Research Paper # 1

Higher Order Derivative-Based Integrated Model for Cuff-Less Blood Pressure Estimation and Stratification Using PPG Signals

1. Objective & Motivation

- Traditional **cuff-based BP measurements** are **bulky and uncomfortable**.
- **Cuff-less, wearable devices using PPG signals** offer a promising alternative.
- Existing methods struggle with **fiducial point detection** in noisy PPG signals.
- This work proposes using **third and fourth derivatives of PPG** to extract **nonlinear features** for better BP estimation.

2. PPG Signal Derivative Features

- **First Derivative (VPPG):** Velocity of blood flow.
- **Second Derivative (APPG):** Acceleration of blood flow.
- **Third Derivative (D3 / "Jerk")**
- **Fourth Derivative (D4 / "Snap")**

3. Nonlinear Features Extracted

1. **Fractal Dimension (FD):** Measures complexity/self-similarity.
   - FD increases in hypertensive subjects (more waveform complexity).
2. **Bubble Entropy (BE):** Quantifies randomness and signal variability.
3. **Lyapunov Exponent (LE):** Captures chaotic behavior in pulse wave dynamics.
4. **Moving Slope (MS):** Max slope between fiducial points in higher derivatives.

4. Regression Models Used for BP Estimation

- **Random Forest (RF)** → Best performance
- **XGBoost**
- **Support Vector Regression (SVR)**

5. Performance Results (MAE ± STD)

Database	Model	SBP MAE ± STD	DBP MAE ± STD
MIMIC-I	RF	0.74 ± 2.42	0.35 ± 1.06
MIMIC-II	RF	1.69 ± 3.76	0.77 ± 1.81
MIMIC-III	RF	1.30 ± 4.05	0.56 ± 1.70

6. Blood Pressure Stratification Criteria

Class	SBP (mmHg)	DBP (mmHg)	Category
Class-I	< 90	< 60	Hypotension
Class-II	90–119	60–79	Normal
Class-III	120–139	80–89	Prehypertension

Class	SBP (mmHg)	DBP (mmHg)	Category
Class-IV	140–159	90–99	Stage-I Hypertension
Class-V	≥ 160	≥ 100	Stage-II Hypertension

7. Comparison with Existing Methods

- Proposed model **outperforms key-point dependent and deep learning methods**.
- Uses only **PPG signals**, making it **efficient for wearable devices**.

8. Standards & Validation

- Achieved **Grade A on British Hypertension Society (BHS)** protocol.
- Demonstrates **clinical reliability** and suitability for **personalized BP monitoring devices**.

Research Paper #2

The Relationship Between Blood Glucose and Clinical Outcomes After Extracorporeal Circulation: A Retrospective Cohort Study

PubMed Link: https://pubmed.ncbi.nlm.nih.gov/40231030

🔍 Study Objective

- Investigated how **postoperative blood glucose levels** affect **90-day mortality** in patients undergoing **ECC-assisted open-heart surgery**.

🧪 Methods

- **Data Source:** MIMIC-IV 2.2 database.
- **Subjects:** 4,033 adult patients post-ECC.
- **Measurement Window:** First **24 hours after ICU admission**.
- Patients grouped into **quartiles** based on glucose levels.
- Statistical tools used:
  - **Kaplan-Meier survival analysis**
  - **Multivariate Cox regression**
  - **Smooth curve fitting**
  - **Restricted Cubic Spline (RCS)**
  - **Subgroup analysis**

📊 Results

- **Nonlinear relationship** observed between glucose levels and mortality.
- **Inflection point:** 119 mg/dL.
  - Above this value, **mortality risk increases significantly**.
- High glucose also correlated with:
  - **Longer ICU stays**
  - **Extended hospitalization**

🚨 Clinical Implications

- **Postoperative hyperglycemia (>119 mg/dL)** increases risk of death within 90 days.
- Emphasizes the need for **tight glucose control** during early ICU recovery after cardiac surgery.

☑ Conclusion

- Maintaining postoperative glucose levels **below 119 mg/dL** may improve survival in ECC patients.
- Supports development of **glycemic management protocols** in cardiac surgical care.

Research Paper#3

📄 EMD-Based Noninvasive Blood Glucose Estimation from PPG Signals Using Machine Learning Algorithms

Link: https://doi.org/10.3390/app14041406

🔍 1. Purpose of the Study

- Introduces a **noninvasive method** to estimate blood glucose using **wrist PPG signals**.
- Focuses on **EMD-derived features** and PPG waveform-based ratios.
- Uses only **PPG signal features**, avoiding external data like BMI, age, or SpO_2.

📦 2. Data Collection & Sensor Setup

- **Sensor:** TMD 3719 with **white LED** (465nm blue, 525nm green, 615nm red).
- **Subjects:** 34 individuals (50% male, 50% female).
- **PPG Sampling Rate:** 24 Hz over 3 minutes per subject.
- **Glucose Measurement:** CareSens II blood glucose meter.

⚙️ 3. Signal Processing

- **Segmentation:** 30-second intervals (720 samples).
- **Preprocessing:**
  - **Polynomial detrending** (3rd order).
  - **Butterworth filters** (low-pass 8 Hz; high-pass 0.5 Hz).
- **Empirical Mode Decomposition (EMD):** Extracts 7 IMFs per signal channel.

📐 4. Feature Extraction

📊 Waveform-Based Features (54 total):

- Includes: ZCR, ACR, kurtosis, variance, PSD, KTE, AR coefficients, SAD, etc.
- **Ratio Features:**
  - **AC/DC values** (signal strength & perfusion index).
  - **R1, R2, R3 ratios:** Combinations of green, red, and blue AC/DCs.

📊 IMF-Based Features (420 total):

- 20 features per IMF × 7 IMFs × 3 wavelengths.

- Includes: Spectral centroid, entropy, slope, band energy, PSER, AEmean, IFmean, etc.

🤖 5. Machine Learning Algorithms Used

- **CatBoost (Best Performer)**
- Random Forest (RF)
- XGBoost (XGB)
- LightGBM

📈 6. Model Results Using Top 50 Features

Model	Pearson's r	RMSE (mg/dL)	MAE (mg/dL)	R^2 Score
CatBoost	**0.96**	**10.94**	**8.01**	**0.92**
XGBoost	0.95	11.86	7.05	0.91
RF	0.94	13.37	8.2	0.88
LightGBM	0.93	14.63	9.21	0.86

☑ 7. Clinical Validation

- **Clarke Error Grid Analysis (EGA):**
  - **100% predictions fall in Zone A (safe clinical range)** using CatBoost.
- Demonstrates **clinical reliability** of the proposed model.

🔬 8. Comparative Insights

- Combines **waveform and IMF features** for higher accuracy.
- Outperforms prior methods based on **SPA or simple statistical features**.
- No need for external data improves **usability for wearable devices**.

🧠 9. Technical Notes on Feature Extraction (Appendix A)

- **Spectral features from IMFs** computed using FFT.
- Includes methods for calculating: **Spectral centroid, entropy, slope, band energy, PSER, AEmean, IFmean**, etc.

🧭 10. Future Work

- Collaboration with medical institutions for **larger datasets**.
- Exploring **deep learning** for improved accuracy.
- Potential integration into **wearable wrist devices** for real-time monitoring.

Research paper #4

Enhancing Non-Invasive Blood Glucose Prediction from PPG Signals via Heart Rate Variability-Based Feature Selection Using Metaheuristic Algorithms 📎 **Link:**
https://doi.org/10.3390/a18020095

🎯 1. Study Objective

- Develop a **non-invasive glucose prediction model** using:
    - **Photoplethysmography (PPG) signals**
    - **Heart Rate Variability (HRV) features**
    - **Metaheuristic feature selection algorithms**

🧪 2. Dataset & Data Collection

- 📊 **52 subjects** (PPG + blood glucose measured via glucometer)
- 📽️ 30 Hz sampling rate, **1-minute PPG recordings**
- 🔍 **Preprocessing** includes:
    - Butterworth filter (0.5–8 Hz)
    - Systolic peak detection via **Elgendi's method**
    - **HR calculation and extraction** of HRV metrics

⚙️ 3. Feature Extraction

💡 *Total = 69 features, from 3 domains:*

- ⏱️ Time-domain (e.g., SDNN, RMSSD, pNN50)
- 🎼 Frequency-domain (e.g., LF/HF, VLF, Wavelet Transform)
- 📈 Non-linear (e.g., entropy, fractal dimensions, DFA, Poincaré)

🚀 4. Metaheuristic Feature Selection Algorithms

Used to reduce feature dimensionality for better prediction:

- ☑️ **Improved Dragonfly Algorithm (IDA)** — 🥇 Best performer
- Binary Grey Wolf Optimizer (bGWO)
- Binary Harris Hawks Optimizer (BHHO)
- Genetic Algorithm (GA)

🤖 5. Machine Learning Models Used

- 💡 Light Gradient Boosting Machine (**LightGBM**)
- Extra Trees Regressor (ETR)
- Random Forest (RF)

📈 6. Final Results – Best Model (IDA-LightGBM)

Metric	Value
Selected Features	18 (from 69)
MAE	**13.17 mg/dL**
RMSE	**15.36 mg/dL**
Zone A (Clarke Error Grid)	**94.74%**
Detection Range	50–150 mg/dL

- All predictions fell in **Zone A or B** — **no risky predictions** in Zones C, D, or E.
- Best model achieved **fast convergence**, **low error**, and **high clinical relevance**.

🧭 7. Comparison with Other Studies

Study	Best Zone A %	Sensor Setup
Islam et al. (Smartphone PPG)	~60%	Mobile camera
Chowdhury et al. (Multimodal)	~79%	Multiple sensors
This Study	**94.74%**	Single-channel PPG only

🧪 8. Conclusion

- IDA-LightGBM offers a **robust, clinically safe, and efficient** method for **blood glucose prediction**.
- Uses only **PPG signal**, avoiding complex multi-sensor setups.
- Strong potential for **wearable integration** and **personalized diabetes care**.

Research Paper #5

Blood Glucose Level Regression for Smartphone PPG Signals Using Machine Learning
📎 **Link:** https://doi.org/10.3390/app11020618

🔍 1. Study Objective

- Proposes a **noninvasive glucose estimation** method using **smartphone video recordings** of fingertips.
- Converts the video into a **PPG signal**, extracts physiological features, and applies **machine learning** for prediction.

📦 2. Data Collection

- **Subjects:** 52 people, aged 17–61, glucose range: 68–211 mg/dL.
- Each subject gave **3 trials**, totaling **191 recordings**.
- **Devices used:** iPhone 7 Plus and OnePlus 6T (preferred for cost-efficiency).
- **Videos:** 60 seconds long, recorded at **30 fps**, resolution: 720p or 1080p.

📐 3. Signal Processing

- Extracted **red channel data** from frames (deepest skin penetration).
- Applied:
  - **Gaussian filter** – smooths out high-frequency noise.
  - **Asymmetric Least Squares (ALS)** – corrects baseline drift.
- Converts averaged red pixel intensity per frame into **PPG waveform**.

📊 4. Feature Extraction

From cleaned PPG signals:

- **Systolic & Diastolic peaks**
- **DelT** (time between systolic and diastolic)
- **First Derivative** – rate of change
- **Second Derivative** – acceleration of change

🤖 5. Machine Learning Models Used

- **Principal Component Regression (PCR)**
- **Partial Least Squares Regression (PLS)** 🏆 *Best performer*
- **Support Vector Regression (SVR)**
- **Random Forest Regression (RFR)**

📈 6. Model Results

Model	**Standard Error of Prediction (SEP)**
PLS	**17.02 mg/dL** 🥇

Model	**Standard Error of Prediction (SEP)**
PCR	17.09 mg/dL
SVR	18.52 mg/dL
RFR	21.88 mg/dL

- **PLS with first derivative characteristics** = most accurate.
- All models validated using **subject-wise split** and **cross-validation**.

🧪 7. Signal Quality Observations

- Flashlight improves PPG signal clarity.
- **Red channel outperforms** green/blue for consistent signal quality.
- Motion artifacts impact signal—corrected using proper filtering.

🧭 8. Conclusions & Future Work

- Smartphone-based glucose prediction is **feasible and fairly accurate**.
- Method is:
    - **Noninvasive**
    - **Low-cost**
    - **Accessible via consumer devices**
- Future plans include:
    - Scaling with more data
    - Platform-independent development
    - Building a **real-time mobile application**

Research Paper #6

A Noninvasive Blood Glucose Estimation System Using Dual-Channel PPGs and Pulse-Arrival Velocity 📎 **IEEE Link:** https://doi.org/10.1109/JSEN.2023.3306343

🔍 1. Objective

- Develop a **noninvasive system** combining:
  - **Dual-channel PPG (530 nm green + 1550 nm NIR)**
  - **Pulse Arrival Velocity (PAV) via ECG**
- Improve glucose estimation using **amplitude ratios + PAV**.

🧪 2. Experiment Setup

- **18 healthy subjects** (aged ~29.4 years)
- Underwent **Oral Glucose Tolerance Test (OGTT)**
  - 75g glucose in 250ml water
  - Measurements taken **before and 30 mins after** glucose intake
- Signals recorded for **3 minutes**
- **Devices used:**
  - ECG (Limb Lead I)
  - Finger-clip PPG sensor (green + NIR LEDs)
  - Data digitized at **500 Hz** using ARM Cortex-M4 microcontroller

📐 3. Feature Extraction

Feature Type	Key Features
Green PPG	Systolic, Dicrotic Notch, Diastolic Peak
NIR PPG	Same as above
Amplitude Ratios	NIR / Green at all 3 fiducial points
PAV	Arm Length / Pulse Arrival Time (PAT)

Total features used: **11**

- 6 amplitude values (3 from each channel)
- 2 PAV values (green & NIR)
- 3 amplitude ratios

📊 4. Statistical & Regression Analysis

- Used **Partial F-Test** to assess feature importance.
- **Best predictors:**
  - **PAV (green & NIR)**
  - **Amplitude ratio of diastolic peaks (Ratiop)**
- Built **16 regression models** with combinations of features.

📈 5. Best Model Performance

Model Combination	RMSE (mg/dL)	Zone A % (CEGA)
PAV + All Ratios (Feature #13)	**7.46 ± 2.43**	**100%**
All Features	9.16 ± 2.72	94.85%

- **Zone A:** Clinically safe predictions in Clarke Error Grid.

🧠 6. Technical Innovations

- First to use **amplitude ratios + PAV** from **dual-wavelength PPG** for glucose prediction.
- **Green light** used for blood volume correction.
- **NIR light (1550 nm)** used for glucose sensitivity.
- Ratio compensates for **optical path variability**.

🧭 7. Conclusion

- Dual-channel PPG with PAV provides **high accuracy** in noninvasive glucose estimation.
- System achieved **100% clinical safety** and **low RMSE**.
- Suitable for **wearable health devices** and future personalized glucose monitoring.