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BiLSTM-TSBGP: A Univariate Blood Glucose Prediction Model for Type-1 Diabetes using Continuous Glucose Monitoring Data

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ABSTRACT

Effectively managing blood glucose levels is crucial for individuals with Type 1 diabetes, as extreme highs or lows can lead to severe health complications. Wearable technologies, such as continuous glucose monitoring (CGM) devices, have emerged as vital tools in diabetes management, enabling patients to monitor glucose levels and administer insulin proactively. These devices provide a wealth of time-series data, making them ideal for machine learning applications. In this study, we developed the BiLSTM-TSBGP (Bidirectional Long-Short Term Memory Univariate Blood Glucose Prediction) model and evaluated its performance on two datasets: the Ohio Type 1 Diabetes Mellitus (OhioT1DM) dataset and the UVA/Padova Type 1 Diabetes Metabolic Simulator dataset. The OhioT1DM dataset, comprising data from 12 subjects, provides continuous glucose monitoring and insulin infusion records at 5-minute intervals. On average, for the Ohio dataset, our model achieved a Root Mean Square Error (RMSE) of 12.89 mg/dL and Mean Absolute Error (MAE) of 10.65 mg/dL for a 30-minute prediction horizon (pH), and RMSE of 17.38 mg/dL and MAE of 12.30 mg/dL for a 60-minute pH. The UVA/Padova dataset, featuring simulated data for 10 adult profiles, yielded RMSE values of 10.71 mg/dL and 16.24 mg/dL for 30-minute and 60-minute pH, respectively, with corresponding MAE values of 7.55 mg/dL and 11.72 mg/dL. Our results show that the BiLSTM-TSBGP model outperformed other models in forecasting blood glucose levels and offering a reliable tool for managing Type 1 diabetes.

Keywords: Blood glucose prediction; CGM devices; Diabetes Management; Deep Neural Network; LSTM

1. INTRODUCTION

Diabetes Mellitus is a persistent medical condition identified by elevated blood glucose levels. According to the 2021 IDF Diabetes Atlas [1], it is reported that 10.5% of the adult population is affected by diabetes, and alarmingly, nearly half of them are unaware of their condition. Furthermore, the IDF's projections for 2045 indicate that a staggering 1 in 8 adults, totaling approximately 783 million people, will be living with diabetes. This projection represents a significant increase of 46% in diabetes prevalence.

Diabetes is classified into Type 1, Type 2, and Gestational Diabetes. The pancreas produces insulin, which facilitates the absorption of blood glucose into cells. In Type 1 diabetes (T1DM), insulin production is minimal or absent, whereas in Type 2 diabetes (T2DM), there is either insufficient insulin production or resistance to its effects [1]. This results in elevated blood glucose levels called hyperglycemia, with symptoms like excessive thirst, urination, and sweating. Uncontrolled hyperglycemia can lead to diabetic ketoacidosis, a severe and potentially fatal complication. Conversely, excess insulin can cause low blood glucose levels or hypoglycemia, leading to symptoms like dizziness, weakness, and,

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Research Article

in severe cases, coma or death. Effective diabetes management hinges on maintaining insulin and glucose balance, necessitating careful adjustment of insulin doses.

Blood glucose levels fluctuate based on a patient's diet and daily activities. To track these changes, sensor based CGM(Continuous Glucose Monitoring) devices have been used to estimate blood glucose levels at different intervals. These devices play a crucial role in diabetes management by providing continuous data on a patient's blood glucose levels and revealing distinct patterns throughout the day. Typically, these sensors are used alongside insulin pumps, which administer basal rate insulin continuously and specific insulin doses after meals to maintain glycemic control [2, 3], Despite the benefits of sensors and insulin pumps in enhancing patient care, there remains a significant challenge. Patients often remain unaware of impending severe hyperglycemic or hypoglycemic events, particularly while they are asleep. However, an opportunity exists to develop accurate prediction models by leveraging previously collected sensor data. These models can forecast future blood glucose levels, helping to prevent adverse events from occurring.

In this study, we used two datasets: the Ohio Type 1 Diabetes Mellitus (OhioT1DM) dataset [4] and the UVA/Padova Type 1 Diabetes Metabolic Simulator dataset [26]. The Ohio Type 1 Diabetes Mellitus dataset, comprising blood glucose data from twelve Type 1 Diabetes patients collected continuously over eight weeks. These individuals wore insulin pumps with continuous glucose monitoring device(CGM), physical activity bands, and reported life events via a mobile application. CGM data was recorded every 5 minutes [4]. We developed BiLSTM(Bidirectional Long Short-Term Memory) model to predict glucose levels 30 and 60 minutes ahead, employing CGM values and assessing model performance using mean Root Mean Square Error (RMSE). The proposed blood glucose prediction model has several potential applications in diabetes management. One of the main applications is the development of an artificial pancreas system, which can automatically adjust insulin delivery based on predicted blood glucose levels. This can help to prevent hypoglycemia and hyperglycemia, which are common complications of diabetes. The model can also be used to provide personalized recommendations for insulin dosing and meal planning, based on predicted blood glucose levels. Additionally, the model can be used to monitor blood glucose levels in real-time and alert patients or healthcare providers when glucose levels are outside of the target range. Overall, the model has the potential to improve diabetes management by providing more accurate and timely information about blood glucose levels, which can help patients to make better decisions about insulin dosing, meal planning, and physical activity.

2. RELATED WORK

Machine learning-based blood glucose prediction for both Type 1 and Type 2 diabetes has garnered significant interest, yielding various methods and applications. However, these approaches primarily rely on glucose measurements, and their prediction accuracy remains below the reliability threshold for critical glycemic conditions. Regression algorithms like SVR, classic statistical techniques such as ARIMA, deep learning neural networks, and even simple persistence algorithms have been explored in this context [5].

This comprehensive literature review explores several methodologies and models for predicting blood glucose levels, focusing primarily on individuals with Type 1 diabetes. Each method offers unique insights and contributions to the field of diabetes management.

The GLYFE benchmark[6] is introduced as a standardized tool for assessing machine-learning-based models that predict glucose levels in individuals with Type 1 diabetes. In addition, it involves evaluating various predictive models on two datasets. Furthermore, the benchmark's significance lies in providing a consistent framework to evaluate model performance and clinical acceptability. Additionally, it offers data flow details and Python source code for the broader research and clinical community. Moving on to GluNet [7] stands out as a deep learning-based approach. It employs a multi-layered dilated convolution neural network (CNN) that integrates historical data, meal information, insulin doses, and other factors to predict glucose levels. Moreover, GluNet's utilization of gated activations, residual and skip connections, and label transform/recover components contributes to improved prediction accuracy. This approach is crucial as it provides a probabilistic distribution of short-term (30-60 minutes) future CGM measurements for individuals with Type 1 diabetes, enhancing glucose level predictions.

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Research Article

Now, considering Various Neural Network Models [8], The study delves into an array of artificial neural network algorithms, including Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional LSTMs, Temporal Convolutional Networks (TCN), and sequence-to-sequence models. The evaluation of these models centers on their ability to predict blood glucose values at 30 and 60 minutes in the future. Notably, the sequence-to-sequence BiLSTM model outperforms the others in terms of accuracy. This research highlights the importance of choosing the most suitable neural network architecture for glucose prediction. Shifting the focus to Recurrent Neural Networks (RNNs) [9], Another approach focuses on recurrent neural networks trained in an end-to-end manner. It requires only the patient's glucose level history to produce predictions. This methodology offers simplicity by eliminating the need for extensive feature engineering or data pre-processing, making it computationally efficient.

Furthermore, when examining the LSTM and Bi-LSTM Models [10], They introduce a deep neural network model that incorporates LSTM and Bi-LSTM layers is a significant contribution. This model, trained and tested on real patient data, outperforms baseline methods in terms of multiple evaluation criteria. Importantly, it has the potential to help individuals with diabetes take proactive measures before the onset of hyperglycemia or hypoglycemia, ultimately enhancing their quality of life.

Regarding Data-Driven Models [11], they review underscores the importance of data-driven models for blood glucose prediction. These models encompass a variety of techniques, from physiological models to deep neural networks. They rely on extensive datasets of self-collected health data, such as continuous glucose monitoring (CGM) data, to learn patterns and relationships between various variables affecting blood glucose levels. The result is personalized recommendations for diabetes management, a promising development for personalized care. Additionally, let's consider Kalman Smoothing [12], it discusses the application of Kalman smoothing to CGM readings. This technique aims to correct errors and reduce abrupt fluctuations in the data, leading to improved learning capabilities in predictive models. Moreover, the interpolated time series of glucose estimates with mean and variance offers a more stable basis for prediction.

The BGLP Challenge evaluated blood glucose (BG) level prediction approaches using the OhioT1DM dataset [4]. These systems were evaluated on identical test dataset for each of 6 T1DM patients, observed results are presented as root mean squared error (RMSE) and mean absolute error (MAE) for prediction horizons(pH) of 30 and 60 minutes. Rankings were based on the total score from these measures. The top ranked model demonstrates that incorporating deep residual forecasting with RNNs, additional variables, and self-supervising loss functions significantly improves blood glucose prediction accuracy and suggests that these enhancements could be advantageous for other forecasting tasks[15]. Whereas pre-training an RNN model on a larger dataset (OpenAPS) enables effective blood glucose forecasting for smaller datasets (OhioT1DM), achieving the lowest RMSE with single-step prediction using univariate data[16]. Another unique deep learning model was designed using a modified GAN(Generative Adversarial Networks) architecture for personalized blood glucose prediction in T1D patients, demonstrating promising accuracy for 30 and 60-minute predictions with potential for clinical application, despite some limitations in detecting hypoglycemia events[17]. Another work develops the MS-LSTM (Multi-lag Structure LSTM)network to effectively capture high-dimensional temporal dynamics and extract long- and short-term glucose fluctuation features, despite challenges with missing data and rapid glucose fluctuations[18]. One more study with single LSTM model with an attention mechanism can effectively predict blood glucose levels for different patients without requiring individual patient data during training, and

robustness to missing data is enhanced by including sequences with missing values in the training process[19]. The poor performer in challenge used LV(latent variable)-based model, a powerful linear method, builds an empirical model using collected data, and its effectiveness is demonstrated with the Ohio T1DM dataset.

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Research Article

TABLE-I SUMMARY OF BLOOD GLUCOSE PREDICTION MODELS

Model Used	Dataset Used	Features Used	Prediction Horizon	Evaluation Metrics	Strengths	Limitation	Future Work
SVR, ARIMA, Persistence Algorithms [5]	Not specified	Glucose history	30-60 min	RMSE, MAE	Simple to implement	Prediction accuracy remains below the reliability threshold for critical glycemic conditions.	Explore hybrid models combining classic and advanced techniques to improve accuracy.
GLYFE Benchmark [6]	GLYFE Benchmark Datasets	Multivariate (glucose, meals, insulin)	30-60 min	RMSE, MAE	Standardized evaluation tool	Limited to Type 1 diabetes datasets and specific evaluation criteria.	Expand benchmark datasets and include metrics for clinical acceptability across diverse populations.
GluNet [7]	Type 1 diabetes datasets	Glucose, insulin, meals	30-60 min	MAE, probabilistic distribution	Robust architecture with gated activations and residual connections	Performance affected by missing or noisy data.	Improve robustness to missing data and integrate more patient-specific factors.
Various Neural Network Models [8]	Publicly available CGM datasets	Glucose, multivariate	30-60 min	RMSE, MAE	Strong performance for BiLSTM, diverse architectures	Models like LSTM, BiLSTM, TCN, and Seq2Seq face challenges in accurately capturing rapid glucose fluctuations.	Enhance architectures to address glucose variability and improve computational efficiency.
Recurrent Neural Networks (RNNs) [9]	Type 1 diabetes datasets	Glucose history	30-60 min	RMSE, MAE	Simplicity, no extensive feature engineering needed	Dependence solely on glucose history limits the inclusion of external influencing factors.	Incorporate additional features like insulin, meal data, and physical activity for better predictions.

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Research Article

LSTM and Bi-LSTM Models [10]	Real patient data	Glucose, multivariate	30-60 min	RMSE, MAE	Captures temporal dependencies effectively	Limited performance in detecting hypoglycemic and hyperglycemic events.	Optimize models for early detection of critical glycemic conditions.
Data-Driven Models [11]	CGM and self-collected health data	Glucose, multivariate	30-60 min	RMSE, MAE	Personalized recommendations	Requires extensive datasets and suffers from missing data or errors in self-collected health data.	Develop methods to handle missing data and enhance data preprocessing techniques.
Kalman Smoothing [12]	CGM datasets	Glucose, multivariate	30-60 min	RMSE, MAE	Reduces abrupt fluctuations, corrects errors	May oversmooth rapid fluctuations in glucose levels.	Integrate Kalman smoothing with advanced models to balance noise reduction and glucose variability.
Deep Residual Forecasting (BGLP Challenge) [15]	OhioT1DM Dataset	Glucose, multiivariate	30-60 min	RMSE, MAE	Incorporates deep residual forecasting with RNNs	Limited to univariate and small datasets; lacks scalability to diverse datasets.	Explore multi-step predictions, scalability for larger datasets, and integration of physiological data.
Pre-trained RNN on OpenAPS Dataset [16]	OpenAPS and OhioT1DM datasets	Glucose, multiivariate	30-60 min	RMSE, MAE	Effective for small datasets, uses pre-training.	Performance dependent on pre-training dataset quality; struggles with personalized predictions.	Extend pre-training to larger and more diverse datasets and refine models for personalized care.
Modified GAN [17]	Type 1 diabetes datasets	Glucose, multtivariate	30-60 min	RMSE, MAE	Promising accuracy for short-term predictions	Limited accuracy in detecting hypoglycemia events.	Improve hypoglycemia detection and assess clinical applicability for real-time

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Research Article

							glucose prediction.
MS-LSTM (Multi-lag Structure LSTM) [18]	Type 1 diabetes datasets	Glucose, multivariate	30-60 min	RMSE, MAE	Captures long- and short-term glucose fluctuation features	Challenges with missing data and rapid glucose fluctuations.	Incorporate advanced imputation techniques and adapt to sudden glucose changes.
Single LSTM with Attention Mechanism [19]	Publicly available CGM datasets	Glucose, multivariate	30-60 min	RMSE, MAE	Effective across different patients, robust to missing data	Requires sequences with missing values during training; limited testing on diverse patient populations.	Test robustness across varied datasets and explore more efficient attention mechanisms.
LV-Based Model [20]	OhioT1DM Dataset	Glucose, multivariate	30-60 min	RMSE, MAE	Empirical model using collected data	Poor online denoising and limited integration with physiological models.	Develop improved online denoising techniques and incorporate personalized physiological models.
MTL-LSTM [23]	OhioT1DM	CGM, fingerstick glucose, bolus insulin, meal carbs	30 minutes, 60 minutes	RMSE, MAE, CEG	Personalized predictions, robust performance, computational efficiency	Limited number of patients (6 in test), sparse demographic analysis	Larger datasets, additional feature engineering (e.g., stress, sleep quality), incorporate free-living data
E-TFT[24]	OhioT1DM	CGM, timestamp, meal, insulin, exercise	30 minutes, 60 minutes	RMSE, MAE, gRMSE	High accuracy, hardware-friendly, interpretable for clinicians	Limited dataset (12 patients), deployment on specific hardware	Validate model in clinical trials, embed into CGM transmitters for real-time Type-1 diabetes management

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Research Article

The study highlights the need for future improvements in online denoising techniques and integration with personalized physiological models to enhance prediction accuracy[20]. Advancements in the Internet of Medical Things (IoMT) and machine learning (ML) are reshaping how diabetes is managed, making it more accurate and personalized. Devices like continuous glucose monitors (CGMs) and wearable fitness trackers now collect important data such as glucose levels, heart rate, and physical activity, providing real-time insights into a person's health. A recent study found that Random Forest (RF) models are highly effective for predicting short-term blood glucose levels, achieving an error of just 18.6 mg/dL for a 30-minute prediction window when using six hours of past data. These advancements show how IoMT and ML can improve the quality of life for people living with diabetes[25].

In Summary, Table-I provides a comprehensive summary of various blood glucose prediction models, highlighting the datasets used, input features, prediction horizons, evaluation metrics, strengths, limitations, and suggested future directions. This comparison offers insights into the advancements and challenges in the field, emphasizing the potential for further improvements in model performance and clinical applicability. These methodologies collectively contribute to the growing body of research aimed at enhancing the accuracy and reliability of blood glucose predictions. The ultimate goal is to improve diabetes management and patient quality of life. Furthermore, the diverse approaches offer various advantages and applications, showcasing the potential for more personalized and effective strategies in diabetes care. Additionally, to automatically correct errors in the CGM readings, the estimated variance can also be utilized to determine at which times the data are reliable.

Finally, when it comes to incorporating LSTM models in the scope of predicting blood glucose levels for Type 1 diabetes patients, it's crucial. LSTM models have the ability to capture temporal dependencies and patterns in glucose data. This enables more accurate and individualized predictions, ultimately contributing to improved diabetes management and patient quality of life.

3. METHODOLOGY

This section presents the architecture of our system, illustrated in Figure 1. The architecture comprises four key components: preprocessing and feature extraction, blood glucose prediction, forecasting evaluation with parameter tuning, and model evaluation. Our primary objective is to enhance blood glucose prediction using LSTM (Long Short-Term Memory) and BiLSTM (Bidirectional Long Short-Term Memory) models, focusing on capturing temporal dependencies in blood glucose data.

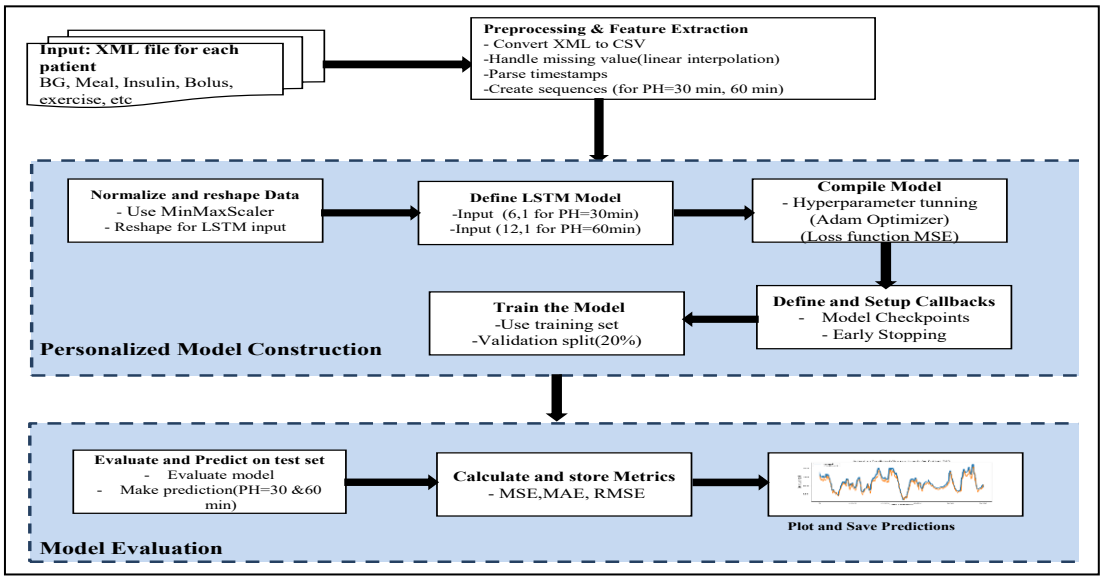

Figure-1. System architecture

The first component involves preprocessing raw blood glucose (BG) data to ensure that the input data is clean, normalized, and enriched. Since this research focuses on a univariate model using only BG values, the preprocessing

Journal of Information Systems Engineering and Management
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Research Article

steps include handling missing values specifically for BG data, smoothing the data, and scaling features for consistency. Missing values are addressed using linear interpolation, which is well-suited for the smooth and continuous nature of BG data, providing a simple and efficient method for estimating short, intermittent gaps without introducing unnecessary complexity. This approach is practical for our single-variable model and avoids the need for more sophisticated imputation techniques, such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), or RNN-based imputers like LSTM or GRU models, which are better suited for accounting for complex temporal dependencies in multivariate data.

The core of our system is the blood glucose prediction module, where we implement the BiLSTM-TSBGP univariate model. This model is chosen for its ability to learn from sequences and capture temporal dependencies, which are essential for accurate blood glucose prediction. This component involves designing the architecture using BiLSTM layers to capture temporal patterns, setting up the optimizer, loss function, and performance metrics, and training the model using historical data with validation splits to monitor performance. Following model training, we evaluate forecasting capabilities and perform parameter tuning to optimize performance. This involves adjusting parameters such as the number of layers, units per layer, and dropout rates, employing k-fold cross-validation to ensure robust performance, and implementing techniques like early stopping and model checkpoints to prevent overfitting by monitoring validation loss and saving the best model configurations.

The final component involves evaluating the trained models using predefined metrics to assess their prediction accuracy. This step includes utilizing Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to measure prediction accuracy, as RMSE penalizes larger errors more heavily and reflects the critical need for accurate blood glucose predictions. Additionally, results visualization is performed by plotting actual vs. predicted blood glucose levels to visually assess model performance. By following this systematic approach, our architecture aims to improve the accuracy and reliability of blood glucose predictions, ultimately contributing to better diabetes management.

A. Dataset used

The Ohio Type-1 Diabetes Mellitus (OhioT1DM) Dataset contains eight weeks of data from 12 individual patients with type 1 diabetes, each identified by a unique ID number. These participants were on insulin pump therapy using Medtronic 530G or 630G insulin pumps and with continuous glucose monitoring device(CGM). They logged life-event data via a custom mobile application and provided physiological data from wearable fitness devices. The first group of six individuals' data was released in 2018 and second group of six individuals' data made available in 2020. Table-II provides details of number of training and test examples for each data contributor.

TABLE-II DATASET DETAILS

Dataset	ID Range	Training Samples	Testing Samples	Release/Source Information
OhioT1DM (2020)	540, 544, 552, 567, 584, 596	>10,666 (per patient)	>2,566 (per patient)	Released during BGLP Challenge (2020)
OhioT1DM (2018)	559, 563, 570, 575, 588, 591	>10,716 (per patient)	>2,608 (per patient)	Released during BGLP Challenge (2018)
UVA/Padova T1DMS	Adult#001–Adult#010	>21,472 (per patient)	>5,369 (per patient)	Simulated (S2013 version, UVA/Padova)

Additionally, we used data generated by the UVa/Padova Type 1 Diabetes Metabolic Simulator (T1DMS), developed at the Universities of Virginia and Padova[26]. This simulator, referred to as UVA, models the dynamics of the human metabolic glucose-insulin system using the Matlab/Simulink environment. Since 2008, UVA has been the only FDA-

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

Research Article

approved simulator for replacing pre-clinical animal testing in evaluating certain diabetes treatment strategies. For our study, we used the S2013 version of T1DMS, which provides 30 patient profiles evenly distributed among adults, adolescents, and children. Specifically, we focused on the 10 adult profiles. The simulations were run for 8 weeks for each of the 10 adult profiles. On average, each patient contributed 21,472 records for training and 5,369 records for testing, providing a much larger dataset compared to the OhioT1DM dataset.

B. Long short term memory (LSTM) networks

The proposed Bidirectional LSTM (BiLSTM)-based blood glucose prediction model is designed to forecast blood glucose levels for prediction horizons (pH) of 30 minutes and 60 minutes ahead using continuous glucose monitoring (CGM) data. The model architecture, as illustrated in Figure 2, begins with an input layer that matches the shape of the training data, excluding the batch size. It consists of two primary stacks. The first stack includes four Bidirectional LSTM layers with 256 units each, interspersed with dropout layers at a 20% rate to prevent overfitting. Similarly, the second stack has four Bidirectional LSTM layers, each with 128 units, also interspersed with dropout layers set at a 20% rate. The output layer is a dense layer designed to forecast blood glucose levels for the next six time steps. To ensure efficient training and accurate predictions, the model is compiled using the Adam optimizer with a learning rate of 0.0002 and the Mean Squared Error (MSE) loss function. For the experiments, a robust methodology was employed. The data preprocessing pipeline addressed missing CGM readings through linear interpolation, ensuring continuity in the time series. The CGM data was normalized to a [0, 1] range using Min-Max scaling to improve convergence during model training and maintain numerical stability. A sliding window technique was applied to create input sequences of fixed length (e.g., 30 data points, equivalent to 2.5 hours), providing context for prediction. The dataset was divided into 70% training, 15% validation, and 15% testing subsets to ensure robust evaluation of the model on unseen data. The ReLU activation function was used to capture non-linear patterns in blood glucose dynamics.

Hyperparameter tuning played a significant role in optimizing the model's performance. A grid search determined the learning rate for the Adam optimizer as 0.0002. Batch sizes of 16, 32, and 64 were tested, with a batch size of 32 providing the best trade-off between computational efficiency and model performance. A dropout rate of 20% was chosen after evaluating rates between 10% and 30%. The validation strategy involved early stopping with a patience of 10 epochs to prevent overfitting, and the MSE loss function was employed due to its sensitivity to large errors, which is critical for accurately predicting extreme blood glucose levels. Evaluation metrics included RMSE, MAE, and prediction accuracy for clinically significant events such as hypoglycemia (<70 mg/dL) and hyperglycemia (>180 mg/dL).

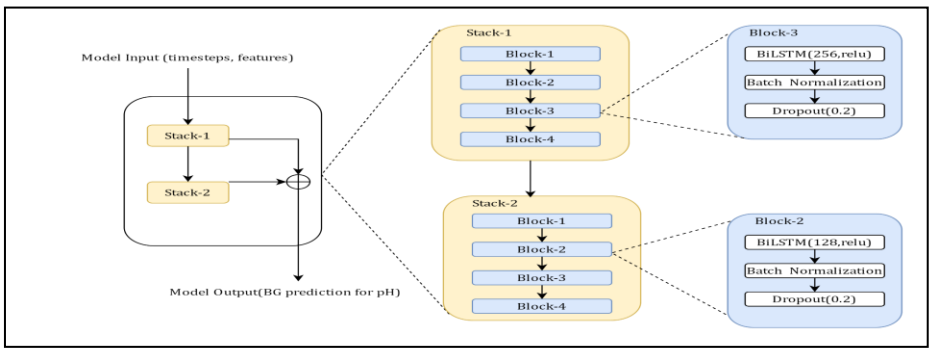

Figure-2. Proposed model BiLSTM-TSBGP architecture

This architecture leverages the strength of BiLSTMs in capturing temporal dependencies and the robustness of dropout in mitigating overfitting, making it well-suited for the complex task of blood glucose prediction. Our model significantly modifies the base model architecture, which is a modified version of N-BEATS. The original N-BEATS model utilized 30 blocks with 4 layers each, with each layer having 512 hidden units and ReLU activations[21]. For this study, we compare our proposed BiLSTM-TSBGP model with the MTL-LSTM model (Table V) and other recent models (Table VI). Unlike models that rely on dense layers, our BiLSTM-based approach incorporates Bidirectional

Journal of Information Systems Engineering and Management
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Research Article

LSTM layers, which significantly improve the model's ability to capture temporal patterns and dependencies in blood glucose data. This enhancement results in superior prediction accuracy and reliability, demonstrating the advantages of the BiLSTM-TSBGP model over both the MTL-LSTM and other state-of-the-art models.

C. 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.

4. EXPERIMENTAL RESULTS

In this section, we present the results of our BiLSTM-TSBGP model for continuous blood glucose (BG) prediction. Table-III highlights the results of the BiLSTM-TSBGP model on the OhioT1DM dataset, while Table-V presents the results on the UVA/Padova dataset. Additionally, a comparative analysis between the BiLSTM-TSBGP model and the MTL-LSTM model is displayed in Table-VI. Furthermore, a detailed comparison between our BiLSTM-TSBGP model and other recent models is presented in Table-VII. These results emphasize the superior performance of the BiLSTM-TSBGP model, showcasing its robustness and accuracy in continuous BG prediction across diverse datasets.

TABLE-III BILSTM-TSBGP RESULTS OF OHIOT1DM DATASET

ID	*pH-30 min*		*pH-60 min*	
	RSME (mg/dl)	***MAE (mg/dl)***	***RSME (mg/dl)***	***MAE (mg/dl)***
540	13.36	10.18	18.35	12.70
544	7.99	6.04	13.97	9.82
552	14.97	13.14	11.62	8.03
567	15.02	11.46	20.88	13.48
584	20.16	18.25	27.85	18.02
596	14.42	12.22	15.67	11.00
559	12.50	9.7	20.03	14.04
563	15.36	13.60	15.88	12.64
570	11.56	9.61	20.09	15.61

Journal of Information Systems Engineering and Management
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Research Article

575	15.64	12.73	20.48	13.47
588	15.56	12.08	25.10	19.55
591	11.52	9.01	17.03	11.97
Mean	**12.89**	**10.65**	**17.38**	**12.30**

TABLE-V BILSTM-TSBGP RESULTS OF UVA/PADOVA DATASET

ID	*pH-30 min*		*pH-60 min*	
	RSME (mg/dl)	***MAE (mg/dl)***	***RSME (mg/dl)***	***MAE (mg/dl)***
adult#001	11.03	7.69	17.16	12.33
adult#002	9.72	7.07	13.80	10.05
adult#003	9.87	7.10	14.69	11.28
adult#004	12.07	7.96	19.76	13.36
adult#005	10.68	7.70	15.67	11.60
adult#006	11.09	7.82	16.55	11.98
adult#007	9.60	6.88	13.87	10.23
adult#008	9.75	6.91	13.67	10.04
adult#009	11.68	8.05	19.06	13.50
adult#010	11.57	8.29	18.22	12.89
Mean	**10.71**	**7.55**	**16.24**	**11.72**

TABLE-VII COMPARATIVE ANALYSIS OF BILSTM-TSBGP AND OTHER MODELS

Model	*RSME (mg/dl)*		*MAE (mg/dl)*	
	pH-30 min	***pH-60 min***	***pH-30 min***	***pH-60 min***
BiLSTM-TSBGP (UVA/Padova)	**12.89±0.87**	**17.38±2.26**	**10.65±0.48**	**12.30±1.32**
BiLSTM-TSBGP	**12.09±2.47**	**18.06±5.29**	**11.88±3.64**	**12.17±3.17**
MTL-LSTM [23]	16.65±3.36	32.19±4.96	10.76±1.57	22.91±3.38
E-TFT[24]	19.09±2.47	32.31±3.79	13.07±1.59	23.24±2.84
N-HiTS[22]	19.63±2.28	33.00±3.66	13.90±1.56	24.50±2.85
NBEATS-LSTM [15]	19.43±2.27	33.82±3.93	13.43±1.56	24.43±2.98

TABLE-VI COMPARATIVE ANALYSIS OF BILSTM-TSBGP AND MTL-LSTM MODEL

ID	Test Sample	BiLSTM-TSBGP				MTL-LSTM			
		RSME (mg/dl)		*MAE(mg/dl)*		*RSME (mg/dl)*		*MAE(mg/dl)*	
		pH-30 min	***pH-60 min***	***pH=30 min***	***pH-60 min***	***pH-30 min***	***pH-60 min***	***pH-30 min***	***pH-60 min***

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Research Article

540	2884	13.36	18.35	10.18	12.70	17.35	36.39	12.07	26.96
544	2704	7.99	13.97	6.04	9.82	14.66	28.42	9.45	19.81
552	2352	14.97	11.62	13.14	8.03	13.01	27.77	9.19	20.61
567	2377	15.02	20.88	11.46	13.48	20.62	38.13	11.95	25.76
584	2653	20.16	27.85	18.25	18.02	21.25	36.65	12.88	25.92
596	2731	14.42	15.67	12.22	11.00	13.05	25.78	9.03	18.41
Mean		**12.09**	**18.06**	**11.88**	**12.17**	**16.65**	**32.19**	**10.76**	**22.91**

Overall, the BiLSTM-TSBGP model achieved the lowest RMSE, recording 12.09 mg/dl for a prediction horizon (pH) of 30 minutes and 17.38 mg/dl for a pH of 60 minutes. These values are significantly lower than latest models [15,22,23,24]. The same comparison is shown in form of graph in figure 3.

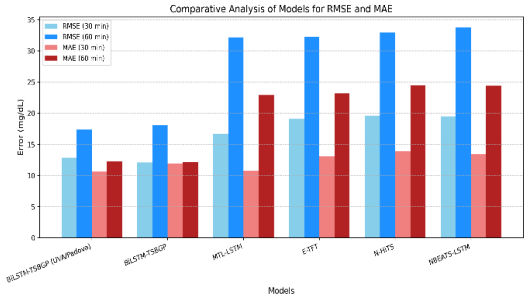

Figure -3. Comparison of BiLSTM-TSBGP model with recent models

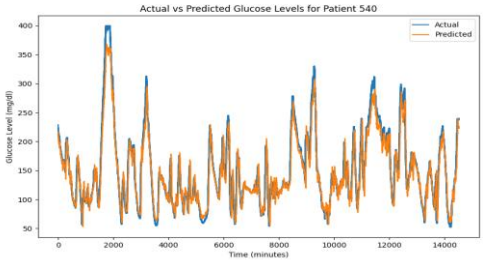

Figure -4. BiLSTM-TSBGP blood glucose prediction for subject 540(30min)

Figure-4 and figure-5 illustrates the actual versus predicted blood glucose levels for the test data of OhioT1DM subject 540 and subject Adult#2 for pH=30 min. The graph demonstrates that our BiLSTM-TSBGP model is sufficiently accurate in predicting both hypoglycemia and hyperglycemia events.

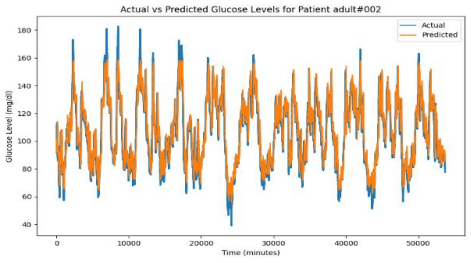

Figure-5. BiLSTM-TSBGP blood glucose prediction for UVA/Padova subject adult#002 (pH=30 mins)

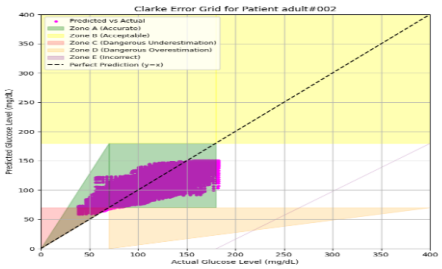

Figure -6. BiLSTM-TSBGP Clinical Error Grid Analysis for subject adult#002 (pH=30 mins)

The Clarke Error Grid analysis for Patient adult#002 in figure-6 demonstrates the clinical accuracy and safety of the blood glucose prediction model. A majority of the predicted values fall within Zone A, indicating highly accurate

predictions closely matching actual glucose levels, while a smaller portion resides in Zone B, representing acceptable predictions that would not result in inappropriate clinical decisions. Notably, there are minimal occurrences in Zones C, D, and E, which correspond to dangerous underestimations, overestimations, or clinically unacceptable errors. These results highlight the model's robustness and reliability for blood glucose prediction, making it a valuable tool for diabetes management. Predictions for adult#002 demonstrate higher clinical reliability and safety due to their clustering in Zone A, representing accurate and clinically acceptable predictions.

5. CONCLUSION AND FUTURE WORK

In conclusion, maintaining stable blood glucose levels is critical for individuals with Type 1 diabetes to avoid life-threatening complications caused by extreme fluctuations. Wearable technologies, such as continuous glucose monitors (CGMs), enable proactive diabetes management by providing real-time data on glucose levels and insulin delivery. This study employed the BiLSTM-TSBGP (Bidirectional Long-Short Term Memory Univariate Blood Glucose Prediction) model to forecast blood glucose levels using data from both the OhioT1DM dataset and the UVA/Padova Type 1 Diabetes Metabolic Simulator dataset. The model achieved high accuracy, with RMSE and MAE values that surpassed those of recent models for 30-minute and 60-minute prediction horizons, demonstrating its superior reliability and precision.

The findings establish the BiLSTM-TSBGP model as a robust and accurate solution for blood glucose forecasting, offering significant potential for improving diabetes management. Future research will extend the model to a multivariate framework by incorporating additional features, such as insulin dosage, carbohydrate intake, and physical activity. Moreover, expanding to larger and more diverse datasets, integrating real-time applications, and developing user-friendly interfaces can further enhance the model's utility and impact on diabetes care. This work highlights the transformative role of machine learning in advancing personalized healthcare for individuals with Type 1 diabetes.

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