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Investigating the Impact of Multiple Inputs on Predicting Glucose Level in Individuals with Type-1 Diabetes through Deep Learning Technique

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Abstract: Type-1 Diabetes is a chronic auto-immune disorder featured by the disability of human body to produce insulin, an enzyme helps to digest carbohydrates. Insulin works with the take-up of glucose from the circulatory system into cells. Without sufficient insulin, glucose aggregates in the blood, prompting hyperglycemia. Uncontrolled hyperglycemia, whenever left untreated, can bring about dangerous intricacies, which can harm the vital organs. Managing type-1 diabetes presents huge difficulties for impacted people, as it requires a sensitive equilibrium of insulin administration, sugar consumption, active work, and cautious observing of blood glucose levels. Despite the progress made in type-I diabetes management, challenges persist. Achieving optimal blood glucose control remains elusive for many individuals. Understanding the complex interplay between these variables and their impact on blood glucose regulation is vital for emerging more effective treatment strategies.

Accurate and timely prediction of glucose level plays a critical role in the effective management of diabetes. Through this paper we aim at investigating the impact of multiple inputs on forecasting of glucose level in individuals with type-1 diabetes by means of deep learning techniques. In our paper, we use the Long-Short-Term-Memory (LSTM) network to study the forthcoming blood glucose pattern when various combinations if inputs, previous blood glucose reading, insulin administrated and carbohydrate intake are provided as inputs. We used the ShanghaiT1DM dataset for the study.

Keywords: Diabetic Meletus, Prediction, Deep-Learning**,** Long-Short-Term Memory (LSTM), Diabetic Management.

I. INTRODUCTION

Diabetes mellitus is a tenacious metabolic disorder marked by preeminent echelons of glucose in the bloodstream. This condition arises due to a deficiency in producing insulin or inadequate absorption of insulin. It is a significant global scenario, imposing a substantial burden on healthcare systems. There are quite a few types of diabetes, with type-1 being one of the primary classifications.

Type-1 diabetes, otherwise known as insulin-dependent diabetes mellitus (IDDM), is an autoimmune disorder which principally affects children, adolescents, and young adults. The cause of type-1 diabetes is that, the immune system misleadingly destroys the beta cells, which is responsible for production of insulin in pancreas. This autoimmune demolition ends in the complete deficiency of insulin, thereby complicating the regulation of blood glucose level.

If left untreated, it may be advanced to a perilous condition called Diabetic Ketoacidosis (DKA). The management of type-1 diabetes requires a multidisciplinary approach, involving insulin therapy, regular blood glucose monitoring, adherence to a balanced diet, and engagement in physical activity. Advancements in technologies in the area of medical science, such as insulin pumps and continuous glucose monitoring systems, have improved diabetes management and enhanced quality of life for individuals with type-1 diabetes. Efforts are being made to better educate patients, their families, and healthcare professionals about type-1 diabetes to improve early detection, enhance self-care practices, and reduce the risk of complications.

Through this paper we are presenting a study on various factors affecting the glucose level in type-1 diabetic patients. Our study utilizes a dataset collected from the Shanhai TiDM dataset,[1] encompassing various demographic and clinical information, as well as continuous glucose monitoring data. We employ a model based on deep neural networks, precisely Long-Short-Term memory (LSTM), to analyse the relationship between multiple inputs and blood glucose levels. The models are trained to learn temporal dependencies and patterns in the data, enabling accurate prediction of future blood glucose levels. Providing different combinations of inputs such as age of the patient, previous blood glucose reading, insulin administrated and carbohydrate intake, the model is evaluated over a time period of 30, 45 and 60 minutes.

II. RELATED WORKS

According to existing studies, the methods for blood glucose prediction can be classified into physiological driven and data driven. Physiological driven methods involve widespread familiarity about the fundamental mechanism for each individual. Data driven approaches focus on the patient's recorded data such as CGM readings, meal intake, bolus insulin infusion rate etc.

In 1999, Bremer and Gough achieved a significant milestone by becoming the pioneers in forecasting forthcoming glucose levels through the utilization of past glucose measurements. Since then, many scientists made use of AI techniques to predict blood glucose level. However, there have been only a few works that have explored using deep learning techniques for the same purpose. Most of the existing works focus on predicting future blood glucose levels, given the current value as input.

One of the challenges in developing deep learning models for hypoglycemia prediction is the lack of large datasets of labelled data. Another challenge is the high dimensionality of the input data, which can make it difficult to train and interpret deep learning models.

Despite these challenges, there is some evidence that deep learning models can be effective in predicting blood glucose. For example, a study entitled "A Deep Learning Approach to Blood Glucose Prediction" by Mhaskar et al. (2020) showed that a deep learning model could predict the upcoming glucose levels up to one hour into the future with an accuracy of 90%. In this model they have used Deep Neural Networks studying the glucose level evaluations from the CGM along with the rate at which the value changes. [12]

In 2018, Taiyu Zhu created a model using Convolutional Neural Network to predict the future blood glucose using casual dilated CNN layers on a modified version of WaveNet. For a prediction horizon of 30 minutes this model showed RMSE of 7267 with a standard deviation of 2.52. [13]

Qingnan Sun suggested a prediction model with a single LSTM layer, a Bi-LSTM layer and a number of fully connected layers for forecasting blood glucose level over prediction horizons 15 minutes, 30 minutes, 45 minutes and 60 minutes (2018). They have used only the previous blood glucose value read from the CGM as input to the model. The model was accurate with maximum RMSE of 36.918 for 60 minutes PH. [4]

Kezhi Li, Chengyuan Liu, John Daniels, Pantelis Georgion and Pau Herrero proposed a model using a combination of CNN and RNN to predict blood glucose in 2019. [14] The model was evaluated on both simulated as well as clinical dataset samples. The model was observed to have an RMSE of 9.38 mg/L in the case of simulated data and 21.07 mg/L for the real clinical data for 30 minutes prediction horizon. For a PH of 60 minutes, it was 18.37 mg/L and 33.27 mg/L respectively.

In the same year, El Idrissi, Touria published a paper "Predicting Blood Glucose using LSTM Neural Network. It was a sequential model with an LSTM layer and two fully connected layers carried out on the real-life data of ten type-1 diabetic subjects. Compared to other models evolved during those times this model was observed to be better one with an RMSE of 12.38 mg/dL. [18]

In 2020, Taiyu Zhu proposed a learning model based on Dilated-Recurrent-Neural-Network (DRNN). This model also used both clinical as well as simulated datasets for training and testing. A deep recurrent neural network (DRNN) was trained on historical data from subjects affected with type 1 diabetes (T1DM). The length of the sequences was tuned to three values: 6, 12, and 18. The model demonstrated its lowest RMSE value at a sequence length of 12, where the RMSE was observed as 7.8 mg/dl with a standard deviation of 0.6 for simulated Type-1 diabetes mellitus (T1DM) subjects. For medical data, the model exhibited an average value of 18.9 mg/dl RMSE alongside a standard deviation of 2.6. [15]

In 2021, a study by Quchani, F., Ghasemi, S., & Jafari, M. aimed to propose an ANN based model for forecasting blood glucose levels in those diagnosed with juvenile diabetes. The model takes as input multiple time-domain features, including the previous blood sugar reading, insulin levels, and meal consumption. The model is trained using a backpropagation algorithm. From the results, it was obvious that the proposed model can foresee blood glucose levels precisely up to one hour into the future. The RMSE of the model was observed to be 2.82 for PH 15, 6.31 for PH 30, 10.65 for PH 45 and 15.33 for PH 60. [17]

Another study by Jaloli M, Lipscomb W, Cescon (2022), addressed the necessity of incorporating the behavioural patterns of type-1 patients for the prediction of future blood glucose level. They studied the effect of stress state and physical activity in blood glucose level quantifying these using raw acceleration and electro dermal activity collected through

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wearable devices. They evaluated their model with LSTM and a hybrid model with CNN and LSTM through time intervals of 30, 60 and 90 minutes. This predictive model has obtained Mean Absolute Error (MAE) of 9.13, 17.75, 31.85 respectively in, Root Mean Square Error (RMSE) of 12.35, 24.71 and 41.64 respectively for the three prediction horizons. [19]

In 2023, Chou C Y Hsu DY and Chou C-H predicted blood glucose level using different varieties of neural networks. The models underwent training using a dataset comprising variables such as pregnancy count, plasma glucose level, diastolic blood pressure, skinfold thickness, insulin level, body mass index, diabetes pedigree function, and age. collected from the outpatients of a a Taipei Municipal medical centre, especially women of age between 20 and 80. [20] The study concluded that the two-class boosted decision tree as the best model, with a score of 0.991as its area under the curve. [20]

Md Shahin Ali, Md Khairul Islam, A Arjun Das, D U S Duranta, Mst Farija Haque and Md Habibur Rahman conducted a study for selecting the best parameters for diabetes detection. They presented a tweaked random forest algorithm with best parameters and feature engineering for early detection of diabetes. The proposed model exhibited an accuracy of 95.83% with 5-fold cross validation and 90.68% without 5-fold cross validation. [21]

In this paper, we aim to explore the influence of different parameters, including carbs, insulin, CGM data, and age, on the prediction of blood glucose levels. Our study focuses on investigating how variations in these parameters impact the accuracy of blood glucose predictions. To achieve this, we systematically supply various combinations of these parameters as inputs to our prediction model. By rearranging and constructing a unique paragraph, we can delve into the intricate relationship between carbs, insulin, CGM data, age, and their collective influence on the predictive capabilities of blood glucose levels.

III. METHODS AND MATERIALS

The experimental study was conducted in multiple chunks, each chunk providing a single combination of inputs: age, previous blood glucose reading, insulin administrated, and carbohydrate intake. Predictions were made for future blood glucose across three different time horizons: 30 minutes, 45 minutes, and 60 minutes.

Here is a more detailed breakdown of the experimental study:

Inputs: The inputs to the experimental study were the age of the patient, previous blood glucose reading, insulin administrated, and carbohydrate intake. These inputs were provided in a unique combination for each chunk of the study.

Prediction horizons: The forthcoming blood glucose levels were projected across three distinct prediction intervals: 30 minutes, 45 minutes, and 60 minutes. Consequently, for each segment of the investigation, the model was conditioned to anticipate the blood glucose concentration at intervals of 30 minutes, 45 minutes, or 60 minutes subsequent to the introduction of input parameters.

Experimental design: The experimental study was designed in a way that would allow the researchers to assess the influence of each input on the impending blood glucose level. For example, the researchers could compare the predicted blood glucose levels for different levels of insulin administrated or carbohydrate intake.

A. Dataset

We used a subset of the Shanhai T1DM dataset for this study. The ShanghaiT1DM dataset is a collection of Continuous Data Monitoring (CGM) data of 12 patients affected with Type-1 Diabetes Mellitus (T1DM) in Shanghai, China. The data was collected in real-life conditions over a period of 3 to 14 days. The dataset includes the date and time of each CGM measurement, the blood glucose level at the time of each measurement, the amount of insulin administrated at times, the amount of carbohydrates ingested at the time of each measurement and other vital information such as age and gender. [1]

For the purpose of our study, the data was rearranged to include each insulin dose, Age, CGM measurement, and carbohydrate intake at the time of the event, along with the CGM readings after 30, 45, and 60 minutes. In order to preserve the privacy of the patients, the Patient Id was replaced by random numbering starting from 1001 to 1012. Additionally, the model training procedure involved allocating 80% of the available data for training purposes, while the remaining 20% was designated for testing and validation. A sample from the dataset is shown in Table 1

TABLE I. SUBSET OF SHANHAI T1DM DATASET

Patient Id	Age	carbs	cgm	insulin	PH 30	PH 45	PH 60
1001	66	84	117	9	127	126	117
1002	68	83	327	0	284	268	259
1003	68	81	171	6	178	187	217
1004	68	83	208	6	255	270	202
1005	37	80	223	6	230	244	252
1006	67	13	84	5	70	84	117
1007	58	0	158	7	140	121	97

B. Long-Short-Term-Memory (LSTM)

Long-Short-Term Memory (LSTM) is a powerful variant of Recurrent Neural Network (RNNs) that exhibits an exceptional ability to capture and retain important information over extended sequences of data. It can be best described as an intricate cognitive assistant, delicately preserving and selectively recalling crucial details from its memory vault.

LSTM possesses a specialized architecture instilled with a prominent capacity to overcome the vanishing or exploding gradient problem commonly encountered in traditional RNNs. Its unique design incorporates an intricate web of gates, resembling an intricate network of synaptic connections, that selectively control the flow of information within the neural structure. Fig: 1 shows the structure of a typical LSTM network.

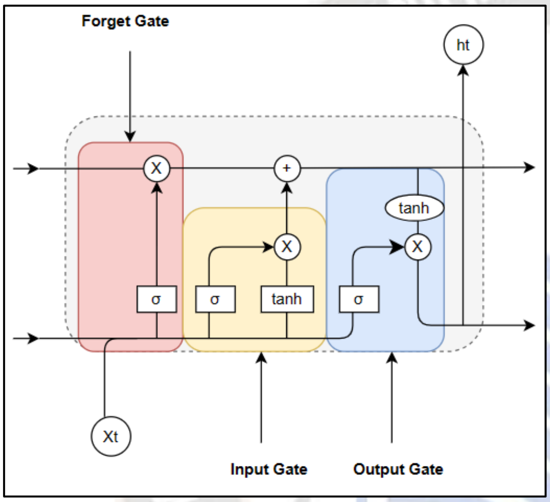

Figure 1. LSTM Unit of repeating layer

A typical LSTM is made up of four neural networks and a number of memory cells connected as a chain. Although Long Short-Term Memory (LSTM) shares a chain-like structure with Recurrent Neural Networks (RNNs), the recurrent module within LSTM possesses a distinct and unique architecture. A single LSTM unit consists of a cell, input and output gates, and a forget gate.

The input gate determines which value to be selected from the input to alter the memory. The forget gate finds out which features are to be rejected from that block. Considering the previous state(ht-1) and the current input (Xt), the sigmoid function outputs a number between 0 and 1 to indicate whether to omit or accept the number in the state of the cell.

C. Model Construction

The model used in this study is constructed using the Keras API from TensorFlow. It is a sequential model consisting of one LSTM layer followed by a dense layer. In order to avoid overfitting of data, 80% of the available data is utilized for training purposes, while the remaining 20% was designated for testing and validation.

The precision of blood glucose prediction relies on several factors, encompassing the eminence of data used for training, intricacy of the model, and the duration of prediction span. Depending upon the blends of features used, the model was executed in four different scenarios.

1. In the first case, four important factors which are the age of the patient, previous blood glucose, carbohydrate intake and insulin administrated are the input parameters to the model

2. Here the three main features that affect the future blood glucose is considered as inputs to the model. The model was trained on datasets containing the previous blood glucose, carbohydrate intake and insulin administrated at the time of the observation

3. In the third case, the model would be trained on the age of the person, former blood glucose value and the insulin dose administrated just after the last observation of CGM. This scenario could help to observe the variation in blood glucose pattern when the carbohydrate intake is not involved in the prediction process.

4. In the third setup only the former blood glucose observation had been taken into consideration.

In all this circumstances, the model was executed for three prediction horizons as mentioned early. For each case, after the respective set of features are extracted, the training and test input data is reshaped to have dimensions (samples, timesteps, features) where timesteps is 1 in this case.

A sequential model is built, adding an LSTM layer with 64 units and Rectified Linear Activation (ReLU) function. ReLu helps the model to learn non-linear dependencies easily. [3] It is calculated using formula given below: -

$$\text{ReLu}: f(x)=\text{maximum}(0,x)$$

It expects input with 1 row and three columns. Then a dense layer is added with a single output unit. The model is trained using the training data. It performs 12 epochs with a batch size of 8.

D. Performance Analysis Metrics

In this study we use the “Root Mean Square Error” (RMSE),[5] and “Mean Absolute Error” (MAE) [5] to evaluate and compare the performance of the prescribed model when executed in each of the scenarios mentioned. These metrics are the most common ways of assessing the performance of prediction models. RMSE is the square root of the mean square of the differences between the actual value and predicted value. [5] MAE is a degree of faults between two observations of the same phenomena.

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IV. RESULTS AND DISCUSSION

In this analysis, the LSTM-based model was executed in four different scenarios, each with its own set of inputs and corresponding results. The model was trained and tested using a dataset consisting of features related to age of the patient, blood glucose levels, namely carbohydrates intake, continuous glucose monitoring (CGM) data, and insulin levels.

A. Case 1

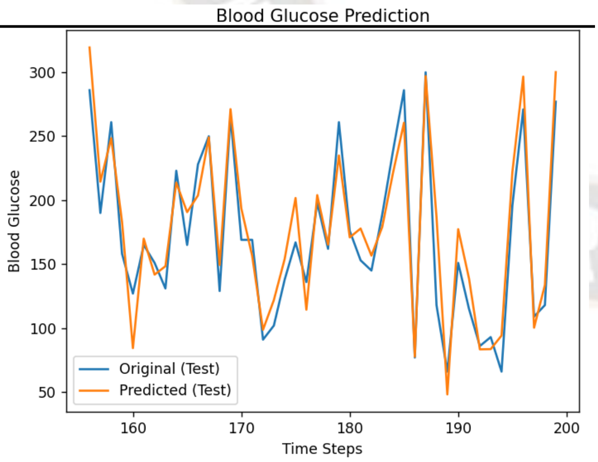
Inputs: Age, Carbohydrates, insulin dose and last CGM reading

For the first scenario, the model was trained on the initial 155 data points, and the predictions were made on the remaining 45 data points. The inputs used were the age of the patient, current CGM reading, carbo hydrate intake at the time of observation in grams and insulin administrated. The Mean Absolute Error (MAE) for this scenario when executed for PH values 30, 45 and 60 were 17.25, 28.55 and 68.53 respectively, indicating a minimum average deviation of approximately 17 units between the predicted and true values when the prediction horizon is 30 minutes. The general estimation of the model is listed in Table 2.

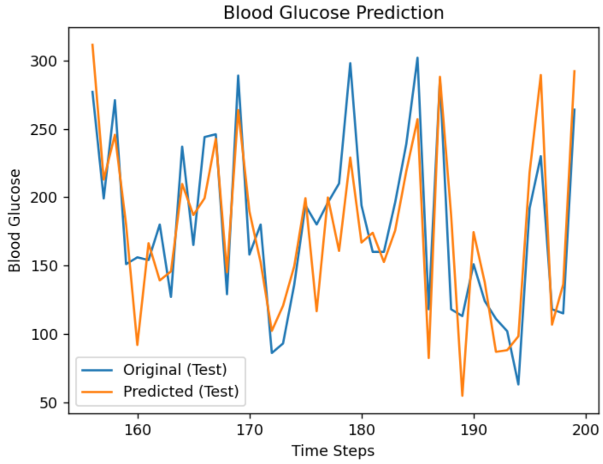
TABLE II. PERFORMANCE ANALYSIS OF THE MODEL WHEN INPUTS ARE AGE, CARBOHYDRATES, INSULIN DOSE AND LAST CGM READING

Evaluation Metric	PH 30	PH45	PH60
MAE	17.25	28.55	43.8
RMSE	21.19	33.52	68.53

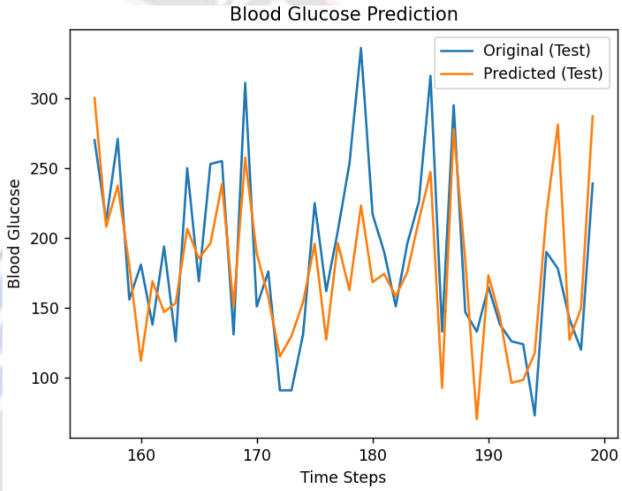
The model's predictions were plotted alongside the actual blood glucose levels, providing a visual representation of the performance and given below in Fig 2



2. a) For Prediction Horizon 30 minutes



2. b) For Prediction Horizon 45 minutes



2. c) For Prediction Horizon 60 minutes

Figure 2. : Actual Blood Glucose level plotted against prediction when inputs are Age, Carbohydrates, insulin dose and last CGM reading

B. Case 2

Inputs: Carbohydrates, insulin dose and last CGM reading

The data is divided such that 80% is used for training and 20% for testing the model. At this point, the carbohydrates intake, insulin dose and previous blood glucose are provided as inputs to the model and it was evaluated for the prediction horizons mentioned earlier. The overall performance of the model when executed in this scenario is given in Table 3.

TABLE III. PERFORMANCE ANALYSIS OF THE MODEL WHEN INPUTS ARE CARBOHYDRATES, INSULIN DOSE AND LAST CGM READING

Evaluation Metric	PH 30	PH45	PH60
MAE	18.18	28.66	35.67
RMSE	22.44	34.52	44.12

Fig 3 shows the graphical representation of the predictions plotted alongside the actual blood glucose values.

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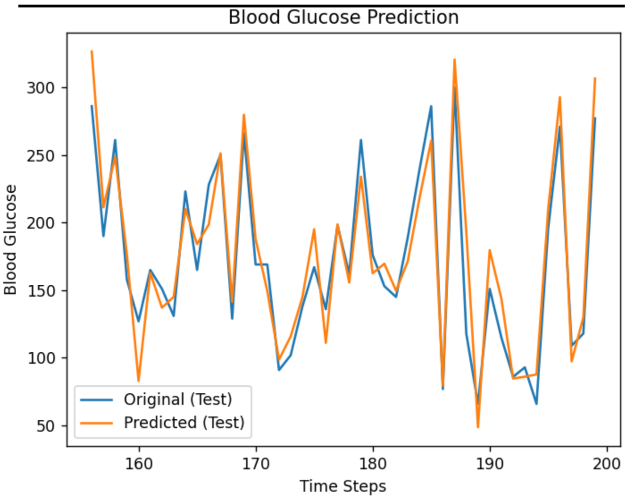
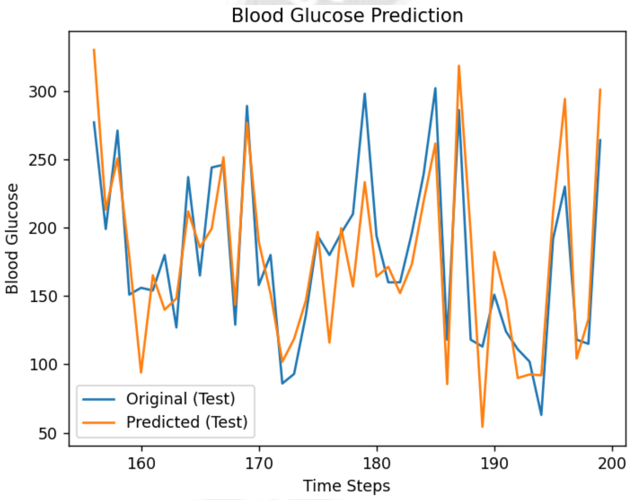
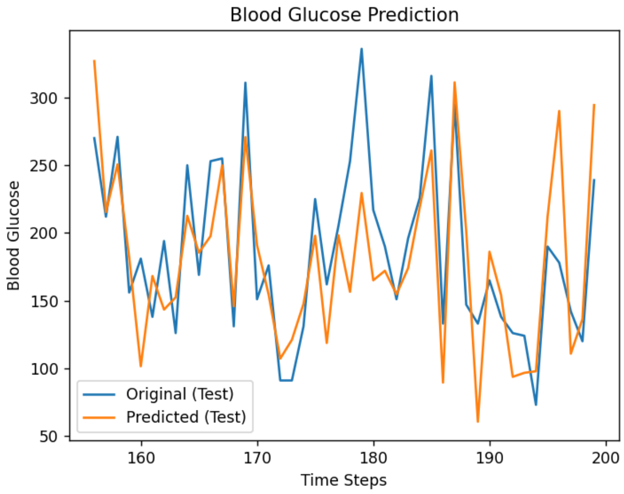


3. a) For Prediction Horizon 30 minutes



3. b) For Prediction Horizon 45 minutes



3. c) For Prediction Horizon 60 minutes

Figure 3. Actual Blood Glucose level plotted against prediction when inputs are Carbohydrates, insulin dose and last CGM reading

C. Case 3

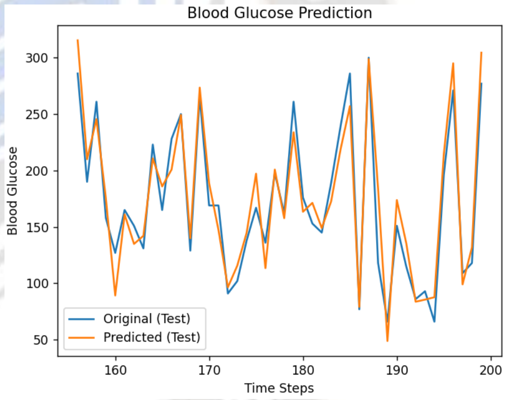
Inputs: Age, insulin dose and last CGM reading

The dataset was split into training and testing set as described in the earlier cases. Here a different combination of inputs is used; the age of the patient, current CGM value and the insulin dose administrated. When evaluated the predictions for PH 30, 45 and 60 minutes, this combination of inputs showed the minimum error rate. Table 4 describes the performance analysis of the model.

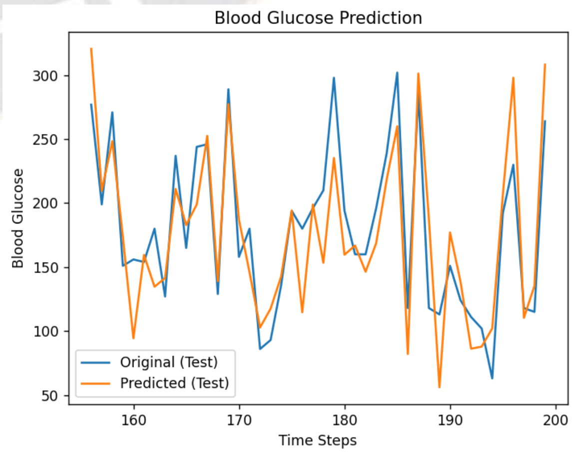
TABLE IV. PERFORMANCE ANALYSIS OF THE MODEL WHEN INPUTS ARE AGE, INSULIN DOSE AND LAST CGM READING

Evaluation Metric	**PH 30**	**PH45**	**PH60**
MAE	16.83	28.12	35.18
RMSE	20.52	38.10	43.56

The visual representation of the predictions was obtained, offering perceptions into the performance of the model performance in this specific scenario. And is shown in Fig: 4.



4. a) For Prediction Horizon 30 minutes



4. b) For Prediction Horizon 45 minutes

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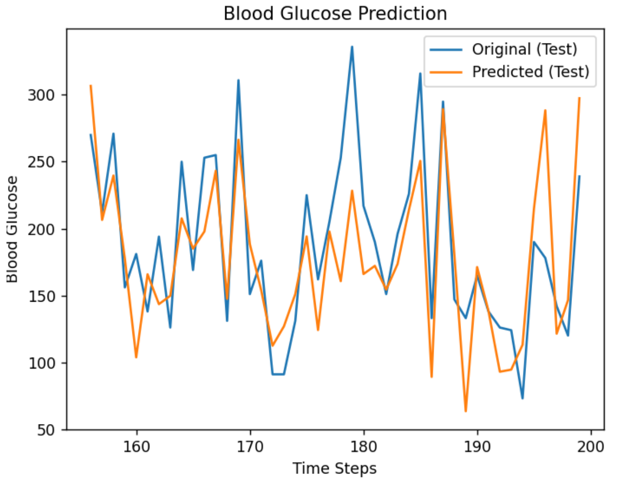


4. c) For Prediction Horizon 60 minutes

Figure 4. Actual Blood Glucose level plotted against prediction when inputs are age, insulin dose and last CGM reading

D. Case 4

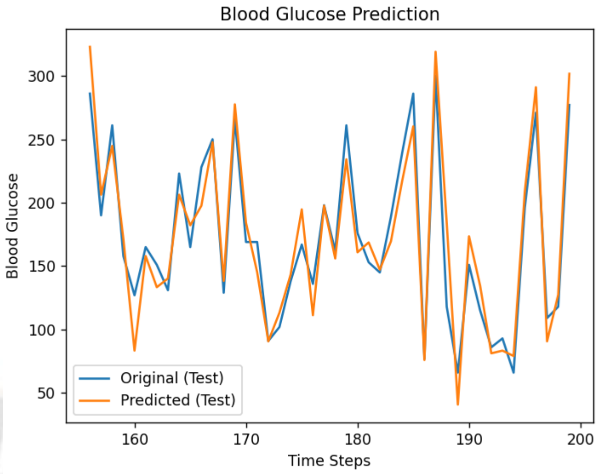
Inputs: last CGM reading

The fourth scenario also followed a similar pattern, with the model being trained on different subsets of the dataset and predictions being made accordingly. In this case only previous blood glucose is given as input to the model and observed the variation in blood glucose pattern. The performance of the model when previous blood glucose reading only is provided as input, can be understood by the MAE and RMSE values given in Table 5.

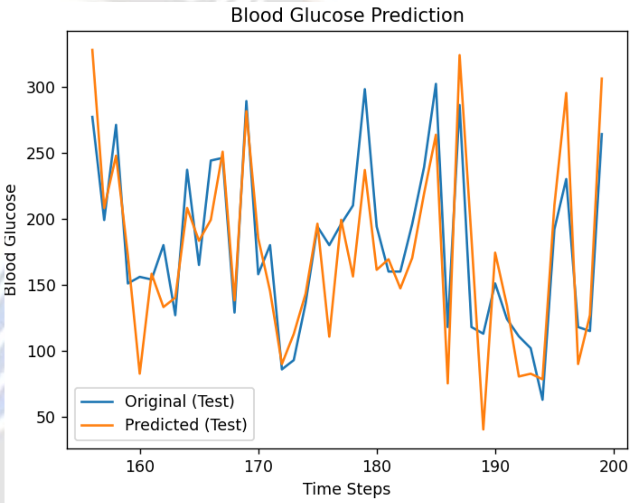
TABLE V. PERFORMANCE ANALYSIS OF THE MODEL WHEN INPUT IS THE LAST CGM READING

Evaluation Metric	PH 30	PH45	PH60
MAE	17.16	28.66	35.55
RMSE	20.17	35.33	46.14

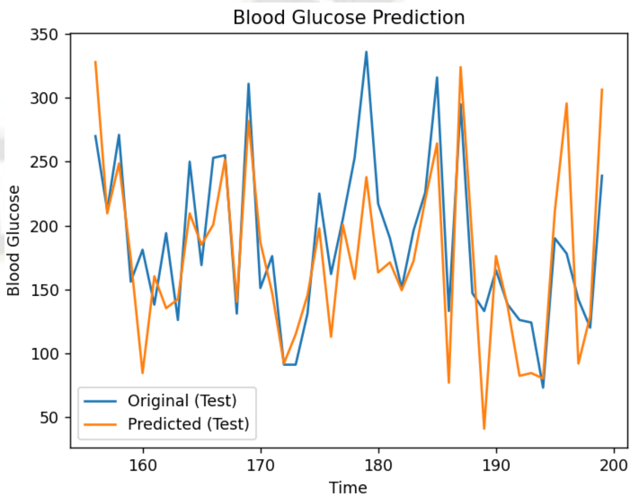
The predicted values along with the actual blood glucose level is portrayed in Fig: 5.



5. a) For Prediction Horizon 30 minutes



5. b) For Prediction Horizon 45 minutes



5. c) For Prediction Horizon 60 minutes

Figure 5. Actual Blood Glucose level plotted against prediction when input is the last CGM reading.

E. Result Analysis

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When we observe the prediction with respect to different combinations of input data, the model shows different level of performance. Also, in all the cases, prediction within 30 minutes show better performance. As the prediction horizon increases, the error rate also gets increased. Fig: 6 provides a visual representation of the overall performance of the model across different prediction horizons, namely PH30, PH45, and PH60 and Table 6 describes the comparison between the four scenarios in terms of RMSE and MAE.

Table 6 illustrates the performance metrics, specifically MAE and RMSE, for different scenarios (Cases 1 to 4) based on the inputs and prediction horizons (PH30, PH45, PH60). These performance metrics provide insights into the accuracy and predictive capabilities of the prescribed model for the specified combinations of input scenarios and prediction horizons. The specific impact of each input on the model's performance varies depending on the scenario.

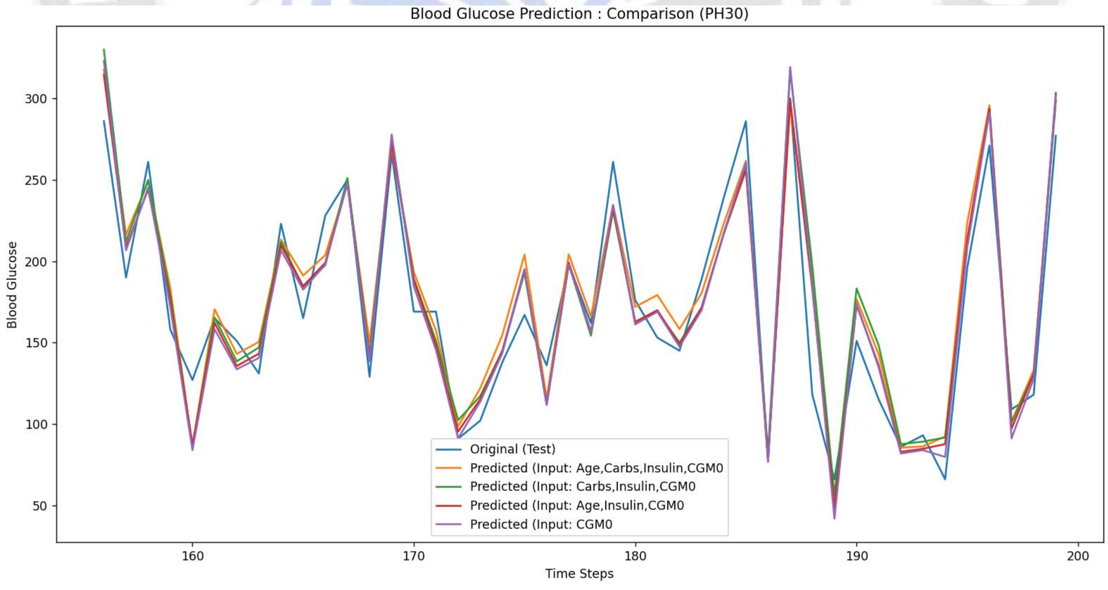
It can be observed that the model generally achieves lower MAE and RMSE for the cases where age is included in the input. In Case 1, where the inputs include age, carbs, insulin dose, and CGM reading, the model achieved an MAE of 17.25 for PH30, 28.55 for PH45, and 43.8 for PH60. The corresponding RMSE values were 21.19, 33.52, and 68.53, respectively.

Moving on to Case 2, which includes only carbs, insulin dose, and CGM reading as inputs, the MAE values were slightly higher compared to Case 1, with values of 18.18 for PH30, 28.66 for PH45, and 35.67 for PH60. The RMSE values also increased, measuring 22.44, 34.52, and 44.12, respectively.

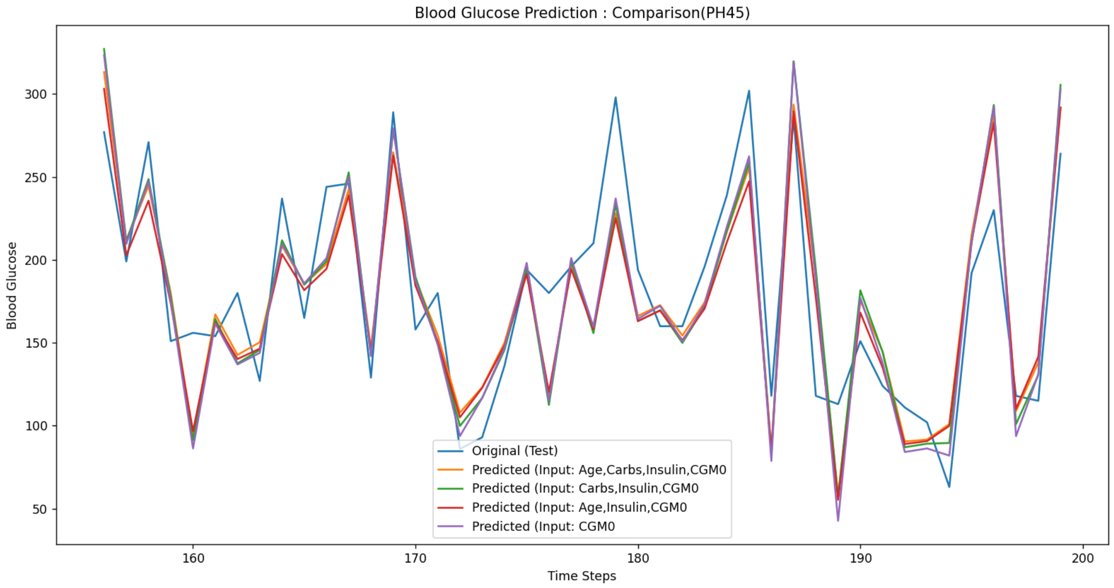
In Case 3, age, insulin dose, and CGM reading were the inputs. The model achieved an MAE of 16.83 for PH30, 28.12 for PH45, and 35.18 for PH60. The RMSE values were 20.52, 38.1, and 43.56, respectively.

Finally, Case 4 considered only the CGM reading as the input. The MAE values were 17.16 for PH30, 28.66 for PH45, and 35.55 for PH60. The corresponding RMSE values were 20.17, 35.33, and 46.14, respectively.

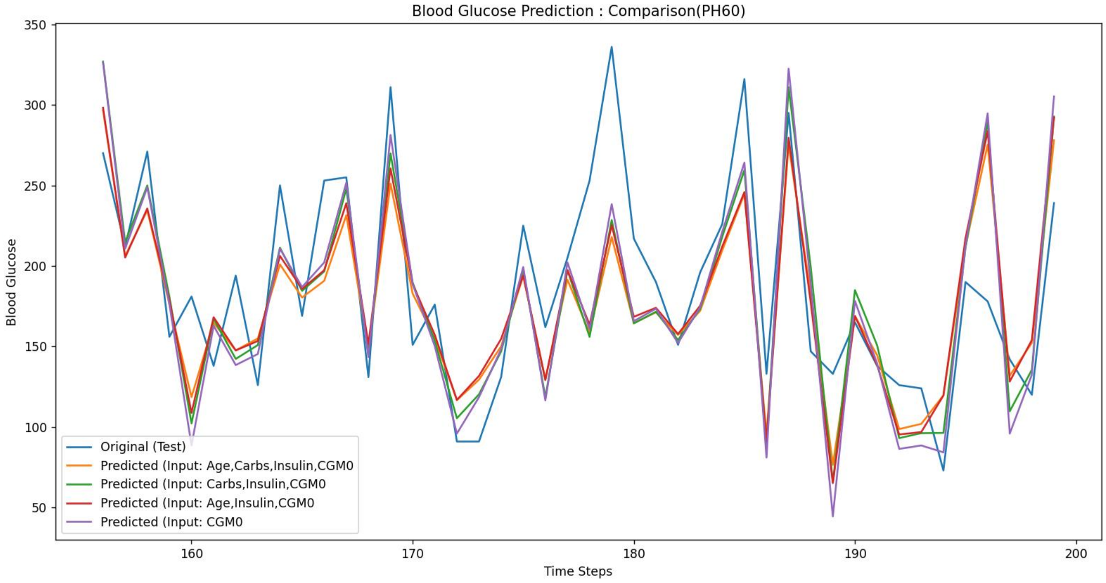
In all the cases, the model was observed to have minimum error rates for prediction horizon of 30 minutes and highest error rate is when the prediction horizon is 60 minutes. Among all the combinations of inputs, the one with age of the patient, CGM reading and insulin dosage was observed to have the minimum MAE value of 16.83



a) Overall Performance for PH30



b) Overall Performance for PH45



c) Overall Performance for PH60

Figure 6. Overall performance of the model across different prediction horizons, PH30, PH45, and PH60.

TABLE VI. COMPARISON OF OVERALL PERFORMANCE EVALUATION OF THE MODEL FOR THE FOUR SCENARIOS

Case	Inputs	Performance Metric	PH30	PH45	PH60
1	Age, Carbs, Insulin Dose, CGM reading	MAE	17.25	28.55	43.8
		RMSE	21.19	33.52	68.53
2	Carbs, Insulin Dose, CGM reading	MAE	18.18	28.66	35.67
		RMSE	22.44	34.52	44.12
3	Age, Insulin Dose, CGM reading	MAE	16.83	28.12	35.18
		RMSE	20.52	38.1	43.56
4	CGM reading	MAE	17.16	28.66	35.55
		RMSE	20.17	35.33	46.14

V. CONCLUSION

There are variants of techniques available using artificial Intelligence for forecasting the blood glucose levels of patients affected with type-1 diabetes. It is a very necessary application nowadays as the quantity of affected community is very huge. All such methods differ in the method they follow, algorithm used, the variety of input used etc. It's also very important to determine the effect of various inputs in the behaviour of the prediction. So here, we propose a study which observes the variation in predicted blood glucose pattern with respect to the change in combination of the input features.

From prior studies, it is apparent that carbohydrates intake, previous blood glucose level and insulin administrated are vital factors for determining the future blood glucose level. But in our study, it was observed that, even by inputting only the previous blood glucose level can predict the upcoming sugar level with remarkable accuracy. But when carbohydrate intake is included in the input, age is also necessary, since the insulin correction (the amount of glucose converted to glycogen by the effect of 1 unit of insulin) of a person varies by age. With respect to our study, we suggest a model which uses Age, Insulin Dose and CGM reading can provide better prediction results. Compared to the other input combinations, this case produced the better result.

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