Development of a Novel Non-invasive Smartphone-Based Blood Components Estimation Technique Using Python

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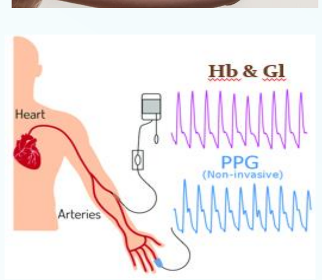
Abstract

This poster proposes an integrated pipeline to estimate hemoglobin and glucose levels from smartphone PPG signals extracted from fingertip videos, consisting of five specialized modules. Firstly, using **Frame Extraction Module**, the system records 10-second fingertip video using smartphone's camera. Therefore, it extracts 300 frames from 10-second fingertip video. Then**, PPG Signal Module** takes the input series of frames and applies our developed PPG signal generation algorithm to identify the region of interest and calculate the PPG value for each frame. Then, PPG signal is generated from the RED channel and applied Butterworth bandpass filter to reduce motion artifacts. After that, **PPG Features Module** extracts characteristic features from the PPG signal, its derivative, and Fourier-transformed signals. Furthermore, **Estimation Module** measures blood components from extracted features using deep neural models. Finally, a **Result Presenting Module**, it sends results to the end-user using a smartphone-based application.

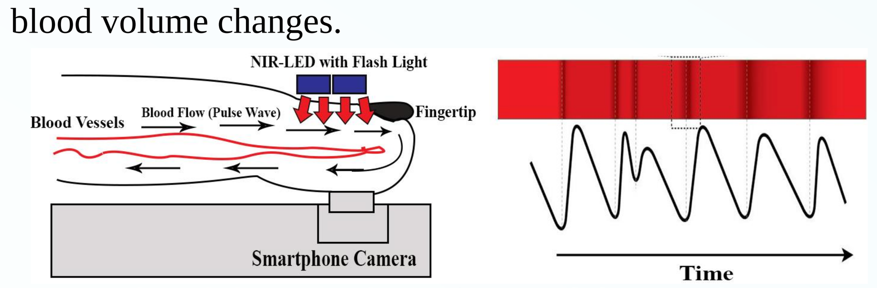
Background

- **Blood Component Levels**
  - ✓ **Hemoglobin**
    - Iron-containing protein found in all red blood cells (RBCs).
    - Normal range for male: $14 - 17$ g/dL and female: $13 - 16$ g/dL
    - Measurement of Hb is crucial for anemia detection(Low Hb Level).
  - ✓ **Glucose**
    - Diabetes is one of the most chronic diseases occurs due to human pancreas loses function to generate insulin [1].
    - Monitoring the Gl level is important to reduce the complication of diabetes.
- **Techniques Used for Measurement**
  - ✓ **Invasive Technique**
    - Blood sample is collected from human body using needle.
    - Painful and have risk of infection.

  - ✓ **Non-Invasive Technique**
    - No blood sample is required only bio-signal such as PPG or spectra.
    - Painless, cheap, quicker and easy.



- **Photoplethysmogram (PPG)**
  - It is an optically obtained plethysmogram that can be used to detect blood volume changes.



Photoplethysmography (PPG) principle by smartphone

Aim and Objectives

Aim

The aim of this research is to develop a smartphone-based system using PPG signal extracted from smartphone video and deep neural network for the estimation of hemoglobin and glucose.

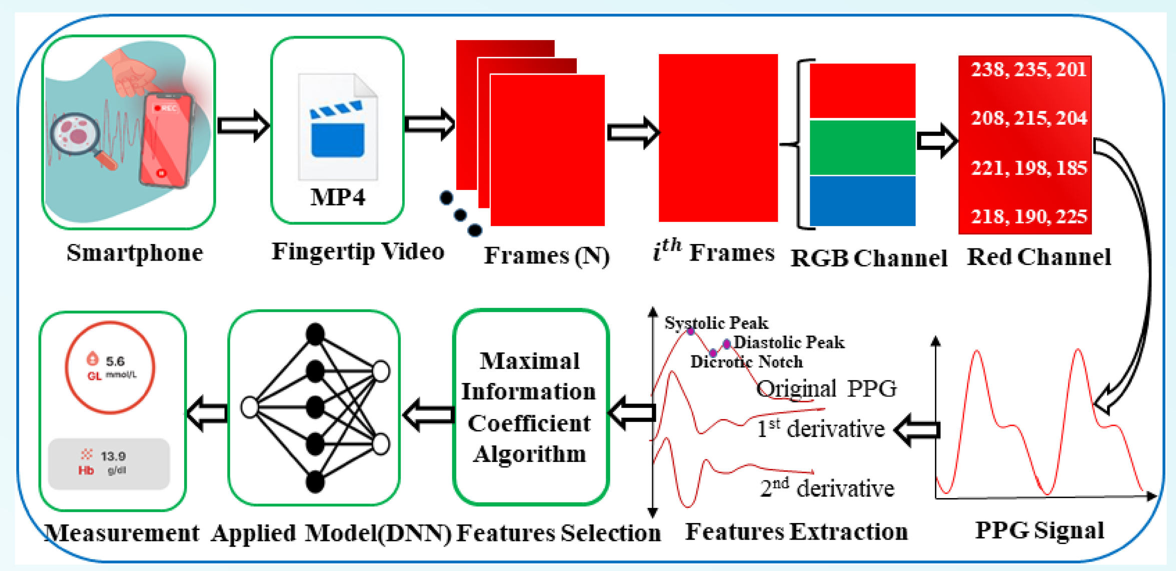
The research **objectives** of this study is to -

- Collect the fingertip video placing index finger on near infrared (NIR-LED) device/kit through smartphone primary camera.
- Generate the PPG signal from the fingertip video and extract optimal PPG characteristic features from the generated PPG signal.
- Develop a smartphone-based low cost, noninvasive hemoglobin and glucose levels estimation models using deep neural network.

Python Package

- **Tensorflow/Keras:** Deep learning
- **Scikit-learn**: Machine learning
- **OpenCV:** Image processing
- **Scipy**: Signal processing
- **Minepy:** MIC feature selection
- **Chaquopy:** Android Studio

Methodology



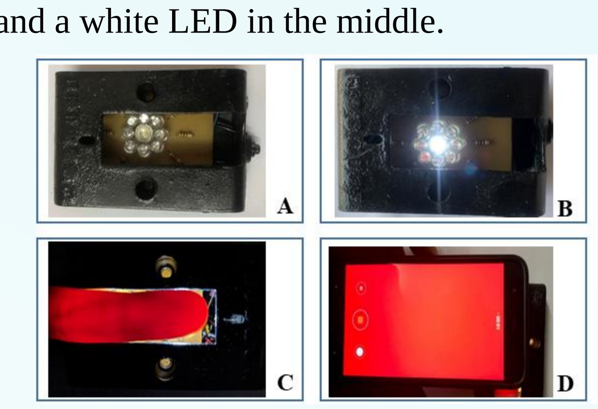
The overall system architecture for non-invasive Hb and Gl levels measurement.

Data Acquisition

A 10 second long video of the right index finger was recorded using a smartphone's primary camera (Nexus 6p and 30 fps), while the finger was illuminated using the data collection kit. The data collection kit/device consists of a circle of eight 850nm NIR-LED and a white LED in the middle.

Physical Index	Statistical Data
Age (year)	0 to 79 ($\mu = 32.81, \sigma = 16.57$)
Gender	59 male (63.5%); 34 (36.5%) female
Hb (g/dL)	7.9 to 21.49 ($\mu = 12.93, \sigma = 2.14$)
Gl (mmol/L)	3.33 to 21.11 ($\mu = 6.64, \sigma = 2.97$)

Patient demographics and clinical laboratory data.



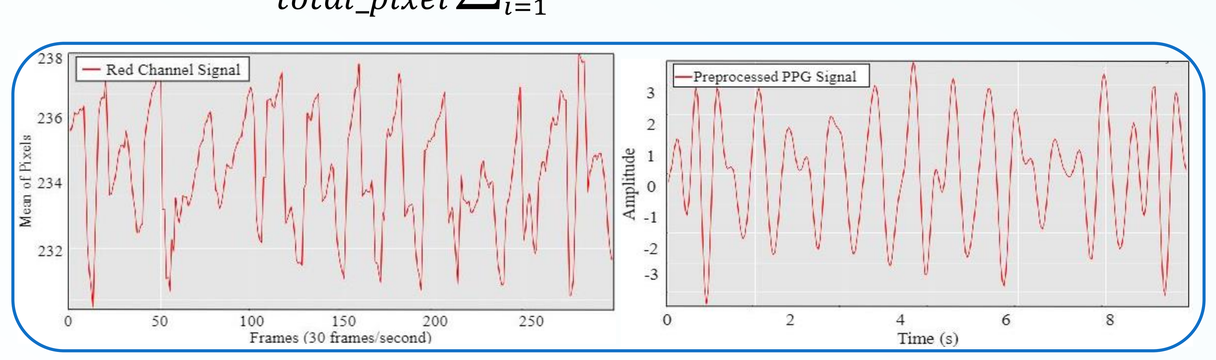
Hardware used to capture fingertip videos: A) A NIR-LED device in turned off, B) Device in turned on, C) Index finger on the device while device is on, D) Record video while LED illuminate the finger.

PPG Signal Generation and Preprocessing

A 10-second (30 fps) video is a series of 300 frames. The **RED** $(225 - 245)$, **GREEN** $(0 - 3)$ and **BLUE** $(15 - 25)$ channels were extracted from each frame of the fingertip video. The **RED** channel is the highest intensity channel. Therefore, the **GREEN** and **BLUE** channels are discarded. PPG's value for i^{th} frame is calculated as the mean of the pixels with intensity above the specific threshold. Butterworth bandpass filter (4th order) [2] applied to minimize the noise and motion artifacts.

$$threshold_i = \frac{1}{2} * \left(intensity_{max}^{i} + intensity_{min}^{i}\right)$$

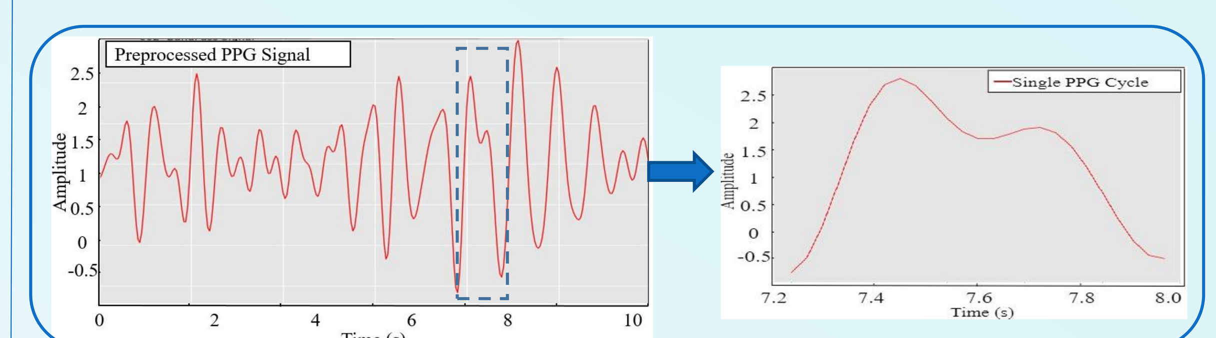
$$PPG[i] = \frac{1}{total\_pixel} \sum_{i=1}^{total\_pixel} intensity > threshold_i$$



Generation of PPG signal from fingertip video using the mean of pixels of each frame above threshold: raw PPG signal, and filtered PPG signal.

PPG Cycle Detection and Selection

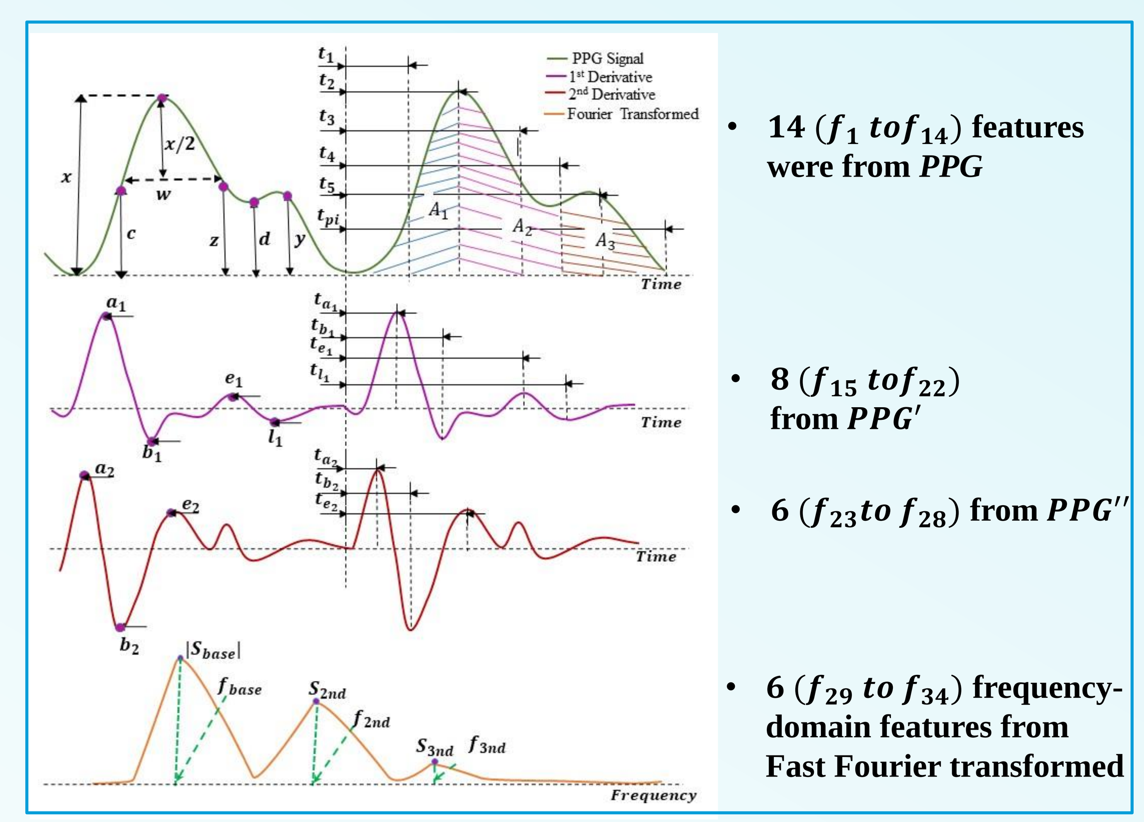
A peck detection algorithm was applied to acquire the single PPG cycle. One single PPG cycle with the highest positive systolic peak was selected from the continuous PPG waveform for feature extraction.



Detection and selection of one single PPG cycle from continuous waveform of PPG signal

Feature Extraction

34 $(f_1 - f_{34})$ time and frequency domain features were extracted from best ***PPG*** signal. Age (f_{35}) and Gender (f_{36}) also included as features.

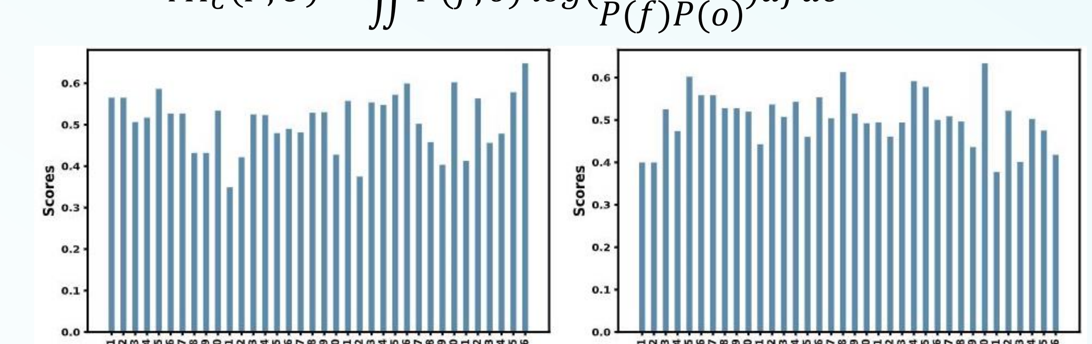


Features extracted from PPG signal and its derivatives as well as Fourier Transformed PPG signal

Feature Selection

Maximal Information Coefficient (MIC) has been applied to discard redundant features. MIC is a theory-based information measure of reciprocal dependency that may account for various linear and non-functional dependencies between variables [3]. For continuous variables, mutual information $MI_C(F, O)$ is formulated as follows:

$$MI_C(F, O) = \iint P(f, o)\ log(\frac{P(f, o)}{P(f)P(o)}) df do$$

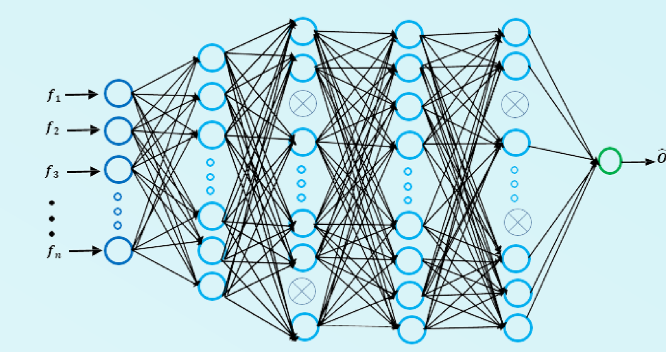


Importance analysis for input features: Hemoglobin and Glucose

Experimental Results

Model Construction and Validation

In this study, a deep neural network was constructed for accurate estimation of Hb and Gl levels. In order to ensure the model's validation, a 10-fold cross-validation technique was used.

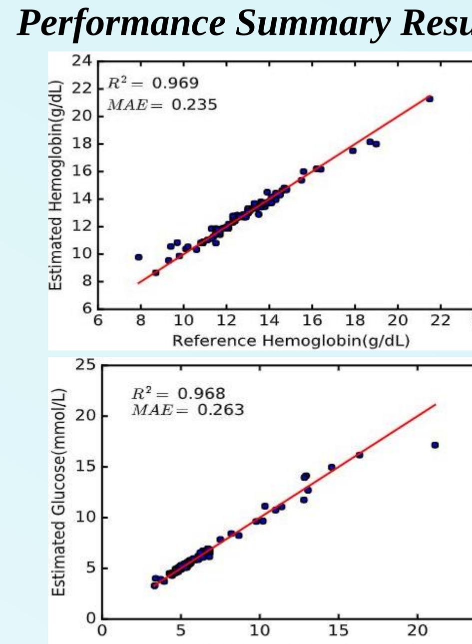


The proposed architecture of DNN model for Hb and Gl estimations

Parameters	Status
Batch size	32
Learning rate α	0.01
The number of hidden layers	4
The number of nodes at 4 hidden layers	(150, 200, 250, 300)
Dropout at 2nd and 4th hidden layers	(0.25, 0.5)
The number of nodes at input layer	36 or optimal feature set
The number of node at output layer	2
Activation function	ReLU, Linear
Optimizer	Adam

Hyperparameters and their values used in DNN models

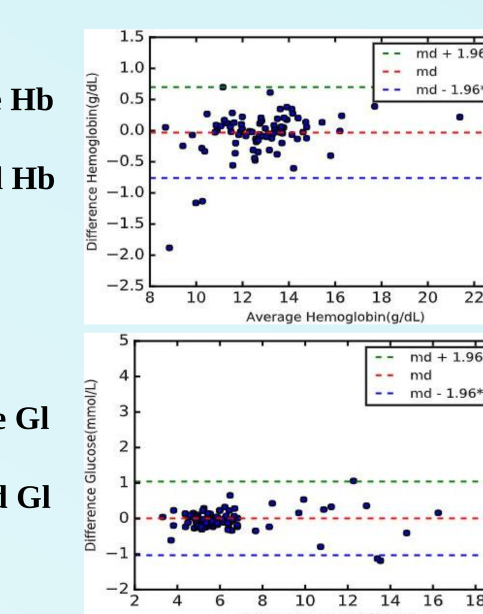
Performance Summary Results



Relationship plots.

Reference Hb Vs Estimated Hb

Reference Gl Vs Estimated Gl



Agreement plots.

Conclusion

Regular hemoglobin and glucose level monitoring prevents long-term and short-term consequences for anemic and diabetic patients, respectively. This paper has proposed a novel non-invasive method to estimate blood Hb and Gl levels with smartphone PPG signals extracted from fingertip videos and deep neural network model. In the future, we want to improve our work using these approaches: the dataset will be diversified to make it more balanced and entire estimating procedure will be conducted on the cloud.

Acknowledgment

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