

Towards Non-Invasive Multiparameter Monitoring from a Single Fingertip Photoplethysmogram: Prototype Design and Preliminary Evaluation of Heart Rate, SpO₂, Blood Pressure, and Glucose Estimation

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Abstract

Diabetes mellitus and hypertension are leading causes of morbidity and premature mortality, yet routine monitoring depends on fingerstick glucometry and pneumatic cuffs, which limit adherence. This paper presents the design and a preliminary, small-cohort evaluation of a low-cost prototype that derives heart rate (HR), peripheral oxygen saturation (SpO₂), systolic/diastolic blood pressure (SBP/DBP), and blood glucose (BG) estimates from a single fingertip photoplethysmogram (PPG). The hardware combines a MAX30102 dual-wavelength sensor (660 nm red, 940 nm infrared), an ATmega328P-based Arduino Nano, and a 3D-printed light-shielding enclosure. The signal pipeline uses lower-envelope detrending and zero-phase Butterworth filtering. HR is obtained by peak detection, SpO₂ by the red/infrared ratio of ratios, and cuffless BP by first-derivative timing and amplitude features. For glucose, autoregressive, Teager–Kaiser energy, spectral-entropy, log-energy, and single-pulse morphological features were supplied to Linear Regression (LR), K-Nearest Neighbors (KNN), and Random Forest (RF) regressors. Data came from 30 fasting volunteers (32 recordings of 30 s each) with fingerstick glucometer, oscillometric cuff, and commercial pulse-oximeter references. On this dataset RF gave the lowest error (RMSE 11.11 mg/dL, MAE 7.85 mg/dL, $R^2 = 0.8655$) and 74.19% three-band classification accuracy, versus RMSE 24.31 and 26.45 mg/dL for LR and KNN. HR and SpO₂ agreed closely with the references, and a single resting BP trial differed from the cuff by about 1.4 mmHg. Because the cohort is small, validation was limited, and glucose may be confounded by correlated physiological variables, these results demonstrate feasibility only. Subject-independent validation, Clarke/Parkes error-grid analysis, and a larger multi-day study are required before any clinical claim can be made.

I. Introduction

Cardiovascular disease and diabetes are major public health burdens. The World Health Organization estimates that about 1.28 billion adults aged 30–79 years live with hypertension, roughly two-thirds of them in low- and middle-income countries, and that an estimated 46% are unaware of their condition [1]. The International Diabetes Federation estimated 463 million adults with diabetes in 2019, projected to exceed 700 million by 2045 [2]. Frequent monitoring of blood pressure and glucose is central to managing both conditions.

Standard methods, however, impose burdens that reduce adherence. Cuff-based oscillometric devices provide intermittent rather than beat-to-beat readings and can be uncomfortable during ambulatory use [3]. Capillary glucose testing requires repeated fingersticks and consumable strips, and pain, cost, and inconvenience are widely reported barriers to testing [4]. This motivates low-cost, comfortable sensing alternatives that could support screening and trend monitoring, especially in resource-limited settings.

Photoplethysmography (PPG) is an optical technique that measures blood-volume changes in the peripheral microvasculature using an LED and photodetector [5], [6]. It is established for HR and SpO₂, and the shape of the pulse waveform carries information about arterial stiffness and wave reflection that has been exploited for cuffless blood-pressure estimation [3], [7]. PPG-based glucose estimation has

also been explored with machine learning [4], [8]–[10], but it remains scientifically unsettled: the physical link between glucose and the PPG waveform is indirect, and reported accuracy is often inflated by small datasets and data leakage [4].

This paper describes a low-cost prototype that estimates HR, SpO₂, SBP/DBP, and BG from one fingertip PPG, and reports a preliminary evaluation against reference devices. Our contributions are: (i) a documented acquisition and conditioning pipeline built from inexpensive components; (ii) first-derivative timing features for resting BP estimation; (iii) a multi-domain feature set (autoregressive, Teager–Kaiser energy, spectral entropy, pulse morphology) for glucose regression; and (iv) a comparison of LR, KNN, and RF on a 30-subject fasting cohort, together with an explicit account of the limitations that prevent clinical interpretation of the results. We deliberately describe this work as a feasibility study.

II. Theoretical Background

A. Optical attenuation in tissue

Light passing through tissue is attenuated according to the modified Beer–Lambert law [5]:

$$I(\lambda) = I_0(\lambda) \cdot \exp[-(\mu_a(\lambda) \cdot L + G(\lambda))] \quad (1)$$

where I_0 is the incident intensity, μ_a the absorption coefficient, L the effective path length, and G a geometry-dependent scattering term. The detected signal separates into a quasi-static DC component, from tissue, bone, and non-pulsatile blood, and a pulsatile AC component synchronous with the cardiac cycle, caused by arterial blood-volume changes [5].

B. Pulse oximetry

Oxygenated (HbO₂) and deoxygenated (Hb) hemoglobin have different absorption spectra: Hb absorbs substantially more strongly at 660 nm, HbO₂ more strongly near 940 nm, and the two coincide at the isosbestic point near 805 nm [5]. The ratio of ratios is

$$R = (AC_{red} / DC_{red}) / (AC_{ir} / DC_{ir}) \quad (2)$$

and SpO₂ is obtained from an empirical calibration curve. In this work we used the common linear approximation

$$SpO_2 (\%) = 110 - 25 \cdot R \quad (3)$$

This relation is a generic approximation; accurate oximetry requires calibration against arterial blood-gas data over a hypoxic range, and optical oximetry accuracy is known to vary with skin pigmentation [15], [16].

C. Cuffless blood-pressure estimation

Blood pressure depends on cardiac output, vascular resistance, and arterial stiffness, and is related to pulse transit time and pulse-wave shape [3], [7]. The first derivative of the PPG ($dPPG/dt$) helps locate fiducial points such as the maximum upstroke slope, the dicrotic notch, and the diastolic peak [12], [14]. Timing intervals derived from these points (systolic time, diastolic time, and their ratio) are known surrogates for vascular tone, but their relation to absolute pressure is individual-specific and generally requires per-subject calibration [3], [7].

D. Physiological basis for glucose estimation

Glucose-related changes in plasma viscosity, erythrocyte deformability, endothelial function, and tissue optical properties have been proposed as mechanisms by which glycemic state may modulate the PPG waveform [4], [9], [10]. Evidence that these effects can be separated from other influences is limited. Age, heart rate, vascular stiffness, medication, and skin temperature also alter PPG morphology, so a model may learn these correlates rather than glucose itself. In this study the PPG-based glucose output is therefore treated as an exploratory estimate, not a measurement.

III. System Architecture

A. Sensing module

The front end is the Maxim MAX30102 module, which integrates a red LED (660 nm), an infrared LED (940 nm), a photodetector, ambient-light cancellation, an 18-bit ADC, and an I²C interface. It operates from a 1.8 V core supply with a 3.3 V LED supply, with programmable LED current up to 50 mA.

B. Processing and acquisition

Acquisition is performed by an Arduino Nano (ATmega328P, 16 MHz, 32 KB flash, 2 KB SRAM, 1 KB EEPROM). The sensor communicates over I²C at 400 kHz and was configured for 100 samples/s. Raw red and infrared samples were streamed over a serial link at 115,200 baud and processed offline in MATLAB and Python (Scikit-Learn, Google Colaboratory).

C. Optical enclosure

A 3D-printed enclosure holds the sensor against the right middle fingertip, blocking ambient light and limiting variation in contact pressure and motion. Contact force was not measured; its variability is treated as a limitation (Section IX).

IV. Signal Conditioning

Raw PPG contains baseline wander from respiration (about 0.15–0.35 Hz) and slower autonomic oscillations, plus high-frequency noise [5], [13].

A. Baseline removal

Trough points of successive beats were detected and joined by a piecewise-linear function to form a lower envelope, which was subtracted from the raw signal to place the diastolic baseline near zero.

B. Filtering

The detrended signal was low-pass filtered with a 4th-order Butterworth filter applied forward and backward (zero-phase filtfilt) so that fiducial points are not shifted in time. The cutoff was set to **8 Hz**. This passes the cardiac fundamental (about 1–2 Hz) and the harmonics that form the systolic peak, dicrotic notch, and diastolic wave, while rejecting higher-frequency noise [13]. Note that the cutoff must be chosen carefully: a cutoff near 1.75 Hz (about 11 rad/s) would attenuate the second and higher harmonics and distort or erase the dicrotic notch and the derivative features used below. A separate FIR stage was not used, since zero-phase Butterworth filtering already avoids phase distortion.

C. Peak and valley detection

Systolic peaks were detected using an amplitude threshold of 0.5 times the maximum of the filtered signal and a minimum peak separation of $0.2 \cdot F_s$ (0.2 s, corresponding to a maximum rate of 300 BPM), which suppresses most dicrotic-wave false detections. Detection was verified by visual inspection of every recording; no sensitivity or false-positive rate is claimed beyond this inspection, because no annotated peak reference was available.

V. Parameter Estimation

A. Heart rate and SpO2

Heart rate is computed from the mean peak-to-peak interval:

$$HR \text{ (BPM)} = 60 \cdot F_s / \Delta T_{pp} \text{ (4)}$$

where $F_s = 100$ Hz and ΔT_{pp} is the mean interval in samples, averaged over the 30-s recording. AC was taken as the peak-to-valley amplitude and DC as the mean level of each filtered channel, from which R and SpO2 follow from Eqs. (2) and (3).

B. Cuffless blood pressure from the first derivative

Three timing features were extracted from each pulse: systolic time (ST, pulse foot to systolic peak), diastolic time (DT, pulse foot to diastolic peak), and the systolic–diastolic interval (TSD, systolic peak to diastolic peak) [12], [14]. A simple empirical model maps mean systolic peak amplitude and the diastolic interval to pressure:

$$SBP = \alpha_1 \cdot \text{mean}(\text{systolic peak amplitude}) + \beta_1$$

$$DBP = \alpha_2 \cdot [1 / \text{mean}(\text{diastolic interval})] + \beta_2 \text{ (5)}$$

with $\alpha_1 = 0.2$, $\beta_1 = 115$ mmHg, $\alpha_2 = 10$ mmHg·s, $\beta_2 = 50$ mmHg. These coefficients were chosen empirically for resting adults and were not fitted on a separate training set or calibrated per subject. The model is therefore a proof-of-concept mapping, not a validated BP estimator.

C. Feature engineering for glucose

Features were computed over each recording in two groups.

Spectral and non-linear features.

- Autoregressive coefficients ($a_1 \dots a_5$) from a 5th-order model fitted with the Yule–Walker equations.
- Teager–Kaiser energy: $\Psi[x(n)] = x^2(n) - x(n-1) \cdot x(n+1)$ [16], windowed with a Kaiser window ($\beta = 5$) and summarized by mean, variance, interquartile range, and skewness.
- Spectral Shannon entropy: $H_s = -\sum P \log_2 P$ from the normalized FFT power spectrum.
- Log energy: $LE = \log_{10}(\sum x(i)^2)$.

Single-pulse morphology.

- Pulse energy $E = \int P(t)^2 dt$.
- Peak amplitude and end amplitude.
- Peak onset time (Pst) and peak endset time (Pet), from derivative zero-crossings.

Because the number of features is large relative to the number of recordings (32), overfitting is a real risk, and feature selection or regularization is required in any larger study.

VI. Machine-Learning Models and Evaluation

Three regressors were implemented in Scikit-Learn: ordinary least squares LR; KNN with $k = 5$ (Euclidean distance); and RF with 100 trees using bootstrap aggregation and random feature subsets [17].

Performance was measured by RMSE, MAE, and R^2 , defined in the usual way:

$$RMSE = \sqrt{[(1/n) \sum (y_i - \hat{y}_i)^2]}, MAE = (1/n) \sum |y_i - \hat{y}_i|, R^2 = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2$$

Predicted and reference glucose values were also grouped into three **analysis bands**: low-range (≤ 100 mg/dL), mid-range (101–140 mg/dL), and high-range (> 140 mg/dL), and multi-class accuracy, weighted precision, weighted recall, and weighted F1 were computed. These bands are used only to summarize error behavior. They are not diagnostic categories: under current ADA criteria, fasting plasma glucose of 70–99 mg/dL is normal, 100–125 mg/dL indicates prediabetes, and 126 mg/dL or higher is consistent with diabetes [19], and glucose below 70 mg/dL is the threshold for hypoglycemia. A value of 100 mg/dL or less is therefore not hypoglycemia.

Validation note. The reported metrics were obtained with the train/test procedure used in the original analysis. The accuracy values (74.19%, 64.52%, 51.61%) correspond to 23, 20, and 16 correct predictions

out of 31 evaluated samples, which is consistent with a very small test set from a 32-recording dataset. With so few samples, and especially if recordings from one subject can appear in both training and test sets, performance estimates are unreliable and can be strongly optimistic [18]. A subject-independent protocol (Section IX) is required to confirm the results.

VII. Experimental Protocol

The study was conducted at the Department of Biomedical Engineering, UET Lahore, under institutional ethical approval and with written informed consent. Thirty volunteers aged 20–50 years were recruited and tested after fasting. Participants rested seated for 10 minutes in a controlled indoor environment before recording. Each recording lasted 30 s with the right middle finger in the enclosure. Thirty-two recordings were obtained in total (some subjects were recorded more than once). Reference measurements were taken at the same session: capillary glucose by an Accu-Chek Active glucometer (code chip 333), blood pressure by an oscillometric cuff, and HR/SpO₂ by a commercial fingertip pulse oximeter.

The glucometer reference is itself imprecise: consumer meters are permitted an error of ± 15 mg/dL ($\pm 15\%$) under ISO 15197:2013 [21]. Reference error therefore forms part of the error reported below. The study population was a healthy-to-mixed fasting cohort without independent clinical diagnosis of diabetes, and the age distribution, sex, skin tone, and medication use were not analyzed.

TABLE I: Distribution of the 32 recordings by reference glucose band

Reference band (fasting glucose)	Recordings	Proportion
Low-range (≤ 100 mg/dL)	15	46.88%
Mid-range (101–140 mg/dL)	11	34.38%
High-range (> 140 mg/dL)	6	18.75%
Total	32	100%

Counts are recordings, not subjects. The original draft listed 4 high-range samples, which is inconsistent with the stated 18.75% (6 of 32); the counts above should be confirmed against the raw dataset before publication.

The cohort contains no clinically hypoglycemic subjects and only a few high-range samples, so the model's behavior at the clinically most important extremes is essentially untested.

VIII. Results and Discussion

A. Signal conditioning

Raw red-channel counts showed baseline offsets in the range of roughly 5.4×10^4 to 5.6×10^4 . After envelope subtraction and zero-phase filtering the baseline was centered near zero and the systolic peak and diastolic wave were visible in the recordings inspected; the dicrotic notch was identifiable in most but not all of them, depending on contact quality. A quantitative signal-quality index was not computed.

B. Heart rate and SpO2

In the example 30-s recording, 33 systolic peaks were detected between $t = 0.90$ s and $t = 27.04$ s. Those 32 intervals span 26.14 s and give a mean rate of $(32 / 26.14) \times 60 \approx 73$ BPM, compared with 70 BPM on the reference oximeter, a difference of about 3 BPM (approximately 4%). The earlier statement of a computed 70 BPM and perfect agreement is not reproducible from these peak times and is withdrawn; HR should be recomputed from the raw file and, ideally, reported as mean absolute error and Bland–Altman limits across all recordings rather than for one example.

For the same recording, $R = 0.44$, which by Eq. (3) gives $SpO_2 = 99\%$, within 1 percentage point of the reference. This is a weak test of oximetry accuracy, because all subjects were healthy and near the physiological ceiling. No desaturated data were collected, so accuracy across the clinically relevant 70–100% range, and across skin tones [15], [16], is unknown.

C. Blood pressure

For one resting trial the estimated BP was 118.6/78.6 mmHg versus 120/80 mmHg from the cuff, a difference of about 1.4 mmHg for each. This agreement is encouraging but is a single comparison with hand-set coefficients. It cannot be used to claim compliance with AAMI/ISO 81060-2, which requires a large, diverse subject sample (at least 85 subjects) spanning a range of pressures, with mean error within ± 5 mmHg and SD of at most 8 mmHg [22]; cuffless devices are additionally covered by IEEE 1708 [23]. Because the model has no sensitivity to pressure change, a constant offset near normal resting values would produce the same result; testing across hypotensive, normotensive, and hypertensive subjects, and after maneuvers that change pressure, is necessary.

D. Glucose estimation

TABLE II: Glucose estimation performance (n = 32 recordings; test set size as noted in Section VI)

Model	RMSE (mg/dL)	MAE (mg/dL)	R ²	Accuracy	Precision	Recall	F1
Linear Regression	24.31	16.22	0.3557	64.52%	0.6823	0.6452	0.6342
KNN (k = 5)	26.45	16.72	0.2374	51.61%	0.5823	0.5161	0.5189
Random Forest	11.11	7.85	0.8655	74.19%	0.7838	0.7419	0.7309

On this dataset RF had the lowest error, with RMSE reduced by 54.3% relative to LR and 58.0% relative to KNN, and the highest R^2 (0.8655) and band-classification accuracy (74.19%). A tree ensemble can capture non-linear feature interactions that LR cannot, which is consistent with this ranking.

These results should be read with caution for four reasons. First, the dataset is tiny (30 subjects, 32 recordings) and the feature set is large, so a flexible model such as RF can fit subject-specific patterns; an R^2 of 0.87 on so few samples is more likely to indicate optimistic evaluation than true explanatory power. Second, the original analysis did not report cross-validation or subject-wise splitting, so leakage between training and test data cannot be excluded [18]. Third, the model may exploit variables correlated with glucose rather than glucose itself. Fourth, RMSE and MAE were not benchmarked against the standard tools for glucose-device assessment: the Clarke or Parkes error grid [20], mean absolute relative difference, or the ISO 15197 accuracy criteria [21]. An RMSE of 11 mg/dL is also not interpretable on its own given the reference meter's own tolerance and the narrow reference range of this cohort. We therefore do not claim that the system measures glucose, nor that it can classify diabetic status. The results show only that, within this small cohort, PPG-derived features were associated with the reference values.

IX. Limitations and Required Further Work

1. **Sample size and validation design.** A larger, multi-visit cohort is needed, including people with diagnosed type 1 and type 2 diabetes, prediabetes, and true hypoglycemia, with fasting and post-prandial or glucose-tolerance data. Models should be evaluated with leave-one-subject-out or grouped k-fold cross-validation, with feature selection performed inside the training folds, and with a final held-out set of unseen subjects. Reporting should include confidence intervals, Clarke/Parkes error-grid zones, and MARD [18], [20], [21].
2. **Confounding.** Age, sex, heart rate, blood pressure, BMI, skin temperature, and medication should be recorded and used as covariates or as control baselines, to test whether the model predicts glucose beyond these variables.
3. **Blood pressure.** Needs subject-specific calibration, a separate training and test set, and testing across a wide pressure range, following AAMI/ISO 81060-2 and IEEE 1708 [22], [23]. Beat-to-beat references would be needed to support any claim of continuous tracking.
4. **Oximetry.** Calibration against arterial blood gas in a controlled desaturation study, with stratification by skin pigmentation [15], [16].
5. **Skin tone, anatomy, and contact.** Optical path length depends on melanin, epidermal and fat thickness, and vascular caliber [5]. Adaptive LED-current control and contact-pressure sensing should be added.
6. **Motion and ambient conditions.** The enclosure reduces steady-state light leakage but does not eliminate motion artifacts. An accelerometer with adaptive noise cancellation and an automatic signal-quality index to reject bad segments are planned.
7. **Continuous operation.** The present device analyzes 30-s recordings offline. Real-time, embedded implementation and long-term recording are future work, and the title claim of continuous

monitoring should not be inferred from this study.

8. **Model class.** Deep models (1D CNN, BiLSTM) may learn features from raw waveforms, but they require much larger datasets than are available here, and their use would increase rather than reduce overfitting risk on the present data.

X. Conclusion

We built a low-cost fingertip PPG prototype based on a MAX30102 sensor and an Arduino Nano and evaluated it on 30 fasting volunteers. Heart rate and SpO₂ estimates were close to commercial-oximeter readings in the cases analyzed, and a single resting blood-pressure trial agreed with an oscillometric cuff within about 1.4 mmHg. For glucose, a Random Forest regressor trained on autoregressive, Teager–Kaiser energy, spectral-entropy, and pulse-morphology features achieved an RMSE of 11.11 mg/dL and R² of 0.8655 on our small dataset, outperforming LR and KNN. Given the cohort size, the lack of subject-independent validation, the limited glucose range, and the absence of error-grid analysis, these figures are preliminary and should not be taken as evidence of clinical accuracy. The prototype is best regarded as an inexpensive research platform for collecting larger datasets; clinical use would require the validation studies outlined in Section IX.

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