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Research Paper

Computational Modeling of Blood Glucose Variations using Physiological PPG Signals and Clinical Attributes

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ABSTRACT

Diabetes is a major global health challenge, with over 537 million adults affected worldwide in 2023, and an estimated 1 in 2 cases remaining undiagnosed, leading to severe complications. Traditional blood glucose monitoring relies on invasive finger-prick tests, which are inconvenient, painful, and unsuitable for continuous monitoring. To address these limitations, this study proposes a supervised learning-based predictive framework using photoplethysmography (PPG) signal patterns and demographic data to estimate glucose levels non-invasively. The dataset includes PPG signal recordings alongside patient demographic attributes such as age, weight, and BMI. In the preprocessing phase, signals undergo denoising, normalization, and feature extraction to generate robust predictive features. Baseline models such as Linear Regression (LR), Ridge Regression (RR), Lasso Regression (Lasso), and Decision Tree Regressor (DTR) are evaluated for performance comparison. The proposed approach leverages Natural Gradient Boosting Regressor (NGBR), which captures non-linear relationships and probabilistic uncertainty in glucose predictions. The model outputs continuous glucose level predictions, offering real-time estimation suitable for personal health monitoring. Experimental results demonstrate that NGBR outperforms traditional regression models in accuracy, robustness, and uncertainty quantification. By integrating this model into a Flask-based web application, patients and healthcare providers can access continuous glucose predictions, enabling proactive management of diabetes, reducing risks of hyperglycemia and hypoglycemia, and improving overall patient quality of life. This approach represents a scalable, non-invasive, and intelligent solution for continuous glucose monitoring using PPG and demographic data.

Key Words: Blood Glucose Prediction, PPG Signals, Machine Learning, Artificial Intelligence in Healthcare, Bio signal Analysis

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1. INTRODUCTION

Diabetes is an incurable chronic disease that occurs either when the pancreas is no longer able to produce insulin, or when the body is unable to utilize insulin properly. This results in poor regulation of blood glucose level, which can lead to severe health complications such as chronic heart and kidney disease if blood glucose levels are not monitored carefully. According to the IDF (International Diabetes Federation) Diabetes author published in 2019, 463 million people in the 20–79 demographic have diabetes and is projected to reach 700 million by 2045. More than 4.2 million people died due to diabetes-related disorders in 2019. The conventional approach to glucose level monitoring requires several apparatuses such as a glucometer, a one-time test strip, and a single-use lancet or lancing device to draw blood [1]. It also requires alcohol pads, gloves, and a band-aid to reduce the risk of infection for the patient. It is an uncomfortable process and one that people with diabetes need to use to monitor their blood glucose level regularly. There is a demand for wearable, non-invasive, and smart health monitoring systems [2]. Previously, there have been studies conducted on non-invasive or minimally invasive wearable devices based on different types of technologies for blood glucose level monitoring. Some of the researchers used sensors built using carbon nanotubes, fluorescence and plasmonic materials to determine the glucose level. These techniques had some issues such as long calibration processes, size, and susceptibility to autofluorescence.

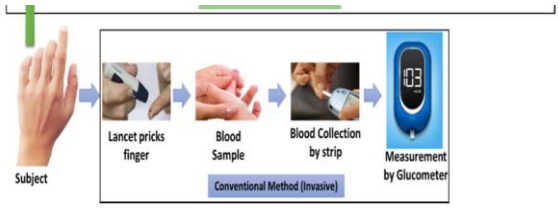


Fig.1. System diagram of non-invasive glucose detection using smartphone camera compared with the conventional glucometer-based technique.

Several electrical techniques have been proposed for blood glucose level monitoring. Shaker, G. et al. experimented with a millimeter-wave radar system to track glucose level changes. Similarly, experimented with glucose monitoring using electromagnetic devices in a noninvasive manner. Other researchers utilized changes in bioimpedance and ultrasound signal to determine a subject's blood glucose level. In general, electrical techniques have room for improvement due to poor selectivity, temperature sensitivity, and skin irritation. A handful of previous studies have explored the potential of optical techniques in tracking changes in blood glucose level. They studied a polarimetric optical measurement method for noninvasive glucose determination. Optical Coherence Tomography (OCT) [3], near-infrared spectroscopy, and mid-infrared (MIR) spectroscopy have also been utilized under laboratory conditions to gauge changes in blood glucose level in diabetic subjects. Unfortunately, optical techniques suffer from a significant lag time of up to 30 min as well as high temperature sensitivity. It is noteworthy that these proposed techniques require intricately organized and expensive laboratory equipment, making it unlikely for them to be used for daily measurement of blood glucose by millions of diabetics without significant reduction in price and complexity. Sensor-based non-invasive techniques have also been proposed for this purpose. Studies have shown the possibility of using GSR (Galvanic Skin Response) sensors [4], saliva, tear-based sensors, and sweat-based sensors in order to measure blood glucose level. These techniques are generally inexpensive and require biological fluid samples other than blood to be collected, thereby reducing the invasiveness of the procedure and the subject's discomfort. Photoplethysmography (PPG) is a low-cost, non-invasive technique that measures the volumetric change of blood in the arteries.

Previously researchers have investigated the estimation of heart rate using PPG signals acquired by various methods such as Endo cavitary sensors [5] and pressure sensors. Some researchers determined the glucose level using smartphone-based on the colorimetric and electrochemical methods this required an external apparatus to collect the sample before analyzing the sample using a smartphone. We also previously demonstrated that PPG could be a useful tool for blood glucose estimation.

2. LITERATURE SURVEY

Islam, T.T.; et al. [6] proposed a smartphone video-based noninvasive technique is proposed for the quantitative estimation of glucose levels in the blood. The videos are collected steadily from the tip of the subject's finger using smartphone cameras and subsequently converted into a Photoplethysmography (PPG) signal. A Gaussian filter is applied on top of the Asymmetric Least Square (ALS) method to remove high-frequency noise, optical noise, and motion interference from the raw PPG signal. These preprocessed signals are then used for extracting signal features such as systolic and diastolic peaks, the time differences between consecutive peaks (DelT), first derivative, and second derivative peaks. Finally, the features are fed into Principal Component Regression (PCR), Partial Least Square Regression (PLS), Support Vector Regression (SVR) and Random Forest Regression (RFR) models for the prediction of glucose level.

Ali, H.; et al. [7] examined the performance of various machine learning (ML) models in predicting Interstitial Glucose (IG) levels using data from wrist-worn wearable sensors. The insights from these predictions can aid in understanding metabolic syndromes and disease states. A public dataset comprising information from the Empatica E4 smart watch, the Dexcom Continuous Glucose Monitor (CGM) measuring IG, and a food log was utilized. The raw data were processed into features, which were then used to train different ML models. This study evaluates the performance of decision tree (DT), support vector machine (SVM), Random Forest (RF), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Gaussian Naïve Bayes (GNB), lasso cross-validation (LassoCV), Ridge, Elastic Net, and XGBoost models. For classification, IG labels were categorized into high, standard, and low, and the performance of the ML models was assessed using accuracy (40–78%), precision (41–78%), recall (39–77%), F1-score (0.31–0.77), and receiver operating characteristic (ROC) curves.

Gudiño-Ochoa, A.; et al. [8] addressed this limitation by employing conditional generative adversarial networks (CTGAN) to generate synthetic data from real-world tests involving 29 healthy and 29 diabetic participants, resulting in over 14,000 new synthetic samples. These data were used to validate machine learning models for diabetes detection and BGL prediction, integrated into a Tiny Machine Learning (TinyML) e-nose system for real-time analysis. The proposed models achieved an 86% accuracy in BGL identification using LightGBM (Light Gradient Boosting Machine) and a 94.14% accuracy in diabetes detection using Random Forest.

Satter, S.; et al. [9] aimed to develop a HbA1c estimation system based on machine learning algorithms using PPG signals obtained from the wrist. We used a PPG based dataset of 22 subjects and algorithms such as extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), Categorical Boost (CatBoost) and random forest (RF) to estimate the HbA1c values. Note that the AC-to-DC ratios for three wavelengths were newly adopted as features in addition to the previously acquired 15 features from the PPG signal and a comparative analysis was performed between the performances of several algorithms.

Owess, M.M.; et al. [10] presented supervised machine-learning models to detect and predict raised blood sugar. The proposed raised blood sugar models utilize diabetes-related risk factors including age, body mass index (BMI), eating habits, physical activity, prevalence of other diseases, and fasting blood sugar obtained from the dataset of the STEPwise approach to NCD risk factor study collected from adults in the Palestinian community. The diabetes risk factor obtained from the STEPS dataset was used as input for building the prediction model that was trained using various types of supervised learning classification algorithms including random forest, decision tree, Adaboost, XGBoost, bagging decision trees, and multi-layer perceptron (MLP). Based on the experimental results, the raised blood sugar models demonstrated optimal performance when implemented with a random forest classifier, yielding an accuracy of 98.4%. Followed by the bagging decision trees, XGBoost, MLP, AdaBoost, and decision tree with an accuracy of 97.4%, 96.4%, 96.3%, 95.2%, and 94.8%, respectively.

Susana, E.; et al. [11] detected the cardiovascular disease can be via photoplethysmography. These characteristics can be used to directly affect BGL monitoring in diabetic patients if PPG signals are used. The Guilin People's Hospital's open database was used to produce the data collection. The dataset was gathered from 219 adult respondents spanning an age range from 21 to 86 of which 48 percent were male. There were 2100 sampling points total for each PPG data segment. The methodology of feature extraction from data may assist in increasing the effectiveness of classifier training and testing. PPG data information is modified in the frequency domain by the instantaneous frequency (IF) and spectral entropy (SE) moments using the time–frequency (TF) analysis. Three different forms of raw data were used as inputs, and we investigated the original PPG signal, the PPG signal with instantaneous frequency, and the PPG signal with spectral entropy.

Gunathilaka, H.; et al. [12]. explored the efficacy of Pulse Wave Analysis (PWA) for distinguishing diabetic from non-diabetic individuals through morphological examination of pressure pulse waveforms. The research unfolds in four phases: data accrual, preprocessing, Convolutional Neural Network (CNN) model construction, and performance evaluation. Data were procured using a multipara patient monitor, resulting in 2000 pulse waves equally divided between healthy individuals and those with diabetes. These were used to train, validate, and test three distinct CNN architectures: the conventional CNN, Visual Geometry Group (VGG16), and Residual Networks (ResNet18). The accuracy, precision, recall, and F1 score gauged each model's proficiency. The CNN demonstrated a training accuracy of 82.09% and a testing accuracy of 80.6%. The VGG16, with its deeper structure, surpassed the baseline with training and testing accuracies of 90.2% and 86.57%, respectively.

Leung, H.M.C.;et al. [13] analysed Blood glucose monitoring is an essential aspect of disease management for individuals with diabetes. Unfortunately, traditional methods require collecting a blood sample and thus are invasive and inconvenient. Recent developments in minimally invasive continuous glucose monitors have provided a more convenient alternative for people with diabetes to track their glucose levels 24/7. Despite this progress, many challenges remain to establish a non-invasive monitoring technique that works accurately and reliably in the wild. This review encompasses the current advancements in non-invasive glucose sensing technology in vivo, delves into the common challenges faced by these systems, and offers an insightful outlook on existing and future solutions.

Chowdhury, M.H.; et al. [14] addressed this need, a cuff-less, continuous, and non-invasive

BP measurement system is proposed using the photoplethysmography (PPG) signal and demographic features using machine learning (ML) algorithms. PPG signals were acquired from 219 subjects, which undergo preprocessing and feature extraction steps. Time, frequency, and time-frequency domain features were extracted from the PPG and their derivative signals. Feature selection techniques were used to reduce the computational complexity and to decrease the chance of over-fitting the ML algorithms. The features were then used to train and evaluate ML algorithms. The best regression models were selected for systolic BP (SBP) and diastolic BP (DBP) estimation individually. Gaussian process regression (GPR) along with the ReliefF feature selection algorithm outperforms other algorithms in estimating SBP and DBP with a root mean square error (RMSE) of 6.74 and 3.59, respectively.

G. Zhang et al. [15] proposed an intelligent, non-invasive blood glucose monitoring system which can differentiate a user's blood glucose level into normal, borderline, and warning based on smartphone photoplethysmography (PPG) signals. The main implementation processes of the proposed system include 1) a novel algorithm for acquiring PPG signals using only smartphone camera videos; 2) a fitting-based sliding window algorithm to remove varying degrees of baseline drifts and segment the signal into single periods; 3) extracting characteristic features from the Gaussian functions by comparing PPG signals at different blood glucose levels; 4) categorizing the valid samples into three glucose levels by applying machine learning algorithms. Our proposed system was evaluated on a data set of 80 subjects. Experimental results demonstrate that the system can separate valid signals from invalid ones at an accuracy of 97.54%

3.PROPOSED METHODOLOGY

The proposed system overview lies on predicting blood glucose levels integrates data collection, preprocessing, machine learning model training, evaluation, and prediction modules in a seamless workflow. Initially, PPG signals and demographic data (such as age, gender, height, weight, heart rate, and pulse characteristics) are collected from patients. This data is stored in a structured CSV format, which serves as the primary dataset for the system. The architecture ensures that the system can handle both single-sample predictions and batch predictions for multiple individuals, providing flexibility in real-world applications. Once the data is collected, it undergoes preprocessing steps. This includes handling missing values, normalizing numerical features using a standard scaler, and splitting the dataset into training and testing subsets.

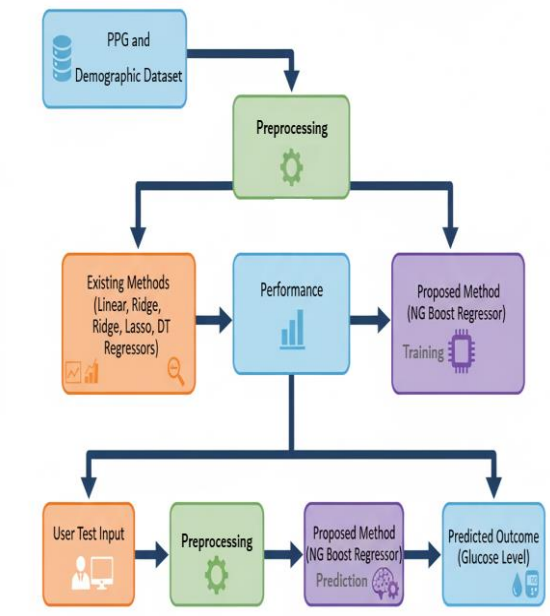


Fig. 2. Proposed system architecture.

The preprocessing module ensures data quality and consistency, which is crucial for the accuracy of predictive models. Feature selection is performed to retain only the most relevant physiological and demographic parameters, enhancing model efficiency while reducing computational complexity. The preprocessed data is then fed into multiple supervised learning models, including LR, RR, Lasso, DTR, and proposed NGBR. Each model is trained, evaluated using metrics like

MAE, MSE, RMSE, and R^2 score, and persisted for future predictions. The system architecture also incorporates a Flask-based web interface that provides dashboards for data visualization, model evaluation results, and endpoints for both single and batch predictions. This modular design allows for easy scalability, maintenance, and integration with other healthcare monitoring systems.

4. RESULTS DESCRIPTION

Fig. 3. displays the main landing page for the Blood Glucose Prediction System. It serves as a central hub, introducing users to the application's core functionalities. The page features a prominent title and tagline explaining its purpose of using PPG signals for prediction. Key navigation options, "Start Analysis" and "View Dashboard," guide users toward the main sections. Below, three distinct cards highlight the system's capabilities: Data Analysis, Machine Learning Models, and Real-time Prediction. The bottom of the page provides a concise system overview and a "Getting Started" guide to help users navigate the application's workflow.

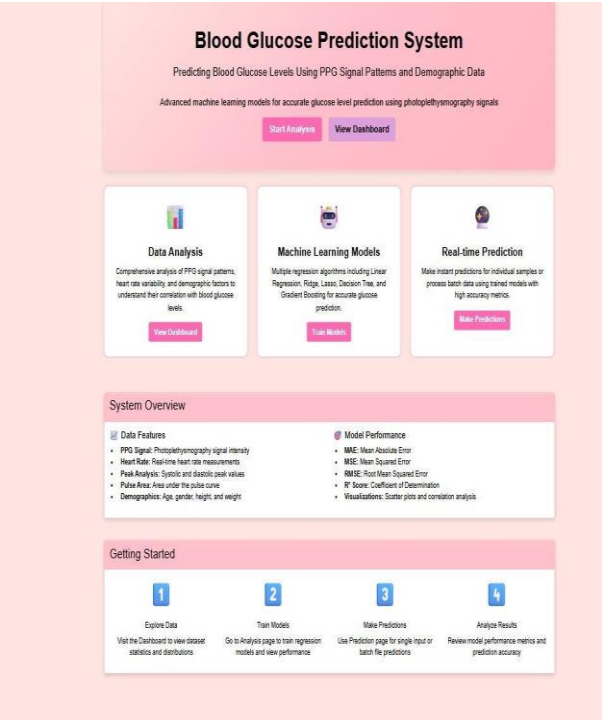


Fig. 3. Home page of the blood glucose prediction system.

Fig. 4. shows the Dataset Dashboard, which provides a comprehensive statistical overview of the data used for the prediction models. At the top, key metrics such as Total Samples (844,946), number of features, mean glucose, and standard deviation are displayed. The main body of the dashboard presents glucose level statistics, including minimum, maximum, mean, and standard deviation values. A histogram visualizes the distribution of blood glucose levels across the dataset. Finally, the page details all the dataset features, categorized into PPG Signal Features, Demographic Features, and the Target Variable (glucose level).

Fig. 5 shows the analysis page after training an NGBR model, a powerful ensemble technique. The model performance results for NGBR are exceptionally strong, with an MAE of only 0.4686 and an almost perfect R^2 Score of 1.0000. This suggests the model has learned the training data extremely well, potentially to the point of overfitting. The interface in this image also shows the results for the Decision Tree model just above it, allowing for a direct and striking comparison between the two tree-based methods, highlighting the significant performance gain from using the boosting algorithm.

Fig. 6 shows the same prediction interface, but this time the RR model has been selected for the calculation. Using the exact same input data as in the previous figure, the RR model also yields a prediction of 111.80 mg/dL. This demonstrates the similarity in predictive output between the LR and RR models for this specific data point. The "Note" on the right reminds the user that models must be trained in the analysis section first, ensuring the prediction functionality is used correctly. The clear layout makes it easy to select a model and interpret the resulting glucose prediction.

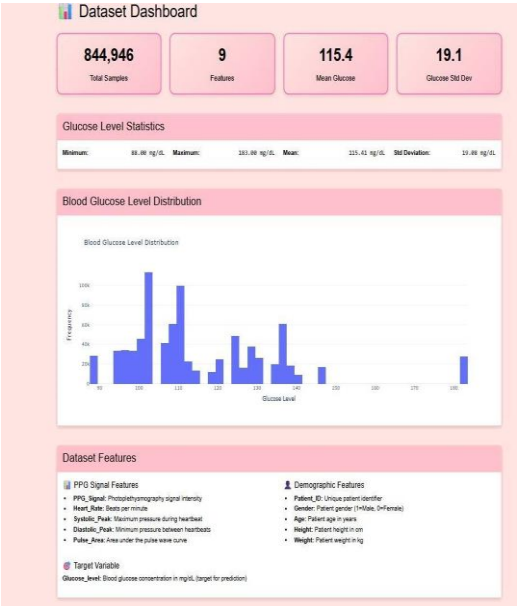


Fig. 4. Dataset dashboard with glucose level statistics and features



Fig. 5. Analysis page displaying NGBR model performance.

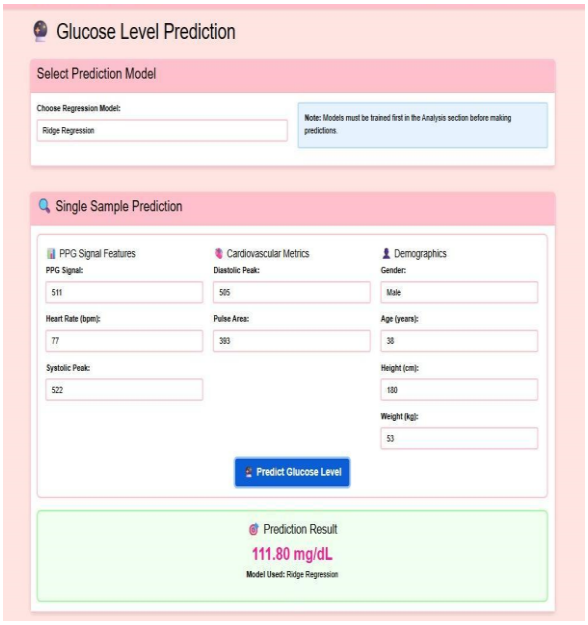


Fig. 6. Glucose level prediction using RR model.

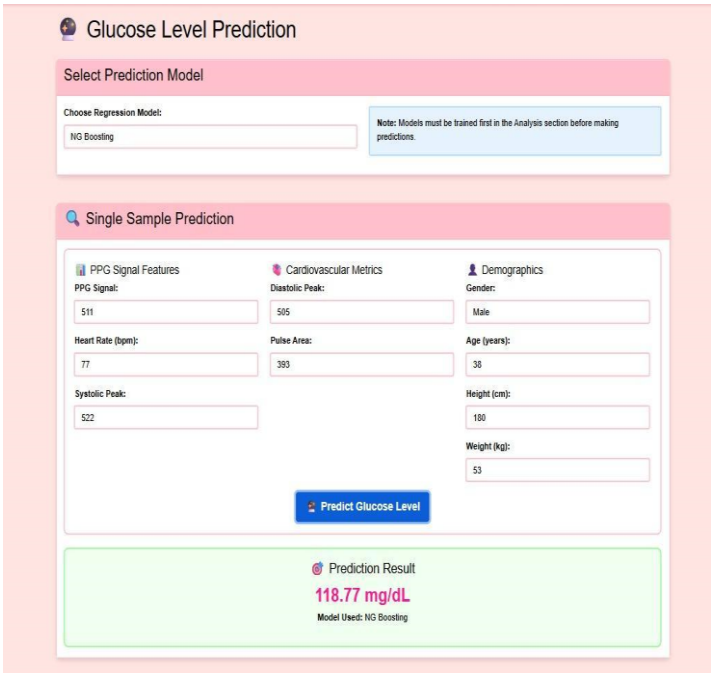


Fig. 7. Glucose level prediction using the NGBR model.

Fig. 7 showcases a prediction made using the Lasso model. With the identical set of input features for the single sample, the Lasso model predicts a blood glucose level of 113.19 mg/dL. This result is slightly different from the predictions made by the Linear and Ridge Regression models, highlighting the subtle variations in how each algorithm weighs the

input features to arrive at a final prediction. The interface consistently specifies which model was used for the calculation, ensuring transparency and allowing the user to compare the outputs of different trained models for the same input data.

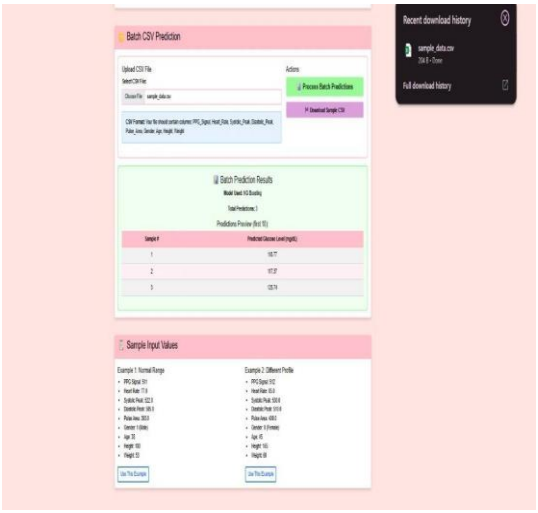


Fig. 8. Batch prediction results after processing a test CSV file.

Fig. 8. displays the Batch CSV Prediction functionality, designed for processing multiple data samples at once. The user has uploaded a file named "sample_data.csv," which the system has processed using the selected NG Boosting model. The "Batch Prediction Results" section confirms that three predictions were made and provides a preview table showing the predicted glucose level for each sample. The interface also offers an option to download the complete results in a new CSV file, making it highly efficient for analysing larger datasets without manual entry.

5. CONCLUSION

This study successfully demonstrates the efficacy of a non-invasive glucose monitoring framework leveraging PPG signals and demographic data. By moving away from painful, invasive finger-prick methods, the proposed system addresses a critical barrier to consistent diabetes management. Through rigorous preprocessing and feature extraction, the model effectively translates physiological signal patterns into actionable health insights. While baseline models like LR and DTR provided a foundation, the NGBR emerged as the superior architecture. NGBR's unique ability to model non-linear relationships while quantifying probabilistic uncertainty ensures that glucose estimations are not only accurate but also reliable for clinical decision-making. The integration of this predictive engine into a Flask-based web application bridges the gap between complex machine learning research and practical patient care. This scalable solution empowers users with real-time monitoring, significantly reducing the risks of both hyperglycemia and hypoglycemia. Ultimately, this research contributes a robust, intelligent tool to the global fight against diabetes, offering a path toward improved patient autonomy, proactive healthcare intervention, and a higher quality of life for millions of undiagnosed or struggling individuals worldwide.

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