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ORIGINAL ARTICLE

Optimized LSTM Model for Accurate Blood Glucose Prediction in Type-1 Diabetes

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Abstract

Objective: Blood glucose levels in diabetes are influenced by various factors, making prediction challenging when considering many variables. Therefore, this study proposes an optimized LSTM model to improve the prediction accuracy of blood glucose using a single variable (CGM), thereby simplifying diabetes management. **Methods:** This study has implemented the LSTM model to predict blood glucose levels in type-1 diabetics for a 60-minute prediction horizon. The grid search technique has been implemented to fine-tune the hyperparameters of the LSTM model. Ohio Datasets were used for this study. Root mean squared error (RMSE) and error grid analysis (EGA) were used for the evaluation of model performance. **Findings:** The proposed study reveals 26.13 $\pm$ 3.25 mg/dl predicting accuracy for a 60-minute prediction horizon. Clark Error grid analysis (CEGA) was used to validate clinical acceptance of the proposed model, and the results provided higher than 97% prediction accuracy in the Ohio dataset. **Novelty:** The patient-specific optimized model has outperformed the conventional LSTM model. The results show a significant improvement in model performance compared to previous work in terms of root mean square error (RMSE).

Keywords: Long-short term memory (LSTM); Grid search optimization technique; Continuous Glucose monitors (CGM); Blood Glucose; Type-1 Diabetes

1 Introduction

Diabetes is a chronic disease that affects the lifestyle of individuals. Diabetes management is one of the challenges facing healthcare at the global level. There are two important types of diabetes: Type-1, which is often diagnosed in childhood or adolescence. It generally happens when the immune system kills the beta cells of the pancreas, which is responsible for insulin production. Type-1 is an incurable disease that significantly affects the lives of individuals as it indicates insufficient insulin generation. While type 2 is more common and generally appears in adulthood, it happens when the body cannot produce sufficient insulin or utilize it properly. Type-2 diabetes can be

controlled by changing lifestyles. In contrast, type-1 diabetes is an incurable disease in which an individual must take exogenous insulin throughout life to avoid severe complications because of elevated blood glucose. As per the International Diabetes Federation (ADF) atlas report (2021), 10.5% of the adult population has diabetes, and half are unaware of it. It is also projected that one in every eight adults will have diabetes by 2045, considering the current growth [1].

Artificial pancreas is crucial in type-1 diabetes management to manage blood glucose within a safe limit. It consists of a continuous glucose monitor (CGM), which measures blood glucose from interstitial fluid in real-time [2]. Based on the level of glucose control, the algorithm adjusts insulin delivery to the bloodstream to keep glucose within a safe limit. This is a conventional way of controlling blood glucose in type 1 diabetes using an artificial pancreas. The problem with the traditional method is that abnormal events happen first, and later, corrective measures are taken based on those events, which may cause serious medical complications [3]. To prevent this serious complication, a next-generation machine learning-based artificial pancreas can be implemented to predict the future value of blood glucose with better accuracy well in advance for specific prediction horizons that allow users to take corrective measures before it happens [4].

These sections provide a brief idea of related work conducted in type-1 diabetes management by focusing more on the performance of various machine learning techniques, selection of input features for the study, type of dataset used (in silico or actual patient data), preprocessing of datasets, predicting machine learning algorithms, and performance metrics used for blood glucose prediction [5].

Majority of the work was carried out on Ohio dataset developed by Ohio University. Therefore, literature consideration for the study includes those that have implemented Ohio dataset or have demonstrated high accuracy in prediction. Important literatures are illustrated in Table 1 by considering model implementation and number of variables used for the study. Literature limitations are also considered to give a brief idea of the research gap in existing study.

Apart from the key literature, other authors have also proposed work in same field by implementing simulated datasets or modified models. Wang et al. (2021) compared different machine learning techniques, e.g., SVM, random forests, linear regression, KNN, and XGBoost, prediction of blood glucose using an in-silico dataset generated from a UVA/PADOVA type-1 diabetic simulator and find that a bidirectional long-short-term memory (LSTM) model has the best prediction result. The result for the 30-minute prediction horizon is RMSE = 7.55$\pm$0.19 mg/dl, R2-SCORE = 0.96 [6]. Carrillo-Moreno et al. (2020) proposed predicting ten different LSTM model configurations for the various PH, with the highest performance obtained for 45 min PH (20.76 mg/dL). The author suggested that the model for 30 minutes outperforms all, considering three features for the study, and suggested adding more for future work to improve model performance [7].

The performance of the predicting algorithms depends on several key parameters. Still, hyperparameters tuning can substantially impact predicting algorithms in a data-driven approach. However, finding the optimum set of configurations for machine learning techniques using optimization techniques is always challenging. Several optimization techniques are available for tuning hyperparameters that enhance the performance of the predicting algorithm, such as grid search and random search, Bayesian optimization, genetic algorithm, etc. The selection of proper optimization techniques for time series prediction depends on several factors, like the complexity of the problem, the availability of computational resources, hyperparameters space, domain knowledge, and the performance requirements of the models. Dhake et al. (2023) proposed two algorithms for tuning hyperparameters in the LSTM and Fast Fourier Transform (FFT) based data decomposition model, and the findings show a 53.42% reduction in RMSE in 90 min. Ahead of the prediction of solar energy [8]. J. Faritha Banu et al. (2022) summarize that hyperparameter-tuned hybrid CNN-LSTM has an increased R2 value of 0.9151, which performs better for stock prediction in financial markets [9]. J. F. Torres et al. (2022) has implemented two optimization techniques, random search, and coronavirus optimization algorithm (CVOA), along with LSTM, for the prediction of electricity consumption. This brings the prediction error below 1.5% [10]. Siyu Zhou et al. (2019) implemented sequence model-based optimization (SMBO) for heterogeneous LSTM structures to predict electricity prices. Optimize model EEMD-LSTM to achieve a MAPE of 7 [11].

Findings of the existing work clearly show that the prediction accuracy of the implemented model is not acceptable for clinical use though majority work has considered number of input features like CGM, Insulin, Carbs, physical activity and others. It is always difficult to manage large number of variables in real time for diabetes management, therefore this research gap has been addressed in proposed work. Proposed work has implemented patient specific optimized LSTM model by considering just CGM as input variable for the prediction of blood glucose level with better accuracy compared to existing work.

The proposed work has implemented a grid search optimization technique for the LSTM model to address the problem, as shown in Figure 1. It takes a time series past glucose value at different timestamps from CGM as input. The linear interpolation technique is used to insert missing data points, and then data normalization is performed to enhance the model's performance when implemented using a machine learning technique. Also, extra features like engineering features, i.e., moving averages and rate of change, can be included as extra input features to find the trend of glucose for the prediction easily. Once time series data is preprocessed, it is ready for further processing. The data set will be divided into training, validation, and testing. Training and

Table 1. Literature Review of Blood Glucose Prediction for Type-1 Diabetes

References	Used Dataset	No. of Input Features used	Model	RMSE (mg/dl)	Limitation
[19]	Replace-BG	3 (past glucose, insulin, and carbohydrate)	CNN-LSTM	27.19 ± 5.59	Accuracy has improved considering greater number of input variables while implementing smaller datasets for improving model robustness.
		DIAdvisor	7(CGM, self-reported insulin intakes for basal, bolus, and correction doses and meal nutrients content for CHO, protein, and lipids)	CNN-LSTM	29.08 ± 5.40
[12]	Ohio Dataset (Only Three patients)	2 (CGM & Operative Carbohydrate)	Bi-LSTM and Vanilla-LSTM	28.25	Improve accuracy compared to other literature while considering limited dataset for evaluation.
[13]	Ohio dataset (2020 Dataset)	14 (CGM, fingerstick glucose, insulin dose (basal and bolus), carbohydrate, GSR, skin temperature, sleep quality, illness,work intensity, Physical Activity, heart rate(HR), room temperature, Step count)	MLR	27.56	The study implemented Fourteen input variables which poses practical complication for real life implementation.
[14]	Ohio dataset (2018 Dataset)	CGM	LSTM	31.40 ± 2.07	A Single variable (CGM) was used for study, but the accuracy was too low to consider for clinical application
[15]	Ohio Dataset (2020 Dataset)	More than two	Bi-LSTM	35 ± 5.4	The study utilized more than two variables; however, the accuracy was not up to marks compared to other study.
[16]	Ohio dataset (2018 Dataset)	4 (CGM, Insulin, Carbohydrate, Activity)	Regression Model	31.72	
[17]	Real and Simu-lated data	CGM	LSTM-Bi-LSTM	36.91	Despite using a stimulated dataset, the study shows very poor accuracy.
[18]	Ohio dataset (2018 Dataset)	5(CGM, Meal, Insulin, HR. Skin Conductance)	LSTM	28.19	Accuracy is improved by considering five input variables.

validation data were considered during the model optimization process. In contrast, testing data was represented to the model once it was optimized to find the model's ability to recognize the unknown data. The optimized model will predict the future value of a specific prediction horizon based on its learning.

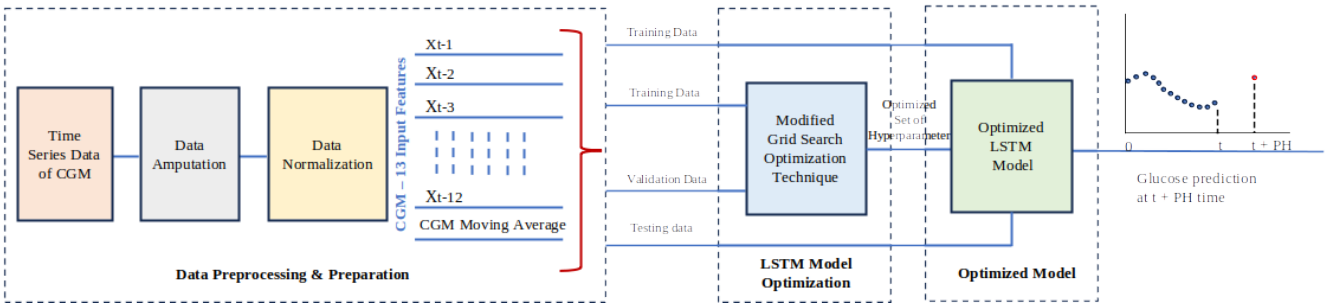

Fig 1. Machine learning-based blood glucose prediction

The proposed work is organized in a logical order. Section II includes the. Section II discusses the methodology which includes dataset used for the proposed research, LSTM model architectures, grid search optimization technique used for hyperparameter tuning of predicting LSTM algorithms, and validation strategy. Section III comprises the results and discussions, and Section IV concludes with future scope.

2 Methodology

2.1 Dataset

The dataset quality and quantity will significantly impact the performance of the blood glucose prediction model. Most of the proposed work has been done in the literature on UVA/PADOVA (FDA approved) [20], AIDA [21], simulator or D1NMAO [22], Replace-BG and DIAdvisor, and the Ohio Dataset [23]. In the proposed work, The Ohio dataset has been used for the following reasons:

1. A maximum number of CGM data samples are available for the study-134790 training samples and 31671 testing samples.
2. Training and testing samples are available separately.
3. The age group of data contributors is broad (20 to 60), which exhibits different glucose dynamics and make the model more robust for prediction.
4. Male and female contributors are available.
5. The model performance can be quickly evaluated by comparing it with the literature, as most researchers have utilized the same dataset.

The Ohio dataset consists of eight weeks of CGM, insulin, carbohydrate intake, and other self-reported life event data for each of the twelve patients, including 19 different important vital parameters at different timestamps. However, the proposed study uses only the CGM feature for the prediction. The Ohio dataset is separated into two sections based on contributions. The first set of contributors consists of 6 patients with IDs 540 to 596, collected in 2020, and the second group consists of patient IDs 559 to 591, collected in 2018. Datasets incorporated training and testing data for each contributor. A total of three females and nine males have contributed. Details of data contributors, along with data samples, are mentioned in Table 2.

2.2 Data Amputation and Normalization

Some patient data points are missing at specific timestamps for unknown reasons. It may be due to the changeover time of the sensors or the malfunction of the sensors. Details of missing data points are mentioned in Table 3. Linear interpolation data imputation techniques have been executed to fill in the missing data point. In this technique, the last value before the missing data point and the value after the missing data point are used to find the missing data point based on the equation:

$$y = y_1 + (x - x_1)\frac{(y_2 - y_1)}{(x_1 - x_2)} \quad (1)$$

Table 2. Details of Ohio dataset contributors and training and testing samples

Patient ID	Gender	Age	Pump model	Sensor band	Cohort	Training Samples	Testing Samples
540	Male	20-40	630G	Empatica	2020	11947	2884
544	Male	40-60	530G	Empatica	2020	10623	2704
552	Male	20-40	630G	Empatica	2020	9080	2352
567	Female	20-40	630G	Empatica	2020	10858	2377
584	Male	40-60	530G	Empatica	2020	12150	2653
596	Male	60-80	530G	Empatica	2020	10877	2731
559	Female	40-60	530G	Basis	2018	10796	2514
563	Male	40-60	530G	Basis	2018	12124	2570
570	Male	40-60	530G	Basis	2018	10982	2745
575	Female	40-60	530G	Basis	2018	11866	2590
588	Female	40-60	530G	Basis	2018	12640	2791
591	Female	40-60	530G	Basis	2018	10847	2760

Where: y = calculated linear interpolation value, x = independent variable, x_1, y_1 = value of the function at one point and x_2, y_2 = value of the function at another point.

Table 3. Missing Data Points Patient Wise in the Ohio Dataset

2020-Data contributor			2018-Data contributor		
Patient ID	Missing points		Patient ID	Missing points	
	Training Data	Testing Data		Training Data	Testing Data
540	1161	169	559	1284	362
544	2048	419	563	972	122
552	2006	1585	570	629	134
567	2678	481	575	1237	129
584	1098	330	588	465	90
596	2753	259	591	1909	86

The data normalization technique is used after linear interpolation to transform the data points into a specific range because machine learning techniques are sensitive to the scale of the input features and perform better after data normalization. In the proposed study, Z-score normalization was implemented, which transformed the value of input features to have 0 mean and one standard deviation. This can be accomplished by subtracting the mean from the feature value and dividing it by the standard deviation as given by the equation:

$$x' = \frac{x - \mu}{\sigma} \tag{2}$$

Where x' is normalized data, μ is the mean, and σ is the standard deviation.

2.3 Data Preparation

The Ohio data set consists of training and testing samples. Only the training dataset is used for model optimization by dividing the training and validation datasets. 70% of datasets are considered for the training phase, while the remaining 30% are used for validating model performance. Once the model is optimized, a testing dataset is implemented to obtain its performance because it is unknown for an optimized model; hence, it correctly assesses the optimized model. The training dataset was separated into two parts using a 70:30 ratio, 70% training and 30% testing. Which were used for training and validation purposes. A separate testing dataset was used for the model evaluation.

The Ohio dataset is provided with intervals of a 5-minute timestamp. In the proposed study, after the data amputation and normalization, sliding window techniques have been implemented for the data preparation, in that a 12-timestamp data sample means 1 hour of CGM data points are considered for the prediction of blood glucose at 60 minutes ahead, as shown in Figure 2. It means that 12 data points are provided to the predicting model as input features at a time. The additional feature, the rolling moving average, was introduced as a 13th feature so that the predicting model could quickly identify the blood glucose trend.

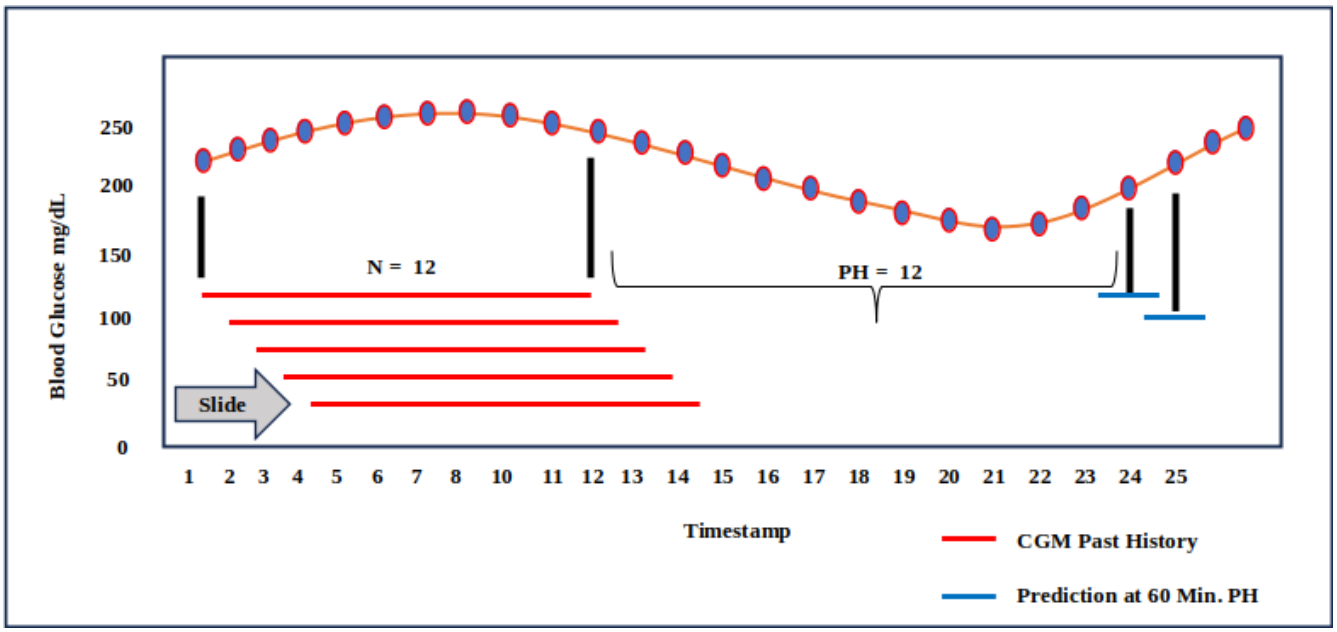

Fig 2. The sliding window technique was used for the data preparation

2.4 Long-Short Term Memory (LSTM) Architecture

Machine learning techniques always play an essential role as predictors for the system. The whole system's performance will depend on the selection of appropriate predictors. Various methods are available for different applications. However, a few techniques have outperformed for time series prediction, like recurrent neural networks, convolutional neural networks, autoregression integrated moving averages, support vector regression, and long short-term memory (LSTM).

The proposed work implemented an LSTM network to predict time series data. LSTM has a simple architecture to define problems and offers higher accuracy than other state-of-the-art machine learning techniques. LSTM is the advanced version of a recurrent neural network, which is designed to overcome the vanishing gradient problem that happens during the process and can recognize the trend of patterns easily compared to other techniques.[24] In the literature, most of the recent work has been done on LSTM for blood glucose prediction, and that is because of the complexity of blood glucose dynamics and the ability of LSTM to mesmerize the complicated pattern or trend in time series data[25]. Figure 3 illustrates the flow of time series data through an LSTM layer; x represents input, and y represents output with T time steps. Here, ht (hidden state) denotes output, and ct denotes cell state at timestamp t.

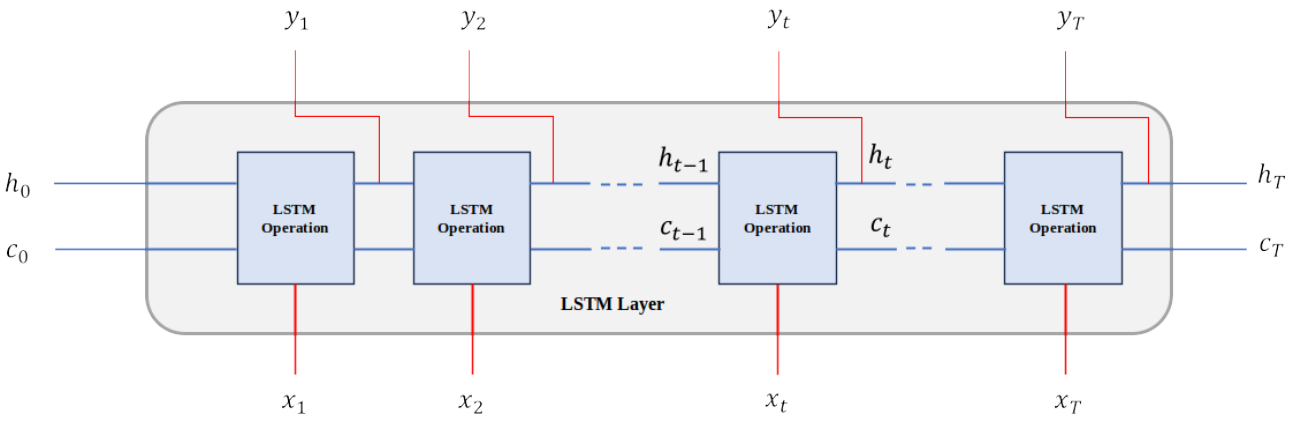

Fig 3. Flow of data through the LSTM layer

For the initial LSTM operation, use the initial state of the recurrent neural network, find the first output using the first time series sequence, and update the cell state c_t at the timestamp t. The operation utilizes the state of RNN (c_{t-1}, h_{t-1}). Any layer of LSTM consists of a two-layer cell state and a hidden layer (also called the output state). Cell state c_t represents the learning at time t in which information can be added or removed from the cell state in successive operations. The layers control their updates using gates. There are four gates, as shown in Figure 4. Details of the gate, purpose, and formula are mentioned in Table 4 [26].

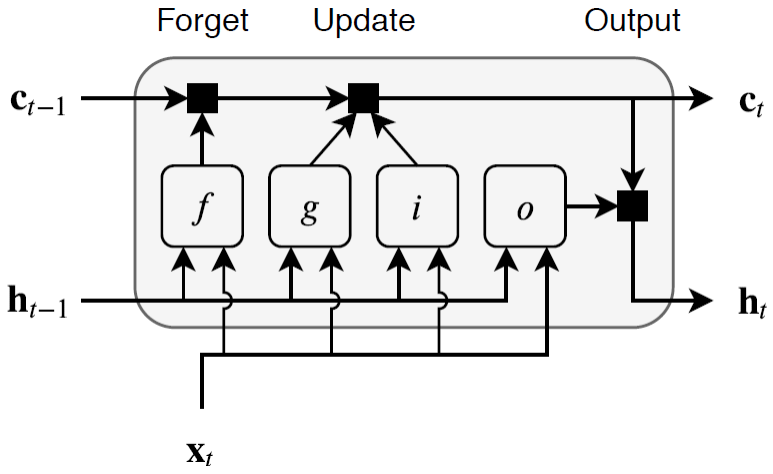

Fig 4. Detail Structure of LSTM cell [26]

Equation 1 shows the learning weights of an LSTM layer as input weights (W), recurrent weights (R), and bias weights (b).

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix} R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix} b = \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix} \tag{3}$$

Where *i, f, g,* and *o* denote the input, forgot, cell, and output gates, respectively. The cell state and hidden state of LSTM are represented by **equations 4 and 5**, respectively.

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{4}$$

$$h_t = o_t \odot \sigma_c(c_t) \tag{5}$$

Table 4. Detail of LSTM gate

Gate	Formula	Purpose
Input gate (i)	$i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i)$	Control cell state update
Forgot gate (f)	$f_t = \sigma_g(W_f x_t + R_f h_{t-1} + b_f)$	Control cell state reset (forget)
Cell candidate (g)	$g_t = \sigma_c(W_g x_t + R_g h_{t-1} + b_g)$	Responsible for adding information to the cell state
Output gate (o)	$o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o)$	Control the level of cell state added to the hidden state.

Where σ_g, σ_c Denotes the gate activation function and the state activation function, respectively.

2.5 Grid Search Optimization Technique

Hyperparameter search for specific machine learning is a crucial task. It presents numerous challenges, such as costly objective function evaluation, randomness, and complex search space. There are two basic optimization techniques: random search and

grid search. Each one-off has its advantages. Random search is better when the search space is too large, while grid search applies to limited-dimensional space.

Conventional grid search optimization finds the optimal solution from the given grid space. However, obtaining a solution does not mean it is the only solution for the best performance of a given problem. To find the appropriate solutions for improving LSTM model performance, a modified grid search technique has been implemented in the proposed study for predicting blood glucose in type-1 diabetics. Figure 5 shows a detailed flow chart of the proposed method.

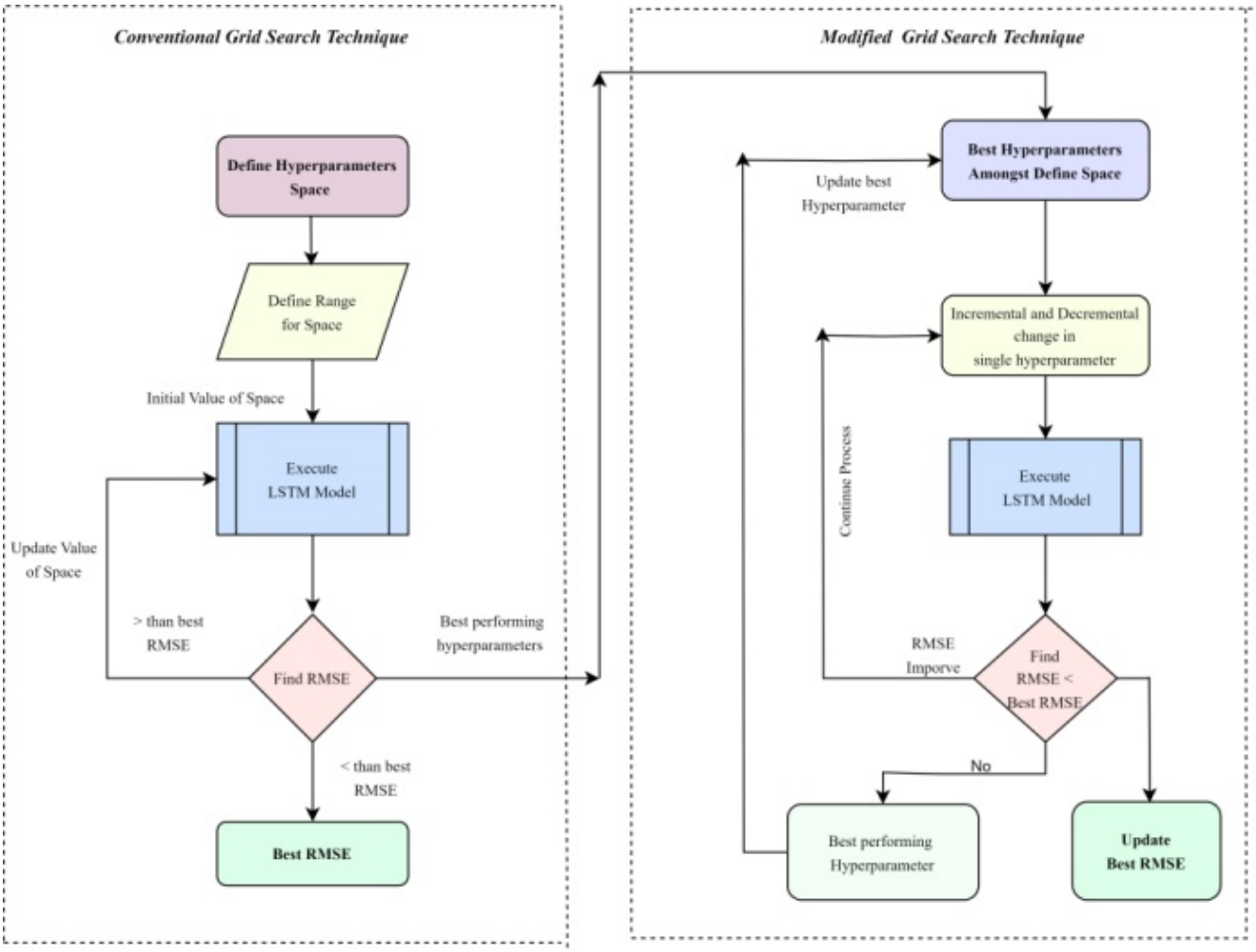

Fig 5. Flow chart of the modified grid search technique

Conventional grid search finds the best set of hyperparameters from the grid's defined space. The proposed modified technique is an extended version of this method. After finding the best hyperparameter conventionally, it focuses on finding the optimum set of configurations using fine-tuning each hyperparameter to improve prediction performance.

In the proposed study, hyperparameters space and range are shown in Table 5 initially defined to find the best-performing configuration in the given range. A few hyperparameters are selected based on trial and error to minimize computation duration for the executions. The drop-out layer is considered 0.10, while the learn rate drop factor is kept constant at 0.5 throughout the study.

There are 1440 combinations possible for the given range of space. After executing the LSTM model with given parameters using the dataset of patient ID 540 in the Ohio dataset, the optimum set of hyperparameter results obtained are as follows:

LSTM units1: [14]

LSTM units2: [7]

Table 5. Initially, define hyperparameters as space and range

Hyperparameters Space	Hyperparameters Range
Number of LSTM units (neurons) in each layer. (three-layer)	LSTM units1: [10, 14, 18, 22, 26, 30] LSTM units2: [3, 7, 11, 16, 19] LSTM units3: [2, 4, 6, 8]
Learning rate for the optimizer.	Learning rate: [0.01, 0.03, 0.05]
Number of epochs (training iterations).	Number of epochs: [250, 300, 350,400]

LSTM units3: [4]

Learning rate: [0.05]

Number of epochs: [300]

2.6 Validation Strategy

Several performance metrics are used to evaluate the performance of the model. The root mean square error (RMSE), R square, mean absolute error (MAE), and correlation coefficient are used. Clark has proposed a technique called Clark's Error Grid Analysis (EGA), which is used to validate the prediction model's performance for clinical acceptability. The RMSE was calculated in this study using **equation 6**, and CG-EGA was considered to evaluate the performance of optimized LSTM. The plot contains five zones (A, B, C, D, and E) in CG-EGA. Where Zone A is clinically accurate, Zone B is not in the ideal range but reasonably safe. Zone C is an over-corrective zone in which there is a discrepancy between the predicted value and the actual value of glucose, which leads to wrong decision-making. Zone D indicates a failure to predict, and Zone E represents a prediction error [27].

$$\text{Root mean Square Error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{N}(y_i(t)-\overline{y}_i(t))^2}{N}} \tag{6}$$

Where N is the number of test samples, and y_i and $\overline{y}_i$ are the actual value and predicted value, respectively.

3 Results and Discussion

The proposed optimized LSTM model using grid search techniques initially processes raw data provided by Ohio and obtains a predicted performance in terms of RMSE of 29.38 $\pm$ 4.20 mg/dl. Then, the same model is considered on process data using linear interpolation, and performance is enhanced to 27.65 $\pm$ 3.12 mg/dl. To improve the prediction accuracy, further modified grid search techniques were used to optimize the LSTM model, which surpasses all the previously reported results mentioned in the literature by achieving an RMSE of 26.16 $\pm$ 2.38 mg/dl.

The performance evaluation of both conventional and modified grid search techniques is recorded in Table 6. Initial hyperparameters obtained using conventional techniques consist of 14, 7, and 3 LSTM units in each layer, while the model used 300 epochs with a learning rate of 0.05 and a dropout layer of 0.10. The achieved prediction result in mg/dl is mentioned as attempt-1 in the table. While the performance of the modified technique has been recorded as attempts -2 after finding hyperparameters using grid search techniques, here, an individual patient-specific model was optimized using the respective dataset. The number of epochs, dropout, and learning rates are kept constant throughout the study, while other parameters are specified in the table. Moreover, the blood glucose-Clark error grid analysis (CG-EGA) technique also considers evaluating the performance optimization model on both datasets collected in 2018 and 2020 by Ohio University, EGA of each patient has been shown in Figures 7 and 8. Zone wise accuracy of each data contributor set is mentioned in Table 7. The overall accuracy in terms of RMSE achieved by the proposed optimized model is presented in Table 8.

We compare the performance of the proposed model in terms of RMSE performance metrics with recently published work on the Ohio dataset and other data sets in the same field of blood glucose prediction for type-1 diabetes. Table 9 shows that the proposed work has outperformed all the others. Out of all the literature, the proposed study has considered the highest number of training and testing samples for a study with a single input feature (CGM). It shows that the model is robust and capable of accurately predicting blood glucose levels with the help of only past CGM data. Literature also considers that the higher the input feature, the higher the predicting accuracy; even most of the best-performing literature has considered more than two input features to improve the model's performance. Moreover, the Ohio dataset was collected in a real-life scenario where a few patients' data had been missing for extended periods. However, we have performed linear imputation for data correction. For

Table 6. Impact of the modified grid search optimization technique on the prediction performance of the LSTM blood glucose prediction model for type- 1 diabetes

Patient ID	Grid Search Optimization Technique Attempt-1 RMSE	Modified Grid optimization Search Technique Optimized Hyperparameters LSTM Unit1	LSTM Unit2	LSTM Unit3	Attempt-2 RMSE
540	27.79	16	8	4	24.84
544	25.72	17	8	-	23.93
552	25.62	15	9	-	24.38
567	25.93	15	7	-	25.69
584	29.44	15	7	3	28.81
596	23.44	15	7	-	23.46
559	33.88	16	9	-	26.56
563	24.99	15	-	-	23.79
570	23.89	16	-	-	25.1
575	30.7	15	7	-	31.44
588	31.53	15	-	-	26.9
591	28.82	16	9	3	29.05
	27.65 ± 3.12	**Mean ± Standard Deviation**			**26.16 ± 2.38**

Table 7. Prediction accuracy of the optimized LSTM model

	Clark Error Grid Analysis					
Ohio Dataset	**Zone-A**	**Zone-B**	**Zone-C**	**Zone-D**	**Zone-E**	**Accuracy (%)**
2020 contributor	80.79	17.044	0.104	2.062	0	97.834
2018 contributor	78.161	18.011	0.101	3.728	0	96.171

Table 8. Effect of Quality of data and Optimization Techniques on the Performance of blood glucose prediction in type-1 diabetes

Ohio data	Grid Search Optimization Technique RMSE (mg/dl)	Modified Grid Search Optimization Technique RMSE (mg/dl)	Model Prediction Accuracy (%)
Raw data	29.38 ± 4.20	28.11 ± 4.17	-
Process data	27.65 ± 3.12	26.13 ± 3.25	97.07

more extended periods, data missing more than 1 hour are randomly deleted data points to make the dataset more accurate after the execution of linear interpolation. Two female contributors, ID 575 and 591, have the lowest performance, possibly because the highest number of samples are missing in their training dataset, as mentioned in Table 3. This indicates that the prediction performance highly depends on the dataset's quality. The glucose dynamics of both patients are shown in Figure 8.

A Clark EGA was also executed on each patient to determine the proposed work's clinical accuracy. The highest accuracy of 97.83% was obtained for the 2020 contributor while using the proposed model, 96.17% accuracy was obtained for the 2018 contributor. It was also discovered that the E zone has no single data point. In contrast, zone C has 0.1 percent of data, indicating a significant difference between the actual and predicted results, possibly leading to fall treatment. Zone D has 2.06 and 3.72% of data points for 2020 and 2018 data contributors, respectively. This suggests a high discrepancy between predicted and actual data points and that a higher level of attention is required for diabetes management.

The proposed study has performed better than previous work in terms of selecting input features, processing data, and implementing the model. Several articles suggest that meals, insulin doses, and physical activity play an important role in the future value of blood glucose. Carbohydrate information, along with CGM, has more impact on predicting accuracy than insulin at the same time, no feature may lead to errors in prediction. So, there are different opinions about selecting features and processing methodology. The quality and quantity of the dataset play a significant role in model evaluation. Some research work has been conducted with the same aim, but the samples used are too small, which is questionable for clinical acceptance. The engineering features of the sample have an excellent impact on the model's performance. In this study, the moving average was considered a separate feature along with CGM, which follows the glucose trend and helps the model predict very efficiently.

Previous studies have considered several ML techniques as predictors for blood glucose. Still, LSTM is simple in structure and can memorize past patterns and based on that, predict future values very effectively and accurately.

Table 9. Comparative analysis of the proposed model with literature work in terms of RMSE mg/dl by considering the number of inputs, datasets, and models used for blood glucose prediction in type-1 diabetes (PH=60 min.). The table shows findings arranged from higher to lower RMSE

Study	Dataset	No. of Input Features	Model	RMSE (mg/dl)
[17]	Real and Simulated data	CGM	LSTM-Bi-LSTM	36.91
[15]	Ohio Dataset (2020 Dataset)	More than one	Bi-LSTM	35 ± 5.4
[16]	Ohio dataset (2018 Dataset)	4 (CGM, Insulin, Carbohydrate, Activity)	Regression Model	31.72
[14]	Ohio dataset (2018 Dataset)	CGM	LSTM	31.40 ± 2.07
[12]	Ohio Dataset (Only Three patients)	2 (CGM & Operative Carbohydrate)	Bi-LSTM and Vanilla-LSTM	28.25
[18]	Ohio dataset (2018 Dataset)	5 (CGM, Meal, Insulin, HR. Skin Conductance)	LSTM	28.19
[13]	Ohio dataset (2020 Dataset)	14 (CGM, fingerstick glucose, insulin dose (basal and bolus), carbohydrate, GSR, skin temperature, sleep quality, illness,work intensity, Physical Activity, heart rate(HR), room temperature, Step count)	MLR	27.56
[19]	Replace-BG	3 (past glucose, insulin, and carbohydrate)	CNN-LSTM	27.19 ± 5.59
	DIAdvisor	7 (CGM, self-reported insulin intakes for basal, bolus, and correction doses and meal nutrients content for CHO, protein, and lipids)	CNN-LSTM	29.08 ± 5.40
Proposed Study	**Ohio Dataset (2018 & 2020 Dataset)**	**CGM**	**Optimized LSTM**	**26.13 ± 3.25**

4 Conclusion

This study has proposed an optimized model consisting of LSTM, which performs the blood glucose prediction 60 minutes ahead and shows significant improvement in prediction accuracy by considering only one CGM input feature compared to previous work in the same field. This finding encourages researchers to consider only one input feature for the next generation of artificial pancreas to control blood glucose. The proposed work has shown performance metrics RMSE of 26.13±3.25 mg/dl for 60 min. PH. More than 1.3 lakh samples were considered for this study using the Ohio dataset. In blood glucose management, several factors, like insulin dose, meal intake, and physical activity, are essential for controlling glucose. The effect of insulin dose, except for recent and previous carbs, is already incorporated in CGM. Our study solely considers CGM for blood glucose prediction, which makes the model more superficial and more robust for artificial pancreas without any human involvement, which reduces the error and improves the performance accuracy. Though the proposed data-driven model doesn't consider the underlying physiological behaviors of the system, In the future, a systematic approach using hybrid models can be implemented for the prediction of blood glucose, considering both a physiological model and a data-driven model.

Moreover, patient-specific models have a significant role in blood glucose management, as every individual has different blood glucose dynamics. In this study, common models used for every patient have a higher RMSE than patient-specific models. This suggests that machine learning abilities can be well explored when the hyperparameters are optimized for specific patients only. The study could be extended to 90 or 120 minutes of PH to give patients more time to take corrective action for any

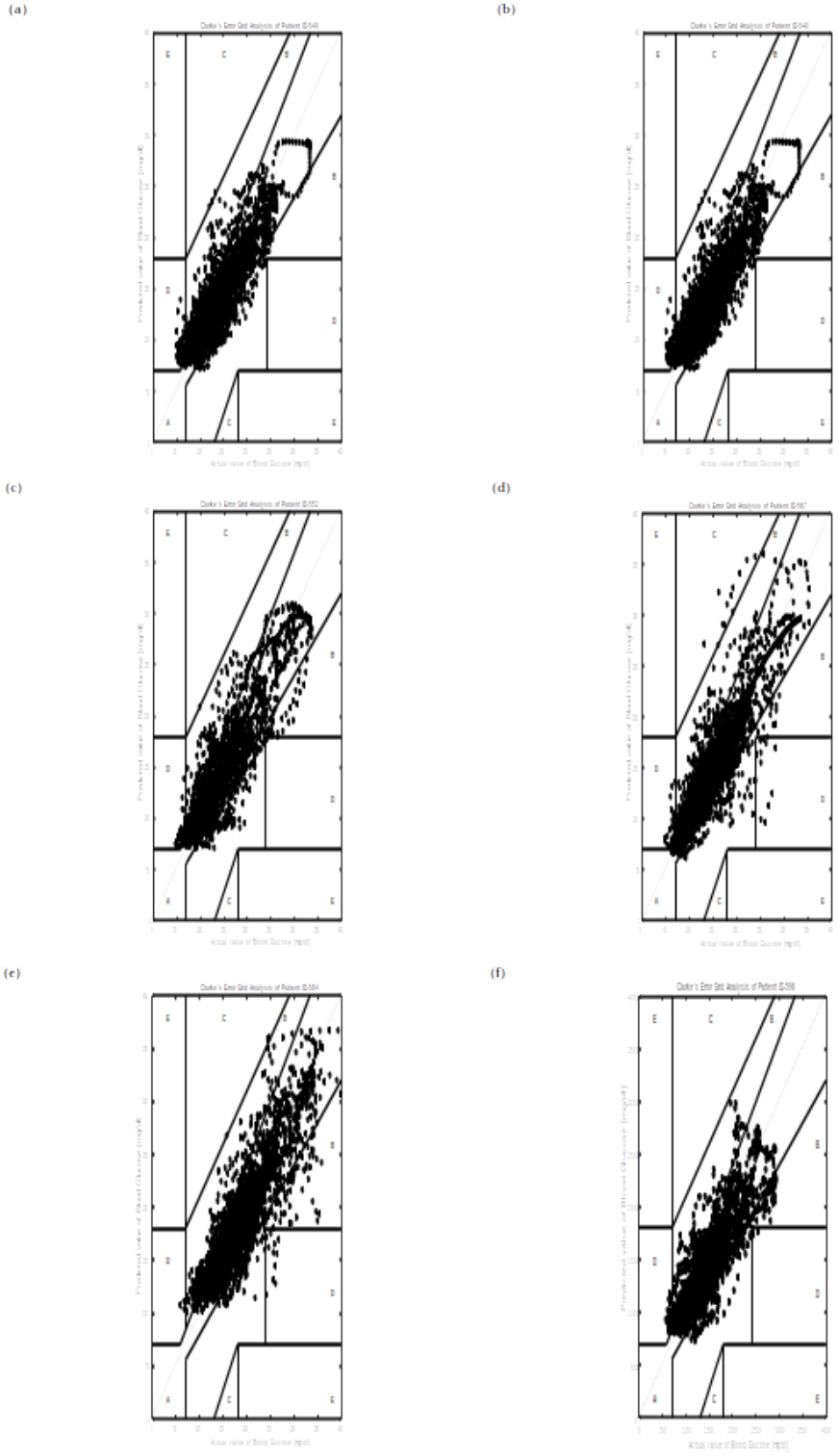

Fig 6. CG-EGA of type-1 diabetic patients contributed in 2020

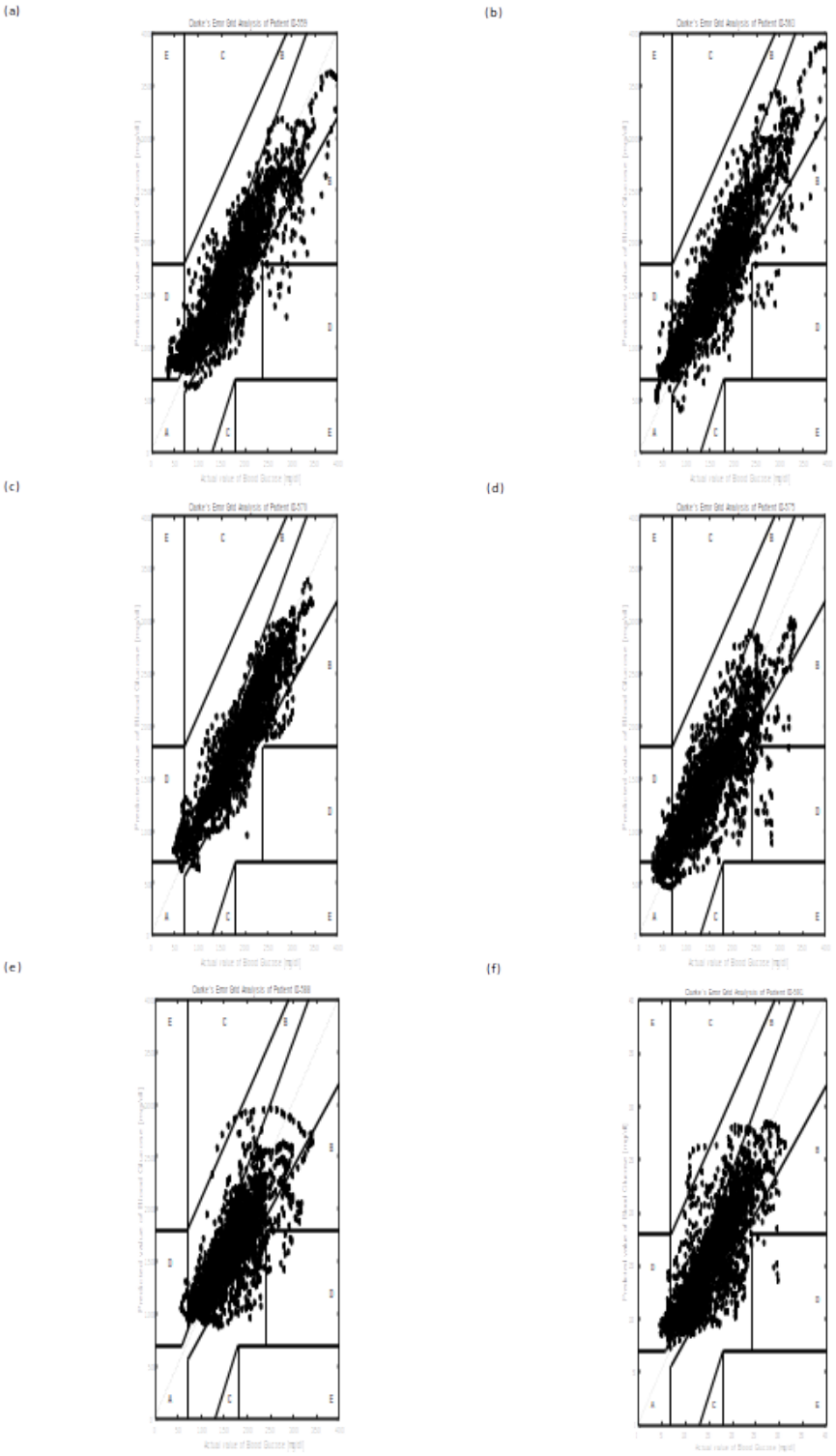

Fig 7. CG-EGA of type-1 diabetic patients contributed in 2018

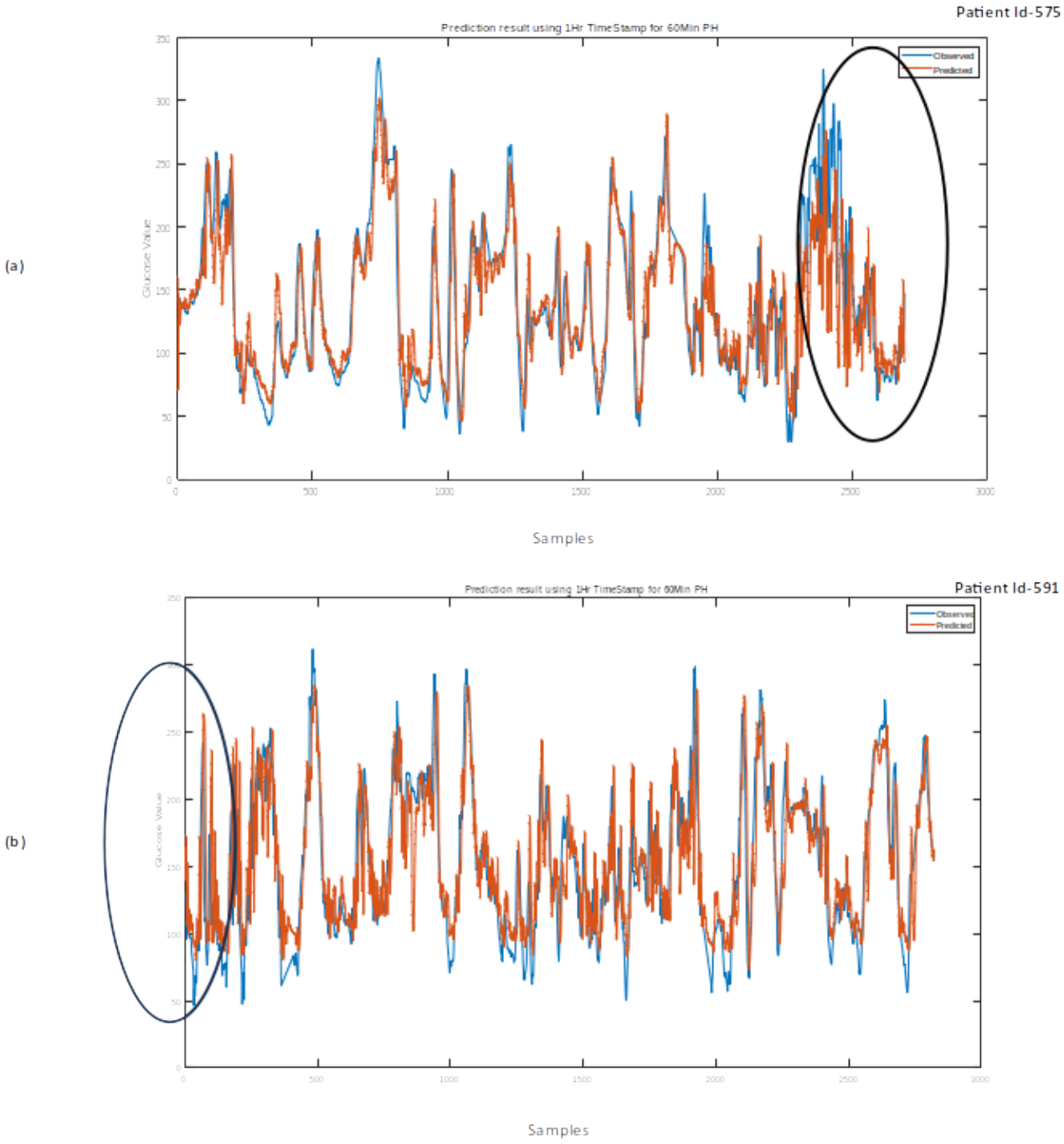

Fig 8. Blood glucose prediction results for patient IDs 575 and 591. The blue line indicates the observed value, while the red line indicates the predicted value

upcoming abnormalities. The transferability of the model is also one of the research gaps to be considered to make the model generalize for everyone.

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