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Research Article

Optimizing Blood Glucose Prediction Accuracy for Type-1 Diabetes with a Stacked LSTM Universal Model

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ABSTRACT

Integrating machine learning in diabetes care has opened the door for the development of a more advanced artificial pancreas. Multiple machine learning models have been applied to diverse datasets, including real and In Silico data, to minimize prediction errors. The goal is to develop a robust system to predict glucose levels with 60 min. of prediction horizon (PH) well in advance to prevent critical medical emergencies. Extensive research has been carried out to improve the predicting accuracy of specific models. However, the interpersonal effectiveness of the model is significant for clinical acceptance and commercial viability. The proposed approach employs a universal optimized stacked LSTM model to validate its applicability across type-1 people with diabetes for blood glucose prediction. The model was trained using the Ohio dataset and tested using the Ohio testing and D1NAMO datasets. The model demonstrates an accuracy of 22.24 ± 2.71 mg/dL RMSE, and 16.21 ± 2.29 MAE, with an EGA of 97.48% accuracy in the Ohio dataset. For the D1NAMO dataset, the model shows an accuracy of 13.79 ± 4.29 mg/dL RMSE, and 10.02 ± 3.31 mg/dL MAE, with an EGA of 96.56% accuracy for a 60-minute prediction horizon. The results obtained from the universal model have surpassed the performance of the existing patient-specific model. This demonstrates the capability of machine learning-based predictors to manage blood glucose in individuals with type-1 diabetes effectively.

Keywords: Machine Learning, Blood Glucose Management, Stacked Long Short-Term Memory Model (LSTM), Continuous glucose monitoring (CGM).

1. Introduction

Diabetes is a chronic condition due to high glucose levels in the blood. It occurs when the body either doesn't produce enough insulin or cannot use insulin effectively. There are two types of diabetes based on this. Type 1 diabetes results from insufficient insulin production in the body. This type of diabetes generally occurs at an early age, although it can develop at any age. According to a global report, 537 million adults are living with diabetes, and this number may increase to 643 million by 2030 [1]. Individuals with type 1 diabetes must take exogenous insulin doses to maintain their blood glucose levels within a healthy range. Failing to do so can lead to serious medical problems, including kidney failure, heart disease, nerve damage, stroke, and vision impairment [2]. Early prediction of blood glucose levels may assist in enhancing diabetes management. Managing diabetes involves considering factors essential in controlling glucose levels, such as intake of carbs, insulin dosage, level of physical activity, and stress levels. Blood glucose control is a complex process, and it is challenging to determine the exact impact of variables on blood glucose. As a result, vast majority of research has focused on a few variables for predicting blood glucose, typically using 2 to 3 variables such as continuous blood glucose monitoring (CGM), meal intake, and insulin dosage for future predictions. The utilization of additional input variables may lead to the development of patient-specific models that lack generalizability over diverse patient population due to inherent variations in individual physiological responses and characteristics. Continuous Glucose Monitoring (CGM) systems provide real-time blood glucose data at regular intervals, encompassing historical records of relevant parameters such as carbohydrate intake, insulin

administration, and physical activity. Consequently, the exclusive reliance on CGM data for predicting blood glucose levels in type-1 diabetes presents an optimal approach for ensuring model transferability across a broad spectrum of type-1 diabetic patients [3].

Machine learning-based decision-making in the medical industry has excellent potential for further growth. Predicting blood glucose levels using machine learning will be crucial for the future development of artificial pancreas for type-1 diabetes care. However, these predictions face limitations in terms of clinical acceptance due to their performance. As a result, researchers have been testing various combinations to find the best approach. Most existing research has focused on developing models specific to individual patients [4]. There are multiple methods to handle the data used for the study, including the machine learning approach, performance metrics for model evaluation, and more [5]. Mario M. Oraganero (2020) developed a deep physiological model to evaluate patient-specific models and a general model for transferability. This research article is the only one that has tried to assess the transferability of the model to other participants and achieved an RMSE of 49.38 mg/dL. However, this value is considerably higher than the average RMSE obtained in patient-specific models [6]. Other articles related to this study focus on the model's performance on specific patients. Some noteworthy personalized performance models include: Hatim Butt et al. (2023) implemented an LSTM-based personalized glycemic profile for a self-monitoring system in people with type 1 diabetes and achieved 14.76 mg/dL and 25.48 mg/dL for prediction horizons of 30 and 60 minutes [7]. John Martinsson et al. (2020) implemented a recurrent neural network to predict PH blood glucose in 60 minutes on an Ohio dataset, achieving an accuracy of 31.403 ± 2.078 mg/dL [8]. Jaloli M et al. (2023) achieved RMSE of 27.19 ± 5.59 and 29.08 ± 5.40 mg/dL (for 60 min. PH) for both replace-BG and DIAdvisor datasets. The author did not test the model's inter-patient robustness for generalization [9]. This indicates that most research on this subject has been concentrated solely on patient-specific models rather than universal ones.

The remainder of this paper is structured as follows. Section II, which discusses Ohio and the D1NAMO dataset used in the study. Section III covers Stacked Long-Short Term Memory (LSTM) Model implementation and model performance for transferability, while Section IV contains results and discussion. Section V concluded work by discussing the future scope.

2. Type-1 Diabetes Dataset

Obtaining a high-quality and quantitative dataset for a thorough investigation is often challenging, directly impacting model performance. We utilized the Ohio University dataset of type-1 patients for the proposed study [10]. We created a data usage agreement for the study. We used the D1NAMO dataset to test the transferability of the predictive model. This open-source dataset is meant for the scientific community to create and assess type-1 diabetes management algorithms [11]. The statistics in Table 1 provide information about the data contributors for the Ohio and D1NAMO project datasets.

Table 1. Statistics: Individual data contributor

Ohio Dataset					**D1NAMO Project Dataset**			
Patient ID	Gender	Age	Training Samples	Testing Samples	Patient ID	Gender	Age	Testing Samples
540	Male	20-40	11947	2884	01	Male	NA	1438
544	Male	40-60	10623	2704	02	Male	20-29	1071
552	Male	20-40	9080	2352	03	Male	20-29	186
567	Female	20-40	10858	2377	04	Male	20-29	984
584	Male	40-60	12150	2653	05	Male	30-39	928
596	Male	60-80	10877	2731	06	Male	30-39	1298
559	Female	40-60	10796	2514	07	Female	30-39	1011

563	Male	40-60	12124	2570	08	Female	60-69	1175
570	Male	40-60	10982	2745	09	Female	70-79	306
575	Female	40-60	11866	2590				
588	Female	40-60	12640	2791				
591	Female	40-60	10847	2760				

3. Methodology

3.1 Stacked Long-Short Term Memory (LSTM) Model

The proposed research employed an optimized stacked Long Short-Term Memory (LSTM) model to predict blood glucose levels 60 minutes in advance. The selection of LSTM is based on its robust long-term dependency and capacity to discern time series patterns over extended durations [12]. Stacked LSTM consists of more depth of network which allows to learn more complex temporal patterns [13]. The process of stacked LSTM model optimization and validation is illustrated in Figure 1. The stacked LSTM model was initially adjusted using grid search techniques to identify the highest performing hyperparameters for improved prediction accuracy. Once the model has been refined, it will be trained with combined training samples from the Ohio dataset. 12 timestamp CGM data used as an input feature for the prediction of blood glucose. A total of 144812 samples are used in model training. This dataset demonstrates the dynamic characteristics of type-1 diabetics because it includes patients of all ages and genders, making it likely acceptable for model transferability validation in the Type-1 community. Stacked LSTM model has been fine-tuned with the following hyperparameters shown in Table 2 to optimize its performance. Adam optimizer was utilized for efficient learning, and these settings collectively enhanced the model's learning capability, leading to accurate blood glucose predictions across a broader prediction horizon. After training and validation, testing was performed using Ohio and D1NAMO project dataset.

Table. 2 Finalized set of best hyper parameters.

Optimizer	Adam
Learning Rate	0.05
epoch	300
LSTM Layer	3
Number of Cells in LSTM Layer-1	14
Number of Cells in LSTM Layer-2	7
Number of Cells in LSTM Layer-3	4
Dropout layer	0.10

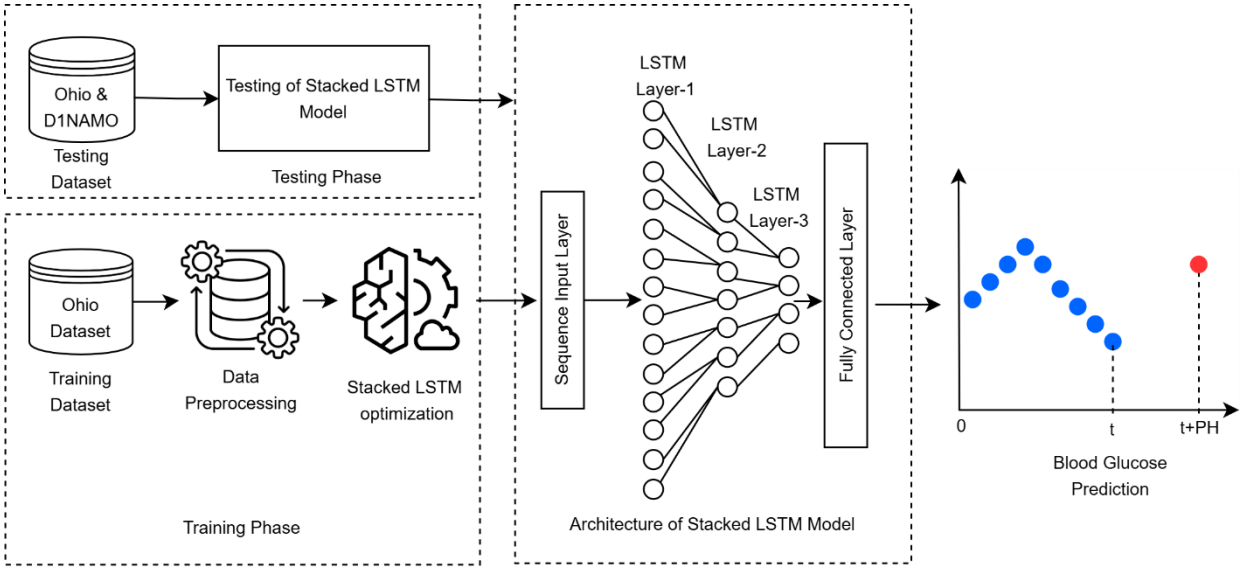

Figure 1. Process of Stacked LSTM model Optimization and validation

3.2 Model Performance

The model's performance was validated by testing it with a type-1 dataset that was not used during the training phase. Ohio dataset provided a separate testing dataset, while the D1NAMO dataset consisted solely of testing datasets. The model's performance was measured using the root mean square error (RMSE) and mean absolute error (MAE) metrics. Error Grid analysis (EGA) was also utilized to ensure the clinical acceptability of the proposed model [14]. The model's accuracy for each Ohio patient and the D1NAMO data set contributor is shown in Figures 2 and 3. In error grid analysis, anticipated values are categorized into five regions: A, B, C, D, and E, each providing information about the model's forecast accuracy. Region A represents the predicted value within 20% of the actual value, while region B contains the predicted value outside of 20% but does not result in fall therapy. Region C indicates unneeded treatment, while region D suggests a failure to notice hyper/hypo occurrences. Table 3 shows the EGA of both datasets, with region E confusing handling hyper/hypo. Figures 4 and 5 display the error grid analysis of patient IDs 540 and D1 from both datasets.

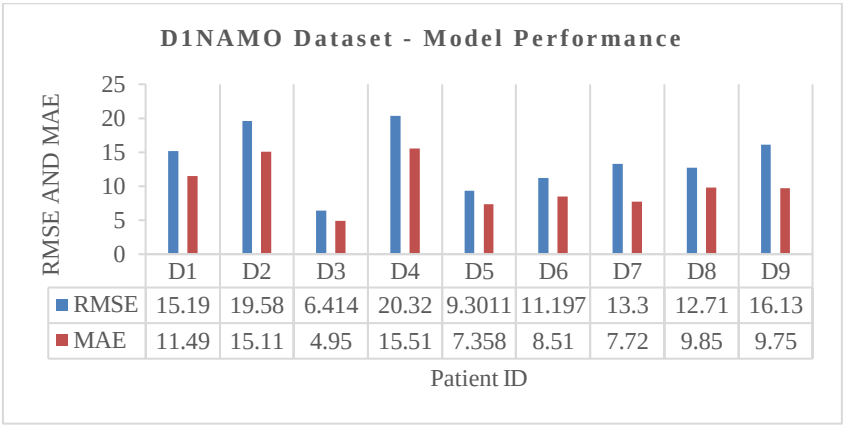

Figure 2. LSTM Model performance on D1NAMO dataset.

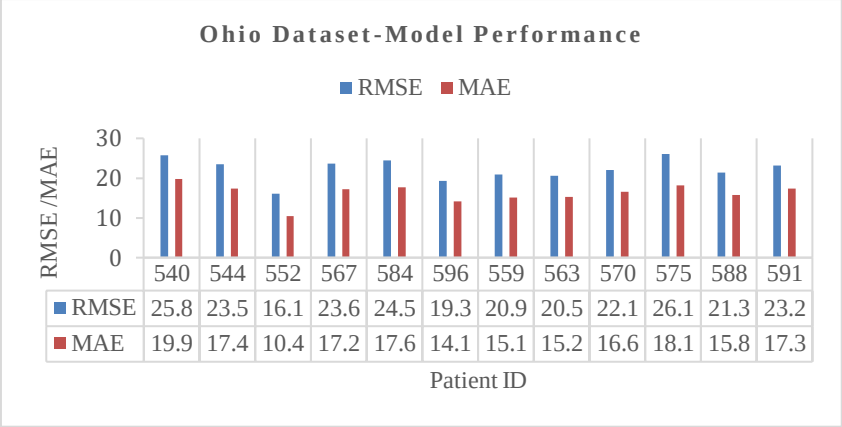

Figure 3. LSTM model performance on Ohio dataset.

Table 3. Error Grid Analysis of Ohio and D1NAMO dataset.

Ohio Dataset							**D1NAMO Dataset**						
Patient ID	A	B	C	D	E	Prediction Accuracy	Patient ID	A	B	C	D	E	Prediction Accuracy
540	74.5	21.6	0	3.85	0	96.15	D1	89.78	7.63	0	2.59	0	97.41
544	81.5	15.3	0	3.15	0	96.85	D2	79.07	13.66	0	7.27	0	92.73
552	89.2	9.3	0	1.45	0	98.55	D3	96.23	1.26	0	2.52	0	97.48
567	79.5	14.4	0	6.12	0	93.88	D4	80.21	15.56	0	4.23	0	95.77
584	82.9	16.3	0	0.88	0	99.12	D5	94.69	3.95	0	1.35	0	98.64
596	86.3	11.7	0	1.98	0	98.02	D6	91.64	6.45	0	1.91	0	98.09
559	85.7	11.6	0	2.79	0	97.21	D7	90.77	5.39	0	3.84	0	96.16
563	87.9	11.7	0	0.43	0	99.57	D8	88.89	7.08	0	4.03	0	95.97
570	87.4	12.3	0	0.32	0	99.68	D9	93.54	3.23	0	3.23	0	96.77
575	79.7	15.3	0	4.96	0	95.04							
588	87.9	11.8	0	0.29	0	99.71							
591	78.7	17.3	0	4.04	0	95.96							

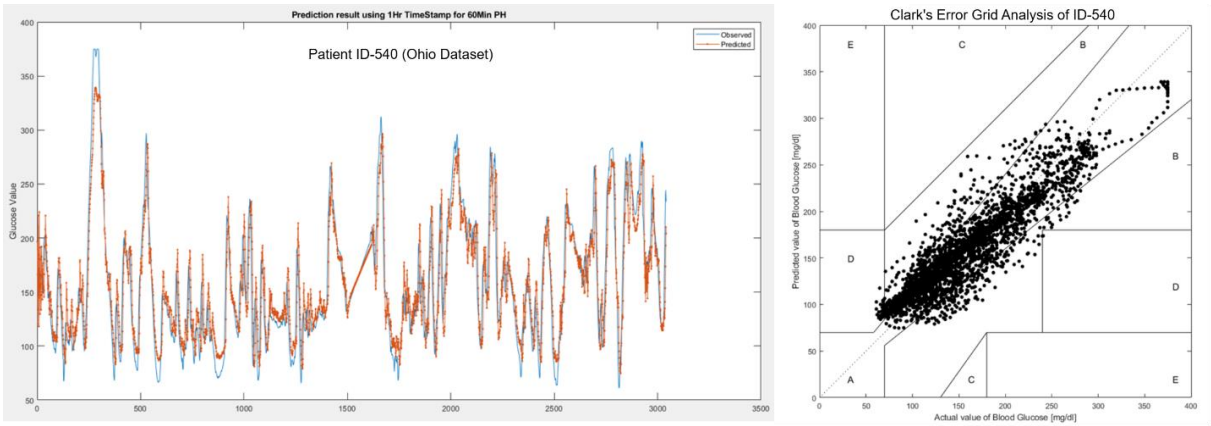

Figure 4. Patient ID-540 (Ohio) blood glucose prediction along with EGA

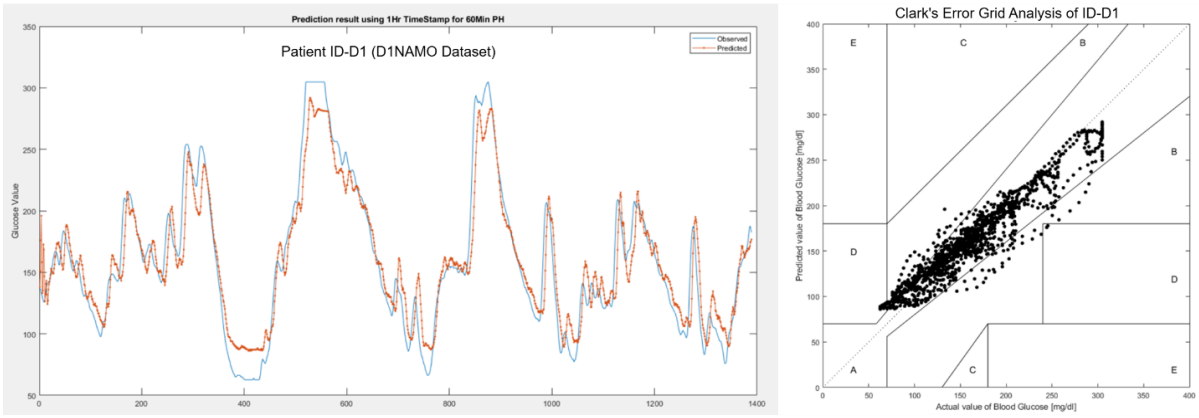

Figure 5. Patient ID-D1(D1NAMO) blood glucose prediction, along with EGA

4 Results and Discussion

The proposed model's prediction accuracy for transferability was tested on two separate datasets: Ohio and D1NAMO. RMSE and MAE were used as performance indicators to evaluate the model's performance, as shown in Table 4. For the Ohio dataset, the proposed model demonstrated a prediction accuracy of 22.24 ± 2.71 RMSE and 16.21 ± 2.29 MAE. The results show that the proposed model can be effectively applied to inter-personal blood glucose management. The model accurately predicted an RMSE of 13.79±4.29 and an MAE of 10.02±3.31 for the D1NAMO dataset. Both datasets were analyzed graphically using EGA, yielding 97.48% for the Ohio dataset and 96.56% for the D1NAMO dataset. Patient specific EGA consolidated in Table 3. The high proportion of EGA indicates a strong alignment between observed and projected values. At the same time, lower RMSE and MAE suggest that the model can accurately predict blood glucose levels, aiding in diabetes treatment in daily life. A comparative analysis of the proposed study with the major literature available for the same study is shown in Table 5. The model outperformed all previous patient-specific models.

Table 4. Predicting the performance of the model in Ohio and D1NAMO datasets.

Performance Metrics	Ohio Contributor	D1NAMO Contributor
RMSE	22.24 ± 2.71	13.79 ± 4.29
MAE	16.21 ± 2.29	10.02 ± 3.31
EGA (%)	97.48 %	96.56 %

Table 5 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.). Findings are arranged from higher to lower RMSE in table.

Study	**Dataset**	**No. of Input Features**	**Model**	**RMSE (mg/dl)**
[18]	Real and Simulated data	CGM	LSTM-Bi-LSTM	36.91
[16]	Ohio Dataset (2020 Dataset)	More than one	Bi-LSTM	35± 5.4
[15]	Ohio dataset (2018 Dataset)	4 (CGM, Insulin, Carbohydrate, Activity)	Regression Model	31.72
[8]	Ohio dataset (2018 Dataset)	CGM	LSTM	31.40±2.07
[7]	Ohio Dataset (Only Three patient)	2 (CGM & Operative Carbohydrate)	Bi-LSTM and Vanilla-LSTM	28.25
[17]	Ohio dataset (2018 Dataset)	5(CGM, Meal, Insulin, HR. Skin Conductance)	LSTM	28.19
[19]	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
[9]	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**	**Stacked LSTM**	**22.24±2.71**
	D1NAMO Dataset	**CGM**	**Stacked LSTM**	**13.79±4.29**

5 Conclusion

Predicting blood glucose levels is essential in diabetes care, particularly in artificial pancreas implementation. While numerous studies have been undertaken on this subject, the primary challenge is ensuring the clinical acceptability of all proposed methodologies. The existing research on blood glucose prediction in type 1 diabetes is primarily tailored to individual patients, which may limit its broader clinical applicability. To address this limitation, we conducted an extensive analysis using a diverse dataset encompassing various age groups. Our findings revealed that the optimized stacked LSTM model outperformed the patient-specific model in performance. The results show that a stacked LSTM model can predict blood glucose levels effectively. Our model's accuracy on the D1NAMO dataset surpasses that of Ohio regarding RMSE and MAE. This is likely due to the D1NAMO dataset being smaller and more accurate, while Ohio's datasets are more extensive and contain missing values at certain time intervals, leading to prediction errors. The current approach uses only CGM as an input for predicting blood glucose levels. However, in the future, we can improve the predictions by including additional factors such as meal intake, insulin dose, and physical activity. There is also potential for enhancing the model architecture and utilizing innovative machine learning techniques to create more reliable solutions for predicting blood glucose levels.

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