Personalized Automated Blood Glucose Forecasting for Type-1 Diabetes Using Machine Learning Algorithms

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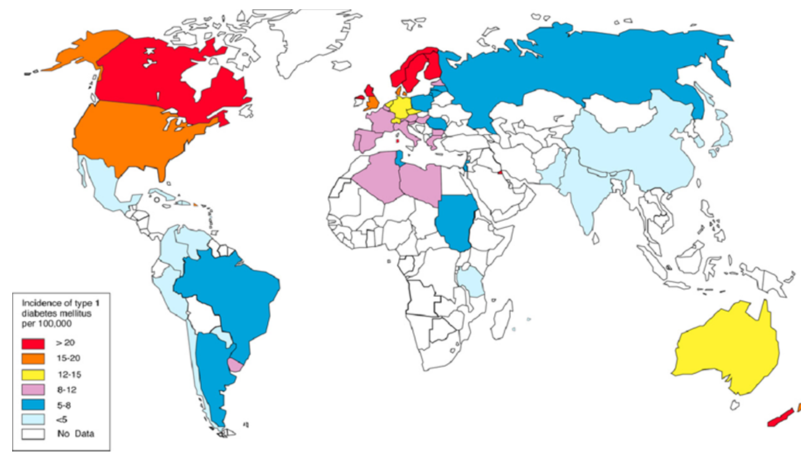
Avijay Sen

Avijay Sen is currently a high school student at Franklin High School. His research interest lies in artificial intelligence, genetics, and microbiology. This research was deeply personal, inspired by my grandma (Didi), who has diabetes.

I created a **website to raise awareness and provide comprehensive resources**, education, and tools for individuals affected by diabetes, focusing on global access and personalized care: **gluco-guide.com**

Introduction

- **Type 1 Diabetes Mellitus (T1DM)** - a chronic condition when the pancreas fails to produce insulin
- **Eighth leading cause of death** and have been approximated to increase by **13.5 - 17.4 million people**
- Fluctuations in managing blood sugar is challenging and can be deadly if not handled promptly
- **Continuous Glucose Monitors (CGM)** are used to measure the blood glucose levels continuously throughout the day
- **Machine Learning (ML)** can be used to evaluate **closed loop insulin delivery system** (CGMS combined with insulin pumps) and **manage effectiveness, safety, and personalization** for T1DM individuals



Related Work

ML for Blood Glucose Prediction

- Previous studies used **SVR, ANN, LSTM, and RNN** for forecasting.
- **Deep learning models** don't always outperform simpler models.

Closed-Loop Insulin Delivery

- **CGM + insulin pumps** improve **glycemic control.**
- **Artificial pancreas systems** automate **insulin dosing.**

Challenges in Prior Studies

- **Small, non-diverse datasets** limit **generalizability.**
- **Short-term trends** analyzed, missing **long-term patterns.**
- **Handling missing data** remains a key issue.

How This Study Differs

- **Personalized models** instead of **generalized approaches.**
- **KNN, RF, and MLP** tested for **accuracy & interpretability.**
- **Hyperparameter tuning** improved **individual glucose predictions.**

Hypothesis

Prediction: **ML models** can accurately predict short-term blood glucose levels, improving **management strategies for T1DM**.

Key Focus: Identifying the best-performing algorithm among **K-Nearest Neighbors (KNN)**, **Random Forest (RF)**, and **Multilayer Perceptron (MLP)**.

Research Question: Can **analyzing CGM data** to develop a method to **fine-tune insulin rates** using various **ML models** improve **T1DM management strategies**? Do these models need to be **personalized**, or can a **uniform model** be effective?

Methods & procedures

Dataset: **Diatrend dataset** (**31 days, 5 subjects**).

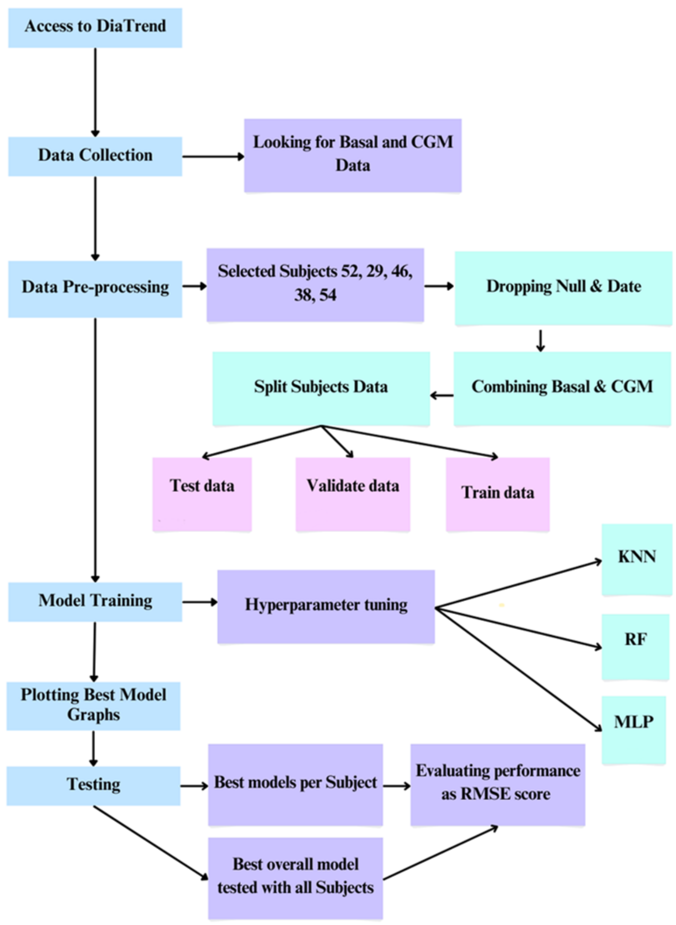
Preprocessing: **Feature extraction** (**glucose mean, standard deviation, insulin infusion rate**), **handling missing values**, and structuring data into **time-series sequences**.

Models Tested:

- **KNN:** Captures **local data trends**.
- **RF:** Handles **complex, non-linear patterns** with **high interpretability**.
- **MLP:** A **neural network** for **deep learning-based prediction**.

Training Strategy: **70% training, 15% validation, 15% test** data split.

Evaluation Metrics: **Mean Squared Error (MSE), Root Mean Squared Error (RMSE),** and **R^2**.



Data Analysis

- **Optimized models** for each subject through **extensive hyperparameter tuning**.
- **Evaluated performance** across subjects to determine the **most reliable model**.
- **RF** and **MLP** outperformed **KNN**.
- **RF achieved the highest R^2 scores** for **Subjects 52 and 54**, demonstrating strong predictive performance.
- **MLP performed best for Subjects 29, 38, and 46**, capturing **complex glucose trends** effectively.
- **KNN** consistently **underperformed**, indicating **limitations in handling glucose variability**.
- **Best-tuned models were visualized through graphs**, showing the impact of different hyperparameter values.
- **Performance metrics were organized into tables**, comparing **MSE**, **RMSE**, and **R^2 scores** across subjects.

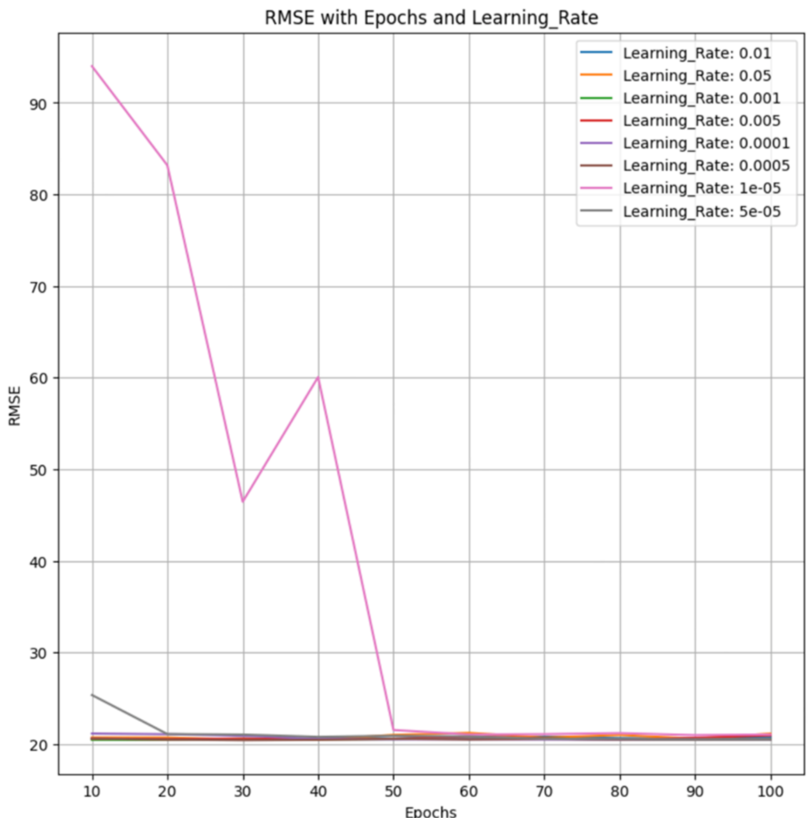
TABLE I. TRAINING RESULTS FOR DIFFERENT SUBJECTS AND MODELS

ID	KNN	RF	MLP
52	MSE: 252.947 RMSE: 15.904 R2 Score: 0.912	MSE: 227.535 RMSE: 15.084 R2 Score: 0.921	MSE: 317.137 RMSE: 17.808 R2 Score: 0.890
29	MSE: 438.806 RMSE: 20.947 R2 Score: 0.857	MSE: 425.273 RMSE: 20.622 R2 Score: 0.861	MSE: 420.411 RMSE: 20.503 R2 Score: 0.863
46	MSE: 814.730 RMSE: 28.543 R2 Score: 0.880	MSE: 717.231 RMSE: 26.781 R2 Score: 0.895	MSE: 820.608 RMSE: 28.646 R2 Score: 0.879
38	MSE: 317.209 RMSE: 17.810 R2 Score: 0.866	MSE: 310.727 RMSE: 17.627 R2 Score: 0.869	MSE: 301.532 RMSE: 17.364 R2 Score: 0.873
54	MSE: 342.127 RMSE: 18.496 R2 Score: 0.772	MSE: 299.137 RMSE: 17.295 R2 Score: 0.800	MSE: 375.030 RMSE: 19.365 R2 Score: 0.750

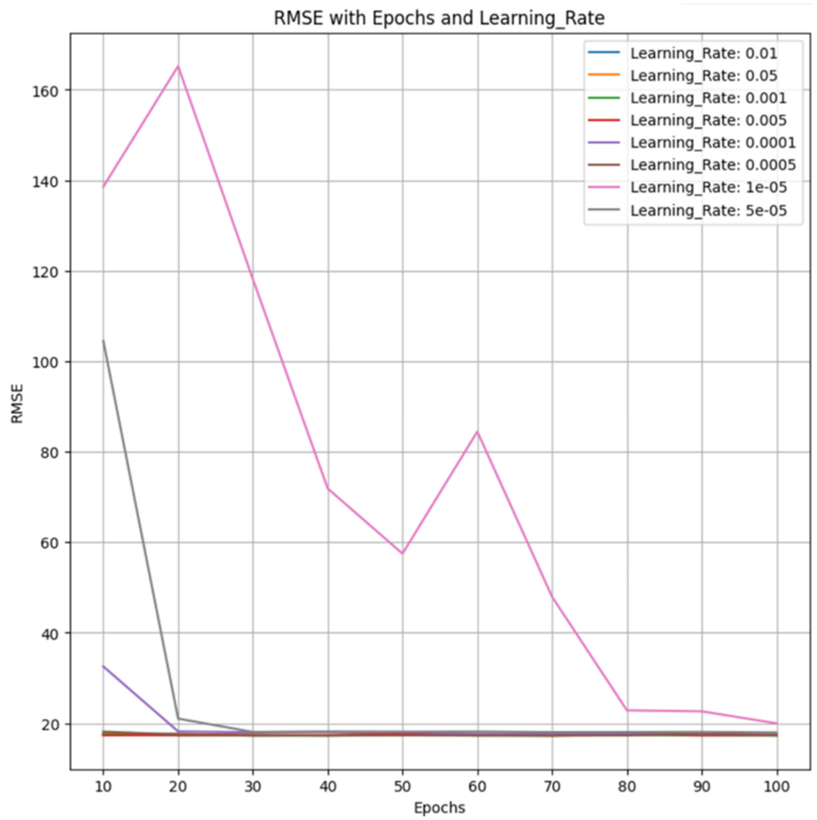
TABLE II. TESTING RESULTS FOR DIFFERENT SUBJECTS AND MODELS

ID	KNN	RF	MLP
52	MSE: 314.087 RMSE: 17.722 R2 Score: 0.926	MSE: 305.725 RMSE: 17.484 R2 Score: 0.928	MSE: 378.007 RMSE: 19.442 R2 Score: 0.911
29	MSE: 414.655 RMSE: 20.363 R2 Score: 0.880	MSE: 391.740 RMSE: 19.792 R2 Score: 0.886	MSE: 385.436 RMSE: 19.632 R2 Score: 0.888
46	MSE: 615.205 RMSE: 24.803 R2 Score: 0.922	MSE: 558.373 RMSE: 23.629 R2 Score: 0.929	MSE: 546.354 RMSE: 23.374 R2 Score: 0.931
38	MSE: 352.870 RMSE: 18.784 R2 Score: 0.800	MSE: 340.414 RMSE: 18.450 R2 Score: 0.807	MSE: 330.102 RMSE: 18.168 R2 Score: 0.813
54	MSE: 235.849 RMSE: 15.357 R2 Score: 0.789	MSE: 224.320 RMSE: 14.977 R2 Score: 0.800	MSE: 293.482 RMSE: 17.131 R2 Score: 0.738

Graphs

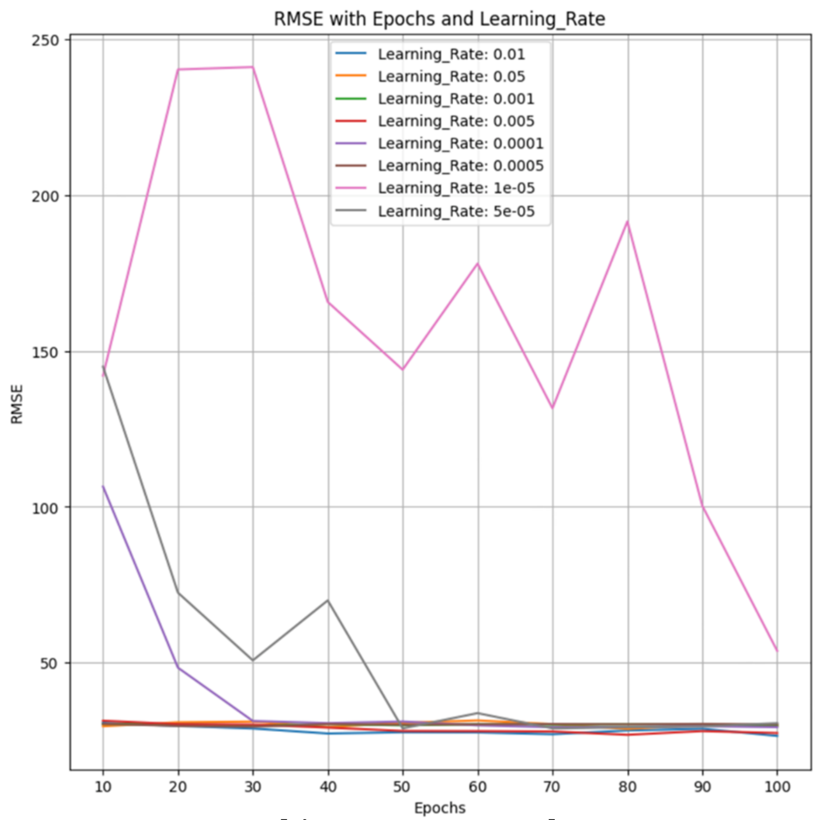


Subject 29 MLP Graph

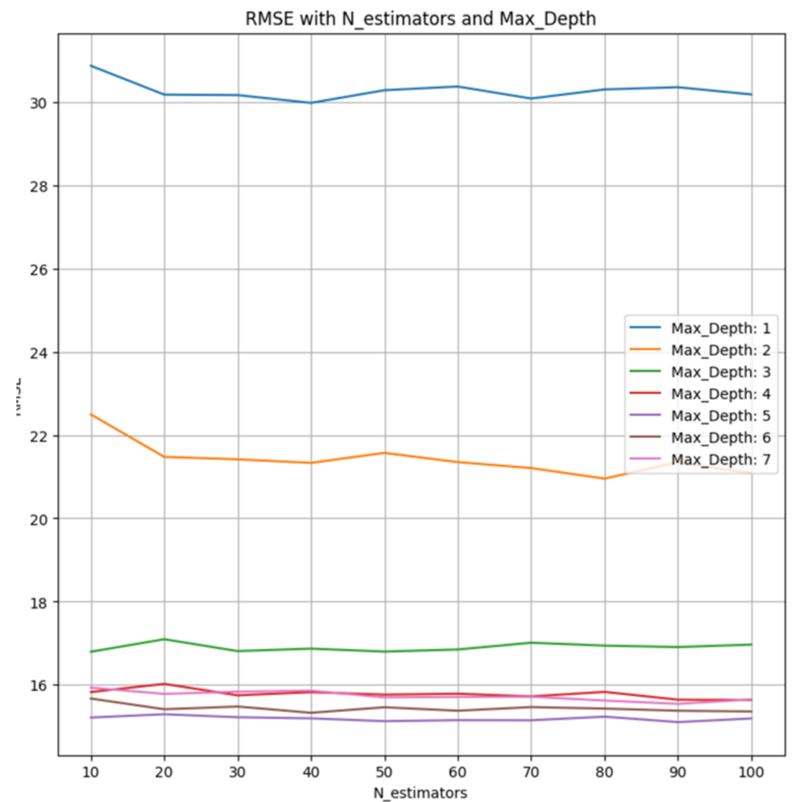


Subject 38 MLP Graph

Graphs cont.

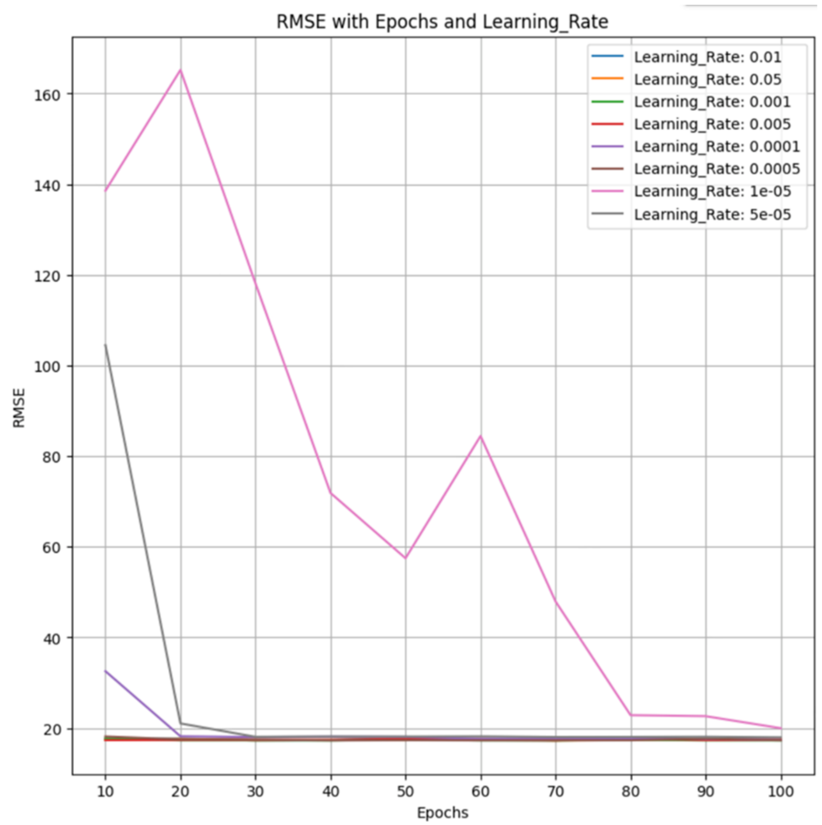


Subject 46 MLP Graph



Subject 52 RF Graph

Graphs cont.



Subject 54 RF Graph

Results/Conclusions

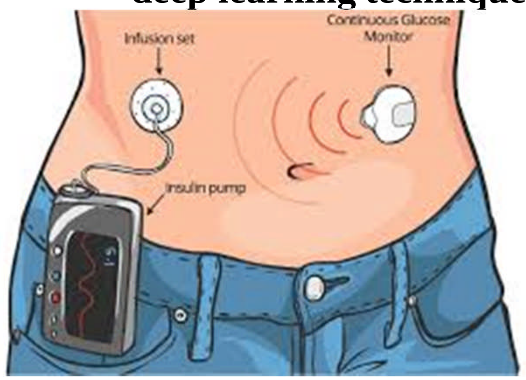
- **RF achieved the lowest RMSE** (**14.98 - 23.62 mg/dL**) across all subjects.
- **Subject-specific models outperformed a uniform model**, proving the need for **personalized predictions**.
- **Errors within ±30 mg/dL** indicate **practical feasibility** for real-world diabetes management.
- **RF outperformed other models** due to its ability to handle **non-linear relationships** and **high data variability** in blood glucose levels.
- **Established a foundation** for an **optimal blood glucose prediction system** using **supervised machine learning**.
- **Models achieved significant predictive performance**, validating their **effectiveness in forecasting glucose levels**.
- **Demonstrated the potential of ML-based personalized glucose prediction** to improve **T1DM management strategies**.

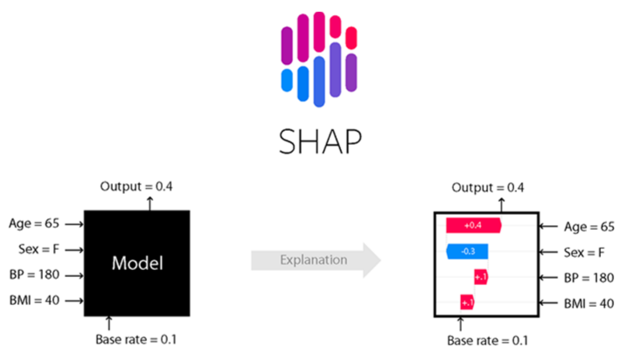
TABLE III. TESTING RESULTS FOR SUBJECTS ON BEST MODEL

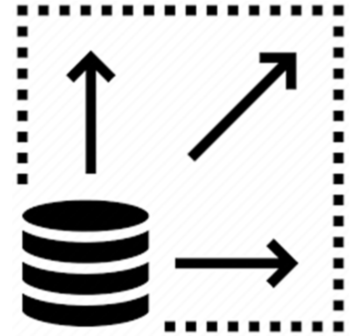
ID	RMSE
52	RMSE: 31.300
29	RMSE: 22.552
46	RMSE: 43.736
38	RMSE: 18.716
54	RMSE: 14.977

Future Research

- **Extend the study** with **more diverse subjects** to improve **generalizability** and model robustness.
- **Explore advanced deep learning models**, such as **LSTMs** and **Transformer-based architectures**, to capture **longer temporal patterns** in blood glucose trends.
- **Integrate models into CGM-insulin pump systems** for **real-world clinical validation** and improved automation in diabetes management.
- **Enhance interpretability** by incorporating **SHAP values** to better understand **feature importance** in predictions.
- **Expand dataset collection** beyond **31 days** to account for **seasonal, dietary, and behavioral variations**.
- **Develop a hybrid approach** combining **ML models** to leverage strengths from **both traditional and deep learning techniques**.







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Abstract

Type-1 Diabetes Mellitus (T1DM) is a chronic condition characterized by the pancreas's inability to produce insulin, requiring continuous monitoring and management of blood glucose levels. Accurate prediction of blood glucose levels can significantly improve patient outcomes by reducing hypo- and hyperglycemic events. This study develops a personalized automated blood glucose forecasting system leveraging the past blood glucose levels and insulin pump data. Utilizing the publicly available Diatrend dataset, encompassing thirty-one days of data for five subjects, we evaluated three machine learning algorithms: K-Nearest Neighbors (KNN), Random Forest (RF), and Multilayer Perceptron (MLP). After hyper-parameter tuning, the performance of each algorithm was assessed using Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and the coefficient of determination (R2), with a particular emphasis on RMSE. The Random Forest model demonstrated superior performance, achieving a test RMSE range of 14.98−23.62 across all subjects. This research highlights the efficacy of supervised machine learning algorithms in predicting blood glucose levels over one-hour intervals for T1DM patients, underscoring the potential of personalized machine learning models to improve diabetes management.