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Bi-LSTM-Based Multivariate Time Series Model for Predicting Blood Glucose in Type-1 Diabetes

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Abstract: Proactive glucose level prediction offers a vital advantage in the daily management of Type-1 diabetes, where unexpected fluctuations can lead to dangerous hypoglycemic or hyperglycemic events. This work introduces a Bi-LSTM-based deep learning model tailored for multivariate time series forecasting, targeting 30-minute and 60-minute blood glucose prediction horizons. Unlike univariate models, our approach incorporates multiple physiological signals—such as CGM values, insulin dosages (basal and bolus), and carbohydrate consumption—to capture the underlying temporal and causal relationships affecting glucose regulation. The model is trained on the OhioT1DM dataset, which comprises high-resolution (5-minute interval) data from 12 Type-1 diabetic subjects. The bidirectional architecture enables the model to process sequential patterns in both forward and backward directions, improving its sensitivity to evolving trends and sharp variations. Evaluation results highlight the model's ability to deliver accurate short- and mid-term predictions, thus supporting timely therapeutic actions and personalized diabetes care.

Keywords: *Diabetes Management; Blood Glucose Prediction; CGM Devices; Deep Neural Network, BiLSTM.*

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I. INTRODUCTION

Type-1 diabetes mellitus (T1DM) is a chronic autoimmune condition characterized by the inability of the pancreas to produce insulin, requiring patients to rely on external insulin administration to regulate blood glucose levels[1].To Maintain glucose within a safe physiological range is vital because both hypoglycemia (low glucose) and hyperglycemia (high glucose) can lead to acute and long-term complications. Despite the availability of continuous glucose monitoring (CGM) systems and insulin pumps, real-time decision-making remains a challenge due to the dynamic nature of glucose metabolism influenced by multiple interdependent factors such as insulin dosage, meal intake, physical activity, and circadian rhythms[2,3].

Recent advancements in artificial intelligence and deep learning have shown promise in enhancing the predictive capabilities of blood glucose monitoring systems. Particularly, recurrent neural networks (RNNs) and their variants have been employed to model temporal dependencies in glucose trajectories. However, traditional univariate models often fall short in capturing the complex physiological interactions that drive glucose dynamics. A multivariate time series approach, incorporating relevant variables such as basal and bolus insulin, carbohydrate intake, and CGM readings, can significantly improve prediction accuracy.

In this study, we propose a Bidirectional Long Short-Term Memory (Bi-LSTM) model tailored for multivariate time series forecasting to predict future blood glucose levels at 30-minute and 60-minute horizons. The Bi-LSTM architecture is designed to learn sequential patterns in both forward and backward temporal directions, enabling the model to capture richer contextual information from the input features. The model is trained and evaluated on the OhioT1DM dataset[4], which contains high-resolution data collected at 5-minute intervals from 12 individuals diagnosed with T1DM. By leveraging multiple physiological inputs and deep sequential learning, our framework aims to provide timely and reliable glucose forecasts that can support early intervention, reduce glycemic variability, and ultimately improve the quality of life for individuals living with Type-1 diabetes.

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II. RELATED WORK

Blood glucose prediction has emerged as a key research focus for improving diabetes management, particularly for Type-1 diabetes where the risk of hypo- and hyperglycemia remains high. A variety of machine learning and statistical models have been applied to forecast glucose levels at 30- and 60-minute horizons. Early methods including Support Vector Regression (SVR), ARIMA, and persistence algorithms provided simple and interpretable solutions, but their accuracy often fell short of the threshold required to manage critical glycemic events effectively [5]. To address evaluation consistency, the GLYFE Benchmark introduced a standardized framework for assessing glucose prediction models using multivariate inputs like glucose, insulin, and meal data [6]. It offers reproducible testing environments but is currently limited to datasets focused on Type-1 diabetes, which restricts broader applicability. Deep learning models have also made significant advances. GluNet, for example, utilizes a deep CNN architecture with dilated convolutions and gated activations to provide probabilistic glucose forecasts. While effective in structured clinical settings, its sensitivity to noisy or missing data limits its reliability in real-world applications [7].

Comparative studies of neural network models show that BiLSTM consistently outperforms LSTM, convolutional LSTM, TCNs, and sequence-to-sequence models for both short- and mid-term glucose prediction [8]. Simpler recurrent architectures, such as RNNs, have also been explored for their low computational complexity and minimal feature engineering, although their reliance solely on glucose history may constrain predictive power [9]. Enhanced versions of LSTM and BiLSTM further improved prediction quality, yet challenges persist in accurately detecting extreme glycemic events [10].

Personalized data-driven models trained on CGM and self-collected health data have demonstrated promise for tailoring forecasts to individual patients [11]. However, these models require large, clean datasets and robust preprocessing to handle variability and missing values. To stabilize CGM input data, Kalman smoothing techniques have been integrated, helping reduce sudden spikes or dips while maintaining signal integrity. Still, excessive smoothing can suppress essential fluctuations needed for accurate forecasting [12]. The BGLP Challenge, using the OhioT1DM dataset, benchmarked a range of models, including deep residual RNNs with multivariate inputs. These models demonstrated strong forecasting performance but faced limitations in scalability and dataset diversity [15]. Another approach employed pre-trained RNNs on the OpenAPS dataset and fine-tuned them on OhioT1DM, improving generalization on smaller datasets but with performance variability tied to the quality of pre-training data [16].

Innovative architectures such as a modified GAN model showed promise in learning patient-specific glucose dynamics, although they struggled with hypoglycemia prediction [17]. The MS-LSTM framework, designed to capture both short- and long-term patterns, also faced issues when dealing with sudden glucose shifts and missing data [18]. Attention-based LSTM models addressed generalizability across patients and showed resilience to incomplete sequences, though validation across larger and more diverse populations remains limited [19]. In contrast to deep learning, latent variable-based linear models offered more interpretable structures but performed poorly under real-time, noisy conditions, underscoring the importance of integrating physiological insights and robust denoising methods [20]. Multitask learning models like MTL-LSTM incorporated glucose, insulin, and carbohydrate intake for personalized predictions, achieving efficient results but limited by the small number of patients in test sets and sparse demographic representation [21]. Similarly, models such as E-TFT showed high accuracy with a minimal feature set and were optimized for hardware deployment, though their use has yet to be validated in clinical environments [22].

Collectively, these studies highlight the evolution of blood glucose forecasting from simple statistical models to advanced deep learning architectures. A notable trend is the shift toward context-aware, adaptive systems that incorporate multivariate physiological data, temporal dependencies, and patient-specific patterns. These advancements set a strong foundation for developing robust models like the BiLSTM-TSBGP, which not only enhances predictive accuracy but also improve resilience to missing data and real-world usability in continuous glucose monitoring environments.

III. METHODOLOGY

This study presents a systematic approach to forecasting blood glucose levels in individuals with Type-1 diabetes using a Bidirectional Long Short-Term Memory (BiLSTM) deep learning model. The methodology is divided into six main components: dataset description, data preprocessing, feature selection, model architecture, model training and validation, and implementation details.

A. Dataset Description

The research utilizes the OhioT1DM dataset, which contains high-resolution physiological and behavioral data collected from 12 individuals diagnosed with Type-1 diabetes. This dataset includes continuous glucose monitoring (CGM) readings captured at 5-minute intervals, along with timestamped records of insulin administration (both basal and bolus), carbohydrate consumption, meal entries, and physical activity logs. The dataset represents real-world, free-living conditions over multiple days for each subject, making it suitable for building personalized and generalizable glucose prediction models.

B. Data Preprocessing

Preprocessing the raw time series data is critical to ensuring consistency and optimizing model performance. First, time alignment was performed to synchronize all sensor readings and event logs to a common 5-minute interval, matching the CGM data frequency. Missing values in CGM signals were imputed using linear interpolation, while missing insulin and carbohydrate entries were either forward-filled or removed depending on clinical context and frequency. To facilitate effective learning, all continuous variables such as glucose, insulin doses, and carbohydrate intake were

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normalized using min-max scaling into a range of [0, 1]. Finally, a sliding window approach was employed to structure the data into supervised learning samples, where each input sequence consists of 6 previous time steps (30 minutes) used to predict future glucose levels at 30-minute and 60-minute horizons.

C. Feature Selection

The model incorporates a multivariate time series input, capturing a range of physiological features known to influence glucose dynamics. These include: (i) CGM values, (ii) basal insulin delivery rates, (iii) bolus insulin doses, and (iv) carbohydrate intake. Additionally, temporal context features such as the hour of day and day of week were encoded as cyclic variables to reflect circadian influences on glucose metabolism. The inclusion of these features allows the model to learn complex relationships between inputs and future glucose trends, thereby improving forecasting accuracy.

D. Model Architecture: BiLSTM

The deep learning model is based on a Bidirectional Long Short-Term Memory (BiLSTM) architecture, selected for its capacity to model sequential data with temporal dependencies in both forward and backward directions. The model starts with an input layer that accepts multivariate sequences of past time steps. It is followed by multiple stacked BiLSTM layers, grouped into two blocks—each consisting of four layers with 256 and 128 hidden units respectively—designed to extract hierarchical temporal patterns. After each BiLSTM layer, a dropout layer with a rate of 0.2 is applied to prevent overfitting. The output from the stacked layers is passed through a dense layer to project the learned features into the prediction space. The final output layer consists of six units representing forecasted glucose values for the next 30 minutes (i.e., six 5-minute intervals). The model was implemented using TensorFlow/Keras, with ReLU activation functions and compiled using the Adam optimizer.

E. Model Training and Validation

The model was trained using the Mean Squared Error (MSE) loss function, which penalizes large prediction errors more heavily and is appropriate for continuous value forecasting. To evaluate the model's performance, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used as primary metrics. Each patient's data was split chronologically into a 70% training set and a 30% testing set, maintaining the temporal structure of the sequences. Additionally, a leave-one-subject-out cross-validation strategy was explored to assess the model's generalization capability across unseen subjects, simulating real-world deployment in personalized care scenarios.

F. Evaluation Matric

To evaluate the predictive performance of our model in the context of blood glucose prediction, we utilize metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Clinical Error Grid Analysis (EGA), to assess the prediction ability of the model with respect to blood glucose prediction. RMSE is the square root of the average squared difference between predicted values and actual values. A lower RMSE indicates better average prediction performance. RMSE is an ideal measure for this model because it penalizes larger errors more heavily, reflecting the critical need for accurate blood glucose predictions. Additionally, RMSE's interpretability in the same units as blood glucose levels (e.g., mg/dL) makes it a clear and meaningful metric for evaluating model performance. MAE is a key metric for measuring the average magnitude of prediction errors without emphasizing larger errors. Unlike RMSE, it treats all errors equally, providing a straightforward measure of typical prediction error. MAE's interpretability in the same units as blood glucose levels (e.g., mg/dL) makes it practical and meaningful for assessing model accuracy. The RMSE and MAE formulation can be illustrated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where, n is the number of observations, yi is the actual blood glucose value and $\hat{y}$i is the predicted blood glucose value, both measured in mg/dl. However, we acknowledge that RMSE alone does not fully capture the clinical implications of the predictions. To address this limitation, we incorporate Clarke Error Grid Analysis (EGA) to evaluate the clinical accuracy and safety of the model's outputs. By leveraging these complementary metrics, we aim to provide a comprehensive assessment of the model's predictive capabilities, ensuring both statistical robustness and clinical relevance.

G. Implementation Details

The model was trained using a sequence length of 6 time steps (30 minutes of historical data) to predict blood glucose values for both 30-minute and 60-minute prediction horizons. Training was conducted in mini-batches of size 32, using the Adam optimizer with a learning rate of 0.001. A maximum of 100 epochs were run with early stopping enabled to avoid overfitting and reduce training time. The model architecture includes approximately 275,910 trainable parameters, striking a balance between representational capacity and computational efficiency.In summary, the BiLSTM-based modeling framework is designed to capture temporal dependencies and multivariate interactions within physiological data, enabling timely and accurate prediction of future glucose levels. This capability is vital for early interventions and risk mitigation in the daily management of Type-1 diabetes.

IV. EXPERIMENTAL RESULTS

This section presents the experimental evaluation of the proposed Bi-LSTM-based deep learning model tailored for multivariate time series for continuous blood glucose prediction using the OhioT1DM dataset.

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Table 1: Proposed Multi Variate BiLSTM Model Results of OhioT1DM Dataset

ID	*pH-30 min*		*pH-60 min*	
	RSME (mg/dl)	***MAE (mg/dl)***	***RSME (mg/dl)***	***MAE (mg/dl)***
540	15.56	12.42	25.72	25.54
544	9.84	7.85	10.61	8.76
552	13.67	10.91	15.58	12.25
567	22.62	18.05	22.46	20.78
584	24.52	19.56	31.36	29.67
596	8.45	6.72	3.81	4.74
559	11.55	9.32	13.73	11.81
563	8.79	7.18	6.07	7.29
570	25.65	21.98	9.8	12.38
575	9.65	7.75	12.79	14.55
588	12.16	9.89	18.48	22.69
591	15.43	12.30	27.01	29.61
Mean	**14.82**	**11.99**	**16.45**	**16.68**

The experiments were conducted in accordance with the design pipeline detailed in methodology Section , including multivariate feature selection, data preprocessing, BiLSTM model architecture, and training configuration. The model's effectiveness was assessed at 30-minute and 60-minute prediction horizons using standard regression metrics—Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) and results re shown in Table 1.

The effectiveness of Bi-LSTM-based deep learning model tailored for multivariate time series for continuous blood glucose prediction approach was further benchmarked against a Multitask Learning LSTM (MTL-LSTM) model[22]. A summary of this comparative analysis is provided in Table 2. Across both short- and medium-term forecasts, our model consistently achieved lower prediction errors. Its bidirectional learning structure allows it to better capture contextual dependencies, offering enhanced prediction reliability compared to the single-directional design of MTL-LSTM[22].

Table 2 Comparative Analysis of Proposed Model And MTL-LSTM Model

ID	Test Sample	Multi Variate BiLSTM Model				MTL-LSTM			
		RSME (mg/dl)		***MAE(mg/dl)***		***RSME (mg/dl)***		***MAE(mg/dl)***	
		pH-30 min	***pH-60 min***	***pH=30min***	***pH-60 min***	***pH-30 min***	***pH-60 min***	***pH-30 min***	***pH-60 min***
540	2884	15.56	25.72	12.42	25.54	17.35	36.39	12.07	26.96
544	2704	9.84	10.61	7.85	8.76	14.66	28.42	9.45	19.81
552	2352	13.67	15.58	10.91	12.25	13.01	27.77	9.19	20.61
567	2377	22.62	22.46	18.05	20.78	20.62	38.13	11.95	25.76
584	2653	24.52	31.36	19.56	29.67	21.25	36.65	12.88	25.92
596	2731	8.45	3.81	6.72	4.74	13.05	25.78	9.03	18.41
Mean		**15.77**	**18.25**	**12.58**	**16.95**	**16.65**	**32.19**	**10.76**	**22.91**

Overall, the Bi-LSTM-based deep learning model tailored for multivariate time series for continuous blood glucose prediction achieved the lowest RMSE, recording 15.77 mg/dl for a prediction horizon (pH) of 30 minutes and 18.25 mg/dl for a pH of 60 minutes. These values are significantly lower than the latest models [22]. Figure-1 and figure-2 illustrates the actual versus predicted blood glucose levels for the test data of OhioT1DM subject 540 and subject 544 for pH=60 min. The graph demonstrates that our model is sufficiently accurate in predicting both hypoglycemia and hyperglycemia events.

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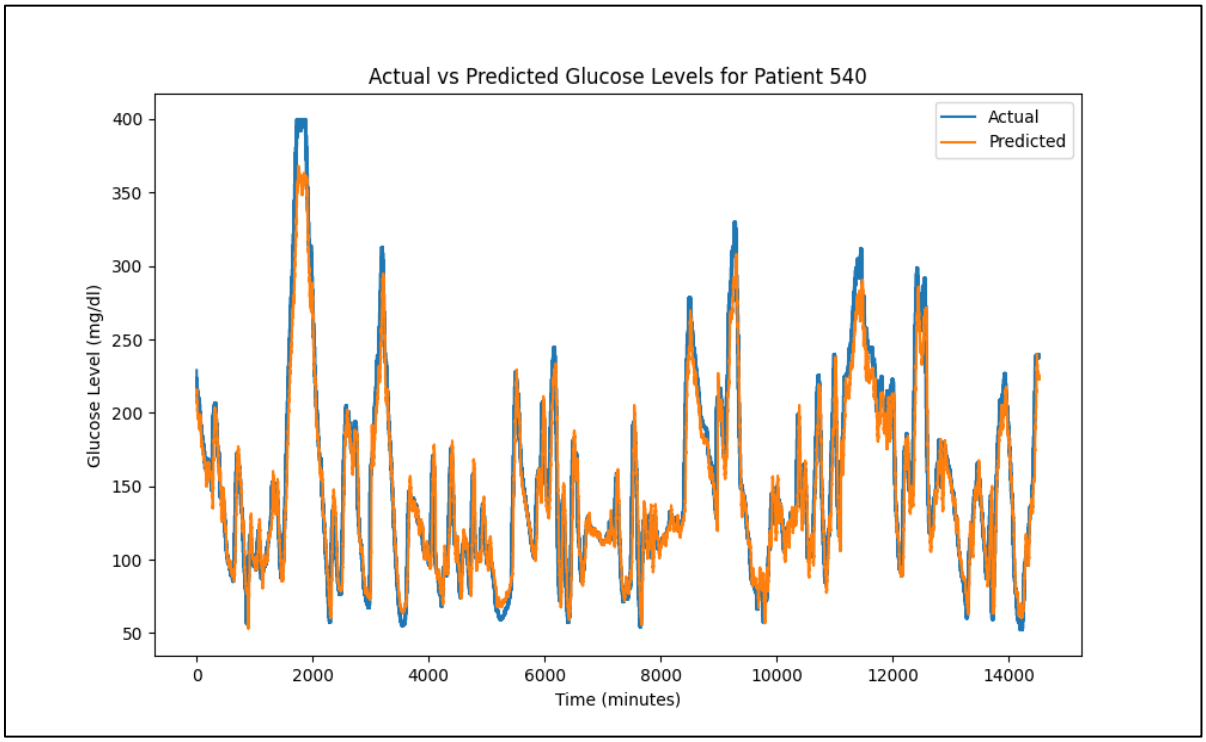

Fig 1: BiLSTM-Multi-Variate Model Blood Glucose Prediction for Subject 540 (pH=30 Mins)

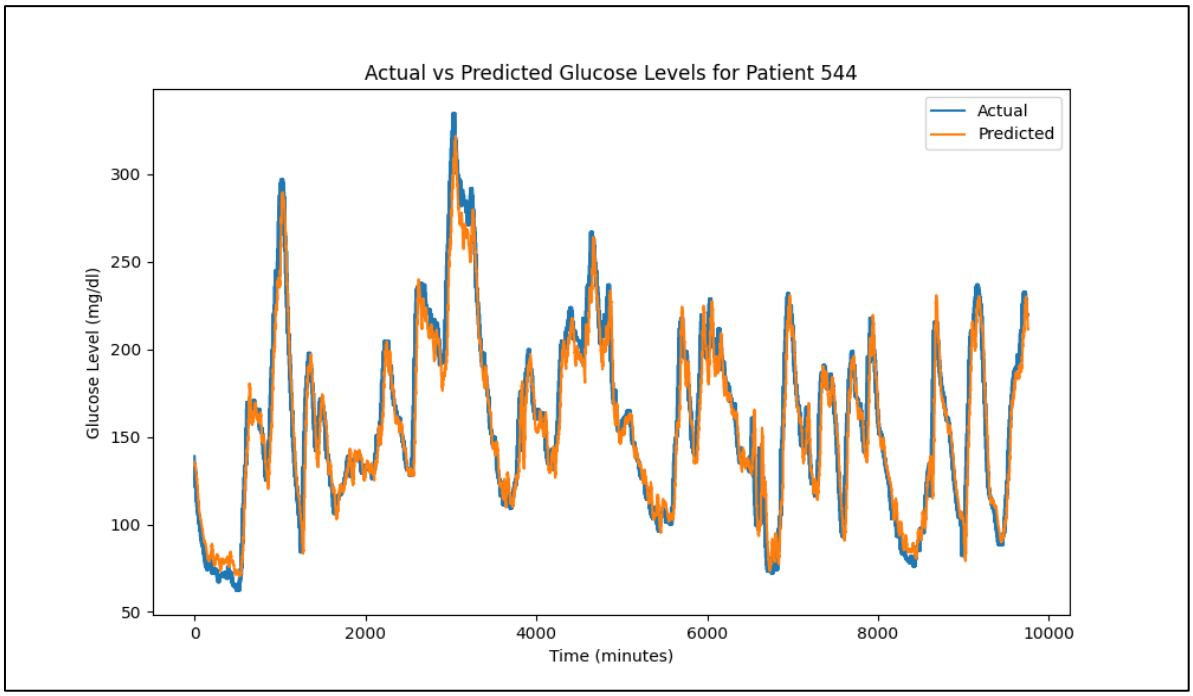

Fig 2: BiLSTM-Multi-Variate Model Blood Glucose Prediction for Subject 544 (pH=60 Mins)

V. CONCLUSION AND FUTURE WORK

Maintaining stable blood glucose levels is critical for individuals with Type 1 diabetes to avoid life-threatening glycemic events. This study introduced a BiLSTM-based multivariate model that integrates CGM readings, insulin delivery, carbohydrate intake, and temporal features to predict future glucose levels using the OhioT1DM dataset. The model achieved high predictive accuracy at 30- and 60-minute horizons, consistently outperforming benchmark models in terms of RMSE and MAE.

These results underscore the effectiveness of multivariate time series modeling and the strength of BiLSTM architectures in capturing complex physiological dependencies. Future work will explore integration of additional contextual data such as physical activity and stress, expand validation to larger and more diverse datasets, and enable real-time deployment through mobile or wearable platforms to enhance personalized diabetes management.

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