A Study on Hemoglobin and Glucose Levels Estimation Techniques Using Optimal PPG Characteristic Features of Smartphone Videos

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Outline

- ❖ Introduction
- ❖ Existing Works
- ❖ Problem Statement
- ❖ Objectives
- ❖ Contributions
- ❖ Proposed Methodology
- ❖ Results and Discussion
- ❖ Conclusion and Recommendation
- ❖ References

Introduction

❖Hemoglobin

- Iron-containing protein found in all red blood cells (RBCs).
- Carries oxygen(O_2) from lungs to tissue of the body.
- Normal range of Hb for male: 14-17 g/dL and female: 13-16 g/dL
- Measurement of Hb is crucial for detection of anemia (Low Hb Level).

❖Glucose

- Diabetes is one of the most chronic diseases occurs due to human pancreas loses function to generate insulin.
- Diabetes are of two types: Type-1 (Juvenile) found in teenagers and Type-2 (mature) most common form of diabetes.
- Monitoring the Gl level is important to reduce the complication of diabetes.

Techniques Used for Measurement

- There are mainly two method to measure the hemoglobin or glucose level.

1) **Invasive Method**

- Blood sample is collected from human body using needle.
- Painful and required much time to produce result.
- Have risk of infection.

Fig. Blood collection using venipuncture.

Techniques Used for Measurement

- There are mainly two method to measure the hemoglobin or glucose level.

2) Non-Invasive Method

- No blood sample is required only bio-signal such as PPG or spectra.
- Painless, cheap, quicker, portable and easy.
- Non-invasive method has 3 functional unit.

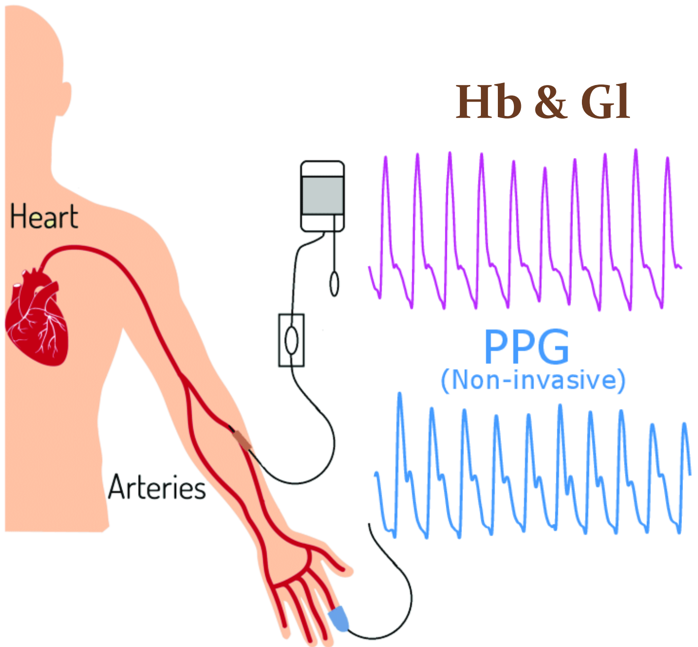


Fig. Non-Invasive measurement technique.

Techniques Used for Measurement

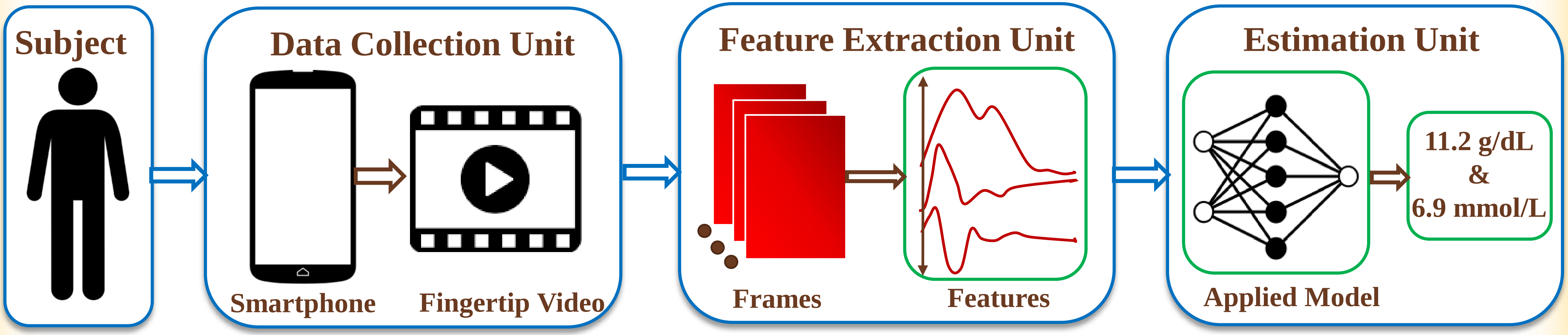


Fig. General System Architecture.

- **Data collection unit**: Collect raw optical or spectral data from the subject.
- **Feature extraction unit:** Extract features reprocessing the row bio-signal.
- **Estimation unit:** Estimate and validate results using different learning models.

Existing Works

Existing Works (Hemoglobin)

Reference	Data	# Participant	Signal	Method	Results
HemaApp [1]	Video	31	Spectra	LR, SVR	R = 0.62
SmartHeLP [2]	Video	75	Spectra	ANN	R = 0.93
Kavsaoğlu et al. [3]	-	33	PPG	CART, LSR, GLR, MVLR, PLSR, GRNN, MLP, SVR	R^2=0.92
Anggraeni and Fatoni [4]	Image	20	-	PCR	R^2=0.81
Glovanni et al. [5]	Image	113	-	KNN	R =0.65

Existing Works (Glucose)

Reference	Data	# Participant	Signal	Method	Results
Chowdhury et al. [6]	Video	18	PPG	PCR	SEP = 18.31
Zhang et al. [7]	Video	14	PPG	KNN	Acc = 86.2
Ramasahayam et al. [8]	-	-	PPG	ANN	RMSE = 5.84
Pai et al. [10]	-	24	Spectra	KBR	RMSEP = 9.64

Problem Statement

- Most of the commercially available devices for hemoglobin and glucose measurement are invasive or minimally invasive.

- Most of the existing methods need special sensor system for the collection PPG or spectral signal.

Objectives

- Develop a low cost smartphone-based system for hemoglobin and glucose measurement from fingertip video.
- Gathering large amount of dataset using smartphone.
- Estimating with more accurately than other non-invasive techniques.
- Make it less expensive.

Contributions

- ➢ Collecting the fingertip video using NIR-LED device through smartphone primary camera.
- ➢ Extraction of PPG characteristic features from the fingertip video
- ➢ Selecting best features using maximal information coefficient (MIC) feature selection method.
- ➢ Develop a smartphone-based low cost hemoglobin and glucose levels estimation models using deep neural networks (DNN)

Proposed Methodology

- System overview
- Data collection
- PPG signal extraction
- Feature extraction
- Feature selection
- Model development
- Experimental analysis

System Overview

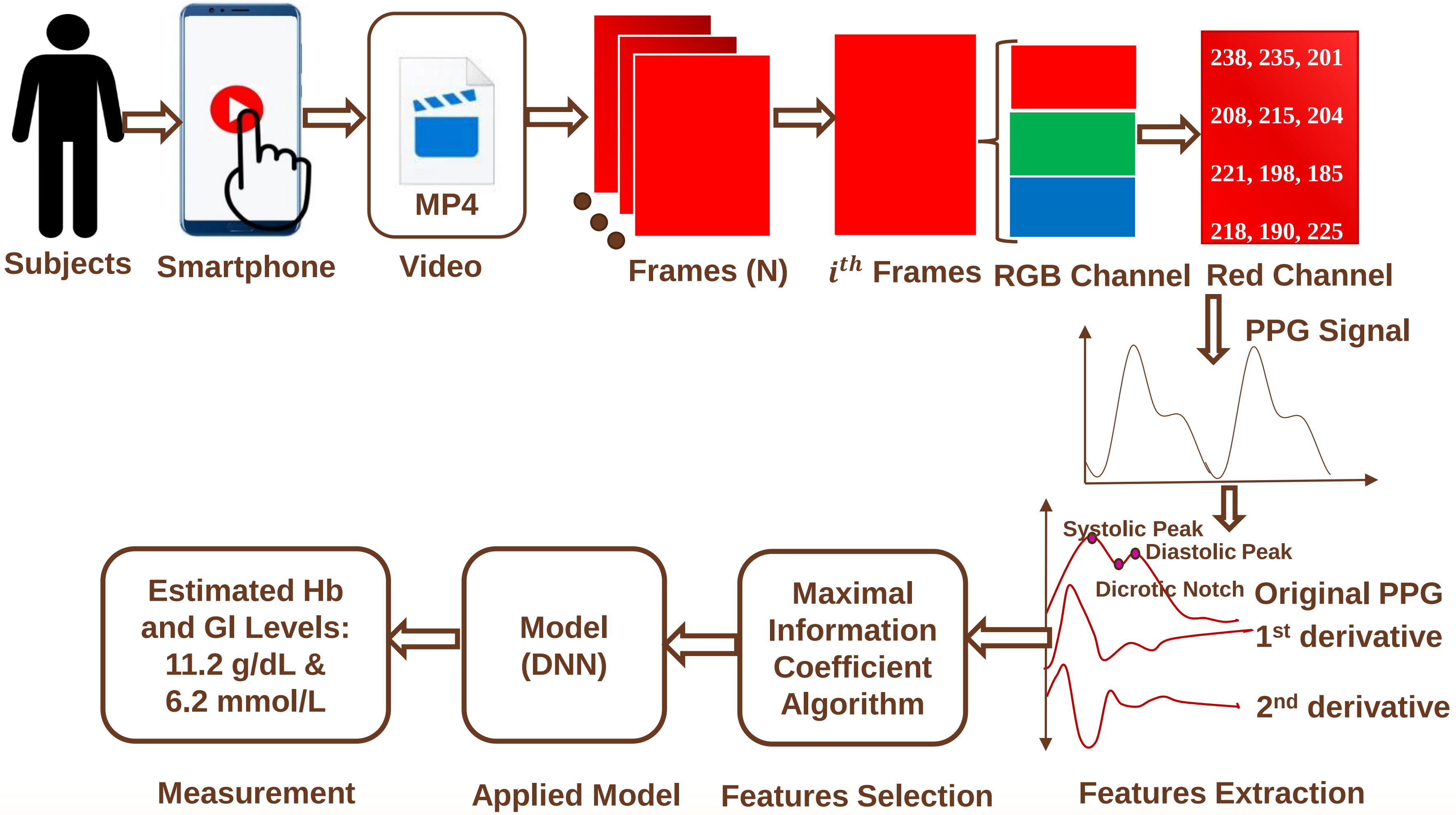
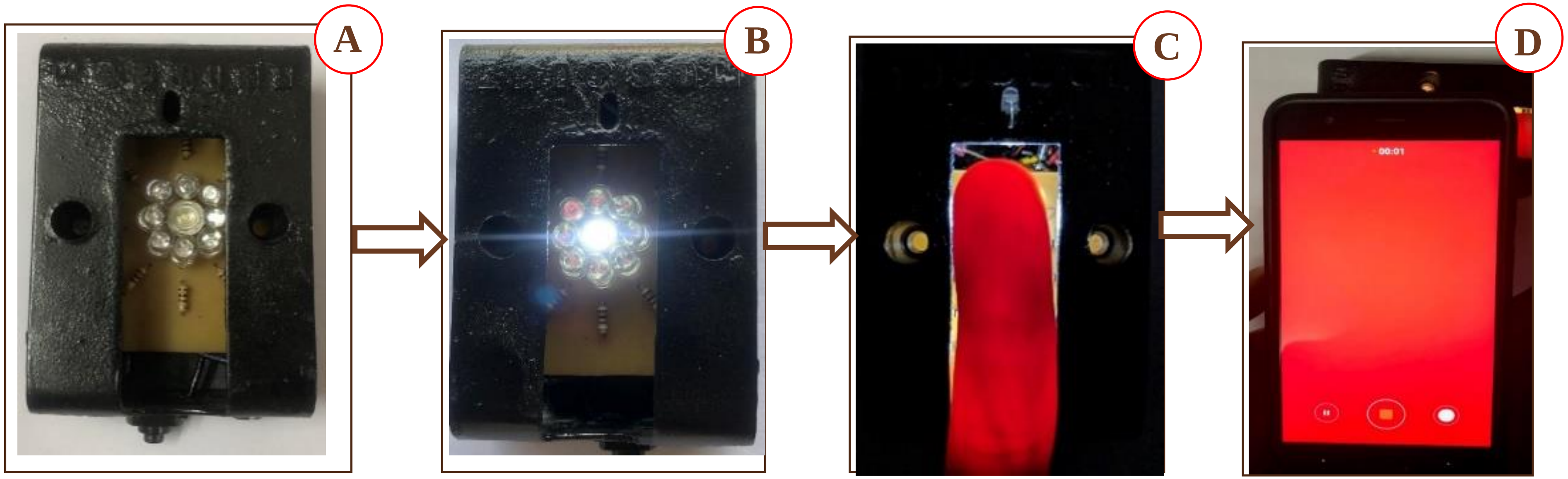


Fig. Proposed System Overview.

Video Data Collection

Data Collection



- Data collection device/kit consist of eight 850-nm NIR-LED and one flash LED.
- Index finger placed on the device and a 15-second fingertip video is captured using Nexus-6p smartphone.

Data Collection

- ❖ **Some precautions while data collection**

Clean and dry the hand

No nail polish is allowed on the video recording finger nail

No infection in the video recording site

Data Collection

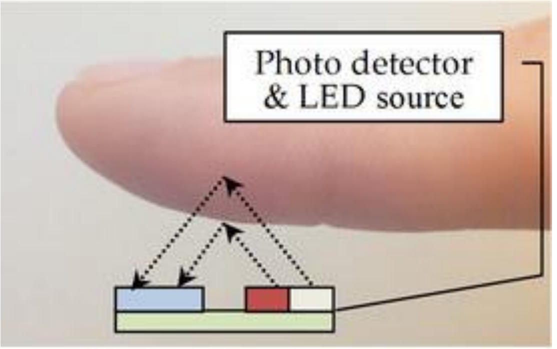
Table: Data set descriptions

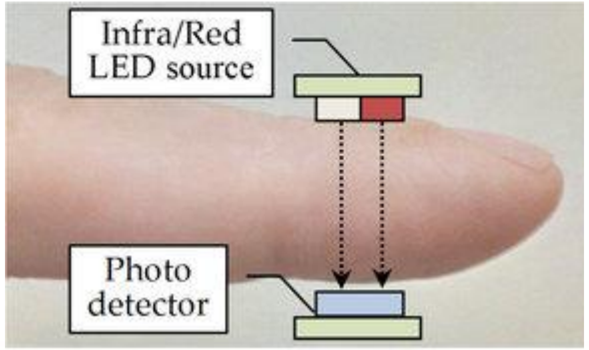
Gold Standard Value	
Hemoglobin	7.9 to 21.49 g/dL
Glucose	3.33 to 21.11 mmol/L
Total Participants 93	
Male	59
Female	34
Age	0 to 79 years

Feature Engineering

PPG Signal Generation

- Photoplethysmogram (PPG) is an optically obtained plethysmogram that can be used to detect blood volume changes.
- PPG signal can be two types:
  1) Reflectance (LED and photo detector are on same side)
  2) Transmittance (LED and photo detector are on opposite side)





PPG Signal Generation Principle

- NIR-LED and smartphone camera are on opposite side of the finger.
- Smartphone camera in combination with the NID-LED is able to detect these small variations in color caused by the blood flow.

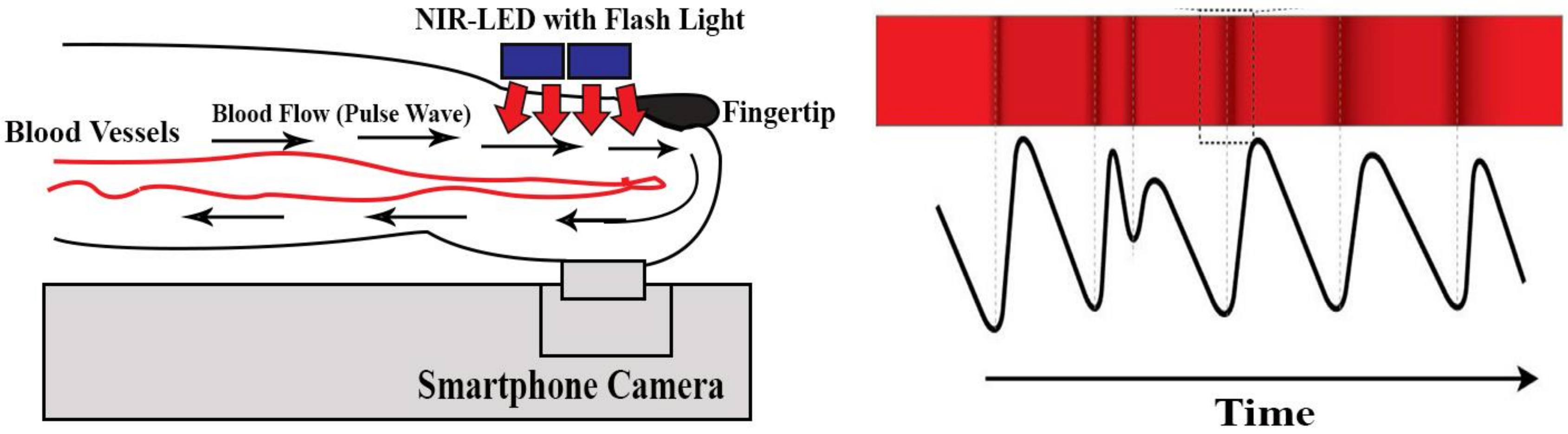


Fig. Photoplethysmography (PPG) principle by smartphone.

PPG Signal Generation

Algorithm 1: Generation of PPG signal from fingertip videos using the mean of pixels of each frame above threshold

```
Input: N-number of videos
Output: PPGSig-generated PPG Signal
/* For NIR-0850 lighting condition, capture 15sec(30fps)
   videos with Nexus-6p smartphone                                  */
for i ← 1 to N do
    /* First 60 frames (2s) and last 90 frames (3s) are
       discarded                                                    */
    Extract only 300 frames for each video;
    /* Initialization list:  ListII                                 */
    List of select highest intensity channel ListII;
    for j ← 1 to 300 do
        /* Calculate the threshold value for each Frame_j           */
        threshold_j = 0.5 * (intensity^j_max + intensity^j_min);
        /* Calculate MeanR, MeanG, MeanB                            */
        Average value of red channel MeanR;
        Average value of green channel MeanG;
        Average value of blue channel MeanB;
        for k ← 1 to 3 do
            if channel_k is red AND channel_k ≥ threshold_k then
                MeanR ← average intensity for red channel from Frame_j;
            else if channel_k is green AND channel_k ≥ threshold_k then
                MeanG ← average intensity for green channel from Frame_j;
            else
                MeanB ← average intensity for blue channel from Frame_j;
        /* Calculate maximum value of channels                      */
        MaxvalC ← max(MeanR, MeanG, MeanB);
        /* Append maximum value from three channels to list:
           ListII                                                   */
        ListII_j ← MaxvalC;
    /* Generate PPG signals:  PPGSig_i                              */
    PPGSig_i ← butterworthFilter(ListII);
return PPGSig
```

Region of Interest (ROI)

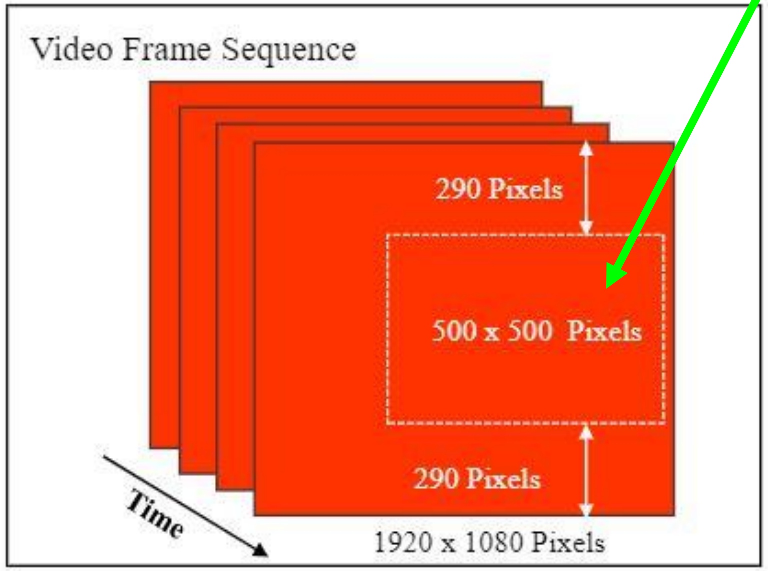


Fig. Frame separation from video.

- Extract the frames from each fingertip video
- The continuous PPG signal is calculated by overall pixel intensity variations in each frame.

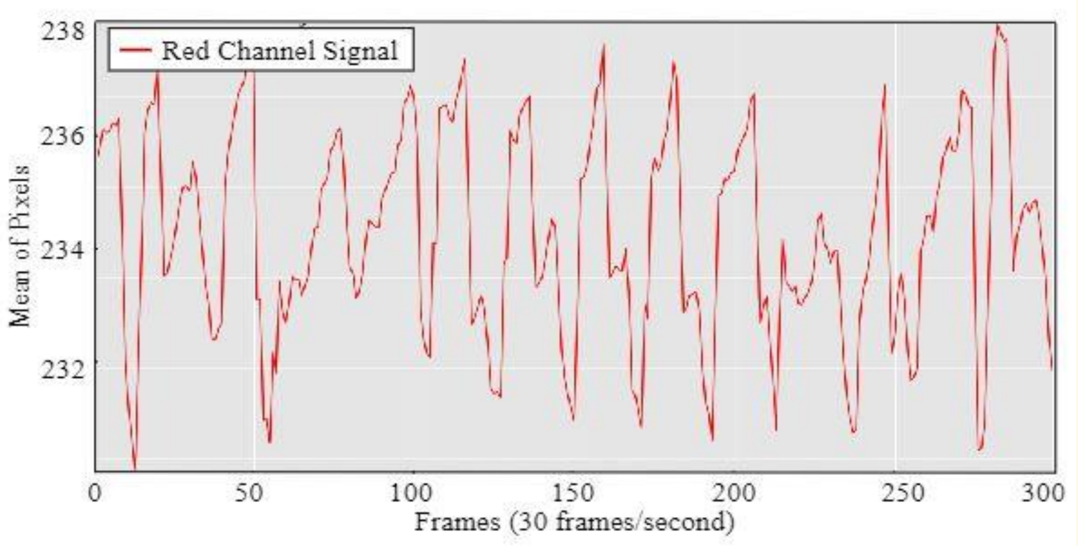
PPG Signal Generation

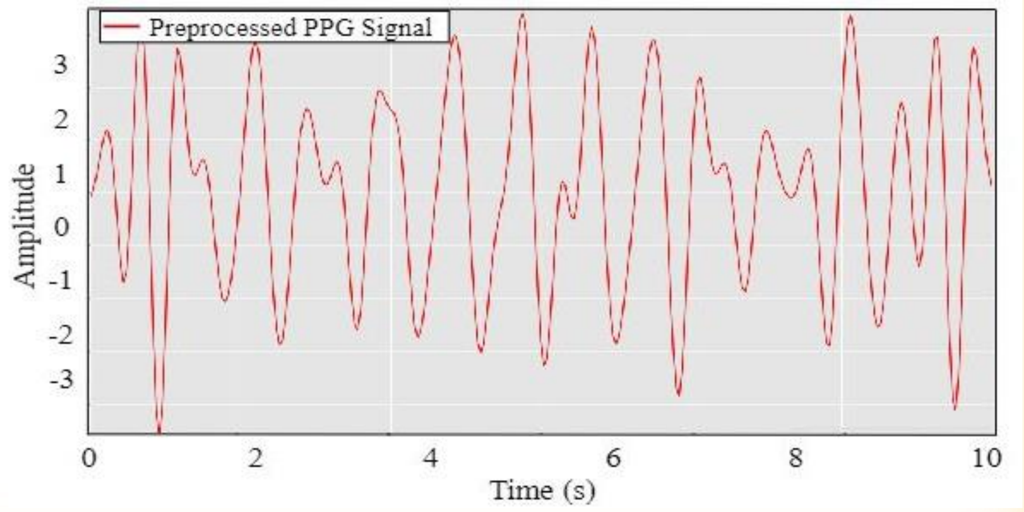
❖ Generate PPG Signal using Mean

- 1st step, for each video data, PPG value of the i^{th} frame is measured by the mean of the pixels as follow:

$$PPG[i] = \frac{1}{total\_pixels} \sum_{i=1}^{total\_pixels} intensity_i$$

- Butterworth bandpass filter (4th order) applied to minimize the noise and motion artifacts.





PPG Signal Generation

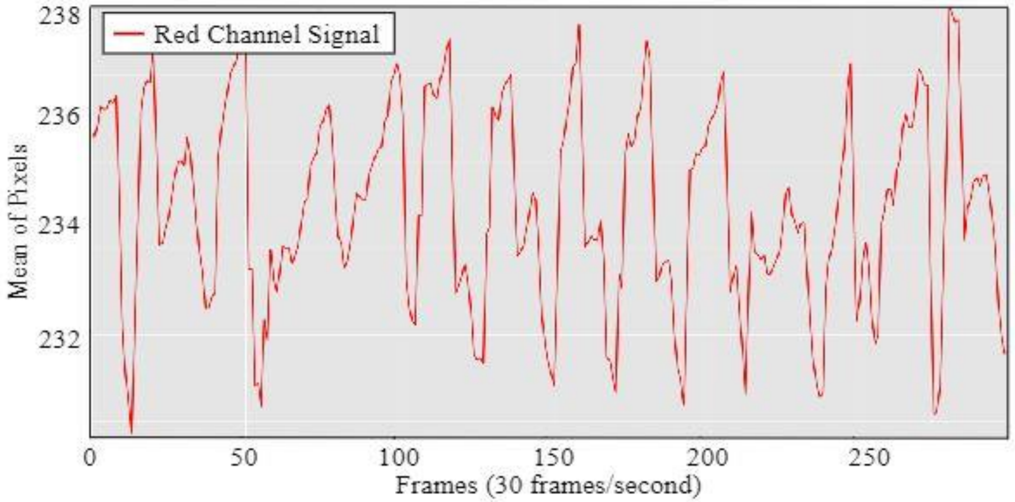
- **Generate PPG Signal using Mean above Threshold**

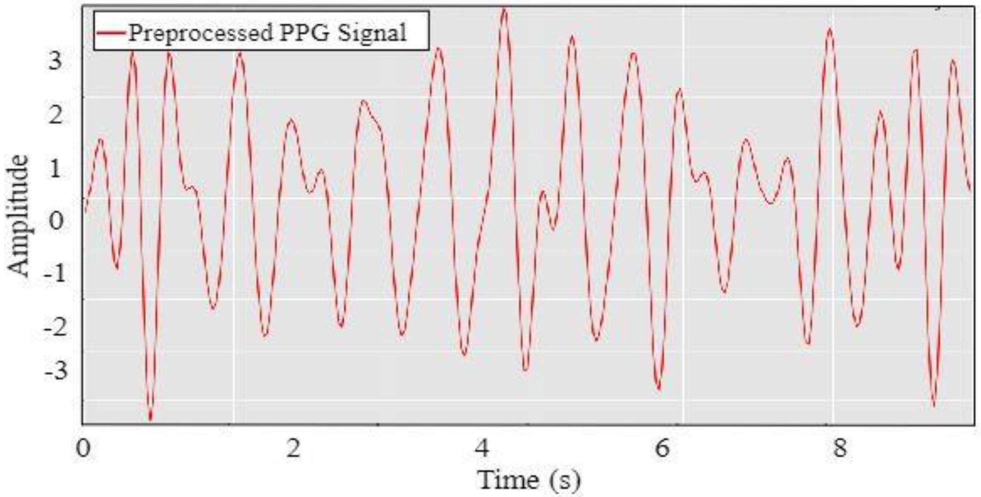
➢ 2nd step, for each video data, PPG value of the $\boldsymbol{i^{th}}$ frame is measured by the mean of the pixels above threshold

$$threshold_i = \frac{1}{2}(intensity^i_{max} + intensity^i_{min})$$

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

➢ Butterworth bandpass filter (4^{th} order) applied to minimize the noise and motion artifacts.





PPG Cycle Detection and Selection

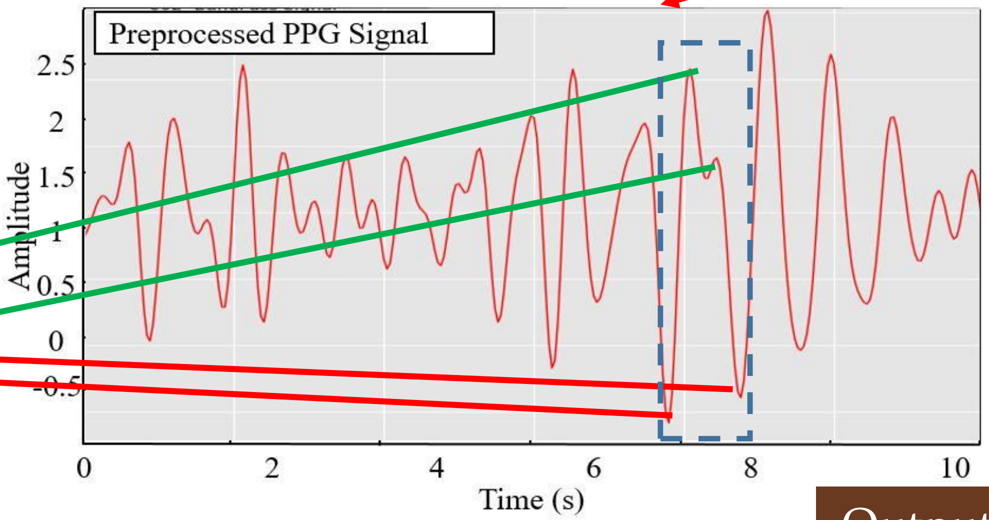
Algorithm 2: PPG cycle detection and selection algorithm

Input: Series of continuous PPG signal S_{PPG}
Output: Best single PPG cycle B_{PPG}

$List_C \leftarrow \phi$;
/* $List_C \leftarrow$ list of valid cycle */
/* Cycle Detection */
while *time_frame* ≥ 10 **do**
  /* Duration of each PPG signal is 10s */
  Detect each cycle C_{PPG} in S_{PPG} as follows: ;
  Consider starting point (S_p), dicrotic notch (z), and ending point (E_p) are consecutive minima (M_a);
  Consider systolic peak (x), and diastolic peak (y) are consecutive maxima (M_x);
  Use *find_peak* from the NumPy module of python to detect the peaks of PPG signal and reduce the search time;
  /* Valid PPG cycle check (Figure 4.7 (a)) */
  if C_{PPG} *contains* (M_a, M_x) **then**
    /* PPG cycle must has typical critical features like systolic peak, dicrotic notch or diastolic peak (Figure 4.9). */
    if *x is greater than y and z is greater than* (S_p, E_p) **then**
      $List_C \leftarrow List_C \cup C_{PPG}$;
    else
      Discard C_{PPG};
  else
    Discard C_{PPG};

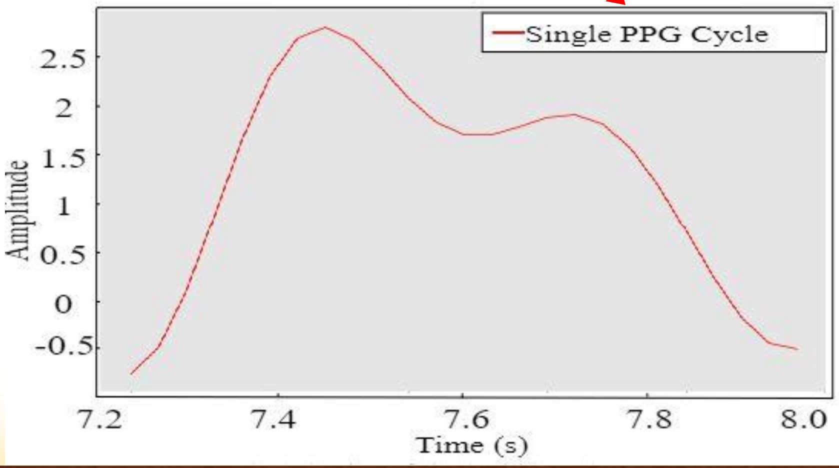
/* Cycle Section */
$B_{PPG} \leftarrow max_x(List_C)$ (Figure 4.7 (b));
/* PPG cycle $List_C$ with the maximum systolic amplitude x */
return B_{PPG};

Input Signal



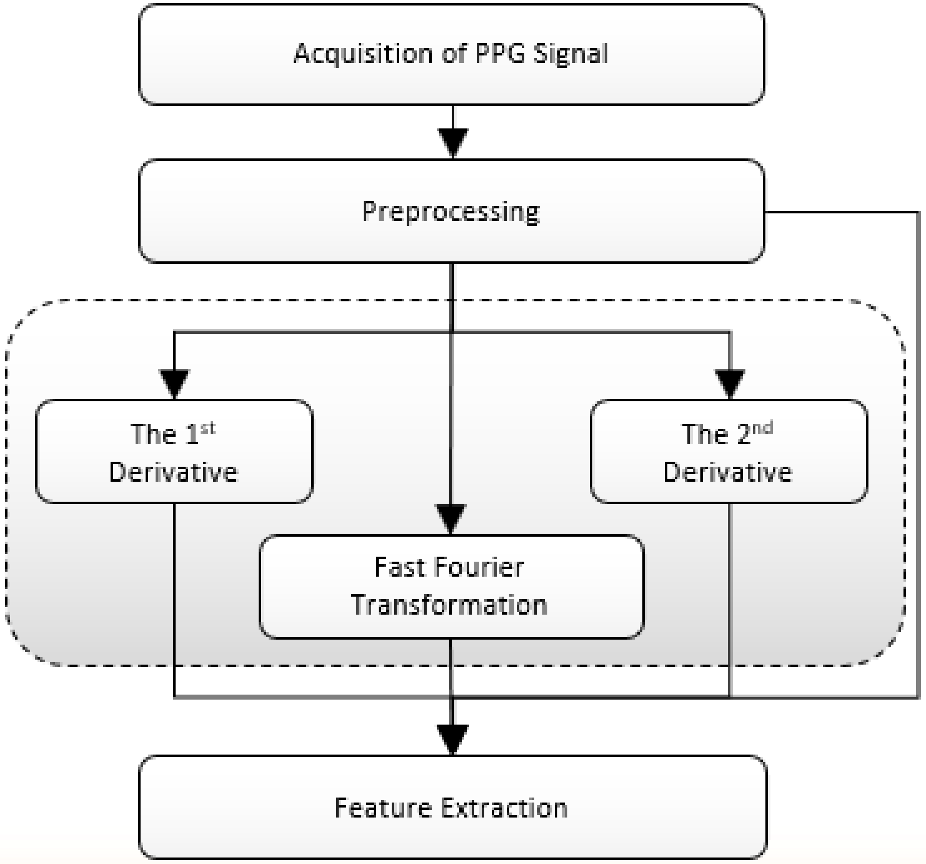
- Series of continuous PPG signal S_{PPG}

Output Signal



- Select the best PPG cycle B_{PPG} with highest amplitude

Feature Extraction



- From B_{PPG}, 34 features were extracted ($f_1 - f_{34}$).
- Age (f_{35}) and gender (f_{36}) also consider as feature.
- Therefore, total features 36.

Feature Extraction

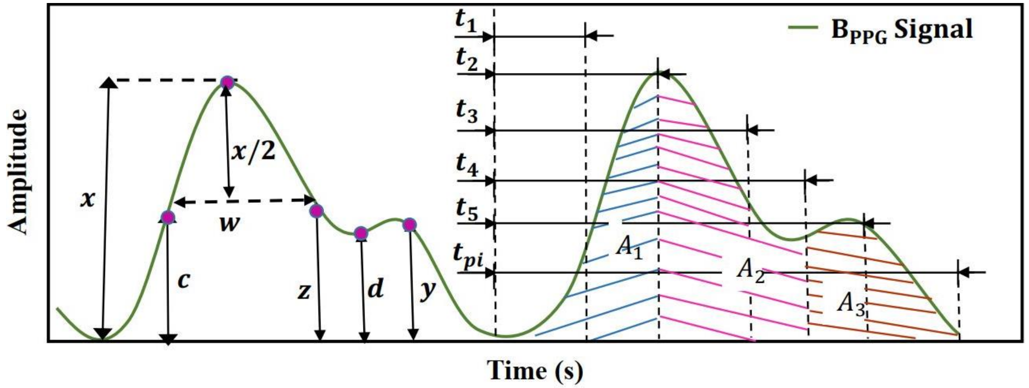


Fig. 14 ($f_1 - f_{14}$) features extraction from B_{PPG} Signal.

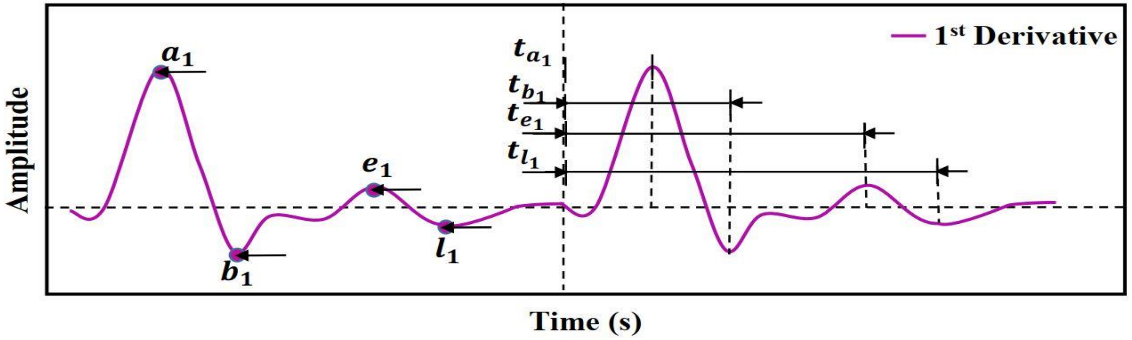


Fig. 8 ($f_{15} - f_{22}$) features extraction from 1st derivative of B_{PPG} Signal.

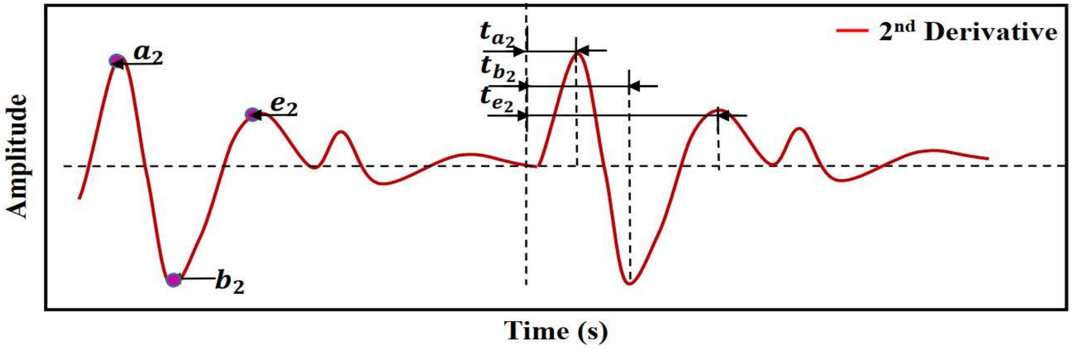


Fig. 6 ($f_{23} - f_{28}$) features extraction from 2nd derivative of B_{PPG} Signal.

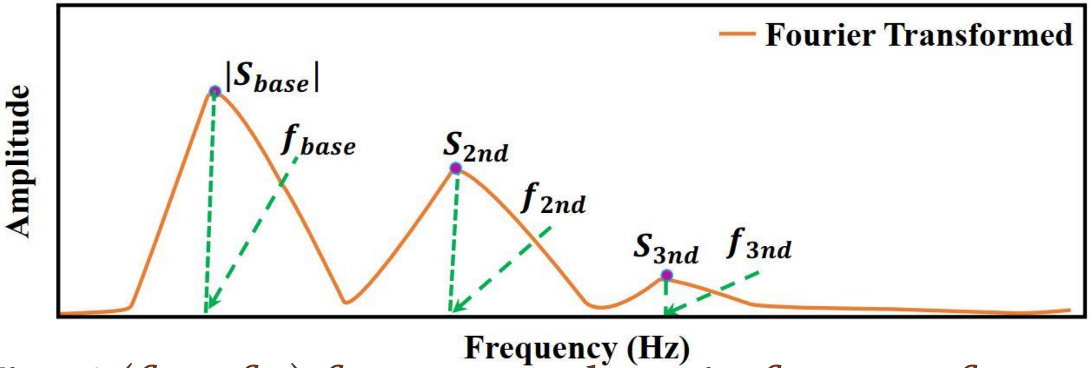


Fig. 6 ($f_{29} - f_{34}$) frequency-domain features from fast fourier transformed B_{PPG} signal.

Feature Selection

- To reduce irrelevant or redundant features selection method using Maximal Information Coefficient (MIC) has been applied.

❖ **Maximal Information Coefficient (MIC)**

- Information theory-based measure of association
- **Formula** $MI_C(F,O) = \int\int P(f,o)\log\left(\frac{P(f,o)}{P(f)P(o)}\right)dfdo$
- P(f, o) denotes the associated joint probabilistic density and marginal probabilistic density functions are P(f), and P(o)
- Measures the mutual information between input features *F* and true values *O*

Feature Selection

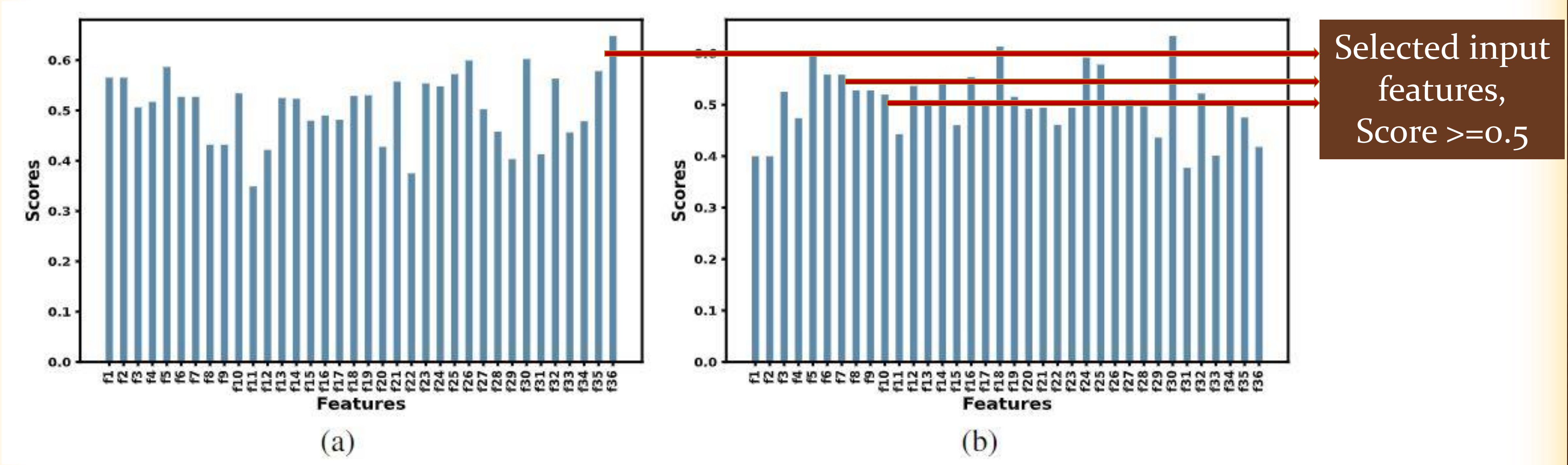


Fig. Importance analysis for input features (a) Hemoglobin, (b) Glucose

Feature Selection

- 22 features for hemoglobin and 21 for glucose out 36 was selected.

Table: List of selected features.

Dataset	Selected Features	Count
Hemoglobin	f_1 f_2 f_3 f_4 f_5 f_6 f_7 f_{10} f_{13} f_{14} f_{18} f_{19} f_{21} f_{23} f_{24} f_{25} f_{26} f_{27} f_{30} f_{32} f_{35} f_{36}	22
Glucose	f_3 f_5 f_6 f_7 f_8 f_9 f_{10} f_{12} f_{13} f_{14} f_{16} f_{17} f_{18} f_{19} f_{24} f_{25} f_{26} f_{27} f_{30} f_{32} f_{34}	21

Model Development

Dataset for Models Training

- **PPG-HbGl1 Dataset**
  - Consists of PPG signal's features (PPG-34), whereas the PPG signal was generated using the mean of pixels of each frame.
  - Dataset consist of 93 rows and 36 columns
  - After using MIC: Dataset will be 93 x 22 for hemoglobin and 93 x 21 for glucose level.
- **PPG-HbGl2 Dataset**
  - Consists of PPG signal's features (PPG-34), whereas the PPG signal was generated using the mean of pixels of each frame above the threshold.
  - Dataset consist of 93 rows and 36 columns
  - After using MIC: Dataset will be 93 x 22 for hemoglobin and 93 x 21 for glucose level.

Artificial Neural Network (ANN)

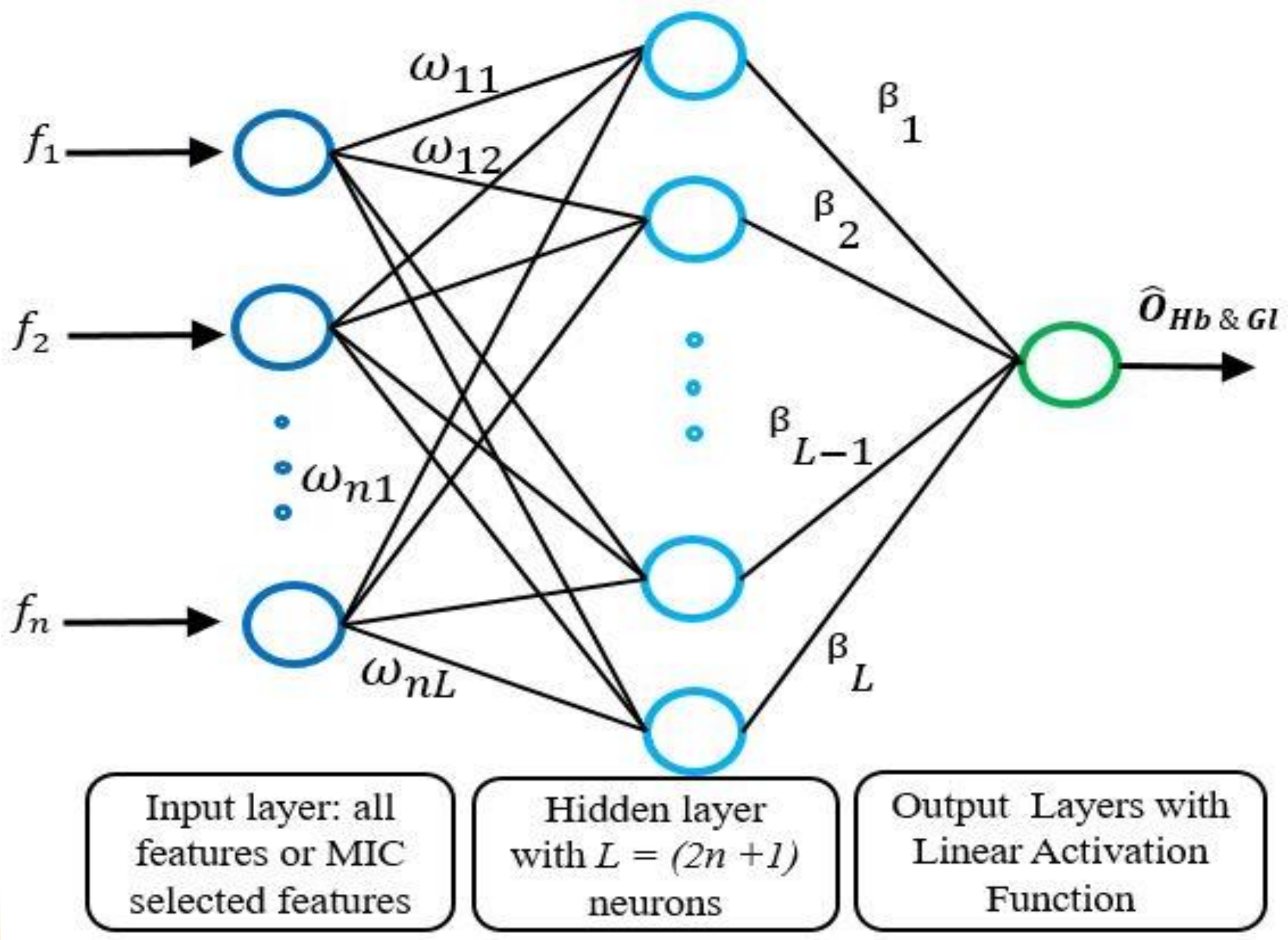
- A gradient descent backpropagation neural network with 3 types of layers:
    1) One Input Layer
    2) One Hidden Layer
    3) One Output Layer
- Equipped with weights, biases and activation functions.
- Number of nodes in hidden layer:

$$L = (2n + 1)$$

- The output of each neuron in a hidden layer:

$$v_j = \sum_j \omega_{ij} f_j + \beta_j$$

Proposed ANN Models Architecture

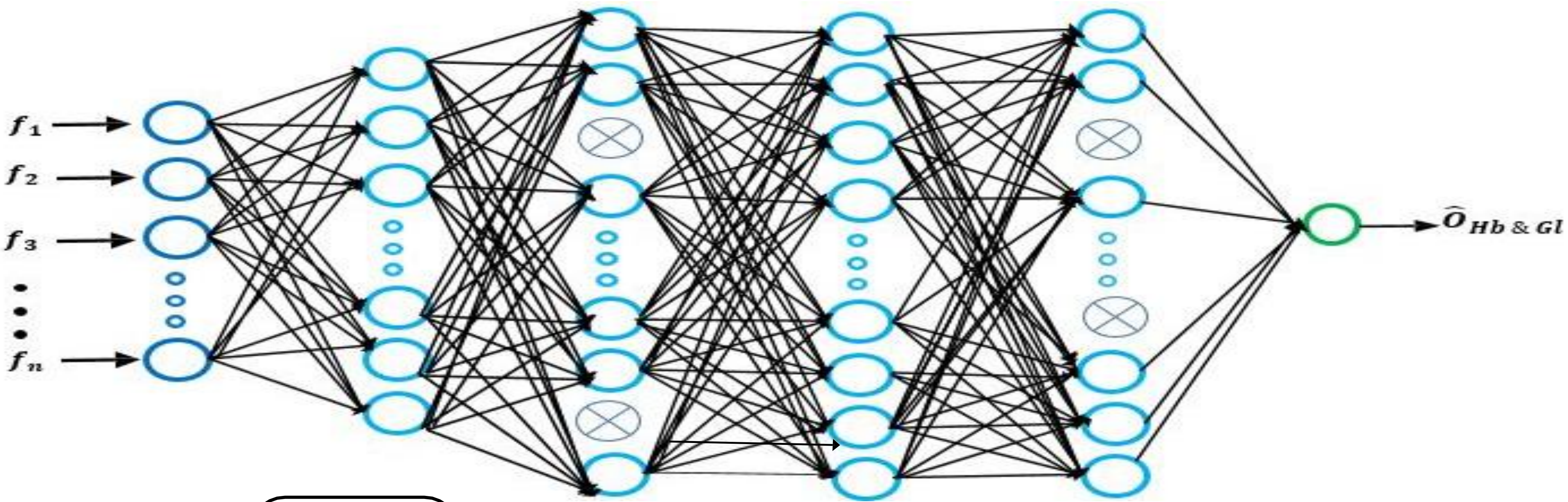


Deep Neural Network (DNN)

- Feed-forward network with 3 types of layer:
  1) One Input Layer
  2) Several Hidden Layers
  3) One Output Layer
- Nodes of each layer receives input from previous layer.
- Equipped with weights, biases and activation functions.
- The output of each neuron in a hidden layer :

$$v_j = \sum_j \omega_{ij} f_j + \beta_j$$

Proposed DNN Models Architecture



Input layer: all features or selected features with MIC

First hidden layer with 150 neurons. Activation Function "ReLU"

Second hidden layer with 200 neurons. Activation Function "ReLU". Dropout 0.25.

Third hidden layer with 250 neurons. Activation Function "ReLU".

Fourth hidden layer with 300 neurons. Activation Function "ReLU". Dropout 0.5.

Output Layers, Activation Function Linear

DNN Models Hyperparameters

- Both Models have the same architecture :

Table: Hyperparameters of the DNN Models

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

Models Validation

Algorithm 3: K-fold cross-validation for each model to estimate the different blood component levels

---

Input: input dataset $D = \{f_i, o_i\}_{i=1}^{m}$ where, $(F \in \mathbb{R}^n,\ O \in Y)$, P^{set} is the set of parameter for each model, M.

Output: Performance evaluation indices.

Divide the dataset D into K-folds ;

```
/* Each folds are approximately equal distribution */
```

for $i \leftarrow 1$ **to** K **do**

- Split D into D_i^{train} and D_i^{test} for i^{th} split ;
- Train the model M with D_i^{train} using P^{set} ;
- Evaluate the performance E_i for M with D_i^{test} ;

Calculate the average performance $E_M = \frac{1}{K}\sum_{i=1}^{K} E_i$;

return E_M ;

- ➢ 10-fold cross validation was applied on dataset.
- ➢ Initially dataset was divided into 10 equal size subsets or folds.
- ➢ Nine folds was used for training models and rest one fold used for validations of models.

Results and Discussion

- ❖ **Performance Evaluating Criteria**
- ❖ **Robustness Performance of Models**
- ❖ **Comparison with Other Works**

Result Analysis

❖ Performance Evaluating Criteria:

- **R^2 Value:** $$R^2 = 1 - \frac{\sum_{i=1}^{n}(o_i - \hat{o}_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2}$$
- **MAE:** $$MSE = \frac{1}{n}\sum_{i=1}^{n}(o_i - \hat{o}_i)^2$$
- **MSE:** $$MAE = \frac{1}{n}\sum_{i=1}^{n}|o_i - \hat{o}_i|$$
- **RMSE:** $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(o_i - \hat{o}_i)^2}$$

where, o_i is i^{th} reference value and $\hat{o}_i$ is the corresponding measurement value as well as n is the total sample.

Result Analysis (PPG-HbGlı Dataset)

Table: Performance measurement of different Models with all features

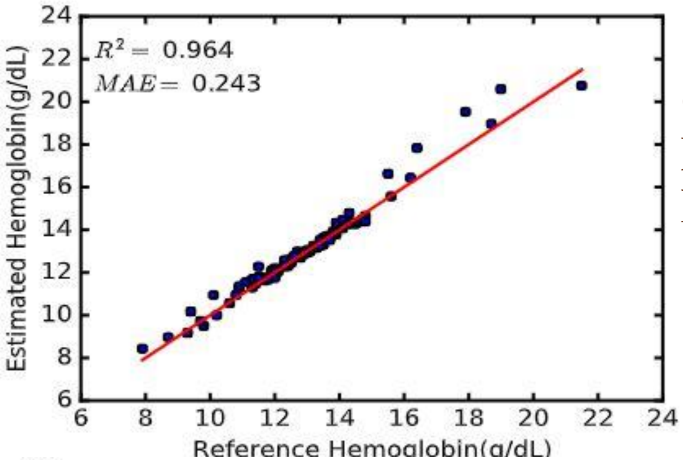
Model	With all features							
	Hb				Gl			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
LR	0.188	0.727	0.878	0.937	0.201	0.843	2.696	1.642
SVR	0.247	0.695	0.815	0.902	0.320	0.954	2.136	1.461
ANN	0.842	0.284	0.726	0.852	0.817	0.439	1.610	1.269
Proposed(DNN)	**0.874**	**0.414**	**0.581**	**0.762**	**0.850**	**0.566**	**1.319**	**1.148**

Table: Performance measurement of different Models with selected features

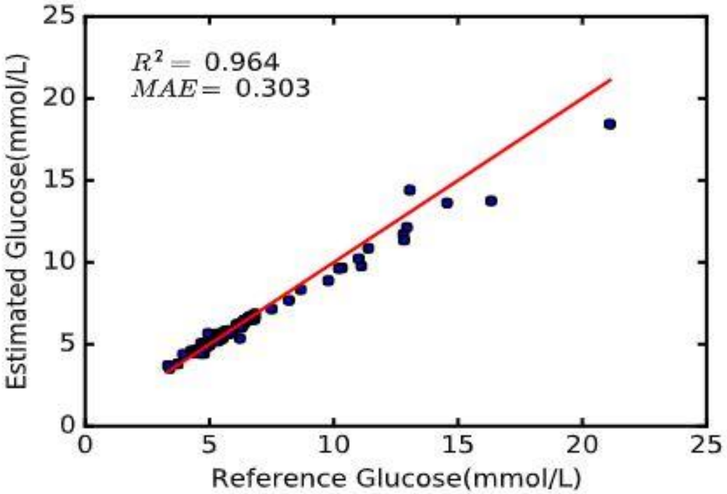
Model	With selected features via MIC (22 features for Hb and 21 features for Gl)							
	Hb				Gl			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
LR	0.281	0.675	0.815	0.924	0.352	0.924	2.201	1.365
SVR	0.421	0.517	0.684	0.769	0.592	0.674	1.799	1.024
ANN	0.901	0.278	0.467	0.683	0.898	0.507	1.031	0.988
Proposed(DNN+MIC)	**0.963**	**0.243**	**0.164**	**0.405**	**0.964**	**0.303**	**0.320**	**0.566**

DNN models along with MIC

Relationship & Agreement (PPG-HbGl1 Dataset)

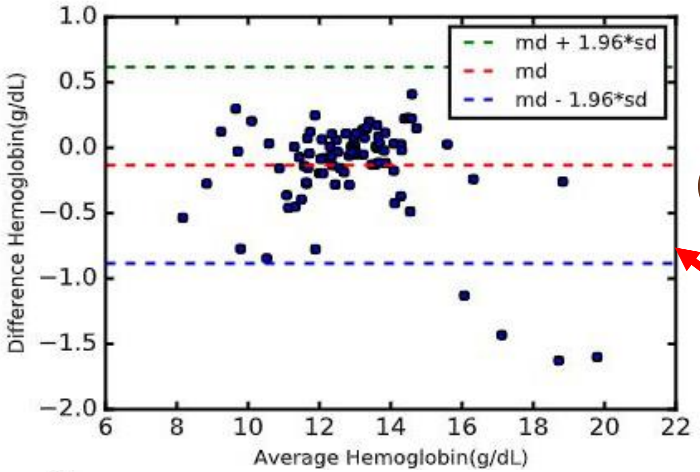


(a) Hb
Reference Vs Estimated Hb

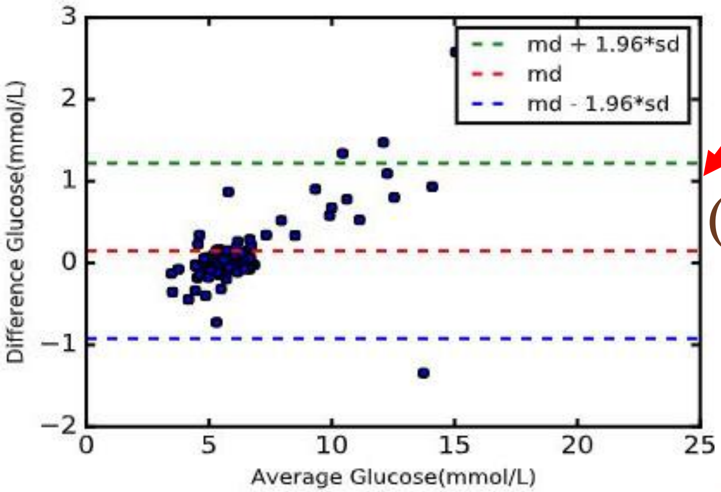


(a) Gl
Reference Vs Estimated Gl

Fig. Relationship plots.



(a) Hb



(a) Gl

Only few numbers are outside of the (md ±1.96 SD) boundary line

Fig. Agreement plots.

Result Analysis (PPG-HbGl2 Dataset)

Table: Performance measurement of different Models with all features

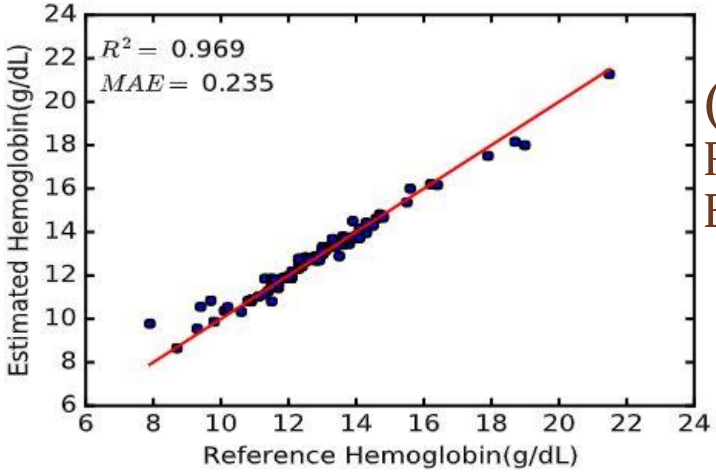
Model	With all features							
	Hb				Gl			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
LR	0.188	0.727	0.878	0.937	0.201	0.843	2.696	1.642
SVR	0.247	0.695	0.815	0.902	0.320	0.954	2.136	1.461
ANN	0.853	0.386	0.678	0.823	0.848	0.490	1.294	1.137
Proposed(DNN)	**0.897**	**0.357**	**0.470**	**0.686**	**0.874**	**0.545**	**1.102**	**1.049**

Table: Performance measurement of different Models with selected features

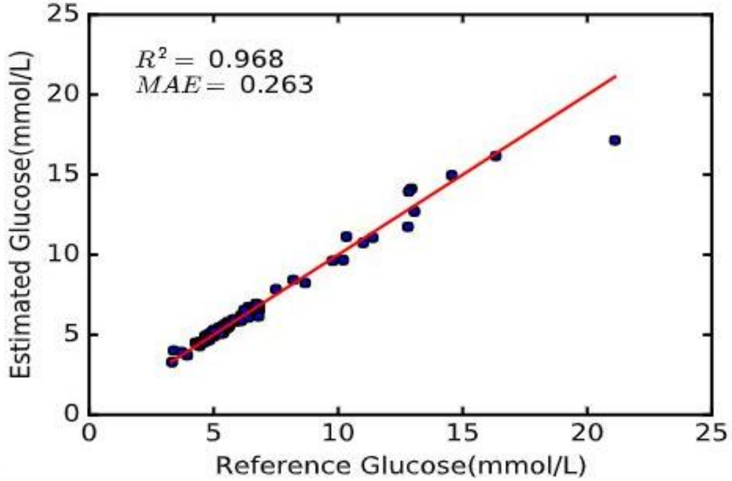
Model	With selected features via MIC (22 features for Hb and 21 features for Gl)							
	Hb				Gl			
	R^2	MAE	MSE	RMSE	R^2	MAE	MSE	RMSE
LR	0.281	0.675	0.815	0.924	0.352	0.924	2.201	1.365
SVR	0.421	0.517	0.684	0.769	0.592	0.674	1.799	1.024
ANN	0.922	0.195	0.359	0.599	0.901	0.407	0.824	0.768
Proposed(DNN+MIC)	**0.969**	**0.235**	**0.139**	**0.373**	**0.968**	**0.263**	**0.280**	**0.529**

DNN models along with MIC perform better for PPG-HbGl2 compared to PPG-HbGl1

Relationship & Agreement (PPG-HbGl2 Dataset)

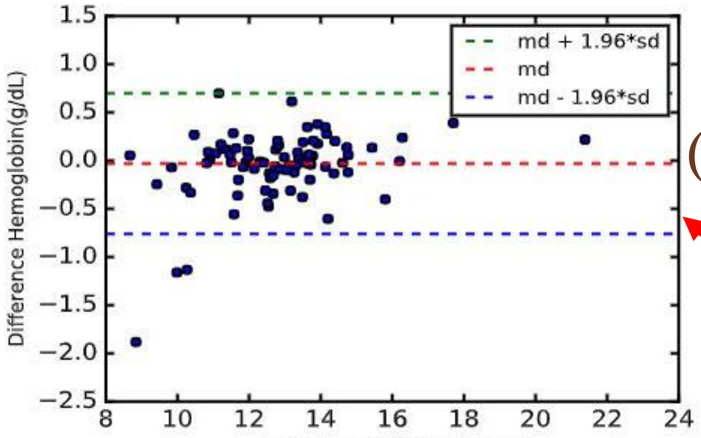


(a) Hb
Reference Vs
Estimated Hb

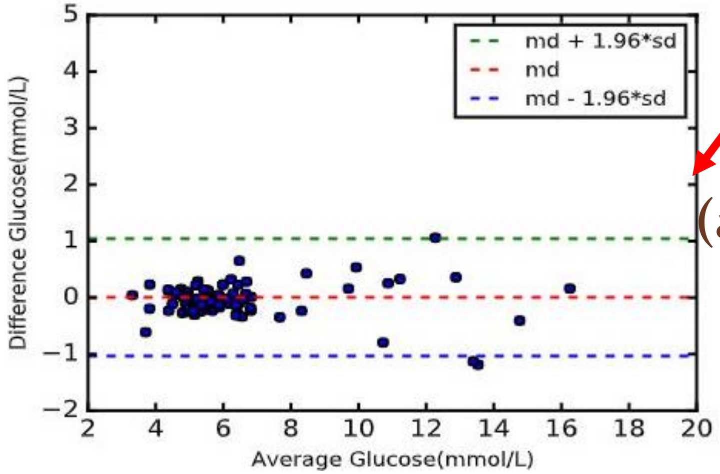


(a) Gl
Reference Vs
Estimated Gl

Fig. Relationship plots.



(a) Hb



(a) Gl

Only few numbers are outside of the (md ±1.96 SD) boundary line

Fig. Agreement plots.

Comparison with Other Works

Table: Comparison of our proposed method with several existing methods using the same dataset.

Authors	Purpose	#Sub	Feature Extraction	Feature Selection	Model	Performance
Golap et al. [10]		93	PPG-46	CFS	MGGP	$R^2 = 0.807$ $R^2 = 0.881$
Haque et al. [11]		93	PPG-46	CFS	DNN	$R^2 = 0.922$ $R^2 = 0.902$
Proposed Method		93	PPG-34	MIC	DNN	$\mathbf{R^2 = 0.969}$ $\mathbf{R^2 = 0.968}$

* = Hemoglobin, = Glucose, PPG-46 = 46 time and frequency domain features, PPG-34 = 34 time and frequency domain features, CFS = Correlation-based Feature Selection, MIC = Maximal Information Coefficient, MGGP = Multigene Genetic Programming, DNN = Deep Neural Network.

Conclusion and Recommendation

- A smartphone-based system introduces to estimate hemoglobin and glucose levels accurately using the deep neural network model.
- An algorithm for the generation of the PPG signal and extraction of features.
- The proposed system performed comparatively well with other established regression models such as LR, SVR and ANN.

Recommendation for Future Work

- Recording the fingertip video data using different smartphones.
- Increasing detest from heterogeneous subjects to make the dataset more balanced.
- Providing cloud based smartphone application to measure hemoglobin and glucose.

Publication from the Thesis Work

❖ **International Conference**

1) S. **M. Taslim Uddin Raju**, and M.M.A. Hashem, “Real-Time Hemoglobin Measurement Using Smartphone Video and Artificial Neural Network,” International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE2022), IEEE, RUET, Rajshahi, Bangladesh, 29 – 31 Dec. 2022. (**Accepted**)
2) **S. M. Taslim Uddin Raju**, and M.M.A. Hashem, “DNN Based Blood Glucose Level Estimation Using PPG Characteristic Features of Smartphone Videos,” 25th International Conference on Computer and Information Technology (ICCIT2022), IEEE, Cox’s Bazar, Bangladesh, 17 – 19 Dec. 2022. (**Accepted**)

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Any Questions?