventions, preventing hypoglycemic or hyperglycemic events. Technology such as Continuous Glucose Monitoring (CGM) Systems, Artificial Intelligence (AI) and Machine Learning (ML), Smartphone Apps and Wearable Devices, Insulin Pumps and Cloud-Based Platforms has played a major role in revolutionizing the way diabetes is managed, especially in the realm of predicting BGL. The integration of wearable sensors, artificial intelligence, and automated insulin delivery systems holds immense promise for the future of diabetes care. The advancements in technology for blood glucose prediction are leading towards more accurate, convenient, and personalized diabetes management.
Constructing prediction of BGL model mainly involves time series forecasting using ML or DL approaches. Accurate predictions using these technologies can significantly help for betterment of life, lower the chance of being diabetic, and enhance overall health.
Blood glucose prediction is a vital area in diabetes management. By leveraging past data and ML techniques, particularly time series models like LSTMs and GRUs, it's possible to forecast future BG and empower individuals with diabetes to make decisions and proactively manage their condition, ultimately improving their health and quality of life. The system outlined in our study demonstrates a comprehensive approach to this challenge by integrating various physiological data streams and employing advanced machine learning models. Predicting BG levels after a few minutes ahead presents unique challenges due to the rapid fluctuations that can occur in blood sugar. The fluctuations over time of BGL depend among other factors of current BGLs, food intake, insulin dose and activity. By anticipating fluctuations, individuals can make decisions about their food intake, exercise, and medication.

In this study, we predicted BG values at horizons of 3, 5 and 10 minutes including current and past glucose value along with Heart rate, Breath rate and daily activity. We also extended this work for predicting diabetes symptoms and its consequences by considering glucose range for diabetic patients.
This paper is organized as: part two literature review, part three explores diabetes symptoms, part four explain dataset used, part five presents techniques used, part six elaborates proposed framework, part seven includes output and remark and part eight concludes the findings and future scope.

2. Related Work

Prediction of blood glucose has become a vital area of research for diabetes people to proactively manage their health condition, avoid extreme glucose levels, and improve their quality of life. This review synthesizes current literature on methodologies.
Current blood glucose prediction models can be broadly classified into:

- Physiological Models: These models simulate the complex physiological processes governing glucose metabolism. They require in-depth knowledge of individual parameters and can be limited by the need for accurate self-reported data (e.g., meals, insulin).
- Data-Driven Models: Leveraging the increasing availability of continuous glucose monitoring (CGM) ML and DL models have shown significant promise. These include statistical models (ARIMA), traditional ML algorithms (SVM, Random Forest, XGBoost), and deep learning architectures (RNN, LSTM, CNN). Neural networks, particularly LSTMs, are frequently employed to capture temporal dependencies in glucose data.
- Hybrid Models: Combining physiological insights with data-driven techniques aims to leverage the strengths of both approaches for improved accuracy and robustness.

CGM technologies introduced different paths to analyze T1DM. Patients can monitor their BGL by using CGM devices. BG prediction has made significant improvements with the advancement of ML and DL techniques.
Together with clinical expertise, we can develop more accurate and reliable BG prediction models to improve the lives of diabetics. Munoz-Organero [5] 2020 has developed the prediction model by considering BG history, food, insulin and the exercise of a patient. Han et al. 2024 [6] investigated BG prediction with weight ensemble optimization using a genetic algorithm, which helped to refine the outcome of the RNN-based algorithms for hospitalized T2DM. Zaidi et al. 2021[7] proposed a BGL prediction system only by considering CGM data. The results state that their designed ANN is accurate and helpful for clinical practitioners. Researchers presented a novel DL model to predict BG of T1DM patients. They performed research by not only considering BG but also considered insulin and food intake to forecast BG values. Zarkogianni et al. [8] presented a combinational method using ANN with one compartmental model to ensure short-term BGL for insulin dose. The input data used here predicted BG of the T1DM patient after each 3 minutes of interval. Results proved that their designed model controls BGL on the condition of realistic meal intakes. Zhu et al. 2023 [9] proposed a unique DL framework to compute personalized BG predictions. They used an attention-based RNN for CGM input. Blood glucose prediction holds immense potential to revolutionize diabetes management. Continuing research and technological advancements are necessary to overcome the challenges and achieve the ultimate goal of accurate and reliable blood glucose prediction.
Blood glucose prediction and forecasting play a major role in the management of diabetes mellitus, offering a proactive approach to glycemic control. These techniques use historical glucose data, insulin doses, meal information, physical activity, and other physiological signals to anticipate future blood glucose levels. Accurate predictions enable timely interventions to prevent both hyperglycemia and hypoglycemia, which are major complications in diabetes care. Recent advancements leverage ML, DL models, and continuous glucose monitoring (CGM) systems to enhance prediction accuracy. Forecasting can range from short-term (15–60 minutes ahead) to long-term predictions, depending on the use case, such as alert systems, insulin dosing recommendations, or lifestyle adjustments. Despite significant progress, challenges remain in model personalization, data quality, and real-time implementation. Nevertheless, blood glucose forecasting holds great promise in developing intelligent decision-support systems for diabetes self-management and improving patient outcomes.

3. Diabetes Symptoms

Accurate estimations for predicted BGL is an important aspect for T1DM patients in order to avoid consequences of hypo and hyper glycemic episodes. Both hypoglycaemia and hyperglycemias conditions can lead to serious complications if left untreated. The table categorizes blood glucose levels into six ranges, each associated with a specific symptom category or diabetes stage:

Table 1: Diabetes Symptoms

Sr. No.	Diabetes Symptoms	Glucose Level Range (mmol /L)	Authors and References
1	Hypoglycemia	Glucose < 3.9	Fabien Dubosson et al. 2018 [10], Takoua Hamdi et al. [11]
2	Regular	3.9 ≤ Glucose ≤ 5.5	Cryer PE 2004 [12], Frier BM [13]
3	Prediabetes	5.6 ≤ Glucose ≤ 6.9	—
4	Mild Hyperglycemia	7.0 ≤ Glucose ≤ 10.0	ADA 2020[14], ADA 2010 [15]
5	Moderate Hyperglycemia	7.1 ≤ Glucose ≤ 13.9	Vinik AI, et al 2009 [16], Muller LM et al 2005[17]
6	Severe Hyperglycemia	Glucose ≥ 14	DCCT 1993 [18] , Stratton IM [19], Kitabchi AE [20]

4. Dataset

The D1NAMO dataset is publically available dataset specifically designed for research on non-T1DM management. It was created by researchers aiming to develop healthcare models based on wearable devices in real-life, as opposed to strictly controlled clinical settings. The D1NAMO dataset was acquired over a 4-day period. This extended data collection period was crucial for capturing the variability in BGL and other physiological parameters that can occur over time, especially in individuals with T1DM. Data was collected in real-life conditions using 3 wearable devices. The dataset includes 20 non diabetic individuals and 9 T1DM patients providing a balanced perspective. The key features of the dataset include Electrocardiogram recordings, Respiratory rate and patterns, Movement data, GM readings, Pictures of consumed meals with annotations. All data points are synchronized with precise timestamps, enabling accurate correlation and analysis.

5. Algorithms

DL has turned out to be a compelling means for predicting BGL. By analyzing various parameters such as diet, exercise, and previous BG readings, DL models can provide more accurate and timely predictions. Combining DL models with wearable devices can enable continuous monitoring and personalized predictions. In general, learning from past experiences to improve future performance is a main aspect of DL, as well as ML.

5.1. LSTM

LSTMs are Cutting-edge models for forecasting. LSTMs can be adapted to predict glucose levels over different time horizons, from short-term to longer-term trends. LSTMs can be relatively robust to noisy CGM data and irregular sampling intervals. Training effective LSTM models typically requires a significant amount of highquality, continuous glucose monitoring data, ideally with accompanying information on meals, insulin, and activity. LSTM's ability to selectively remember, update, and use information over long sequences is its key strength, making it ideal for tasks involving sequential data.

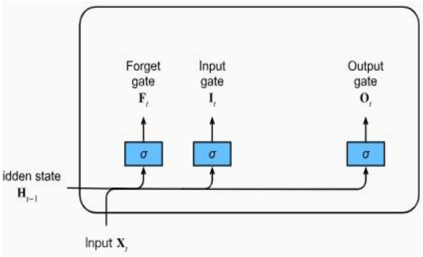
Forget gate: decides which amount of information from the previous cell state to keep or discard.

Input gate: manages the amount of new information that is allowed to enter the cell state.

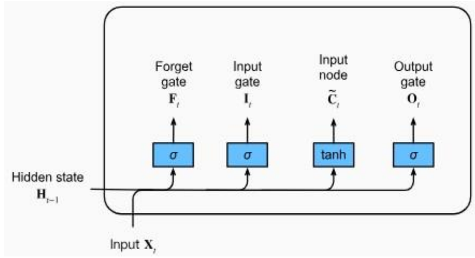
Output gate: governs the flow of information from the internal memory cell to the output.

These gates use sigmoid activation (σ) and weighted inputs ([ht-1, xt] concatenated) with biases. A candidate cell state ($\tilde{C}_t$) is created using a tanh activation function (Equation. The new cell state (C_t) is then updated by combining the forgotten information and the new input information. Finally, the hidden state (ht) is evaluated using the output gate and the tanh of the current cell state. This process, illustrated in Figure 1, allows LSTMs to manage information flow and learn long-term dependencies.

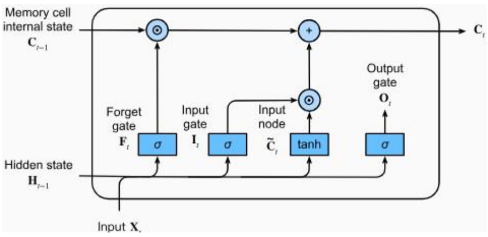
LSTMs have emerged as a powerful and promising technique for blood glucose prediction. Ongoing research focuses on addressing the challenges and developing more robust, personalized, and clinically useful LSTM- based prediction systems.



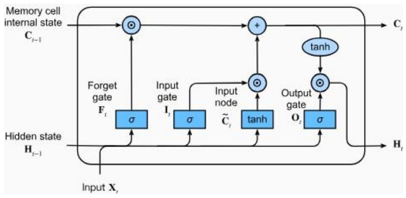
a. Forget gate, Input gate and Output gate



b. Input node



c. Memory Cell internal state



d. Hidden state

FC layer with activation Function Element Operator Copy Concatenate

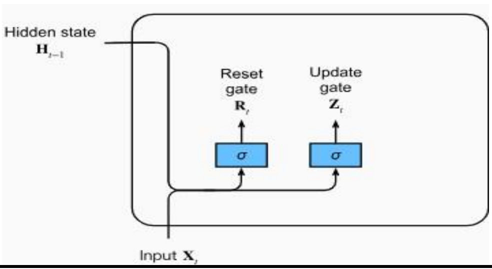
Fig 1: Computing different states of LSTM model

5.2. Gated Recurrent Unit (GRU)

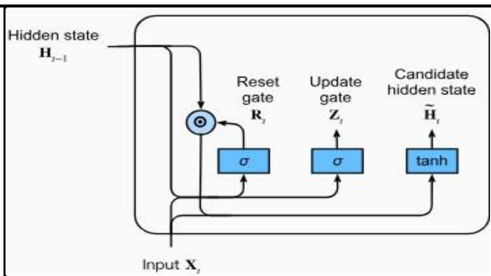
Gated Recurrent Units (GRUs) are another type of recurrent neural network (RNN) architecture that has gained significant traction in time series forecasting, including blood glucose prediction. They were introduced as a simplification of the Long Short-Term Memory (LSTM) networks, aiming for similar performance with a less complex structure.

GRU is a simplified version of LSTMs, designed for fast training and good handling of vanishing gradients. The forget and input gates combined into a single update gate. Subsequently, a reset gate and an update gate are employed to determine the extent to which the current hidden state is replaced with a new value.Candidate hidden state computed from the current input and the previous hidden state. This streamlined structure, as shown in Figure 2, makes GRUs computationally more efficient than LSTMs.

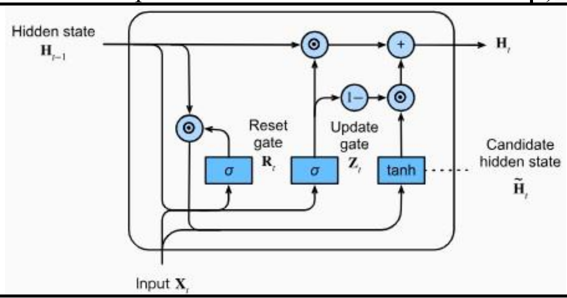
GRUs are simpler with fewer parameters, which can lead to faster training and potentially better generalization on smaller datasets. LSTMs, with their separate cell state and three gates, offer more control over the flow of information.



a. Reset and Update Gate



b) Candidate hidden state



c) Hidden state

Fig 2: Computing different steps of GRU Model

6. Proposed Framework

The architecture of our proposed Continuous BGL model is illustrated in Figure 3 which highlights of two major tasks as:

1. Forecasting future blood glucose levels using time series models (LSTM, GRU) and evaluating the accuracy of these forecasts.
2. Predicting diabetes symptoms using a classification model (SVM) and evaluating the performance of this prediction.

The list of parameters considered for this experimentation include CGM recording generated after each 5 minutes of interval, along with Heart rate, Breath rate, activity and Peak acceleration. All patients' data together combined by adding timestamp as index column and adding one more column of patient number. Missing values and outliers replaced with mean values of the respective attribute. We consider two different types of networks namely LSTM and GRU predict BGL. These models are defined by their architecture, specifically the number of layers and nodes per layer. To mitigate the vanishing gradient problem, we employed GRU and LSTM models. Furthermore, we optimized the models by exploring various hyper parameters, including the optimization algorithm, activation function, batch size, and learning rate. The BGL predictions were carried out for 3, 5 and 10 minutes of horizon. RMSE, MAE and MAPE metrics were used for evaluating performance of three models. Predicted glucose values are further categorized into diabetes symptoms (hypoglycemia, regular, prediabetes, Mild hyperglycemia, Moderate hyperglycemia and severe hyperglycemia) and its consequences using SVM discussed in table1. Finally the SVM model performance is measured by evaluating performance metrics.

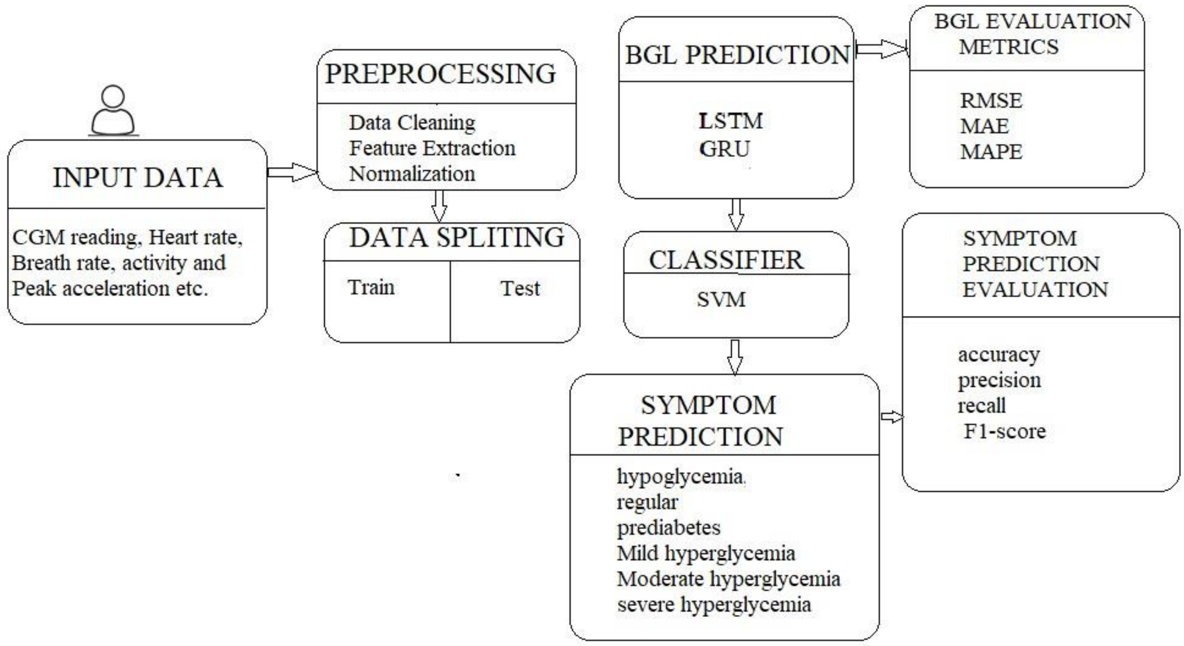


Fig 3: Architecture of the BGL and Diabetes

7. Result and Discussion

Blood glucose level forecasting is the process of predicting an individual's future blood BG levels based on various input data and computational models. This is a important aspect of diabetes management, aiming to help individuals proactively avoid hyperglycemic and hypoglycemic events.

Figure 4 and 5 represents predicted glucose levels for single diabetic patients using LSTM and GRU model respectively. The graph presents **a** blood glucose level forecasting analysis over time using actual and predicted glucose values. It consists of four subplots comparing real-time glucose data with predictions made for short intervals (3, 5, and 10 minutes ahead).

It is observed that, 3–5 minutes glucose prediction is more reliable and closely matches actual data. 10 minutes Longer-term prediction introduces some error, which is expected due to the variability in glucose influenced by many dynamic factors (e.g., meals, insulin, and activity). These types of forecasts are crucial for building realtime glucose alert systems and automated insulin delivery algorithms.

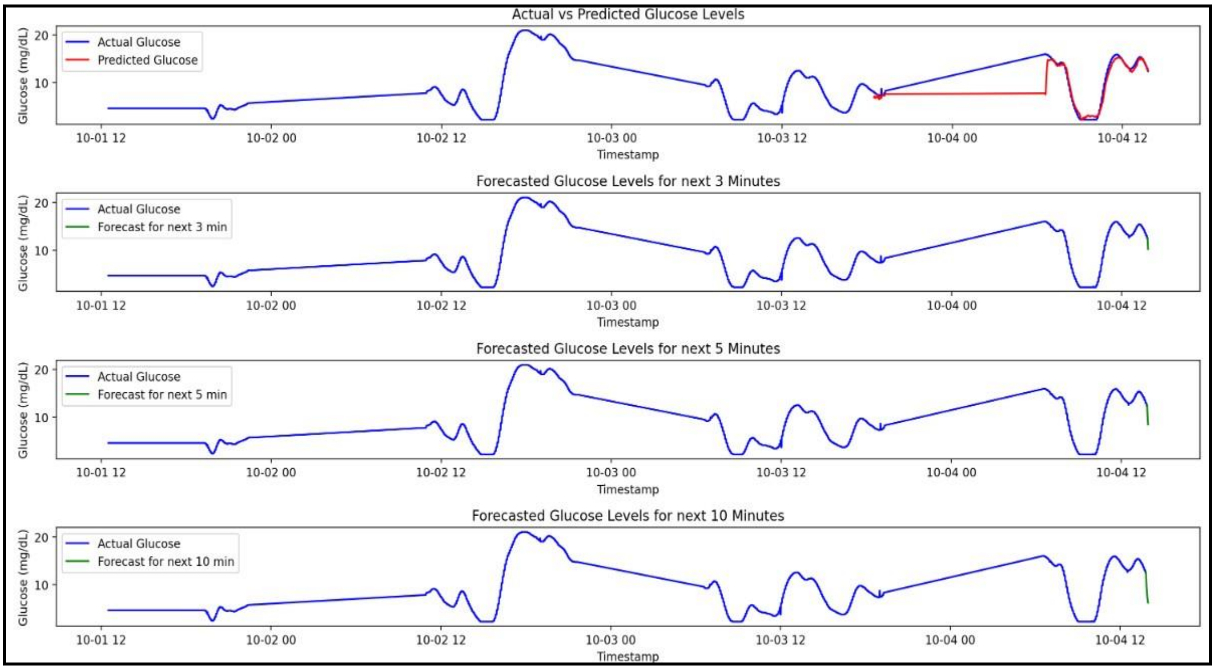


Fig 4: BGL prediction horizon for 3, 5 and 10 minutes for a single Diabetic patient using LSTM Model

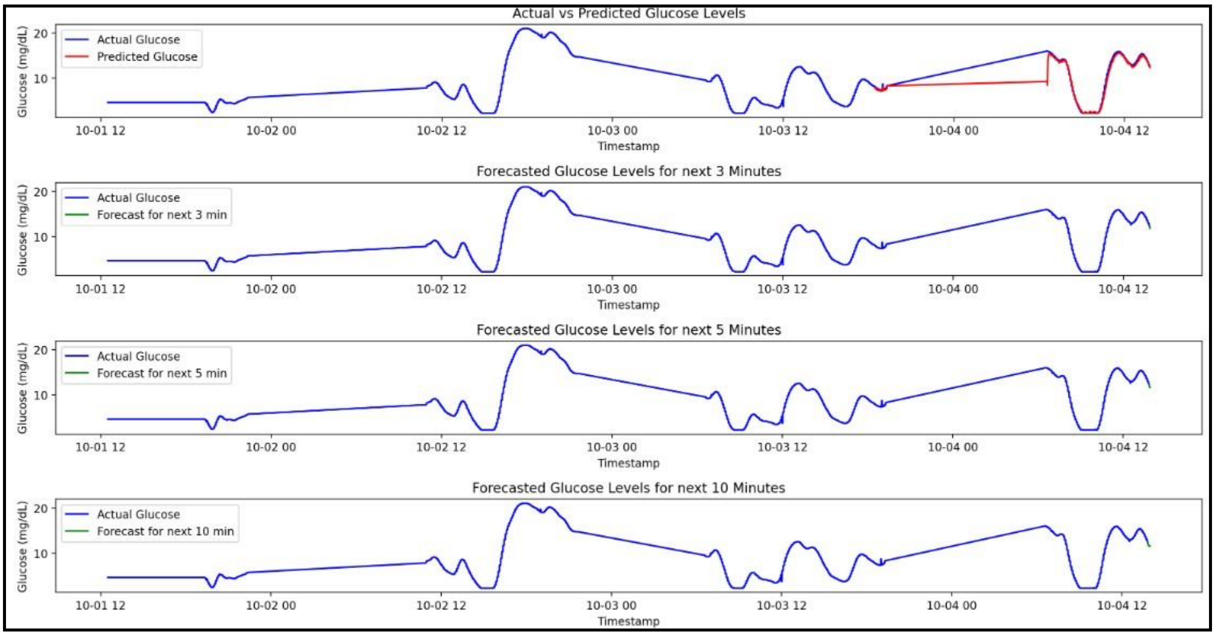


Fig 5: BGL prediction horizon for 3, 5 and 10 minutes for a single Diabetic patient using GRU Model

Figure 6 illustrates comparative results obtained for BGL prediction. Three models BGL Predicted in terms of RMSE, MAE, MAPE by comparing the performance of LSTM, GRU model.

The model achieved relatively low RMSE and MAE values, indicating good accuracy. We found that the GRU model performed well with RMSE 0.165, MAE 0.133 and 1.605 MAPE. Whereas values for evaluation metric MAPE are quite higher as compared to evaluation metric RMSE and MAE.

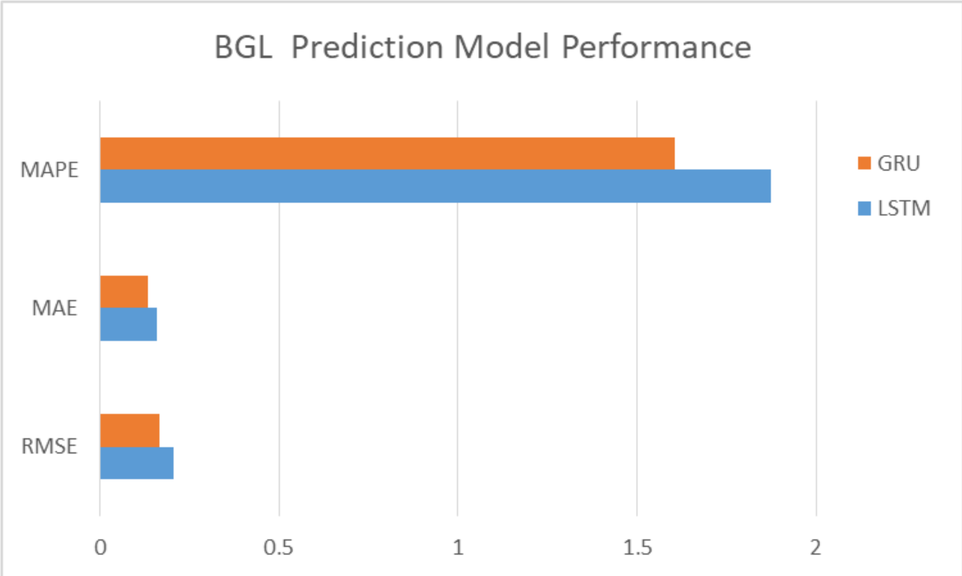


Fig 6: Statistical testing result of LSTM, GRU Model for BGL Prediction

In addition to this we also generated a classification result for predicted Diabetes symptoms along with its consequences. The SVM model outperformed diabetes symptoms. Using SVM we got 99.27% accuracy, precision, recall and F1-score. We compared our study with an existing system where the Bhimireddy et al. [21] obtained RMSE values for sequence-to-sequence blood glucose prediction models at 30 Minutes horizon using LSTM, BiLSTM and CNN-LSTM as 20.8, 20.6 and 21.1 respectively for 5 subjects.

Following figure 7 displays a Confusion Matrix for a SVM model that has been trained to classify diabetes symptoms into six different categories (represented by the numerical labels 0 through 5) as mentioned in table 1.

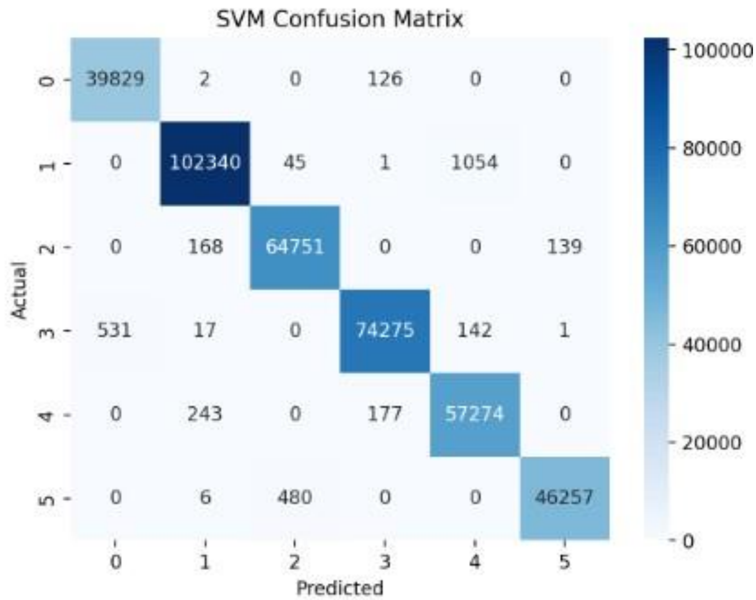


Fig 7: SVM confusion Matrix for classifying Diabetes Symptoms

8. Conclusions

Blood glucose prediction stands as a pivotal and rapidly advancing field within diabetes management. Driven by the increasing prevalence of the condition and the availability of real-time data from CGM systems, significant progress has been made in developing methodologies to forecast future glucose levels.

The rapidly growing field of BG prediction holds immense promise for improving the lives of diabetics, offering a powerful tool for proactive and personalized care. Prediction of BGL can help individuals to take early precautions and manage their BGLs. For BGL prediction we got RMSE 0.165, MAE 0.133 and 1.605 MAPE. Study shows that for T1DM patients GRU performed better model than LSTM. Study also extended to predict Diabetes symptoms and its consequences. Predicted BGL categorized into a total six categories based on glycemic events. We achieved 99.27 % accuracy for predicting diabetes symptoms using SVM. In conclusion, this study empowers individuals with T1DM to manage their condition and mitigate the risks of both hypoglycemic and hyperglycemic episodes. This model has the potential to significantly improve diabetes management if made available to doctors. By providing personalized insulin dosage recommendations, it could empower both doctors and patients to achieve better blood sugar control and reduce the risks associated with diabetes. In future, work can be extended by Combining glucose data with meal and insulin dose and predicting horizon for 30 and 60 minutes by considering large patient dataset which can provide a more comprehensive understanding of diabetes management.

Declarations

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