2024 IEEE Global Humanitarian Technology Conference (GHTC) | 979-8-3503-7734-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/GHTC62424.2024.10771574

Enhancing Type 1 Diabetes Management through Machine Learning

Anav Bordia
High School
Basis Independent Silicon Valley
San Jose, United States of America
abordia01@gmail.com

***Abstract*—Type 1 diabetes (T1D) is an autoimmune condition where carbohydrate metabolism is disrupted due to insufficient insulin secretion. In the pursuit of metabolism, it is important to maintain tight glycemic control. Current insulin pumps require user input for dose adjustments, leading to suboptimal glycemic control and artificial pancreas are expensive and fail to account for various factors. This study investigates the application of machine learning (ML) for insulin delivery in T1D patients. The purpose is to support underserved T1D patients with an ML control solution for better diabetic management and better health. We propose regression models utilizing time to predict insulin dosages based on a large patient dataset. To apply to patients across the world an app was built that implements this algorithm with insulin dosage suggestions that continuously learn through a feedback loop. The optimal regression model was an LSTM model trained on data from only one patient. The model achieved a root mean squared error of 1.0055. In addition to the model, a feedback loop was implemented for the model to adapt to the specific patient who is using the app for insulin dosage suggestions. This has yet to be tested out in a study.**

Keywords—type 1 diabetes, blood glucose, insulin, neural network, feedback loop

I. Introduction

A. Background Information

Diabetes is a significant global health concern, affecting over 500 million people worldwide. T1D is a chronic disorder characterized by the dysregulation of carbohydrate metabolism due to a deficiency in insulin secretion by pancreatic beta cells [5]. People with T1D rely on daily insulin injections to manage their blood glucose levels. This typically involves administering fast-acting insulin to counteract elevated blood glucose and long-acting insulin to maintain baseline levels throughout the day. However, this method requires constant vigilance and precise calculations by the patient based on factors such as carbohydrate intake, physical activity, and current blood glucose readings.

To aid in insulin management, insulin pumps were developed to deliver a continuous dose of fast-acting insulin, replacing the need for long-acting insulin. During meals or hyperglycemic episodes, patients can manually administer additional doses through the pump [7]. The latest advancement in this field is the hybrid closed-loop system, which uses a model predictive control algorithm to automatically adjust insulin delivery based on continuous glucose monitoring, with minimal input required from the patient [4, 8]. However, these systems are often expensive, limiting their accessibility [3]. These systems cannot also account for numerous factors as shown in Fig. 1.

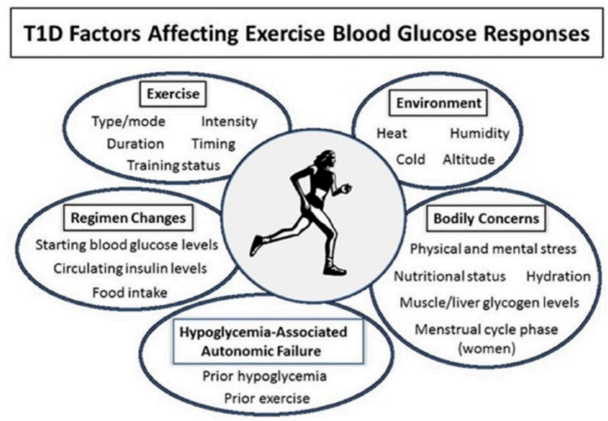

Fig. 1. Various type 1 diabetes factors that affect blood glucose levels [9].

Despite these advancements, calculating accurate individualized insulin dosages without taking into account the amount of exercise remains a challenge. As the prevalence of T1D continues to rise, especially in lower-income populations, there is a pressing need for affordable and effective diabetes management solutions [6]. Traditional artificial pancreas systems are expensive and may not be accessible to underserved communities. As of 2020, 1.42 million Americans have T1D, and a report from the CDC shows an increase of approximately 30% in diagnoses of diabetes in the United States demonstrating the growth of T1D [1].

Some open-source alternatives to artificial pancreas are do-it-yourself (DIY) automated insulin delivery (AID) apps. By integrating data from continuous glucose monitors (CGM) and applying them to insulin pumps these open-source applications take in various information and apply an algorithm to it [10]. As noted by [12], these applications require effort to maintain and tune the system. These applications require patients to be aware of what they're doing every day and frequent monitoring of blood glucose which may be hard for underserved communities where access to CGMs is limited. Many people from underserved communities have less access to CGMs [11].

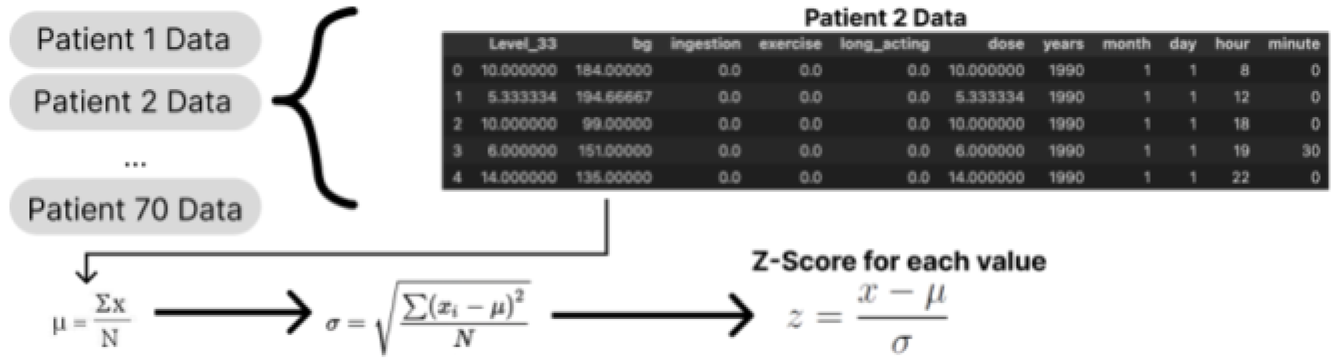

Fig. 2. Visualization of processed dataset before z-score normalization and the z-score normalization process.

1) *Research Objective*

Although DIY AID apps are aimed at similar purposes as this study, they fail to learn from patient input, require CGMs, and need patients to understand more of themselves. Our research aims for the model to learn the diabetic trends about the patient from minimal human intervention and infrequent blood glucose levels.

This study aims to develop an open-source machine learning model using clustered T1D patient data to provide an affordable diabetic management solution. We implemented this model in an application designed to assist underserved T1D patients by continuously learning from patient inputs and offering personalized insulin dosage recommendations. The model leverages a pre-trained insulin prediction algorithm, which is further refined through a feedback loop based on individual patient data. By minimizing prediction errors and adapting to user-specific needs and factors, our approach aims to improve blood glucose management for T1D patients in poorer communities. The objective of this study is to develop a model that accurately predicts insulin requirements based on variables such as blood glucose levels, thus enhancing diabetes management for underserved populations.

I. Methods

A. *Data Interpretation and Preparation*

The data used in our study needed to have readings of food intake, blood glucose level, and insulin dosages taken by patients. The Diabetes Dataset was retrieved from the UCI Machine Learning Repository and contained this information [2]. This dataset originated from Michael Kahn from Washington University. The data repository consists of 70 datasets, where each dataset was from the records of an individual diagnosed with type 1 diabetes. Each record contains four columns consisting of a date, time, a value, and a code that illustrates the meaning of the value as shown in Table I.

I. Table I

Example Patient Data Before Processing

Date	*Time*	*Code*	*Value*
03-16-1989	08:00	33	1
03-16-1989	08:00	34	8
03-16-1989	18:00	62	243
03-16-1989	18:00	33	1

The label used from these codes is the regular insulin dose (33) and the remaining codes were used as the features. The codes and their corresponding meaning are listed here:

33 = Regular insulin dose
34, 35 = Long Acting Insulin Dose
48, 57 = Unspecified blood glucose measurement
58, 59, 60, 61, 62, 64 = blood glucose levels
65 = Hypoglycemic symptoms
66 = Typical meal ingestion
67 = More-than-usual meal ingestion
68 = Less-than-usual meal ingestion
69 = Typical exercise activity
70 = More-than-usual exercise activity
71 = Less-than-usual exercise activity
72 = Unspecified special event

The data was converted into a more readable format by pivoting the table by making the codes the column headers and the values the data points. However, pivot_table mishandled the data frame formatting by creating parent and subheaders. To improve readability, the headers were merged into parent headers. Now, several columns that had similar meanings could be combined to simplify and reduce unnecessary columns. For example, all the blood glucose codes (58, 59, 60, 61, 62, 64) were put into one column named "bg".

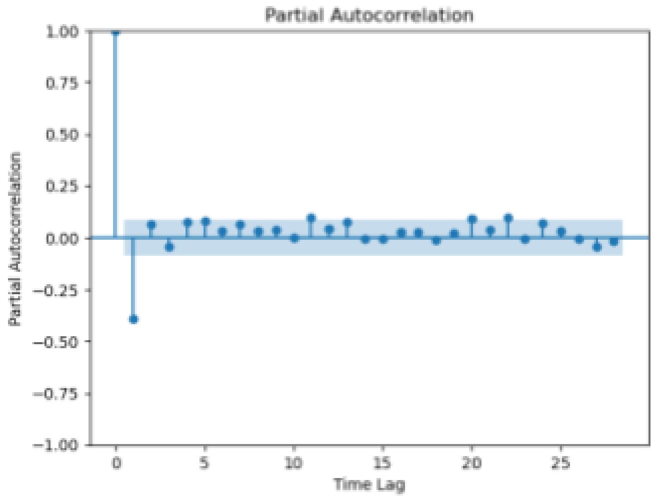

Fig. 3. PACF graph for the individual patient dataset

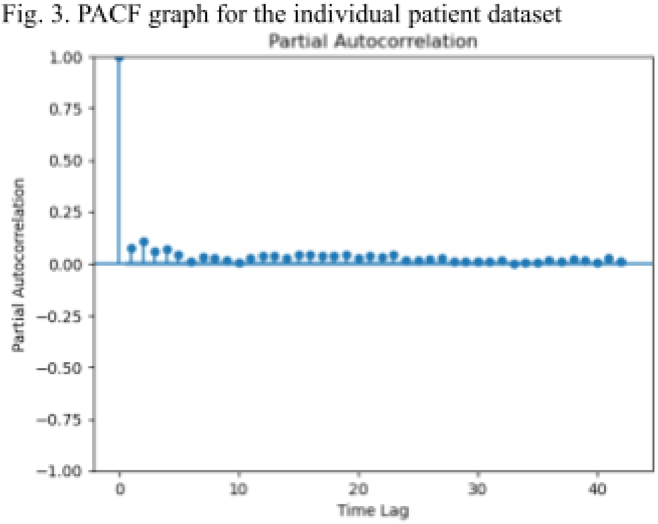

Fig. 4. PACF graph for the aggregated dataset of 70

Although it is important to differentiate between preprandial and postprandial glucose levels, combining all these glucose measurements into one column aims to enable the model to learn the overall relationship between past and current glucose levels. By doing so, we hope the model can discern patterns and correlations that contribute to more accurate insulin dose predictions. Additionally, it reduces the inputs a patient has to give from 6 to 1 for all blood glucose levels.

Initially, the date/time data was converted into UNIX timestamps. However, we extracted the minutes and hours of the day from these timestamps, as this information was more relevant for our analysis of daily diabetes management routines. Diabetes management involves specific daily patterns, such as insulin shots at regular times (e.g., breakfast, lunch, dinner, and bedtime). By using integers to represent the time of day, we could directly capture and model these daily patterns without the added complexity of handling months and years, which are less relevant for this purpose.

Additionally, using simplified integer representations for the time of day such as minutes and hours, allowed for easier data handling and made the input more interpretable, directly aligning with our goal of modeling daily insulin usage patterns and blood glucose levels. This approach also helped reduce dimensionality and avoid potential issues related to varying month lengths or leap years. Finally, to ensure the model ran properly, all null values and illegal data types were dropped.

Z-scores were used to normalize the features of the dataset. Normalizing the features allows for mathematical operations to compute faster due to a smaller range of values. The label does not need to be scaled as the label is already in the intended units and scaling them could change their meaning and interpretation.

Due to the nature of T1D, data is related to time whereas previous data affect current data. Due to the different models tested, the dataset was changed accordingly, taking advantage of T1D's temporal dependencies. The first dataset just utilized the largest dataset from a single patient. This was used for the specialized models. The second dataset contained the aggregated pre-normalized data of all 70 patients, which was then normalized. The normalization took place after aggregation to maintain a standard. The third dataset was time-lagged by 1 step.

The single-patient dataset was used to develop a specialized model tailored to an individual patient's needs. The reasoning behind this approach is to create a highly personalized model that can accurately predict insulin requirements based on the unique patterns and characteristics of a single patient's data. It was to create a baseline model that the other models would be tested against. The data were built using the patient with the most extensive records to provide the model with more data. This dataset is crucial for understanding how individualized data can improve prediction accuracy and insulin management for a single patient, providing insights into personalized diabetes care.

The aggregated dataset was used to develop a generalized model applicable to a broader population. This dataset aims to capture common patterns and trends across multiple patients, and provides a large model that can be used in diverse settings. It was used to check the common trends among many patients. Due to each patient having different states of the pancreas and how their body works, many important trends may not be captured.

Due to the temporal dependencies inherent in T1D data, it's important to incorporate time lag. The time lag is when a model not only trains on the current data but also past data values of the explanatory variables. The number of time lags used depends on the correlation of the current data with the old data. There are two ways to find the correlation of the current data with the old data: autocorrelation function, and partial autocorrelation function. In managing T1D, the correlation of past and present insulin doses provides valuable insights into the temporal patterns and dependencies in insulin requirements. While the ACF measures the correlation between a time series and its past values, the PACF isolates the direct effect of past values on the current value, without the values of other intermediate values. PACF measures the correlation between the observation of a timer series at one time and another time and removing other factors that may affect both time lags. PACF isolates how much current values are related to past values from other past values.

The autocorrelation function is defined in Eq. (1) where k is the kth time lag, it is the value measured at that time lag and ȳ is the average of all the values.

$$\rho(k) = \frac{\frac{1}{(n-k)}\sum_{t=k+1}^{n}(y_t-\bar{y})(y_{t-k}-\bar{y})}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t-\bar{y})^2}\sqrt{\frac{1}{n-k}\sum_{t=k+1}^{n}(y_{t+k}-\bar{y})^2}} \tag{1}$$

The PACF can be modeled through the Durbin-Levinson algorithm shown in Eq. (2). PACF reduces confounding influences on the correlated two-time lags.

$$\begin{pmatrix} \rho(0) & \rho(1) & \dots & \rho(k-1) \\ \rho(1) & \rho(0) & \dots & \rho(k-2) \\ \vdots & \vdots & \vdots & \vdots \\ \rho(k-1) & \rho(k-2) & \dots & \rho(0) \end{pmatrix} \begin{pmatrix} \phi_{k1} \\ \phi_{k2} \\ \vdots \\ \phi_{kk} \end{pmatrix} = \begin{pmatrix} \rho(1) \\ \rho(2) \\ \vdots \\ \rho(k) \end{pmatrix} \tag{2}$$

Utilizing the PACF equation, a PACF plot can be generated for the insulin doses. We first generated a plot for the individual dataset (Fig. 3). We found that a dose from 1-time lag still correlates to the current insulin dose; however, the doses from further before have minimal correlation. For the aggregated data, the time lags were different. As shown in Fig. 4, the correlation of the time-lagged data of insulin doses was insignificant and random due to the consistency in the correlation over the 40+ time lags for fast-acting insulin doses.

A third dataset was created for the individual patient with features from one time lag ago. Which should improve the model trained on this data. To account for how previous data influences the insulin doses a patient takes, we utilized a Long Short-Term Memory (LSTM) model, which excels at capturing temporal dependencies.

B. *Machine Learning Techniques*

Linear regression is a statistical method for modeling the relationship between the label and the features. Linear regression was used because the output for this model was a numerical value. Linear regression is used to predict the necessary amount of insulin needed based on various features, such as blood glucose levels and exercise, through a linear relationship. This linear relationship represents the relationship between the variables in a way that minimizes the root sum of the squared errors between the predicted insulin values and the actual values to get an ideal model. Linear regression can be modeled through the following equation where k represents the feature, and w represents the weight of each feature on the algorithm:

$$y = w_1x_1 + w_1x_1 + \dots + w_kx_k + b \tag{5}$$

Rectified Linear Unit (ReLU) is a nonlinear activation function used in deep-learning neural networks. It is a piecewise linear function that returns the input value if it is positive, and zero otherwise. This removes all negative outputs by converting them to zero, making it a more realistic model as it would be impossible to give a negative dosage for insulin. A ReLU function can be simply defined through the equation shown in Eq. (6):

$$f(x) = max(0, x) \tag{6}$$

C. *Generalized Models*

The generalized models were the models that were trained on the aggregated dataset. The generalized models were simple due to the lack of temporal correlation. The models that were tested were the linear regression model and feed-forward neural networks. The linear regression model attempts to find a linear model that best reduces the value of a loss function. A feedforward neural network is an artificial neural network in which the information flows in only one direction. One neural network tested for the aggregated dataset had a linear activation layer and a ReLU activation layer, while another had two linear activation layers and one ReLU layer.

D. *Specialized Models*

The specialized models were trained on data from a single patient, allowing them to learn and adapt to the specific insulin requirements, lifestyle, and metabolic responses of that patient. These models are tailored to individual T1D patients, accounting for personal habits, meal patterns, exercise routines, and other unique factors that influence blood glucose levels, thereby achieving higher precision in predicting insulin dosages and reducing the risk of hypo- or hyperglycemia.

The models can continuously learn from new patient data when implemented in an application, adapting to changes in the patient's lifestyle or health condition over time.

Several model architectures were developed. A linear regression model was used to create a baseline evaluation metric. A feedforward neural network consisting of linear and ReLU activation layers was developed in the hopes of reducing the number of negative outputs since the ReLU function makes all negative values 0.

To utilize the correlation in the temporal data, a Recurrent Neural Network was developed. RNNs are a class of neural networks designed to process sequential data by maintaining a memory of previous inputs. A specific type of RNN is the Long Short-Term Memory. LSTM is a type of RNN that is capable of learning long-term dependencies. It is designed to remember information for long periods, making it suitable for sequential data. LSTM networks are well-suited for time series prediction due to their ability to capture temporal patterns, which are critical in T1D management given the hourly, daily, and longer-term patterns related to the patient's schedule and pancreatic function.

Additionally, a linear regression model was trained on the dataset with a time lag, incorporating current values and features from one step into the past to utilize temporal information.

E. Model Testing and Evaluation

The root mean squared error (RMSE), which measures the square root of the average squared difference between the predicted values and the actual values of a regression problem was used to evaluate the performance of the model and was used for the models in this paper. Supervised learning algorithms most commonly use RMSE to minimize the error and maximize the accuracy of the model. The model's parameters are the 6 features (Days, Hours, Long-acting Insulin, Blood Glucose, Ingestion, and Exercise) that are paired to one label (regular insulin). Due to the output of the model being continuous numeric outcome variables, the problem is a regression problem.

$$RMSE = \sqrt{\frac{\Sigma\ (y_i - y_i)^2}{n}} \tag{3}$$

The R2 score is a statistical measure that represents the proportion of variance in the dependent variable accounted for by the independent variables. This score allows for a comparison between different models to determine which one provides a better fit to the data. The R2 score provides a different way to see the model's effect. A score that is closer to 1 means more of the data's variability is accounted for. This value is used to check the variance that was accounted for by the model. The equation for the R2 score can be modeled where ŷi is the predicted value, ȳi is the average, and yi is the actual value of the data point.

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y_i})^2}{\Sigma(y_i - \bar{y})^2} \tag{4}$$

Overfitting is a common problem in machine learning where a model learns the noise in the training data and performs poorly on new, unseen data. Overfitting occurs when a dataset is too complex and captures the random fluctuations in the training data instead of the underlying patterns and relationships. There are multiple ways to prevent overfitting and one of them is splitting the data into training and validation sets which was done in a 9:1 ratio.

Additionally, the model needs to be evaluated on test data. For the generalized model, the dataset was split into a 9:1 ratio so that 10% of the dataset was used for testing and the other 90% for training and validation. For the specialized models, there were two tests performed on them. The first was checking how well the model learned the patient's trends from the individual patient data. The individual patient data was split into the same ratio as the generalized model. For the second test, the specialized models were tested on other patient data. This is to check if the trends of one patient can be generalized to other patients. If the RMSE remained the same in both the validation and testing set, then the trends between patients are most likely similar. However, if the RMSE varied differently there is no easily trackable correlation between different T1D patients.

F. Application

An application was built through Flask. This application serves to predict insulin doses that T1D patients should take based on their inputs. This application aims to provide an accessible interface for patients to manage their insulin dosages based on their data inputs. The application allows patients to input various data points relevant to their insulin management. These inputs include blood glucose levels, carbohydrate intake, physical activity, and other lifestyle factors. Upon receiving the input data, the application utilizes a machine learning model, specifically an LSTM network, to predict the appropriate insulin dose and a feedback loop to constantly improve the model. Each patient has a personalized model that is trained on their historical data, allowing for highly individualized predictions. As patients use the application and provide feedback on the insulin dose suggestions, the model learns from these interactions. This ongoing learning process allows the model to adapt to changes in the patient's lifestyle or health conditions. The model tracks data history and develops personalized models for each patient through a feedback loop that constantly improves the model.

A feedback loop is a process of using the output of a model and receiving feedback based on the input data of the user to improve models over time. The goal of the loop is to train the model over more batches of data that relate to the patient. If the model prediction and the actual dose taken by the patient differ then the specific data gets stored so that the model learns from its major errors. The application uses blood glucose levels as the primary metric for determining the reward. The model is not retrained after every single input to ensure computational efficiency and avoid overfitting to very recent data points. Instead, the model is retrained on a batch of 10 inputs from the user. By using a feedback loop, the model can be tuned to a specific patient's lifestyle and demographics.

II. Results

A. Generalized Models

Three generalized models were trained and tested on the aggregated data of the 70 patients. The one-layer linear regression model was fast and simple and achieved an RMSE of 5.3298. If a person were to be injected with 5 units of insulin more or less than what was ideal, the person would most likely face hypoglycemia and serious health repercussions. For the linear model, the R2 score was also low around 0.0976. A score of 1 means that the model can understand all the variability in the data. A score of 0.0976 is relatively low, meaning that the model barely understood the changes and variability in the data. The second model consisted of two layers, excluding the input layer. The first layer consisted of 50 nodes trained on the linear activation function and the output layer consisted of 1 node trained on the ReLU activation function. This model achieved an

II. TABLE II

Evaluation of generalized Models

Models	Generalized Models	
	RMSE	*R^2 score*
Linear	5.2398	0.0976
50 Linear + 1 ReLU	4.1124	0.1144
50 Linear + 10 ReLU + 1 Linear	3.5100	0.3580

accuracy of 4.1124, which is considerably better than the linear model. However, this model only accounts for 0.0168 more variance in the data than the linear model with an R2 score of 0.1144. The last model that was trained on the aggregates consisted of two hidden layers. The first layer consisted of 50 nodes that were trained on the linear activation function and the second layer consisted of 10 nodes that were trained on the ReLU activation function. The output layer was made up of 1 node trained on the linear activation function. This model achieved a RMSE value of 3.5100 and a R2 score of 0.3580. This model was able to account for more variability in the data than the other generalized models that were tested and trained.

B. Specialized Models

Four specified models were trained and tested on an individual's T1D data. Some of these models were tested on another patient's data. The purpose was to find out the generalizability of trends found in one patient. The linear model established a baseline evaluation metric and achieved an RMSE of 3.8993 and an R2 score of 0.1048. This model wasn't able to account for most of the data meaning that it was most likely guessing the values. The feedforward neural network model was able to capture non-linear relationships between features and labels so it was better for this task. As can be seen in Table III, the model with 50 nodes in the first hidden layer and 1 ReLU node in the output layer achieved a low RMSE of 1.8025 and an R score of 0.6040. This model was able to account for more than 50% of the patient's data with only an error of around 2 units of fast-acting insulin. The LSTM model which takes advantage of temporal features, which are prominent in diabetes, achieved the best RMSE score of 1.0055. This error means that on average the model's predictions are only 1 unit away from the ideal shot, assuming the patients take the ideal insulin shots based on their data. This model has the highest R2 score of 0.8767 in which the model accounts for 87% of the variability in the data. The last model that was tested on the data from the same patient that the model was trained on was another linear model; however, this model was trained on a dataset that had features from one step into the past. This dataset had a time lag of 1 step and the linear model trained and tested on this data achieved a RMSE of 2.2068 and an R2 score of 0.3620. Although this model was worse than the LSTM model, it performed significantly better than the linear model trained without a time lag. It reduced the RMSE by 1.6925 demonstrating the temporal dependencies in type 1 diabetes.

III. TABLE III

Evaluation of Specialized Models Tested on Different Data from the Same Patient

Specialized models tested on the same patient's data	Specialized Model	
	RMSE	*R^2 score*
Linear	3.8993	0.1048
50 Linear + 1 ReLU	1.8025	0.6040
LSTM	1.0055	0.8767
Linear on Time Lag Data	2.2068	0.3620

IV. TABLE IV

Evaluation of Specialized Models Tested on Data from a Different Patient

Specialized models tested on a different patient's data	Specialized Model	
	RMSE	*R^2 score*
Linear	21.8278	0.0787
LSTM	1.5637	0.7371
Linear on Time Lag Data	1.9618	0.586

These same models were also tested on data from another patient. The purpose was to understand if the trends in one patient exist in another or if the trends the model understands are patient-specific. The linear model performed poorly and achieved a very low R2 score. This means the model isn't able to understand the relation between the features and the variation in the label. The same LSTM model from Table IV achieved an RMSE of 1.5637 which is surprisingly low and accounted for 0.7371 of the variation in the data. The linear model trained on the data with a time lag got an RMSE of 1.9618 which is similar to the error it got when tested on the data from the same patient it was trained on.

Comparing the baseline evaluation linear models used for the patient data and the aggregate data, the specialized model performed better by achieving a root mean squared error that is 1.3406 less than the generalized model. Although both models achieved a relatively high error for insulin dosing, the specialized model performed better when tested on its data. However, it performed way worse than the generalized model when tested on data from another patient. Overall, the specialized models performed better than the generalized models demonstrating the importance of the model learning personal trends. However, by training on the individual data, the model was also able to learn common trends among other patients as seen in the evaluation of the LSTM model. The LSTM specialized model achieved a low RMSE when tested on the two different data.

III. Discussion

In the field of type 1 diabetes management, there is still room for technological improvement. The most recent work is the development of artificial pancreas, an expensive technology that manages a patient's glucose levels through a control algorithm. These control algorithms fail to account for different activities patients might perform like exercise which significantly reduces blood glucose levels. With the power of artificial intelligence, all these unknown factors can be predicted through constant training under a patient. Additionally, the use of artificial intelligence and the removal of expensive technology allows people around the world in low-income populations to have access to technology that helps them better manage their glucose levels. Through artificial intelligence, models can predict insulin doses at only certain times and take in patient input without needing to continuously be in control of shots.

In this study, artificial intelligence was used to provide a way for underserved populations to have access to management technology through the use of an application. Patients need to input various data like blood glucose levels and the model suggests the amount of insulin a patient should take. Through reinforcement learning, the model can constantly learn and personalize to the specific patient from its mistakes and attempt to reach blood glucose levels in the ideal range of 80-120 mg/dl.

The LSTM model trained on patient-specific data performed the best by achieving the best evaluation metrics. The RMSE was only 1.8025 units off when testing against different data from the same patient it was trained on. The model learned the patient-specific trends while also learning common trends among diabetic patients. When tested on data from a different patient, the model was able to perform well achieving a RMSE of 1.5637. The recurrent neural network model performed far better compared to the models not trained on past data which shows that the temporal dependencies in diabetes are prominent. This model could be very helpful when implemented in the real world for underserved communities.

IV. Conclusion

In this study, we aimed to leverage artificial intelligence to provide accessible and effective diabetes management tools, particularly for underserved populations. By developing various models, we sought to improve the prediction of insulin doses based on patient-specific data and temporal patterns.

Key findings show that the LSTM model trained on individual patient data performed exceptionally well. It achieved the lowest RMSE, indicating high accuracy in predicting insulin doses by capturing patient-specific trends and temporal dependencies. The success of the RNN was evident, as the model adapted to individual T1D patient data, enhancing its personalization and effectiveness.

The specialized models, particularly the LSTM, outperformed the generalized models, underscoring the importance of a personalized approach in diabetes management. These findings suggest that AI can play a crucial role in providing cost-effective and precise diabetic care, making advanced management tools accessible to low-income populations.

However, the study has its limitations. The models' performance may vary with different patient demographics and lifestyle factors, and the reliance on patient input for data entry could affect consistency. Future research should focus on enhancing model accuracy, exploring additional data types like continuous glucose monitoring, and integrating other machine learning techniques to further improve predictions. Techniques like ensemble models which can utilize feature-specific models like a blood glucose model with a model that uses all the data. Most importantly, the application developed utilizing the feedback loop should be tested on patients to understand the model's outcome.

Overall, this study highlights the potential of AI in transforming diabetes management. By providing personalized, adaptive, and affordable solutions, we can better support individuals in maintaining optimal glucose levels and improving their quality of life.

References

1. "More people being diagnosed with type 1 diabetes," JDRF. (2023, January 20). https://www.jdrf.org/blog/2020/02/18/more-people-being-diagnosed-type-1-diabetes/
2. M. Kahn (1994). Diabetes. UCI Machine Learning Repository. https://archive.ics.uci.edu/ml/datasets/diabetes
3. What is an artificial pancreas - who makes it and the cost. Prescription Hope. (2023, April 28). https://prescriptionhope.com/blog-what-is-an-artificial-pancreas/
4. R. Nimri, T. Battelino, L. M. Laffel, R. H. Slover, D. Schatz, S. A. Weinzimer, et al. (2020, September 9). Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes. Nature News. https://www.nature.com/articles/s41591-020-1045-7
5. Sanofi. (2019). Type 1 diabetes: Causes, factors. Intolife. https://www.intolife.in/about-diabetes/
6. G. A. Gregory, T. I. G. Robinson, S. E. Linklater, F. Wang, S. Colagiuri,, C. de Beaufort, et al. (2022). Global incidence, prevalence, and mortality of type 1 diabetes in 2021 with projection to 2040: a modelling study. The lancet. Diabetes & endocrinology, 10(10), 741–760. https://doi.org/10.1016/S2213-8587(22)00218-2
7. C. Berget, L. H. Messer, & G. P. Forlenza. (2019). A Clinical Overview of Insulin Pump Therapy for the Management of Diabetes: Past, Present, and Future of Intensive Therapy. Diabetes spectrum : a publication of the American Diabetes Association, 32(3), 194–204. https://doi.org/10.2337/ds18-0091
8. E. Matamoros-Alcivar et al., "Implementation of MPC and PID Control Algorithms to the Artificial Pancreas for Diabetes Mellitus Type 1," 2021 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), Soyapango, El Salvador, 2021, pp. 1-6, doi: 10.1109/ICMLANT53170.2021.9690529.
9. S. R. Colberg, R. Laan, E. Dassau, & D. Kerr. (2015). Physical activity and type 1 diabetes: time for a rewire?. Journal of diabetes science and technology, 9(3), 609–618. https://doi.org/10.1177/1932296814566231
10. Heinemann, Lutz, and Karin Lange. ""Do It Yourself" (DIY)-Automated Insulin Delivery (AID) Systems: Current Status From a German Point of View." *Journal of diabetes science and technology* vol. 14,6 (2020): 1028-1034. doi:10.1177/1932296819889641
11. "Continuous Glucose Monitors," American Diabetes Association. https://diabetes.org/advocacy/cgm-continuous-glucose-monitors#:~:text=With%20the%20benefits%20and%20ease,to%20CGMs%20than%20their%20counterparts.
12. Hng, Tien-Ming. "Do-It-Yourself (DIY) Closed Loop Systems: Perspectives of an Endocrinologist." *Journal of diabetes science and technology* vol. 14,6 (2020): 1104-1106. doi:10.1177/1932296819890855