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Glucose Level Prediction of LIBREPRO CGM Sensor Data Using Machine Learning Algorithm for Enhanced Diabetes Mellitus Management

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***Abstract*—** "India now carries 20 percent of the global burden of diabetes. There is an immense need and progress to be made to identify the possible fluctuation of blood glucose before hand with minimal errors and thereby enabling proactive decision making. As per statistics one in 15 people in UK have diabetes, including one million people who have type 2, but haven't been diagnosed. In this paper, focus is to use data science(An interdisciplinary field that uses skills from various fields such as statistics machine learning, artificial intelligence, visualization etc.) algorithms like time series machine learning to derive meaningful and appropriate information from large volumes of blood glucose level and related data for precise forecasting of upcoming blood glucose level fluctuations. Not only can the patient and physician be informed beforehand, to avert complications, but it also aids in predicting response to certain medications with ease. In this case, time series machine learning algorithm is implemented on 15 days LIBRREPRO Continuous Glucose Monitoring (CGM) Sensor dataset of 10 different patients. A comparison of performance evaluation metrics of the different time series machine learning algorithms is drawn. Simple exponential smoothing(SES) Algorithm, with alpha and beta of 0.99 provided the least Root Mean Square Error (RMSE) of 7.98mg/dL for 15-minute prediction, 19.47mg/dL for 30-minute prediction. The Theil's U coefficient was 0.12 for 15-minute, 0.39 for 30-minute prediction.

***Keywords*—** *Glucose Prediction, Machine Learning, SES, MA, RMSE, Theil's U, LIBREPRO, CGM Sensor, Data Science, Time Series Forecasting, Moving Window Walk Forward Validation.*

I. INTRODUCTION

Diabetes is a serious condition where blood glucose level is too high. There are two main types, namely Type 1 and Type 2 [1]. A person is said to be in hypoglycaemia state when the glucose level is below 70 mg/dl. Hypoglycaemia can cause immediate symptoms of weakness, confusion, dizziness, sweating, shaking, and, if not treated in time, seizures, coma or death. If it is above 200mg/dl two hours after eating or greater than 126 mg/dL when fasting, the person is said to be in a hyperglycaemia state. Hyperglycaemia can lead to long-term complications including blindness, amputations, kidney failure, strokes, and heart attacks [2,3]. Therefore pressing the need to give a proactive alert of hypoglycaemia or hyperglycaemia state beforehand using data science to the medical team for providing timely treatment.

In this paper, time series machine learning algorithms are focused to forecast one step ahead(15 minutes prediction horizon), two step ahead(30 minutes prediction horizon) and three step ahead(45 minutes prediction horizon) forecast .

In section II we provide an overview of the recent research carried out in effective diabetes management using data science. Section III contains freestyle librepro visual report. Section IV comprises of time series forecasting model. Section V consists of the technique used in time series forecasting which is named as moving window walk forward validation technique. Section VI comprises of different time series forecasting algorithms implemented to forecast blood glucose level at different step aheads. Section VII consists of results and discussions. Section VIII concludes the research work.

II. RELATED WORK

Maintaining blood glucose level within permissible limits is an effortful task. Especially Type I Diabetic patients need to monitor the blood glucose level on a regular basis and must receive timely palliative treatment if alerted with hypoglycaemic or hyperglycaemic states. Since real time monitoring of blood glucose levels results in time stamped data, we use time series based forecasting method within

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data science to forecast blood glucose values. Hence we have done a Literature Survey on time series based forecasting Techniques, though many other methods can be used for Diabetes Mellitus Management.

Sparacino et al. [4] predicted future glucose levels by collecting data from 28 type 1 diabetic volunteers for 48 hours through a CGM device every 3 minutes. The behaviour of a first-order polynomial and a first-order autoregressive model were compared. Tests with different forgetting factors and Prediction Horizons (PH) were performed. They conclude that the auto-regressive model yielded more accurate predictive results when compared to the polynomial one with PH of 30 minutes. However since the dataset was restricted only to 2 days data, the effectiveness of the result needs to be tested for larger dataset.

Jensen, M. H et.al[5] have used machine learning approach namely Auto-Regressive Integrated Moving Average (ARIMA) and Support Vector Regression (SVR) model for hypoglycaemia prediction. They claim that SVR model has outperformed clinical diagnosis in predicting 23% of hypoglycaemic events 30 minutes in advance.

Marling et al. [6] divided the available dataset of patients into training and testing data. Initial 7 days data was used to train the model and last 3 days data was used to test. Moving Average (MA), SES and Support Vector Machine (SVM) techniques were used. SVM outperformed by obtaining RMSE of 18.0 mg/dL for 30 minute PH and RMSE of 30.9 mg/dL for 60 minutes PH. Neural Network based approach for predicting glucose level is employed in [7-12].

Meriyan et.al. [13], have used two separate patient databases collected under hospitalized (disturbance-free) and normal daily life conditions using CGM sensor at every 5-minute interval. The time-series model was integrated with recursive identification and change detection methods to enable dynamic adaptation of the model to inter-/intra-subject variability and glycaemic disturbances. Prediction performance is evaluated in terms of glucose prediction error and Clarke Error Grid analysis (CG-EGA). CG-EGA analysis results in accurate readings of 90% or more.

V. Petridis[14] has used Bayesian Combined Predictor (BCP), a probabilistically motivated predictor for time series prediction. The BCP outperforms conventional predictors. Jaques Reifman et.al. [15] has shown data-driven AR models provide sufficiently-accurate and clinically-acceptable estimates of glucose levels for PH of 30 minutes. AR models are shown to be portable. It reduces model tuning and data collection for model development when migrating between patients. Most of the literature study is carried out on CGM sensors, which requires finger print calibration. Hence creating the room for error in predictions for different individuals.

In this paper we have used LIBREPRO Sensor, which is inexpensive and free of finger print calibration [16]. Though there is no initial calibration, accuracy is good. This supports portability. The prediction algorithm can be generalized over different age groups, gender, Type I or II, or gestation diabetic patients. But LIBREPRO provides non real time data, it collects 14 days data. This data is available as a visual report that shows trends and patterns in glucose levels, high and low blood sugars, and glucose variability from the two weeks during which the sensor was worn. This is downloaded by a reader device in the office of the medical team. A Flash Glucose Monitoring reader is used to scan the sensor [1, 17]. As LIBREPRO does not provide real time warning system, to compensate this in this paper we employ Time Series Machine Learning Algorithms in data science for enabling the warning system by continuously providing the glucose values beforehand. In the next section we provide the detailed visual report of LIBREPRO sensor reading.

III. FREESTYLE LIBREPRO VISUAL REPORT

Abbott′s Flash Glucose Monitoring(AGP) System continuously measures glucose in interstitial fluid through a small (5mm long, 0.4mm wide) filament that is inserted just under the skin by a doctor. The sensor is disposable and is held in place with a self-adhesive pad and remains on the back of the arm for up to 14 days, requiring no patient interaction with the sensor or finger-prick calibration. It records glucose levels every 15 minutes, capturing up to 1340 glucose readings over 14 days. Figure1. shows LIBREPRO sensor and reader.

Figure 1. Abbot LIBREPRO Sensor and Reader

The AGP provides a systematic approach to interpreting dense glucose data from glucose monitoring systems. AGP provides more certainty with regard to interpreting trends over time [18]. As shown in Figure 2 the AGP graph gives

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the daily average reading. In this case the daily average reading is measured to be 109mgl/dL. The time during which the glucose crosses the target range of (above 140mg/dL and below 80mg/dL) hyper and hypo range is recorded.

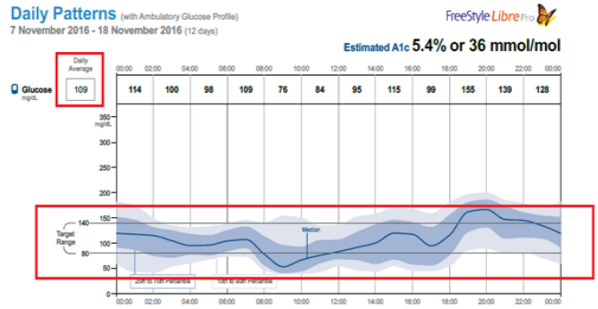

Figure 2. Snapshot of LIBREPRO AGP Graph (Courtesy: Jnana Sanjeevini Diabetes Hospital and Medical Center, Bangalore)

The Report also provides a daily glucose analysis as shown in Figure 3.

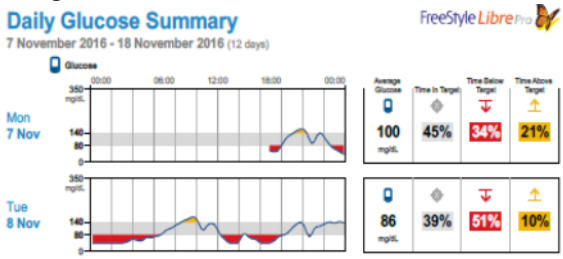

Figure 3. Daily Glucose Summary

On a daily basis the average glucose reading is recorded and the percentage of time - the data within the target, or the data in hypoglycaemic state or in hyperglycaemic state are recorded which will provide the medical team with enough information for diagnosis.

IV. TIME SERIES FORECASTING MODEL

In this Section Time Series Machine Learning Algorithms within data science is implemented to predict blood glucose levels on a continuous time basis is discussed. The dataset used is from LIBREPRO CGM Sensor. The algorithms discussed are implemented on 10 different Type I diabetic patient datasets consisting of 10 days reading. The blood glucose level is measured every 15 minutes once, hence giving us 960 reading per patient. The total dataset consists of 9600 readings. The readings are verified and taken from "Jnana Sanjeevini Diabetes Hospital and Medical Centre", Bangalore. The block diagram of Time Series Machine Learning Algorithm implementation is shown in Fig 4.

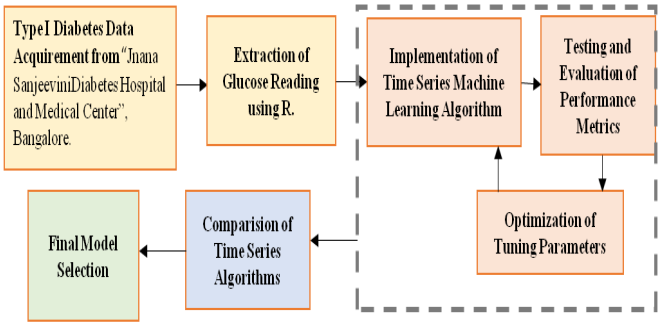

Figure 4.Time Series Forecasting Model Implementation Block Diagram

Fig 4 shows the block diagram of model implementation. Initially we acquire the data, it is necessary to obtain a sufficient set of verified datasets related to the problem. Next we pre-process the data using R Software limiting the glucose reading to 10 days. During implementation, the time series machine learning models are built and tested for various performance metrics. And if required, the tuning parameters are varied and tested again on an iterative basis to obtain optimized tuning parameters specific to the algorithm. Later, we compare the various algorithms implemented and the algorithm for which satisfactory results are obtained over the entire dataset of 9600 readings, is finalized and accepted. The next section details out the cross-validation method used to create subsets of the entire dataset of individual patients.

V. MOVING WINDOW WALK FORWARD VALIDATION TECHINQUE

Since the goal of time series forecasting is to obtain accurate predicted values beforehand. The traditional methods, such as train-test splits and k-fold cross-validation used in machine learning, do not work for time series data. The reason being the temporal characteristic of data is ignored [19].The suitable time series predictor evaluation methods used are:

- •Train-Test Split
- •Multiple train Test Splits
- •Walk Forward Validation [21].

In this paper, Walk Forward Validation is used to forecast at every time step. This method, as shown in Fig 5 consists of a moving window of defined length. Each moving window consists of:

- •Training Window: Which contains actual data
- •TestingWindow:Which contains forecasted data
- •Validation Window:(Test window itself): This is considered for Performance Evaluation

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. Because a moving window is used to train the model, the author prefers to call this method as Moving Window Walk Forward Validation Technique [MWWFV].

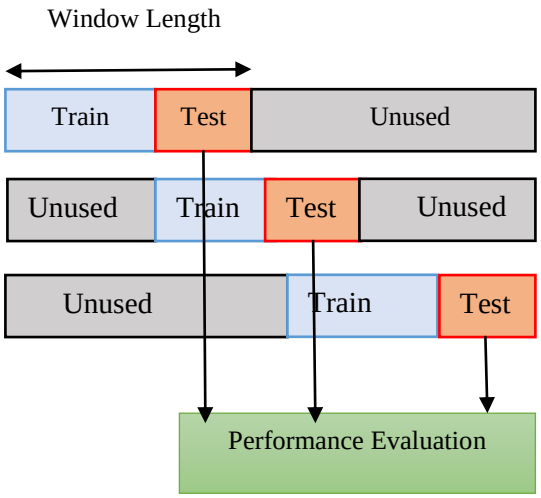

Figure 5. Illustration of MWWFV Technique

Dataset of each individual consists of 960 time-stamped readings. This dataset is divided into 10 equally spaced slots. In each slot a moving window of constant length 24 is chosen. To cover 1 slot of time series data, the window needs to move forward 4 times. Hence to cover the entire time series dataset of each individual, the windows needs to move forward 40 times. For a PH of 15 minutes, the Test window is of length 1 and Training Window is of length 23. Similarly, for a PH of 30 minutes, the Test window is of length 2 and Training Window is of length 22 and this repeats for further PH. The performance evaluation is carried out on each Test Window. The average of each performance metric result obtained during performance evaluation is considered for the final analysis. The performance metrics used during evaluation are:
Root Mean Square Error (RMSE)
Mean Absolute Error (MAE)
Mean Absolute Percentage Error (MAPE)
Theil's U- Statistic[21, 22].
Brief explanation of each of the performance metrics is done in the next subsection.

A. *PERFORMANCE METRICS*

An error in forecast is the difference between avalid or actual reading and its forecasted value. The error is expressed as:

$$\mathbf{e(t) = y(t) - \hat{y}(t)} \quad (1)$$

Where, e(t) represents forecast error at time instant 't', y(t) represents actual value at time instant 't' and represents predicted value at time instant 't'. The performance metrics used as a measure to validate the forecast data accuracy is defined as follows.

Root Mean Square Error:
RMSE is a scale dependent measure. It is expressed as:

$$\mathbf{RMSE} = \sqrt{\mathbf{mean}\ (\mathbf{e(t)})^2} \quad (2)$$

RMSE is widely used performance metric as it heavily penalizes bad forecasting.

Mean Absolute Error:
MAE is also a scale dependent measure. It is expressed as:

$$\mathbf{MAE} = \mathbf{mean}(|\mathbf{e(t)}|) \quad (3)$$

Normally RMSE tend to mask good performance due to a few bad forecasting values. This is avoided in MAE.

Mean Absolute Percentage Error:
MAPE is a percentage error measure. The percentage error is expressed as:

$$\mathbf{p(t)} = \mathbf{100} * \frac{\mathbf{e(t)}}{\mathbf{y(t)}} \quad (4)$$

MAPE is given as:

$$\mathbf{MAPE} = \mathbf{mean}\ (|\mathbf{p(t)}|) \quad (5)$$

MAPE is normally used on time series with different units. This is not of good use for the problem defined in this paper.

Theil's U- Statistic:
The Theil's U Statistic was developed by Theil in 1996. It can be interpreted as dividing the RMSE of the proposed forecasting method by the RMSE of a naïve model. Theil's U Statistic is given as:

$$\mathbf{U} = \sqrt{\frac{\sum_{t=1}^{n-1}(\mathbf{FPE_{t+1}} - \mathbf{APE_{t+1}})^2}{\sum_{t=1}^{n-1}(\mathbf{APE_{t+1}})^2}} \quad (6)$$

Where,

$$\mathbf{FPE_{t+1}} = \frac{\mathbf{F_{t+1}} - \mathbf{Y_t}}{\mathbf{Y_t}} \quad (7)$$

FPEt+1 is forecast relative change.

$$\mathbf{APE_{t+1}} = \frac{\mathbf{Y_{t+1}} - \mathbf{Y_t}}{\mathbf{Y_t}} \quad (8)$$

APEt+1 is actual relative change.

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If
U is equal to 1, it means that the proposed model is as good as the naïve model.
U is greater than 1, there is no point in using the proposed forecasting model since a naïve method would produce better results.
U is smaller than 1 it indicates that the proposed model gives more accurate forecasts than a naïve model [23].
The forecast algorithms implemented are discussed in the next section.

VI. TIME SERIES FORECAST ALGORITHMS FOR BLOOD GLUCOSE LEVEL PREDICTION

The various Time Series Forecast algorithms implemented and tested are as follows [22,23]:

1. **Naïve Algorithm**

Naïve Algorithm is a forecasting method in which the last glucose reading in the train window will be replicated as the forecasted reading in the entire test window. Naïve Algorithm is used only for comparison with other high-end Time Series Algorithms. The forecast value is the latest value in the train window described by the following Equation.

$$\hat{Y}_{t+k} = Y_t \qquad (9)$$

The performance metric obtained by using Naïve Algorithm for a PH of 15minutes, 30minutes and 45 minutes is as listed in Table 1.

Table 1: Performance Metrics for Naïve

PH (min)	RMSE	ME	MAE	MAPE
15	9.08	0.11	6.82	5.26
30	20.37	0.44	15.30	12.07
45	20.41	1.20	22.11	17.63

As seen in Table 1, forecasted values for a Prediction Horizon of 15 minutes is more accurate. Since, it has obtained a least RMSE of 9.08mg/dL.

2. Moving Average Algorithm

In Simple Moving Average Algorithm, author has considered the latest 4 readings from the training window. And, its average is taken as the forecasted value. The MA for an order 4 is computed as given:

$$\hat{Y}_t = \frac{1}{4}(Y_{t-1} + Y_{t-2} + Y_{t-3} + Y_{t-4}) \qquad (10)$$

As this process is repeated, every time the average is computed by neglecting the oldest data and considering the next latest data, thereby moving smoothly throughout the entire dataset. The performance metric obtained by using Simple Moving Average Algorithm for a PH of 15minutes, 30minutes and 45 minutes is as listed in Table 2.

Table 2: Performance Metrics for Simple Moving Average of Order 4

PH (min)	RMSE	ME	MAE	MAPE	U
15	18.09	0.78	13.86	10.76	0.29
30	26.58	1.66	20.77	16.18	0.55
45	34.10	2.45	27.01	21	0.79

As per Theil's U Statistics, since the value of U is less than 1, the Simple Moving Average technique is better than Naïve. The least RMSE of 18.09mg/dL is obtained for PH of 15 minutes. The plot of forecasted versus actual reading for PH of 15, 30 and 45 minutes is as shown in Fig. 6.

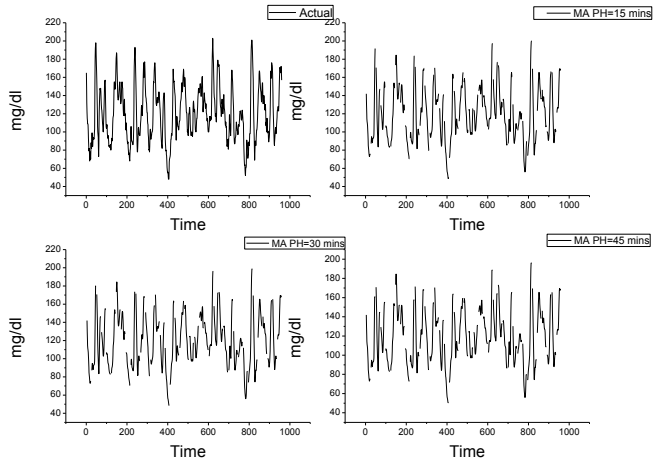

Figure 6. Actual and Predicted Values for PH of 15, 30 and 45 minutes(Time vs mg/dl)

From Fig 6. it can be observed that for a PH of 15 min, the predicted values closely follows the actual values and as the PH increases the plot is discontinues. The MA Algorithm tends to smoothen the dataset, by removing randomness in data.

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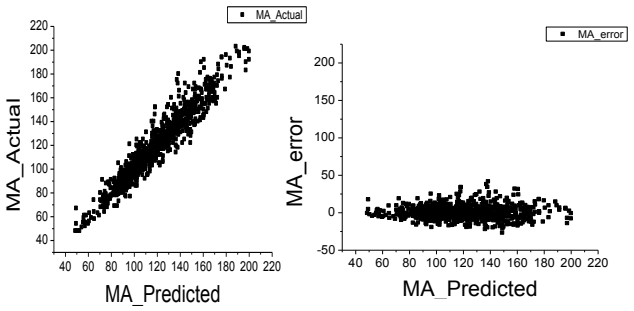

Figure 7. Moving Average Cluster Plot (a). Predicted versus Actual Plot (b). Error versus Predicted Value

Plot 7a indicates that for 15 minutes PH, there is correlation between forecasted and actual values. But when error i.e. actual minus predicted values are plotted against the predicted values, It is observed that the error is not symmetrically distributed, which indicates there is need for improvement.

3. Exponential Smoothing Algorithms

As the data subsets on which MA is implemented has no trend and seasonality, the obtained performance was good. However in MA method, equal weightage is provided to each dataset. But, when forecasting blood glucose levels, it becomes necessary to have a weighted distribution, wherein we give more weightage to the latest reading and decrease the weights for older data. This is achieved through exponential smoothing techniques. There are many variants of exponential smoothing procedures available. The different variants implemented in this paper are as described:

A. Simple Exponential Smoothing (Pegels A-1)

SES is implemented as:

$$\mathbf{F_{t+1} = F_t + \alpha(Y_t - F_t)} \quad (11)$$

Where,
Ft+1 is the new forecast value, Ft is the previous forecasted value, Yt is the actual observed data. (Yt - Ft) represents error between the forecasted and observed value. α is a constant that lies between 0 to 1.
A weight of α is applied on the latest observed value Yt, and weight of (1-α) is applied on the previous forecasted value Ft. If the error is added to the previous Ft then it is called as "Additive Error" and if it's multiplied it is termed as "Multiplicative Error". The equation used for multiplicative error [24] is as given:

$$\mathbf{F_{t+1} = F_t(1 + \alpha e(t))} \quad (12)$$

$$\boldsymbol{e(t) = \frac{y(t) - \widehat{F(t)}}{\widehat{F(t)}}} \quad (13)$$

The performance metric obtained by using SES with Additive Error Algorithm for a PH of 15minutes, 30minutes and 45 minutes for different α is as listed in Table 3.

Table 3: Performance Metrics for SES ANN

α = 0.1					
PH (min)	RMSE	ME	MAE	MAPE	U
15	31.16	1.56	24.66	17.73	0.63
30	35.83	1.97	28.48	20.51	0.94
45	40.19	2.09	31.99	23.14	1.25
α = 0.2					
PH (min)	RMSE	ME	MAE	MAPE	U
15	23.96	1.53	18.89	13.87	0.42
30	30.77	2.12	24.29	17.87	0.68
45	36.83	2.49	29.19	21.57	0.95
α = 0.3					
PH (min)	RMSE	ME	MAE	MAPE	U
15	19.42	1.19	15.13	11.35	0.33
30	27.49	1.89	21.62	16.72	0.59
45	34.45	2.45	27.37	20.69	0.84
α optimal (value = 0.99)					
PH (min)	RMSE	ME	MAE	MAPE	U
15	9.08	0.14	6.81	5.26	0.15
30	20.24	0.56	15.02	12.02	0.46
45	28.40	1.27	22.10	17.63	0.72

As per Theil's U Statistics, since the value of U is less than 1, the SES technique is better than Naïve. The least RMSE of 9.08mg/dL is obtained for PH of 15 minutes. As α increases from 0 to 1, the effect of smoothing in forecast increases. The plot of actual versus forecasted reading for PH of 15 minutes is shown in Fig.8.

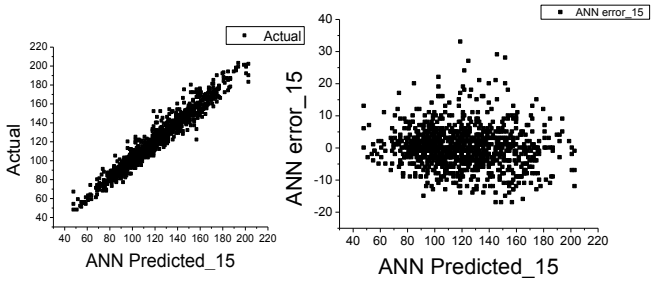

Figure 8. ANN Cluster Plot ,(a). Predicted versus Actual Plot (b). Error versus Predicted Value

Plot 8a indicates that for 15 minutes PH, there is correlation between forecasted and actual values. The error plot, in Fig 8b. is symmetrically distributed, but still the Y axis is unbalanced which indicates there is need for improvement.
The graph of α variation with respect to RMSE, in order to obtain the optimal value is as shown in Fig. 9.

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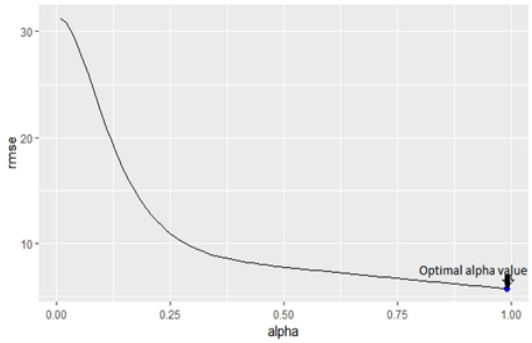

Figure 9. ANN RMSE Plot(alpha vs rmse)

As, seen from the graph shown in Fig 9. The minimal RMSE is obtained for α of 0.99. Hence this is taken as the optimal value.

The performance metric obtained by using SES with Multiplicative Error Algorithm for a PH of 15minutes, 30minutes and 45 minutes for different α is as listed in Table 4.

Table 4: Performance Metrics for SES with MNN

α = 0.1					
PH (min)	RMSE	ME	MAE	MAPE	U
15	35.94	1.75	28.52	20.59	0.94
30	31.16	1.56	24.64	17.73	0.63
45	40.19	2.09	31.99	23.14	1.25
α = 0.2					
PH (min)	RMSE	ME	MAE	MAPE	U
15	30.72	2.11	23.51	17.88	0.68
30	23.96	1.53	18.89	13.87	0.42
45	36.83	2.49	29.19	21.53	0.95
α = 0.3					
PH (min)	RMSE	ME	MAE	MAPE	U
15	27.49	1.89	21.62	16.27	0.58
30	19.42	1.19	15.13	11.35	0.33
45	34.45	2.45	27.37	20.65	0.83
α optimal (value = 0.99)					
PH (min)	RMSE	ME	MAE	MAPE	U
15	9.08	0.14	6.81	5.26	0.15
30	20.25	0.57	15.20	12.02	0.46
45	24.40	1.27	22.10	17.63	0.72

The plot of actual versus predicted reading for PH of 15 minutes is shown in Fig. 10.

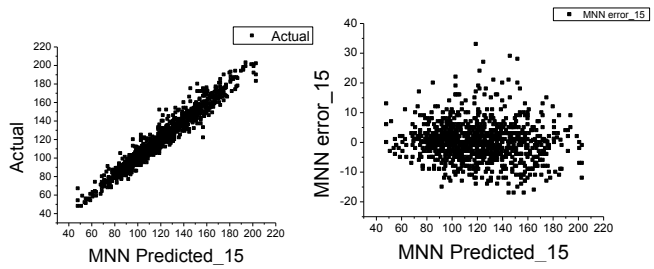

Figure 10. MNN Cluster Plot (a). Predicted vs Actual Plot (b). Error vs Predicted Value

Plot 10a indicates that for 15 minutes PH, there is correlation between forecasted and actual values. The error plot, in Fig 10b. is symmetrically distributed, and clusters around the center. This indicates MNN has better performance over MA and ANN algorithms.

The graph of α variation with respect to RMSE, in order to obtain the optimal value is as shown in Fig. 11.

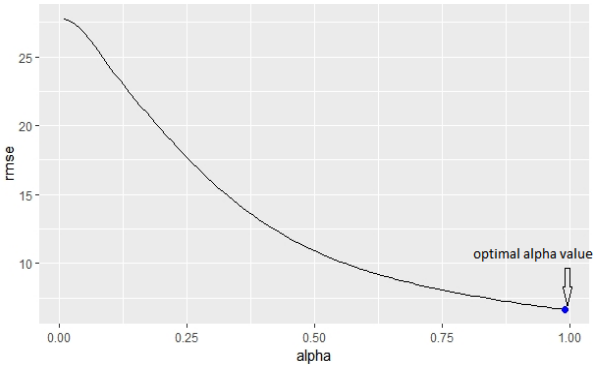

Figure 11. MNN RMSE Plot(alpha vs rmse)

As, seen from the graph shown in Fig 11. The minimal RMSE is obtained for α of 0.99. Hence this is taken as the optimal value.

B. Holt's Linear Method

Holt's Linear Method is described by the equations given:

$$\mathbf{L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1})} \quad \textbf{(14)}$$

$$\mathbf{b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}} \quad \textbf{(15)}$$

$$\mathbf{F_{t+m} = L_t + b_{tm}} \quad \textbf{(16)}$$

Here two smoothing constants α and β are used, whose values lie between 0 and 1. Lt denotes an estimate of the magnitude of the data at time t. bt denotes an estimate of the slope at time t, it represents the trend. btm denotes the trend multiplied by the number of periods 'm' ahead to be forecast. As the forecasted value is sum of Lt and btm, this Holt's method is also referred to as "Holt's Additive (Pegel's B-1)".If Lt and btm are multiplied, then the method is referred to as "Holt's Multiplicative (Pegel's C-1)". The performance metric obtained by using Additive Error based Holt's Additive Algorithm for a PH of 15minutes, 30minutes and 45 minutes for different α and β is as listed in Table 5.

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Table 5: Performance Metrics for Holt's AAN

α = 0.1	β= 0.1				
PH (min)	RMSE	ME	MAE	MAPE	U
15	25.45	1.94	19.34	26.28	0.37
30	33.99	3.61	25.81	24.38	0.49
45	42.0	4.71	32.11	32.40	0.68
α = 0.2	β= 0.2				
PH (min)	RMSE	ME	MAE	MAPE	U
15	18.57	-0.04	13.60	11.14	0.27
30	27.29	1.09	20.49	17.39	0.50
45	36.06	2.78	26.35	29.24	1.22
α = 0.3	β= 0.3				
PH (min)	RMSE	ME	MAE	MAPE	U
15	14.58	-0.72	10.65	8.93	0.21
30	24.24	-0.26	17.77	17.47	0.44
45	32.4	0.69	24.4	21.34	0.68
optimal (α = 0.99; β=0.99)					
PH (min)	RMSE	ME	MAE	MAPE	U
15	7.98	-0.15	5.91	4.57	0.12
30	19.47	-.61	14.27	11.91	0.39
45	28.40	1.27	22.10	17.63	0.72

The plot of forecasted versus actual reading is shown in Fig. 12.

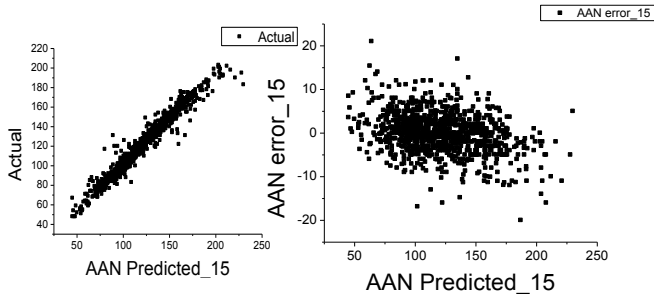

Figure12. AAN Cluster Plot (a) Predicted vs Actual Plot (b). Error vs Predicted value

Plot 12a indicates that for 15 minutes PH, there is correlation between forecasted and actual values. The error plot, in Fig 12b. is symmetrically distributed, and clusters around the center. The Y axis is also balanced; indicating AAN has better performance over MA, ANN, and MNN algorithms.

The variation of RMSE for varying α and β value is shown in Fig 13. The optimal value of α and β is taken as the constant that results in least RMSE.

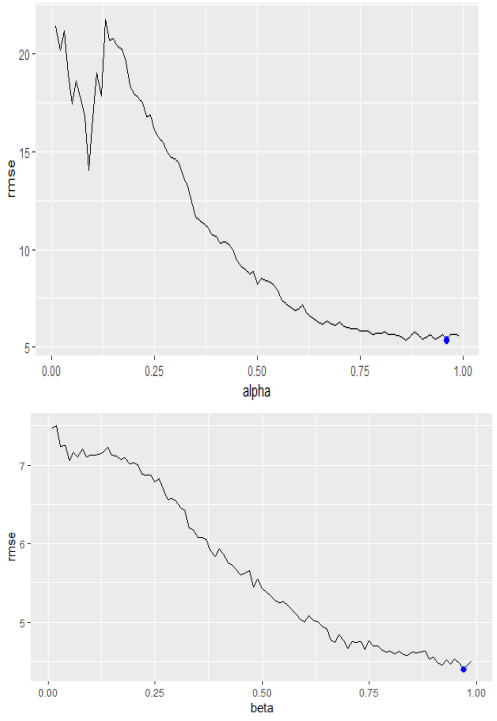

Figure 13. AAN RMSE Plot (a). RMSE versus alpha plot(alpha vs rmse) (b). RMSE versus beta plot (beta vs rmse)

From the graph, shown in Fig. 13(a) and 13(b), it is evident that the optimal value of α and β is 0.99.

The performance metric obtained by using Multiplicative Error based Holt's Additive Algorithm for a PH of 15minutes, 30minutes and 45 minutes for different α and β is as listed in Table 6.

Table 6: Performance Metrics for Holt's MAN

α = 0.1β=0.1					
PH (min)	RMSE	ME	MAE	MAPE	U
15	27.09	2.54	19.84	15.46	0.37
30	35.16	4.11	26.11	21.95	0.51
45	44.04	5.78	32.83	33.17	0.62
α = 0.2	β= 0.2				
PH (min)	RMSE	ME	MAE	MAPE	U
15	19.12	-0.89	14.03	11.48	0.28
30	27.90	0.40	20.61	21.47	0.49
45	37.44	0.22	27.71	36.58	0.56
α = 0.3	β= 0.3				
PH (min)	RMSE	ME	MAE	MAPE	U
15	14.85	-1.20	10.88	8.70	0.23
30	24.10	-1.19	17.72	15.05	0.47
45	32.57	-1.04	24.19	23.29	0.69
optimal (α = 0.99; β= 0.99)					
PH (min)	RMSE	ME	MAE	MAPE	U
15	8.08	-.09	5.89	4.61	0.12
30	19.63	-.22	14.26	11.53	0.40
45	28.83	0.33	22.01	18.62	0.60

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The plot of forecasted versus actual reading is shown in Fig. 14.

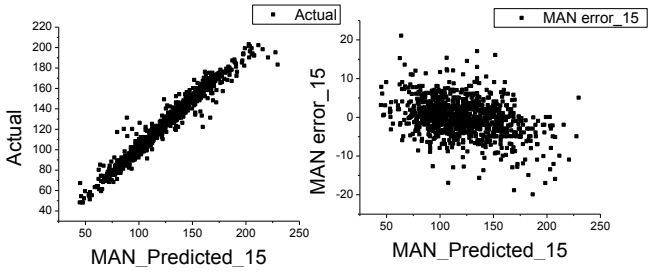

Figure14. MAN Cluster Plot (a). Predicted vs Actual Plot (b) . Predicted vs error (predicted vs actual)

Plot 14a indicates that for 15 minutes PH, there is a strong correlation between forecasted and actual values. The error plot, in Fig 14b. is not symmetrically clustered around the center, indicating AAN has better performance over MA, ANN, MNN and MAN algorithms.

The graph of RMSE versus α and β value is shown in Fig 15.

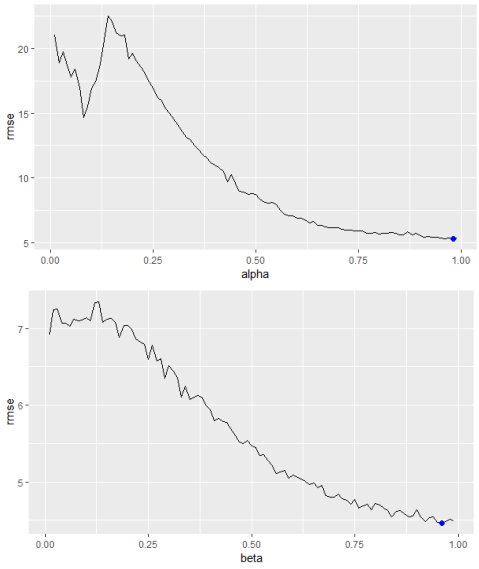

Figure 15. MAN RMSE Plot (a). RMSE versus alpha plot(alpha vs rmse) (b). RMSE versus beta plot(beta vs rmse)

The optimal value of α and β is found to be 0.99 from fig15(a) and fig 15(b).

The performance metric obtained by using Additive Error based Holt's Multiplicative Algorithm (AMN), resulted in unstable performance and couldn't be captured. It resulted in unpredicted mean and infinite variance. This is supported by Hyndman **[24].**

The performance metric obtained by using Multiplicative Error based Holt's Multiplicative Algorithm for a PH of 15minutes, 30minutes and 45 minutes for different α and β is as listed in Table 7.

Table 7: Performance Metrics for Holt's MMN

α = 0.1	β=0.1				
PH (min)	RMSE	ME	MAE	MAPE	U
15	30.76	7.71	20.68	14.94	0.388
30	39.91	10.28	28.81	20.29	0.56
45	52.93	14.02	36.84	24.54	0.71
α = 0.2	β=0.2				
PH (min)	RMSE	ME	MAE	MAPE	U
15	20.58	2.84	14.3	10.55	0.291
30	31.02	4.58	21.70	16.41	0.51
45	40.88	7.02	29.15	22.45	0.71
α = 0.3	β=0.3				
PH (min)	RMSE	ME	MAE	MAPE	U
15	15.30	1.04	10.94	8.16	0.22
30	25.88	2.00	18.35	14.34	0.48
45	34.87	3.46	25.28	20.47	0.71
optimal (α =0.99 β=0.99)					
PH (min)	RMSE	ME	MAE	MAPE	U
15	8.504	0.36	6.11	4.65	0.133
30	20.63	0.87	14.85	11.52	0.41
45	31.26	2.11	22.76	18.11	0.66

The plot of forecasted versus actual reading is shown in Fig. 16.

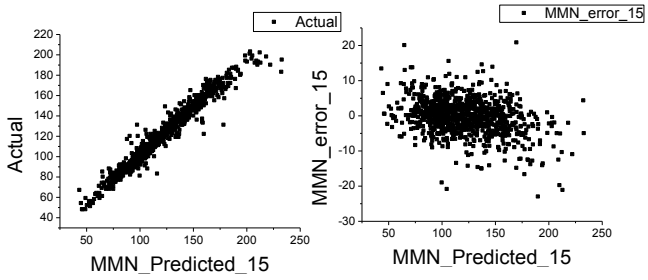

Figure16. MMN Cluster Plot (a). Predicted vs Actual Plot (b) Error vs Predicted Value(predicted vs actual)

Plot 16a indicates that for 15 minutes PH, there is a strong correlation between forecasted and actual values. The error plot, in Fig 16b. is not symmetrically clustered around the center, indicating AAN has better performance over MA, ANN, MNN,MAN and MMN algorithms. The optimal value of α and β is found to be 0.99.

VII. RESULTS AND DISCUSSION

Table 8 gives the comparison of all the algorithms implemented for a PH of 15 minutes. Optimal alpha and beta values are taken into consideration.

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Table 8. Performance Evaluation Metrics Comparison Table of ML Algorithms implemented on LIBREPRO Dataset

Sl No	Algorithm	RMSE	ME	MAE	MAPE	U
1	Naive	9.08	0.11	6.82	5.26	NA
2	Moving Average	18.09	0.78	13.86	10.76	0.29
3	SES-ANN	9.08	0.14	6.81	5.26	0.15
4	SES-MNN	20.25	0.57	15.20	12.02	0.46
5	**Holts- AAN**	**7.98**	**-0.15**	**5.91**	**4.57**	**0.12**
6	Holts-AMN	135.91	-131.45	131.45	∞	NaN
7	Holts-MAN	8.08	-0.09	5.89	4.61	0.12
8	Holts-MMN	8.504	0.36	6.11	4.65	0.133

The comparison table reveals that Holt's Linear AAN method results in least RMSE of 7.98 mg/dL. The Theil's U statistic is 0.12, indicating this is the best algorithm for Glucose value prediction on LIBREPRO Dataset. Fig 17 shows the summarized cluster plot of all error versus predicted values for all the algorithms.

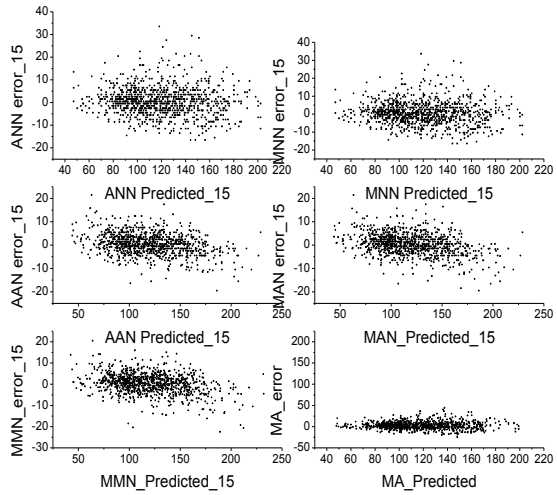

Figure 17. Cluster Plot f ML Algorithms implemented on LIBREPRO Dataset

In AAN algorithm, the error of actual minus predicted glucose levels lies between -20mg/dL to 20mg/dL. The error plot is symmetrically distributed and balanced, hence indicating that AAN algorithm is best suited for Glucose value prediction on LIBREPRO Dataset. This is also verified through the RMSE plot shown in Fig 18.

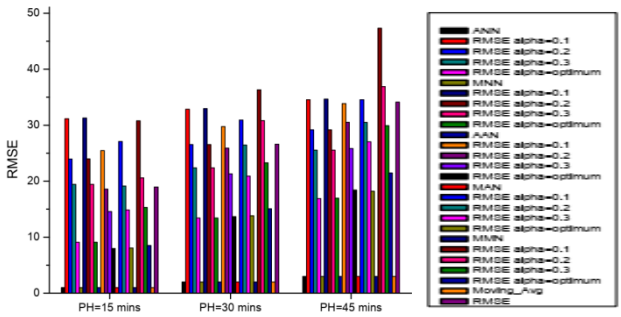

Figure 18. RMSE Plot of ML algorithms implemented on LIBREPRO Dataset

Fig 18. illustrates the RMSE values for PH of 15 min, 30 min and 45 min of all the ML Algorithms implemented on LIBREPRO Dataset. It can be verified that the least RMSE is obtained for AAN algorithm making it the popular choice for implementation. To validate this claim, the author has implemented the ML algorithms on OhioT1DM dataset obtained from OHIO University [25]. Table 9 gives the comparison of all the algorithms implemented for a PH of 15 minutes. Optimal alpha and beta values are taken into consideration.

Table 9. Performance Evaluation Metrics Comparison Table Of ML Algorithms Implemented On OhioT1DM Dataset

Sl No	Algorithm	RMSE	ME	MAE	MAPE	U
1	Naive	16.72	0.76	7.38	8.08	NA
2	Moving Average	23.78	2.8	16.09	12.01	0.41
3	SES - ANN	16.74	0.755	10.06	8.10	0.25
4	SES - MNN	16.58	0.54	9.86	8.03	0.25
5	**Holts- AAN**	**16.11**	**1.15**	**7.42**	**4.81**	**0.24**
6	Holts- MAN	18.27	-1.14	11.34	10.09	0.31
5	Holts- MMN	18.69	-0.2	11.55	10.01	0.29

The comparison table reveals that Holt's Linear AAN method results in RMSE of 16.11 mg/dL. The Theil's U statistic is 0.24, further validating AAN is the best algorithm for Glucose value prediction on OhioT1DM dataset.

VIII. CONCLUSION

Precise forecasting of upcoming blood glucose level incessantly prevents the ill effects of unforeseen fluctuations in blood glucose. In this paper Time Series Machine Learning Algorithm is implemented on 15 days LIBRREPRO Continuous Glucose Monitoring (CGM) Sensor dataset of 10 different patients. A comparison of performance evaluation metrics of the different algorithms

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implemented using R software is drawn. Holts Linear AAN Algorithm, with alpha and beta of 0.99 provided the least Root Mean Square Error (RMSE) of 7.98mg/dL for 15 minute, 19.47mg/dL for 30 minute and . 28.40 mg/dL for 45 minutes prediction horizon. The Theil's U coefficient was 0.12 for 15 minute , 0.39 for 30 minute and 0.72 for 45 minutes prediction horizon. Hence the author concludes that AAN Algorithm is best suited for a PH of 15 minutes on LIBRREPRO dataset. To verify, the Time Series Machine Learning Algorithms were also implemented on OhioT1DM dataset obtained from OHIO University. The performance metrics evaluation table revealed that Holt's Linear AAN method results in RMSE of 16.11 mg/dL and Theil's U statistic of 0.24 for PH 15 minutes. Supplementing the claim that AAN is the best algorithm for Glucose value prediction even on OhioT1DM dataset. Hence the author concludes AAN is an effective algorithm in predicting blood glucose level.

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