**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-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 SpO₂.

### 📦 ****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)** | **R² 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** 🥇 |
| 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.