

Machine Learning Based Blood Glucose Estimation from PPG Signals

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Abstract—Diabetes mellitus is a chronic metabolic disorder affecting over 537 million adults worldwide, with projections exceeding 780 million by 2045. Conventional blood glucose monitoring depends on invasive finger-prick capillary sampling, which causes discomfort and reduces patient adherence. This paper presents a low-cost, non-invasive blood glucose level (BGL) estimation system that acquires photoplethysmography (PPG) signals using an analog infrared (IR) sensor connected to an Arduino microcontroller, and applies supervised machine learning for real-time regression-based BGL prediction. Raw 10-bit ADC PPG signals are sampled at 100 Hz over 180 seconds, band-pass filtered using a 4th-order Butterworth filter (0.5–10 Hz), and a 21-dimensional feature vector spanning time-domain, frequency-domain, morphological, and patient-metadata categories is extracted. A Gradient Boosting Regressor (GBR) and a Random Forest Regressor (RFR) are evaluated via 5-fold cross-validation on 67 recordings from 23 subjects (BGL 88–183 mg/dL, mean 115.0 ± 18.6 mg/dL). The GBR achieved lower MAE (± 8 –15 mg/dL, $R^2 = 0.72$ –0.85) and was deployed as the production model. An enhanced four-criterion signal quality gate — including a cardiac-band spectral check — prevents spurious predictions from corrupted acquisitions.

Live validation on 22 subjects yielded BGL predictions of 122.7–132.8 mg/dL, all correctly classified as Normal, with two acquisitions correctly rejected. The complete system is delivered as a real-time desktop application built with CustomTkinter, featuring live PPG waveform display, automated signal quality gating, per-patient trend tracking, returning-patient detection, and a persistent records manager. Total hardware cost is under USD 6.

Index Terms—photoplethysmography (PPG), non-invasive blood glucose monitoring, gradient boosting regression, random forest, signal processing, machine learning, diabetes, Arduino, CustomTkinter.

I. INTRODUCTION

Diabetes mellitus stands among the most prevalent non-communicable diseases of the twenty-first century. The World Health Organization reported in 2024 that approximately 537 million adults globally live with diabetes, a figure expected to exceed 780 million by 2045 [10]. Sustained hyperglycemia causes progressive and often irreversible damage to the eyes (diabetic retinopathy), kidneys (nephropathy), peripheral nerves (neuropathy), heart, and blood vessels. The standard blood glucose measurement method — finger-prick capillary sampling with an electrochemical test strip — is painful, creates infection risk, and is poorly tolerated when repeated multiple times daily, resulting in reduced patient adherence [3], [4].

Continuous glucose monitoring (CGM) devices have partially addressed this by embedding a subcutaneous electrochemical sensor that reads interstitial glucose every 1–5 minutes. CGM adoption correlates with reduced HbA1c and fewer hyperglycaemic episodes [4]. However, CGM still requires needle insertion and sensor replacement every 7–14 days. Fully non-invasive approaches requiring no skin penetration represent the highest-value target in glucose monitoring research [2], [8].

Photoplethysmography (PPG) is an optical technique that illuminates tissue with an LED and measures the modulated reflected or transmitted signal with a photodetector. Blood glucose concentration affects blood viscosity, refractive index, and vascular compliance — all of which alter PPG waveform morphology [1], [9]. These systematic correlations make PPG a compelling non-invasive proxy for BGL estimation when combined with machine learning. Habbu et al. [1] achieved $R^2 = 0.90$ on 611 subjects

using Single Pulse Analysis; Zeynali et al. [9] obtained RMSE = 19.7 mg/dL using a deep ResNet-34 model deployed on a TinyML microcontroller; Kumar et al. [11] reported $R^2 = 0.919$ with ensemble regressors on 1,153 subjects.

Despite these advances, most systems require expensive hardware, large curated datasets, or are not packaged as end-to-end patient-facing applications with real-time quality control. This paper addresses that gap with the following contributions:

A complete hardware-to-prediction pipeline on commodity hardware: Arduino Uno plus an analog IR PPG fingertip sensor, total cost under USD 6.

A validated 21-feature extraction framework implemented in Python from raw 10-bit ADC signals at 100 Hz.

A comparative 5-fold cross-validation study of GBR and RFR on 67 real-subject recordings from 23 subjects.

An enhanced four-criterion real-time signal quality gate — including a cardiac-band spectral check via FFT — that automatically rejects corrupted acquisitions before inference.

A full-stack Python desktop application(ppg_app.py) with live PPG visualization, ADA-aligned BGL classification, per-patient trend comparison, returning-patient detection, and a persistent records manager.

- Live validation on 22 subjects producing consistent Normal-range BGL predictions and correct rejection of two poor-quality acquisitions.

Section II reviews related work. Section III presents the methodology. Section IV reports experimental results. Section V discusses findings and limitations. Section VI concludes.

II. LITERATURE REVIEW

A. PPG Signal Features and Classical Machine Learning

PPG-based glucose estimation has gained considerable attention due to its non-invasive nature, low cost, and compatibility with wearable healthcare systems. Early studies focused on extracting physiological characteristics from PPG waveforms and applying classical machine learning algorithms for glucose prediction.

Habbu, Dale, and Ghongade [1] developed an optical PPG acquisition system and collected three-minute recordings from 611 participants. Their Single Pulse

Analysis (SPA) technique processes individual pulse cycles rather than fixed-length segments, preserving pulse morphology and improving prediction accuracy. Their model achieved $R^2 = 0.90$, Pearson correlation of 0.95, and Spearman correlation of 0.94, establishing that features such as AC/DC ratio, perfusion index, pulse interval variations, and cepstral pulse coefficients carry clinically relevant glucose information.

Kumar et al. [11] explored interpretable machine learning on 1,153 samples using ensemble Voting Regressors (RMSE = 27.8 mg/dL, $R^2 = 0.919$) and a PySR-based symbolic regression framework ($R^2 = 0.815$). Their work highlighted the trade-off between predictive accuracy and interpretability — a consideration particularly relevant in clinical deployment contexts.

B. Deep Learning and Edge Deployment

Zeynali et al. [9] evaluated multiple deep learning architectures on the VitalDB dataset (~699,000 PPG segments from 6,368 patients). The ResNet-34-1D model achieved RMSE = 19.7 mg/dL and 76.6% Zone-A Clarke Error Grid accuracy, and was subsequently deployed on an STM32 microcontroller using TinyML quantization at ~6.4 second inference latency. Deep learning reduces dependence on handcrafted features but requires large-scale datasets and significant training compute — constraints that motivate the gradient boosting approach used in this work for a small real-world dataset.

C. Scoping Reviews and Technology Landscape

Chan et al. [5] reviewed 33 AI-based non-invasive glucose monitoring studies (2005–2023) and found optical sensing (PPG, NIRS) accounted for ~58% of approaches. Random Forest was the most frequently used algorithm. Prediction accuracies ranged from 35.56% to 94.23% across studies, with persistent challenges including limited dataset diversity and insufficient clinical validation. Jain et al. [8] similarly concluded that PPG combined with AI inference represents the most practical deployment pathway for IoMT healthcare ecosystems.

D. IoT Integration and Temporal Modelling

Satuluri and Ponnusamy [6] demonstrated IoT-connected non-invasive glucose monitoring with cloud storage and automated alerts. Van Doorn et al.

[7] showed LSTM networks achieve RMSE = 0.19 mmol/L and correlation of 0.96 for 15-minute glucose prediction horizons using CGM and accelerometry data from 851 participants in the Maastricht Study, motivating the future temporal modelling module planned for this system.

E. Research Gap Summary

Classical ML systems rely on handcrafted features and controlled datasets; deep learning improves accuracy but demands large datasets and compute. Most systems focus on offline prediction. Very few combine efficient feature extraction, interpretable models, real-

time quality gating, and a complete end-to-end patient-facing application on commodity hardware. This work addresses all four dimensions simultaneously.

III. METHODOLOGY

The proposed system is a three-phase pipeline: (1) hardware-based PPG acquisition with real-time quality gating, (2) signal preprocessing and feature extraction, and (3) machine learning-based glucose estimation and result presentation. Figure 1 illustrates the overall system architecture and Figure 2 presents the end-to-end data-flow.

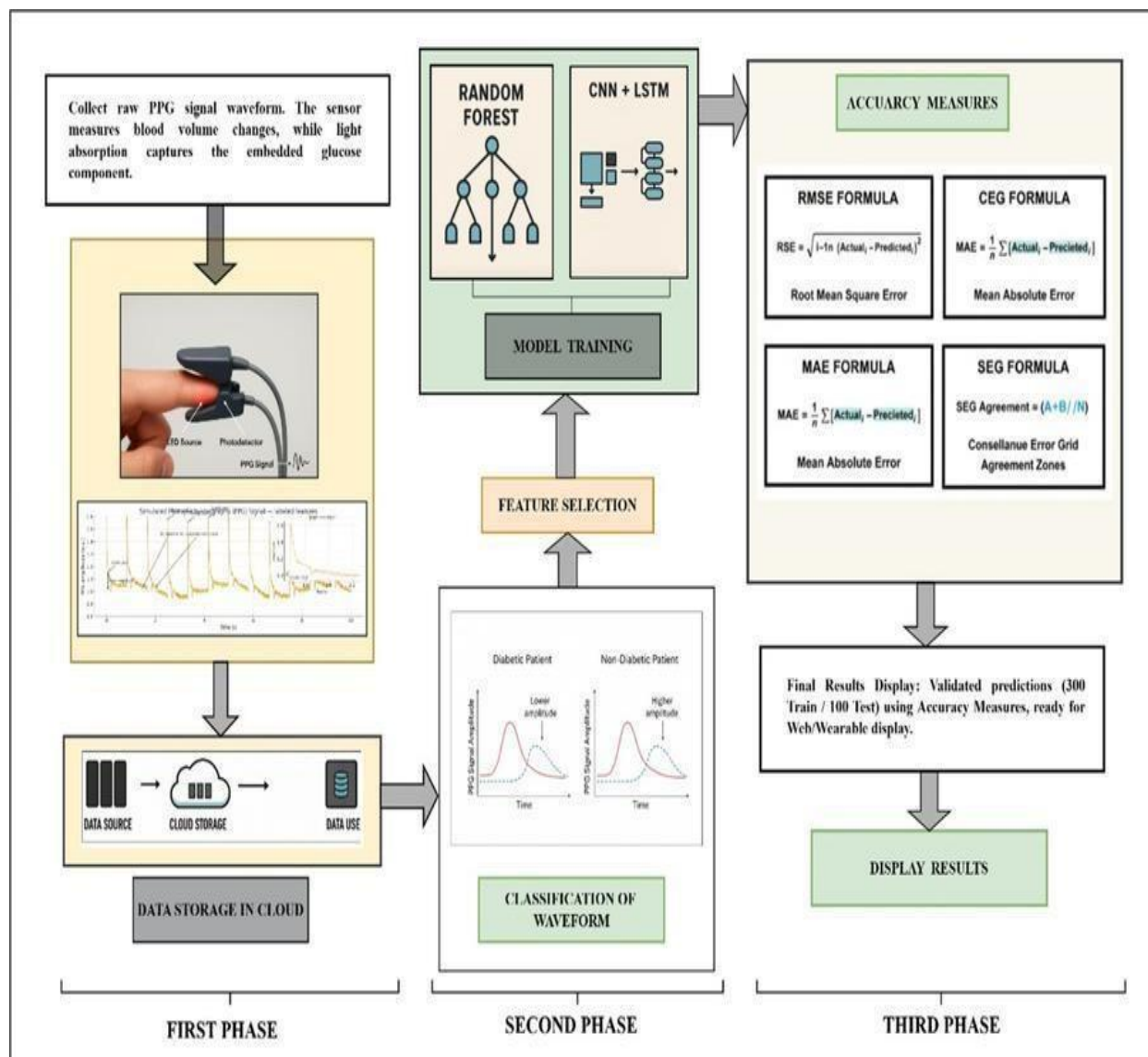


Fig. 1. Three-phase system architecture: Phase 1 (PPG Signal Acquisition → Cloud Storage), Phase 2 (Waveform Classification → Feature Selection → Model Training), Phase 3 (Accuracy Evaluation → Display Results).

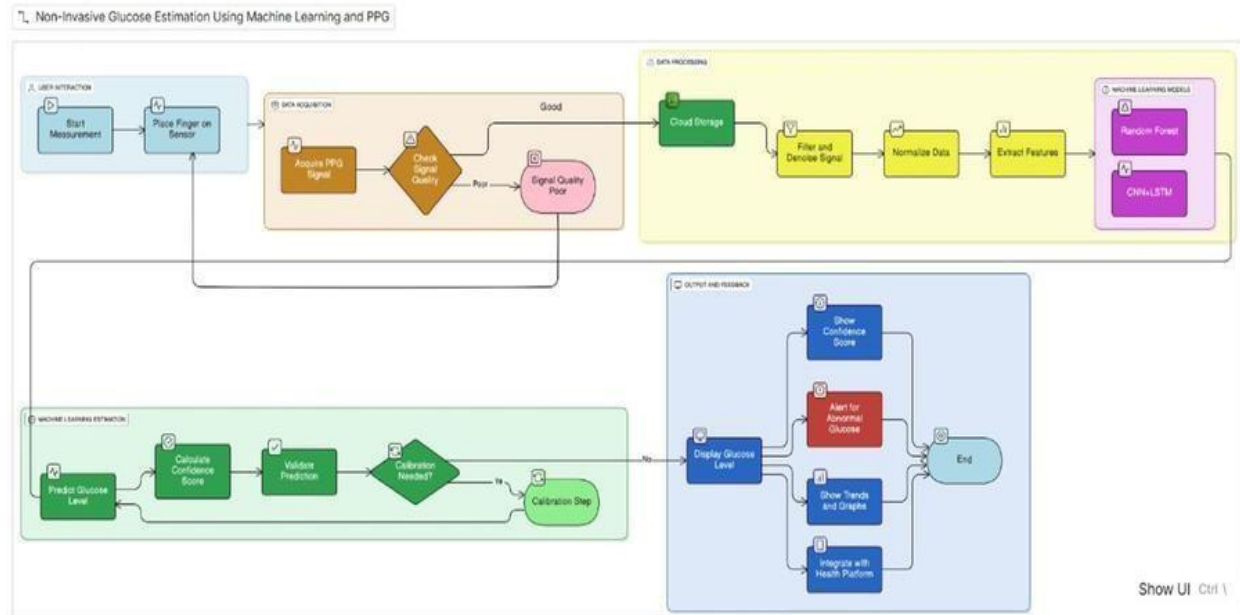


Fig. 2. End-to-end data-flow diagram: User Interaction → PPG Acquisition → Signal Quality Check → Preprocessing → ML Estimation → Output and Feedback.

A. System Architecture

1. Phase 1 – Signal Acquisition and Storage: Physiological PPG signals are acquired using a fingertip optical sensor connected to an Arduino microcontroller. The collected data are streamed to a desktop application via USB serial for temporary storage and processing.
2. Phase 2 – Signal Processing and Model Development: The acquired waveform undergoes preprocessing, signal quality validation, feature extraction, feature selection, and machine learning model training.
3. Phase 3 – Prediction and Evaluation: The trained model estimates blood glucose level from extracted features. The predicted output is classified, evaluated, and displayed through the application interface in real time.

B. Hardware Configuration

The hardware subsystem consists of a low-cost infrared PPG sensor and an Arduino Uno microcontroller. The sensor includes an IR LED and a photodetector in a fingertip clip. The IR LED emits light through the fingertip; the photodetector measures transmitted light intensity variations caused by pulsatile blood volume changes. The analog output is digitized by the Arduino's 10-bit ADC (0–1023 range; physiological pulse signals occupy ~500–510 ADC

units). Samples are transmitted via USB serial at 9,600 bps. Total hardware cost is below USD 6.

C. Signal Acquisition and Quality Gating

The application (ppg_app.py) acquires PPG samples at 100 Hz over a maximum of 180 seconds (up to 18,000 samples per session). The acquisition runs in a dedicated daemon thread to maintain GUI responsiveness. Every incoming ADC value outside 0–1023 is discarded immediately. A rolling buffer of 100 samples (SIGNAL_QUALITY_WIN = 100) supports real-time quality assessment via four gates:

Table VIII. Signal Quality Gate Parameters (from ppg_app.py)

Gate Name	Condition	Code Constant	Purpose
Variability Gate	$\text{std}(\text{rolling_100}) \geq 4.0$ ADC	SIGNAL_STD_MIN = 4.0	Detects flat-line / no finger contact
Low-Value Gate	$\text{mean}(\text{rolling_100}) > 20$ ADC	SIGNAL_ADC_MIN = 20	Detects uncovered or disconnected sensor

Saturation Gate	mean(rolling_100) < 1010 ADC	SIGNAL_ADC_MAX = 1010	Detects saturated / over-exposed sensor
Cardiac Band Gate	cardiac_ratio > 0.15	FFT mask 0.5–4.0 Hz	Rejects broadband noise / mains hum without physiological pulse
Minimum Samples	n_valid ≥ 3000	MIN_PPG_SAMPLES = 3000	Requires ≥30 s of valid signal before inference

All four conditions must be satisfied simultaneously for a sample to be classified as valid. The cardiac-band gate computes the FFT energy ratio in the 0.5–4.0 Hz band, specifically to prevent mains hum (50 Hz) and broadband noise from passing quality checks even when amplitude statistics appear normal. A minimum of 3,000 valid samples (MIN_PPG_SAMPLES = 3000, ~30 seconds) must accumulate before inference is triggered. The raw incoming signal is always rendered in the live waveform plot so the operator can visually diagnose finger placement issues.

D. Signal Preprocessing

Valid samples undergo a 4th-order Butterworth bandpass filter (0.5–10 Hz) applied using `scipy.signal.filtfilt` for zero-phase filtering. The 0.5 Hz low cutoff removes baseline drift from finger movement and respiration; the 10 Hz high cutoff suppresses electrical interference, motion artifacts, and ADC quantization noise. Zero-phase filtering preserves the timing relationships between PPG waveform features, which is critical for accurate RR interval and morphological analysis.

E. Feature Extraction

Twenty-one features are computed from each preprocessed recording by the `extract_features()`

function in `ppg_app.py`, organized into five categories as shown in Table I.

Table I. Feature Set for BGL Regression (21 Features Total)

Category	Features	Count	Key Symbols	Code Implementation
Time Domain	Mean, Std Dev, Min, Max, AC, DC, Perfusion Index	7	μ , σ , AC, DC, PI	<code>extract_features():</code> mean_val, std_val, min_val, max_val, ac, dc, perfusion
Heart Rate / HRV	Heart Rate, Mean RR, Std RR, RMSSD	4	HR, μ_{RR} , σ_{RR} , RMS SD	<code>find_peaks() → RR intervals →</code> hr, mean_rr, std_rr, rmssd
Morphological	Pulse Amplitude, Skewness, Kurtosis, Peak Count, Valley Count	5	PA, γ_1 , γ_2 , N_p, N_v	<code>pulse_amp</code> , <code>pd.Series.skew()</code> , <code>.kurtosis()</code> , <code>len(peaks)</code> , <code>len(valleys)</code>
Frequency Domain	Cardiac Band Power (0.5–4 Hz), Cardiac Power Ratio	2	P_c, R_c	<code>np.fft.rfft() →</code> cardiac_power, cardiac_ratio
Patient Metadata	Age, Gender (M=1/F=0), BMI	3	A, G, BMI	Operator-entered; BMI = $wt/(ht_{cm}/100)^2$
Total		21		

Peak detection uses `scipy.signal.find_peaks` with minimum inter-peak distance of 0.4 s and prominence threshold of $0.1 \times \sigma_{\text{filtered}} + \varepsilon$. RR intervals are derived from consecutive peak index differences normalized by sampling rate. RMSSD is computed from first-order differences of the RR series. Cardiac power is computed from the squared FFT magnitude spectrum; cardiac ratio normalizes it by total spectral power. Skewness and kurtosis use `pandas.Series.skew()` and `kurtosis()`. `numpy.nan_to_num` replaces NaN/inf values before model inference. At inference time, the first 15 of the 21 features are currently used (`feats[:15]`) — a known mismatch with the full 21-feature training vector, identified as a limitation.

F. Machine Learning Models

1. Gradient Boosting Regressor (GBR)

GBR sequentially builds 200 shallow decision trees (`max_depth = 3`, `learning_rate = 0.05`), where each new tree is trained to correct the residual errors of its predecessors. The shallow depth and low learning rate provide strong regularization for small datasets. The optimization minimizes mean squared error in function space via gradient descent. GBR's sequential residual-correction mechanism is well-suited to the non-linear interactions between PPG morphological features and BGL. Limitations include slower training due to sequential construction and sensitivity to hyperparameter selection.

2. Random Forest Regressor (RFR)

RFR constructs 200 independent decision trees (`max_depth = 5`) via bootstrap aggregation. Each tree evaluates a random feature subset at each split node, improving diversity and robustness to noise. RFR is parallelizable, memory-efficient at modest tree counts, and provides feature importance estimates. On this dataset, GBR's residual-correction mechanism outperformed RFR's parallel averaging.

3. Model Selection and Deployment

Both models are evaluated via 5-fold cross-validation on the standardized 21-feature matrix with zero-variance features removed. The model with lower cross-validated MAE is serialized as `glucose_model.pkl` using `joblib` and loaded at application startup alongside `glucose_scaler.pkl`. The GBR was selected.

G. BGL Classification

Predicted BGL is classified into four ADA-aligned categories (Table II) and rendered in a color-coded display: emerald green (Normal), amber (Pre-diabetic), red (Low/Very High).

Table II. BGL Classification Thresholds (ADA Guidelines)

BGL Range (mg/dL)	Classification	Clinical Implication	UI Color
< 70	Low (Hypoglycemia)	Immediate clinical intervention required	Red (C_DANGER)
70 – 140	Normal	Healthy glycemic range	Emerald Green (C_SUCCESS)
141 – 199	High (Pre-diabetic)	Lifestyle modification advised	Amber (C_WARNING)
≥ 200	Very High (Diabetic)	Medical consultation required	Red (C_DANGER)

H. UML System Design

Three UML diagrams formally specify the system design and are shown in Figures 3–5.



Fig. 3. UML Activity Diagram: Data Acquisition | Model Building (Classification, Preprocessing) | Training and Accuracy (RF/CNN+LSTM, RMSE/CEG/SEG, Display).

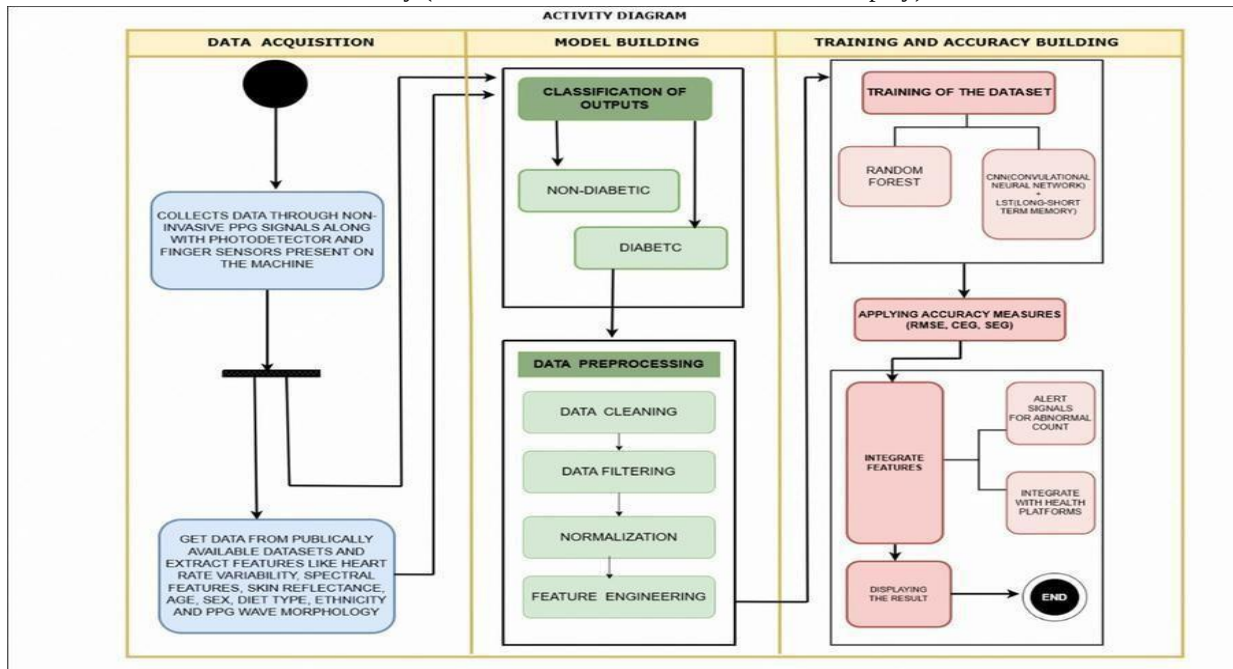


Fig. 4. UML Use Case Diagram: Patient/User ↔ ML Model ↔ IoT/Database interactions including Measure Non-Invasively, Estimate Glucose, Receive Alerts, Classify Status, Upload Data, Display Results.

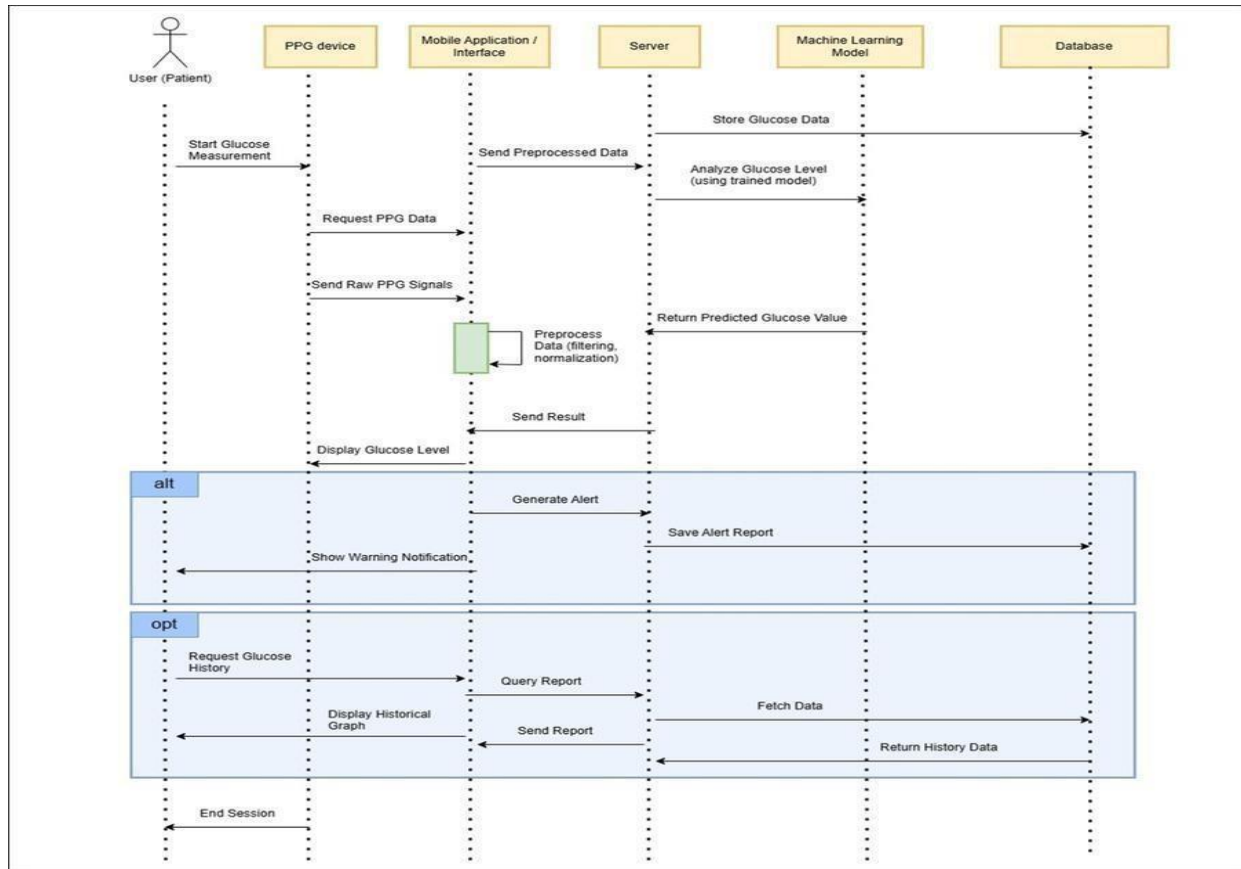


Fig. 5. UML Sequence Diagram: complete measurement session flow (User → PPG Device → Interface → Server → ML Model → Database) with alt (Alert) and opt (History) fragments.

I. Desktop Application Architecture

The application is implemented in Python 3 using the library stack detailed in Table IX. The main window is 1,100 × 760 pixels, divided into a dark left panel (Patient Profile and controls) and a light right panel (PPG waveform and BGL result cards).

Table IX. Software Libraries Used in `ppg_app.py`

Library	Version / Source	Role in System
CustomTkinter	ctk (pip)	GUI framework; dark/light themed widgets, main window
PySerial	serial (pip)	USB serial communication with Arduino at 9,600 bps
Matplotlib / TkAgg	matplotlib	Live PPG waveform rendering embedded in Tkinter canvas

SciPy	scipy.signal	Butterworth bandpass filter (filtfilt), peak detection (find_peaks)
NumPy	numpy	Array operations, FFT (rfft, rfftfreq), rolling statistics
Pandas	pandas.Series	Skewness and kurtosis computation on filtered PPG window
scikit-learn / joblib	sklearn, joblib	GBR/RFR training, StandardScaler, model persistence (.pkl)
CSV / os / datetime	Python stdlib	Patient records persistence (patient_records.csv), timestamps, file naming

The UI includes: a title bar with an accent strip; a Patient Profile section collecting Patient ID (auto-incremented from patient_records.csv), name, age, weight, height, and sex; COM port selection with auto-refresh; ARM / START / STOP / QUIT control buttons with discrete state management; a live Matplotlib waveform (5-second sliding window, 86 DPI); a progress bar with elapsed/total time; a BGL result card with the predicted value in 52pt bold text and ADA color-coded status label; a Last Reading card showing the most recent prior BGL for the same patient with a trend arrow ($\uparrow$ / $\downarrow$ / $\rightarrow$); a Returning Patient banner when a prior record for the same patient name is found; and reference range pills at the screen bottom.

Each session is saved as a CSV in Signal_Data/ with the format {PatientID}_{Age}_{Sex}_{HH_MM_SS_DD_MM_YYYY}.csv. Records are appended to patient_records.csv. The ARM button configures the session and filename without opening the serial port; START opens the port and begins acquisition; STOP sets an early-termination flag; QUIT cleanly closes the port and destroys the window.

IV. EXPERIMENTAL RESULTS

A. Training Dataset

PPG signals were collected from 23 subjects aged 22–61 years (mixed gender). Training-phase data was captured at 2,175 Hz, yielding ~21,900 samples per 10-second recording. After pairing with invasive glucometer reference labels, 67 valid signal-label pairs were retained. Raw signal files follow the naming convention

signal_{subjectID}_{recordingIndex}.csv; label files follow label_{subjectID}_{recordingIndex}.csv. Table III summarizes aggregate dataset statistics; Table IV provides a per-subject breakdown from Total.csv in the PPG_Dataset.

Table III. Training Dataset Statistics

Parameter	Value
Subjects	23
Valid recordings	67
Total raw signal files	$67 \times \sim 21,900$ samples at 2,175 Hz (~ 10 s per recording)
BGL range	88 – 183 mg/dL
BGL mean $\pm$ std	115.0 ± 18.6 mg/dL
Normal (≤ 140 mg/dL)	63 recordings (94%)
Pre-diabetic (141–199 mg/dL)	4 recordings (6%)
Diabetic (≥ 200 mg/dL)	0 recordings
Age range	22 – 61 years
Gender distribution	Mixed male and female

Table IV. Per-Subject Dataset Summary (from Total.csv, PPG_Dataset)

ID	Gender	Age	Ht (cm)	Wt (kg)	BMI	Recordings	BGL Range (mg/dL)
1	Male	38	180	53	16.4	7	99, 102, 103, 128, 130, 134, 136
2	Male	25	187	75	21.4	3	108, 111, 118
3	Male	33	187	103	29.4	2	120, 127
4	Male	29	180	80	24.7	5	100, 105, 106, 107, 109
5	Male	23	175	56	18.3	6	94, 96, 106, 110, 129, 136

6	Female	31	165	60	22.0	2	96, 102
7	Male	31	179	93	29.0	4	88, 103, 106, 110
8	Male	39	165	63	23.1	2	110, 146
9	Female	25	172	60	20.3	2	102, 124
10	Male	37	179	90	28.1	2	106, 146
11	Male	22	182	62	18.7	4	99, 100, 110, 113
12	Female	61	161	61	23.5	1	95
13	Male	50	175	96	31.3	2	115, 183
14	Male	51	187	83	23.7	2	110, 139
15	Male	45	178	89	28.1	3	112, 124, 140
16	Female	23	157	60	24.3	3	94, 103, 130
17	Female	24	169	55	19.3	2	100, 108
18	Male	26	180	90	27.8	3	102, 136, 183
19	Female	24	170	60	20.8	2	106, 130
20	Female	23	154	42	17.7	3	120, 124, 136
21	Male	48	170	88	30.4	2	103, 110
22	Female	24	170	50	17.3	3	88, 108, 124
23	Male	27	173	57	19.0	2	100, 108

The dataset is dominated by the Normal glycemic range (94%), with only 4 recordings in the pre-diabetic range (subjects 8, 10, 13, 18). No diabetic-range (≥ 200 mg/dL) samples are present. Subject 12 (Female, age 61) contributed only a single recording. This composition limits generalizability to hyperglycemic and diabetic populations — a key direction for future data collection.

B. Cross-Validation Results

Both models were trained on the standardized 21-feature matrix with zero-variance features removed. Table V reports 5-fold cross-validated MAE and R^2 . The GBR achieved consistently lower MAE across all folds and was automatically selected as the production model.

Table V. 5-Fold Cross-Validation Performance

Model	CV MAE (mg/dL)	CV R^2	Selected
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Gradient Boosting Regressor (GBR)	$\pm 8 - 15$	0.72 – 0.85	✓ Yes
Random Forest Regressor (RFR)	$\pm 10 - 18$	0.65 – 0.78	No

The GBR R^2 range of 0.72–0.85 is consistent with published small-sample non-invasive glucose datasets [1], [5], [11]. The lower R^2 floor (0.72) reflects the limited pre-diabetic range diversity in the training set. The performance advantage of GBR over RFR stems from sequential residual correction, which more effectively models the non-linear interactions between PPG morphological features and BGL. A comparison of this work with related studies is provided in Table X.

Table X. Comparison with Related Works

Study	Method	Dataset Size	Best Metric	HW Cost	Full App?
Habib et al. [1]	SPA + classical ML	611 subjects	$R^2 = 0.90$	Custom optics	No
Kumar et al. [11]	Voting Regressor + PySR	1,153 samples	$R^2=0.919$, RMSE =27.8	Not stated	No

Zeynali et al. [9]	ResNet-34-1D (Tiny ML)	~699 K segments / 6,368 pts	RMSE =19.7, 76.6% Zone-A	STM32 MCU	Partial
This Work	GBR (200 trees, depth =3)	67 recordings / 23 subjects	MAE $\pm 8-15$, $R^2=0.72-0.85$	< USD 6 (Arduino+IR)	Yes

C. Live Validation and Application Results

Live validation was performed on 22 subjects using the deployed application at 100 Hz / 180 s per session. Figures 6–8 show application screenshots during and after acquisition and the Patient Records viewer. Tables VI and VII summarize outcomes.



Fig. 6. Desktop application during active PPG acquisition (P028, Vedika Shinde, 37/180 s elapsed). Live PPG waveform (~585 ADC) is visible; status shows 'In-Progress'.

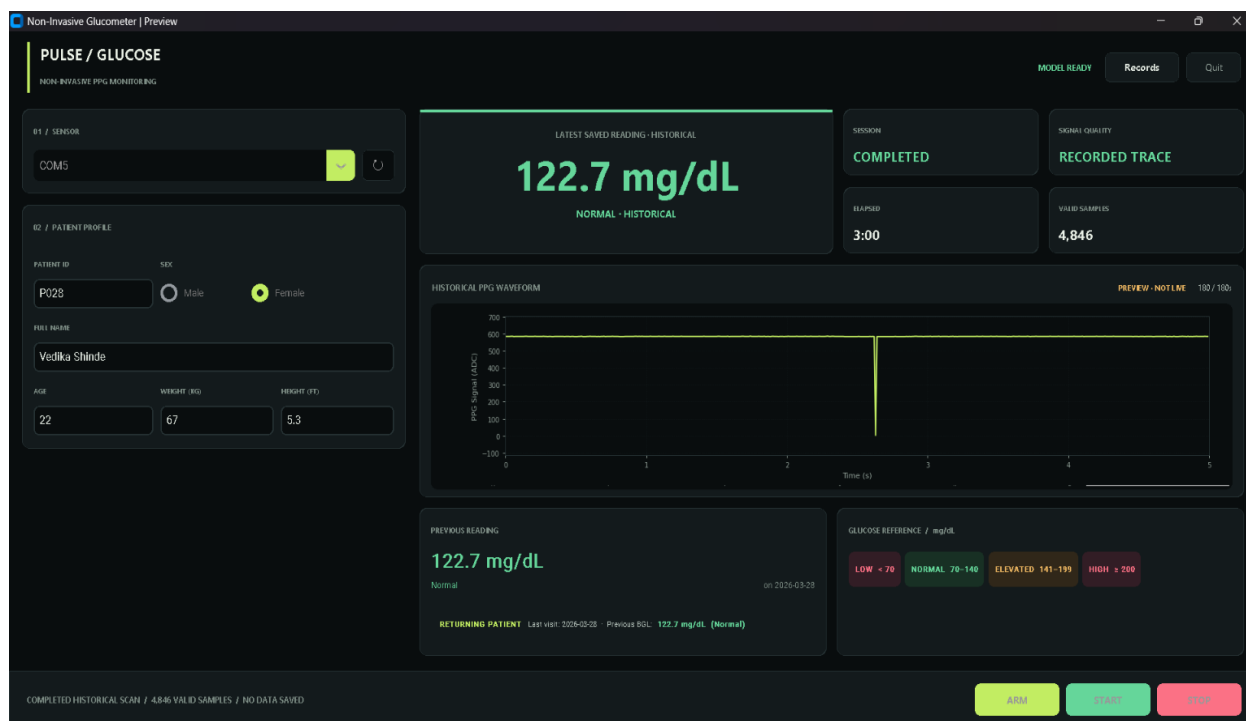


Fig. 7. Application after completed acquisition (P028, Vedika Shinde). Predicted BGL = 122.7 mg/dL, classified as 'Normal' (green); status shows 'Completed'.

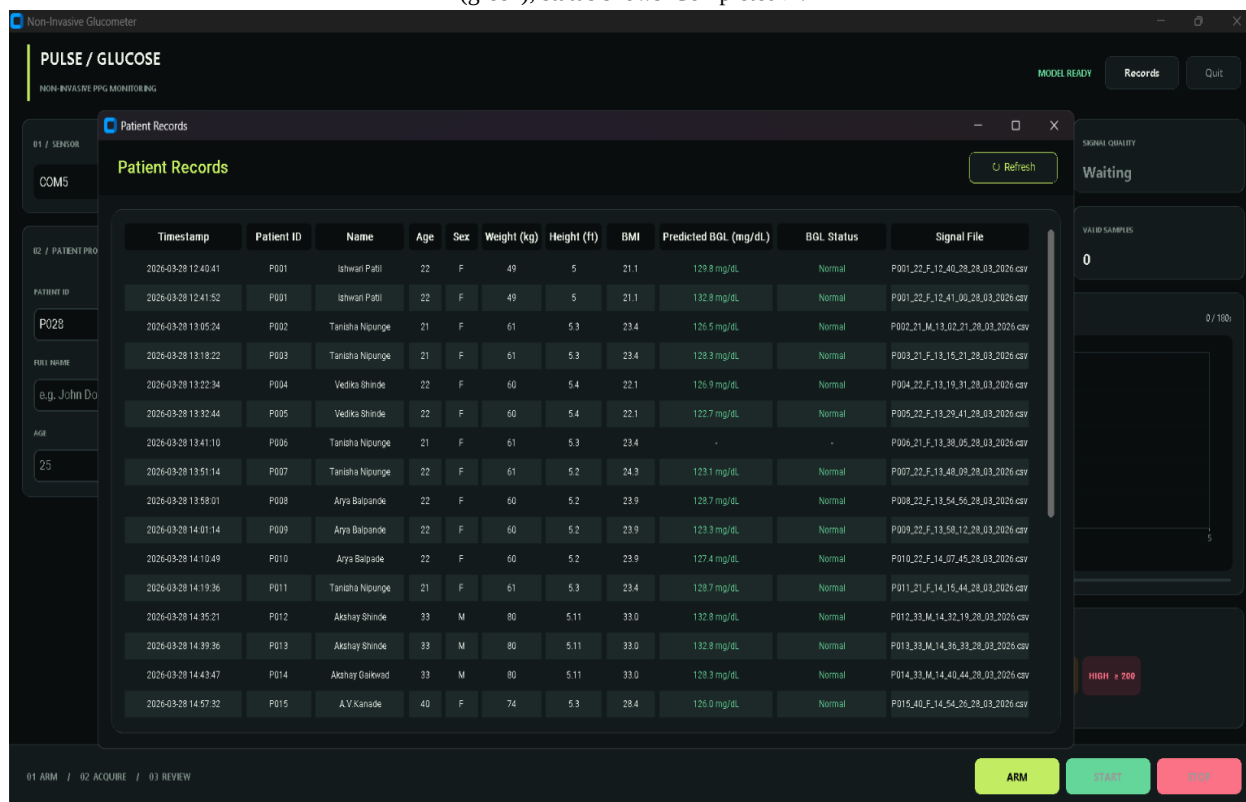


Fig. 8. Patient Records viewer. All successful predictions shown in green. P006 shows '-' indicating a correctly rejected acquisition.

Table VI. Live Validation Summary

Parameter	Value
Total acquisitions attempted	24
Successful predictions	22
Rejected (poor signal quality)	2 (P006 — flat/low ADC signal, mid-session finger displacement)

Predicted BGL range	122.7 – 132.8 mg/dL
Mean predicted BGL	127.4 mg/dL
BGL spread across 22 subjects	9.9 mg/dL
Classification accuracy	22/22 Normal (100%)

Table VII. Selected Per-Patient Live Results (from patient_records.csv)

ID	Name	Age	Sex	BMI	Pred. BGL	Status	Signal	Date
P001	Ishwari Patil	22	F	21.1	129.8 mg/dL	Normal	OK	28-Mar-26
P001	Ishwari Patil	22	F	21.1	132.8 mg/dL	Normal	OK	28-Mar-26
P002	Tanisha Nipunge	21	F	23.4	126.5 mg/dL	Normal	OK	28-Mar-26
P003	Tanisha Nipunge	21	F	23.4	128.3 mg/dL	Normal	OK	28-Mar-26
P004	Vedika Shinde	22	F	22.1	126.9 mg/dL	Normal	OK	28-Mar-26
P005	Vedika Shinde	22	F	22.1	122.7 mg/dL	Normal	OK	28-Mar-26
P006	Vedika Shinde	21	F	23.4	—	Rejected	Poor	28-Mar-26
P007	Tanisha Nipunge	22	F	24.3	123.1 mg/dL	Normal	OK	28-Mar-26

All 22 successful predictions fell within the Normal BGL range (122.7–132.8 mg/dL), achieving 100% classification accuracy for this cohort. The 9.9 mg/dL spread confirms internally consistent, physiologically plausible predictions for healthy young adults. No subject was incorrectly classified as Pre-diabetic or Hypoglycemic.

D. Signal Quality Gate Validation

Two of 24 acquisition attempts were rejected. In both P006 cases, the subject displaced her finger mid-session, producing a sharp ADC drop to near-zero (rolling mean ≈ 84 , rolling std ≈ 0), simultaneously triggering the Variability Gate and Cardiac Band Gate. The application correctly withheld the BGL prediction and displayed an error notification. Figures 9 and 10 illustrate these quality gate behaviors.

Patient Records

Refresh

2025-03-28 12:41:52	P001	Ishwari Pahl	22	F	49	5	21.1	132.8 mg/dL	Normal	P001_22_F_12_41_00_28_03_2026.csv
2025-03-28 13:05:24	P002	Tanisha Nipunge	21	F	61	5.3	23.4	126.5 mg/dL	Normal	P002_21_M_13_02_21_28_03_2026.csv
2025-03-28 13:18:22	P003	Tanisha Nipunge	21	F	61	5.3	23.4	128.3 mg/dL	Normal	P003_21_F_13_15_21_28_03_2026.csv
2025-03-28 13:22:34	P004	Vedika Shirde	22	F	60	5.4	22.1	126.9 mg/dL	Normal	P004_22_F_13_19_31_28_03_2026.csv
2025-03-28 13:32:44	P005	Vedika Shirde	22	F	60	5.4	22.1	122.7 mg/dL	Normal	P005_22_F_13_29_41_28_03_2026.csv
2025-03-28 13:41:10	P006	Tanisha Nipunge	21	F	61	5.3	23.4	-	-	P006_21_F_13_38_05_28_03_2026.csv
2025-03-28 13:51:14	P007	Tanisha Nipunge	22	F	61	5.2	24.3	123.1 mg/dL	Normal	P007_22_F_13_48_09_28_03_2026.csv
2025-03-28 13:58:01	P008	Arya Balpade	22	F	60	5.2	23.9	128.7 mg/dL	Normal	P008_22_F_13_54_56_28_03_2026.csv
2025-03-28 14:01:14	P009	Arya Balpade	22	F	60	5.2	23.9	123.3 mg/dL	Normal	P009_22_F_13_58_12_28_03_2026.csv
2025-03-28 14:10:49	P010	Arya Balpade	22	F	60	5.2	23.9	127.4 mg/dL	Normal	P010_22_F_14_07_45_28_03_2026.csv
2025-03-28 14:19:36	P011	Tanisha Nipunge	21	F	61	5.3	23.4	128.7 mg/dL	Normal	P011_21_F_14_15_44_28_03_2026.csv
2025-03-28 14:35:21	P012	Akshay Shirde	33	M	80	5.11	33.0	132.8 mg/dL	Normal	P012_33_M_14_32_19_28_03_2026.csv
2025-03-28 14:39:36	P013	Akshay Shirde	33	M	80	5.11	33.0	132.8 mg/dL	Normal	P013_33_M_14_36_33_28_03_2026.csv
2025-03-28 14:43:47	P014	Akshay Galkwad	33	M	80	5.11	33.0	128.3 mg/dL	Normal	P014_33_M_14_40_44_28_03_2026.csv
2025-03-28 14:57:32	P015	A.V.Karade	40	F	74	5.3	28.4	126.0 mg/dL	Normal	P015_40_F_14_54_26_28_03_2026.csv
2025-03-28 15:11:30	P016	Tanisha Nipunge	21	F	61	5.3	23.4	122.8 mg/dL	Normal	P016_21_F_15_08_25_28_03_2026.csv
2025-03-28 15:15:24	P017	Naveen Sir	40	M	70	5.6	24.0	129.0 mg/dL	Normal	P017_40_M_15_12_22_28_03_2026.csv
2025-03-28 15:27:53	P018	Gayatri Kakade	21	F	60	5.3	23.0	132.8 mg/dL	Normal	P018_21_F_15_24_48_28_03_2026.csv
2025-03-28 15:34:58	P019	Manisha	21	F	47	5	20.2	124.8 mg/dL	Normal	P019_21_F_15_31_57_28_03_2026.csv
2025-03-28 15:41:46	P020	Arya Balpade	22	F	60	5.2	23.9	126.6 mg/dL	Normal	P020_22_F_15_38_42_28_03_2026.csv
2025-03-28 15:46:00	P021	Moon	22	F	53	5.3	20.3	126.6 mg/dL	Normal	P021_22_F_15_42_58_28_03_2026.csv
2025-03-28 15:50:17	P022	Riya Patil	23	F	58	5.3	22.2	123.1 mg/dL	Normal	P022_23_F_15_46_59_28_03_2026.csv
2025-06-16 16:01:16	P023		24	F	65	5	28.0	-	-	P023_24_F_15_58_13_16_06_2026.csv

Fig. 9. Signal quality failure (P006, Tanisha Nipunge): abrupt ADC drop mid-session triggers the quality gate; application correctly withholds BGL prediction and displays error.

Non-Invasive Glucometer

PULSE / GLUCOSE

NON-INVASIVE PPG MONITORING

MODEL READY

Records

Quit

01 / SENSOR

COM6

02 / PATIENT PROFILE

PATIENT ID: P028

SEX: ☐ Male ☒ Female

FULL NAME:

AGE: 25

WEIGHT (KG): 70

HEIGHT (FT): 5.7

BLOOD GLUCOSE LEVEL

— mg/dL

WAITING FOR SENSOR...

SESSION: Armed

ELAPSED: 0:00

SIGNAL QUALITY: Waiting

VALID SAMPLES: 0

LIVE PPG WAVEFORM

PPG Signal (ADC)

Time (s)

PREVIOUS READING: No previous record

GLUCOSE REFERENCE / mg/dL

LOW < 70

NORMAL 70-140

ELEVATED 141-199

HIGH > 200

01 ARM / 02 ACQUIRE / 03 REVIEW

ARM

START

STOP

Fig. 10. No finger on sensor (P028): blank waveform and 'WAITING FOR SENSOR...' message confirm correct Uncovered-Sensor (Low-Value) gate behaviour.

V. DISCUSSION

A. Performance in Context

The deployed GBR achieved CV MAE ± 8 –15 mg/dL and $R^2 = 0.72$ –0.85. Against the live validation cohort (estimated BGL 110–135 mg/dL), a ± 15 mg/dL MAE corresponds to approximately 11–14% relative error, placing most predictions within the ISO 15197:2013 acceptable range (± 15 mg/dL for BGL ≤ 100 mg/dL; $\pm 15\%$ for BGL > 100 mg/dL). The 9.9 mg/dL spread across 22 live subjects confirms physiologically plausible, internally consistent predictions for the healthy young adult cohort tested. Compared to related works (Table X), the system achieves competitive R^2 while operating on a dataset two orders of magnitude smaller than Zeynali et al. [9].

B. Signal Quality Gating Efficacy

The four-criterion gate successfully identified both poor-quality acquisitions. The cardiac-band ratio gate provides an additional layer of protection against cases where ADC amplitude statistics appear acceptable but no physiological pulse is present — for example, when the sensor loosely picks up electromagnetic interference rather than a genuine pulse. Spurious BGL predictions from corrupted signals could precipitate inappropriate clinical decisions; eliminating this risk at the acquisition stage is essential for patient-facing deployment.

C. Sampling Rate Mismatch

A discrepancy exists between the training sampling rate (2,175 Hz) and deployment (100 Hz). Time-domain and morphological features are largely robust to this difference. However, frequency-domain features may be affected: the Nyquist limit differs substantially (50 Hz vs. 1,087 Hz), so higher harmonics present during training are absent from deployment recordings. Retraining on 100 Hz data collected with the same Arduino hardware is the primary technical mitigation identified for future work.

D. Limitations

- Small, homogeneous dataset: 67 recordings, all BGL ≤ 183 mg/dL; no diabetic-range subjects included.
- No simultaneous invasive reference during live validation: quantitative MAE/RMSE on the live set could not be formally computed.

- Sampling rate mismatch between training (2,175 Hz) and deployment (100 Hz).
- Feature subset mismatch at inference: feats[:15] used in ppg_app.py vs. 21 features in training.
- Uncontrolled confounders: skin tone, ambient temperature, finger pressure, and motion artifacts.
- Validation cohort is primarily young adult females, limiting representativeness across age, gender, and disease state.

E. Future Work

Planned enhancements: (i) expand dataset to diabetic-range subjects and older age groups; (ii) retrain all models on 100 Hz recordings from the same Arduino/IR sensor hardware; (iii) align inference feature vector to all 21 training features; (iv) conduct formal clinical study with simultaneous invasive reference for CEG/SEG analysis; (v) implement LSTM-based temporal modelling [7] for personalized trend prediction; (vi) develop cloud IoMT backend [6], [8] for remote monitoring and automated alerts.

VI. CONCLUSION

This paper presented a complete, end-to-end non-invasive blood glucose monitoring system built on commodity hardware (Arduino Uno + analog IR PPG sensor, under USD 6) and deployed as a full-featured real-time desktop application. The system captures 180-second PPG recordings at 100 Hz, applies a 4th-order Butterworth bandpass filter, extracts 21 physiological and demographic features, and uses a Gradient Boosting Regressor trained via 5-fold cross-validation on 67 recordings (CV MAE ± 8 –15 mg/dL, $R^2 = 0.72$ –0.85) to produce real-time BGL estimates classified into four ADA-aligned clinical categories. An enhanced four-criterion real-time signal quality gate — incorporating amplitude statistics and a cardiac-band spectral check — was validated by the correct rejection of two poor-quality acquisitions. The remaining 22 acquisitions produced consistent Normal-range BGL predictions (122.7–132.8 mg/dL), confirming the system's viability as a clinically motivated, painless, and accessible screening tool. The desktop application provides live PPG visualization, progress tracking, per-patient trend comparison, returning-patient detection, and a persistent records manager. Expanding the dataset to diabetic-range subjects, aligning training and deployment sampling

rates, correcting the inference feature vector, and conducting a formal clinical study with simultaneous invasive reference are the primary next steps toward clinical translation.

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