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Pareeksh: A health diagnosis system using IOT for early detection and prevention

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***Abstract*---**The changes in the body conditions are reflected in the flow of blood throughout the body. These changes can be measured as body signals using appropriate sensors. With an improvement in technology and miniaturization of sensors, the healthcare sector has witnessed significant advancement over the years. The signals measured by such sensors carry important information regarding a person's health and this paper presents a method to utilize the same.The signals acquired from the PPG and ECG sensors are filtered and denoised. Statistical analysis is performed on these signals and important features are extracted. This set of features are given to a trained machine learning model which produces the classifications that confirm the health status of the subject for further investigations.

***Keywords*---**naadisignal, ppg signal, ECG signal SVM, KNN algorithms, diagnosis, detection.

Introduction

Most of the people in today's world suffer from diseases, some of which such as cardiac related issues go undetected owing to subtlety of symptoms ant the complexity and high cost of diagnostic procedures. Access to quality healthcare services and expensive diagnostic checkups is a challenge for many patients,

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especially those residing in remote and rural areas and also for people with disabilities and old age, often leading them to be ignorant of their underlying health concerns. Sensor based testing and remote analysis bring in automation in the healthcare sector and improve its accessibility. Patients can receive quality healthcare from the comfort of their homes by making efficient use of the emerging technologies. Ancient ayurvedic practitioners called NadiVaidyas carried out their diagnosis based on the variations in a person's pulse signals combined with carefully acquired knowledge and experience. The variations in these signals reflect the health status of the subject. PPG and ECG signals are acquired from the patient which are then filtered to remove the noise and powerline interferences. Useful features are extracted from these signals, which are then given to a trained machine learning model which predicts the health classifications. [3]

Objectives

- To acquire human body signals including ECG, PPG, SpO_2 and body temperature using sensors.
- To perform statistical analysis and apply KNN, SVM and Naïve Bayes algorithm to classify the signals into various health classifications.
- To display and store these readings using LabVIEW and develop user interface for the patient's interaction with the doctor.

Methodology

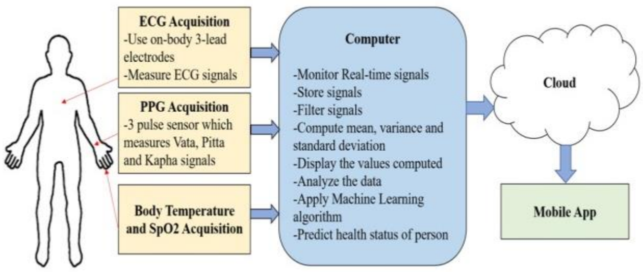

Fig. 1. Proposed methodology.

The methodology has been divided into three units.

Data acquisition

- PPG signals are acquired by fastening the pulse sensors on the subject's wrist on the radial fossa artery using a sensor sensor strap.[4]
- The sensor strap is placed on the right hand for males and the left hand for females while the subject has to stay still and relaxed while acquisition is in progress.
- ECG signals are acquired using the ECG sensor module by placing the L-pad on the left arm, R-pad on the right arm and Common pad on the left or right ankle obeying Einthoven's triangle.
- If the observed waveform is of proper shape, it can be stored.

- Body temperature is acquired using an IR temperature sensor by placing the palm of the subject in front of the sensor.
- SpO_2 level is acquired using a sensor designed for the same.
- myRIO-1900 is used to read all the above mentioned signals by connecting it to LabVIEW.

Filtering and processing

- The PPG signals are filtered with a low pass filter having a cut-off frequency of 10Hz to remove noise.
- The ECG signals are filtered with a low pass filter having a cut-off frequency of 20Hz to remove powerline interference and other high frequency noise. Further a high pass filter having a cut-off frequency 5Hz to remove baseline wander.[1]
- The filtered data is then used to extract useful features which include number of cycles, mean cycle time, mean pulse area, arithmetic mean, RMS, Standard deviation, variance, kurtosis, median, mode, skewness, maximum, minimum and range.
- These features are given to a machine learning model to confirm thee health status.

Data communication

- The results obtained can be communicated to the user via the LabVIEW front panel.
- The results can as well be communicated with the doctor for further assistance.

Implementation
Hardware implementation
PPG signal acquisition

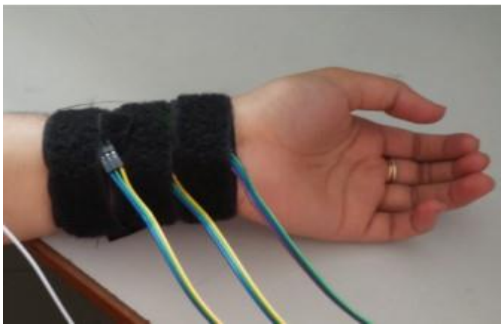

Fig. 2. Placement of PPG sensors on the wrist.

The Vata, Pitta, and Kapha signals are acquired using 3 pulse sensors which are attached to the velcro straps and connected to myRIO. The pulse sensors are placed on the wrist below the thumb where the pulse is observed and the velcro straps are fastened around the wrist as shown in figure 2. The sensors used are optical pulse sensors which work on the principle of "Photoplethysmography"

(PPG). PPG is a simple low cost optical technique that is used to detect blood volume changes in the microvascular bed of tissue. It works works with a supply voltage of 3.3V or 5V and utilizes 4mA of current. It includes circuits for amplification and noise cancellation.[6]

ECG signal acquisition

Fig. 3. Placement of ECG sensor pads

The ECG signal is acquired using AD8232 ECG sensor module by placing the L-pad on the left arm, R-pad on the right arm, and the common pad on the left or right ankle obeying the Einthoven's triangle, and connected to myRIO as shown in figure 3. The AD8232 is an integral signal conditioning block for ECG and other biopotential measurements, which is designed to extract, amplify, and filter small biopotential signals in the presence of noisy conditions. It has an operating voltage of 3.3V and is provided with a 3.5mm jack for biomedical pad connections.[5]

Software implementation
Labview main VI

The main VI has the user interface in the front panel and the functional "g" code in the block diagram. The VI is designed to acquire and store the signals and incorporates sub VIs which carry out filtering of the signals, performing statistical analysis, and extracting useful features from it. The main VI is structured as a flat sequence.

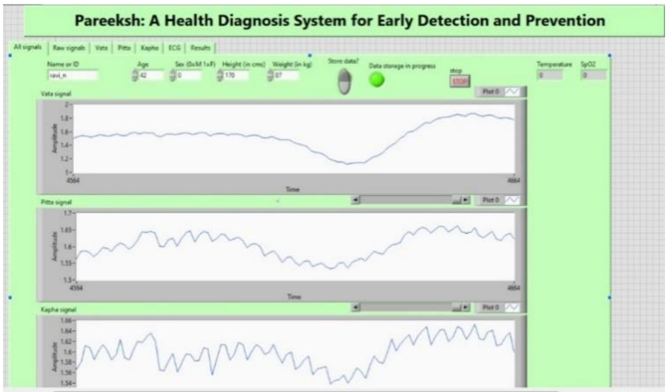

Fig. 4. Front panel showing the user interface.

The front panel shown in figure 4 has the user interface which takes in user inputs- name, age, sex (0=M 1=F), height (in cm), and weight (in kg). It has windows for observing the waveforms and a start and stop button to initiate and terminate the data storage process. The front panel is designed using the Tab controls which allows grouping of the controls and indicators and allows them to be displayed in an organized fashion for ease of the user.

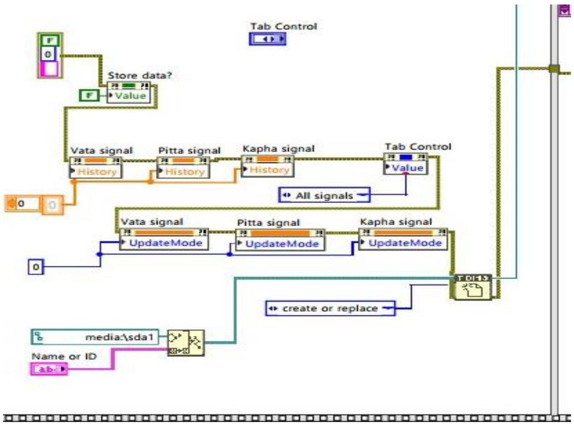

Fig. 5. Block diagram of the main VI showing initialization of the front panel objects

In the block diagram indicated in figure 5, the error cluster is formed which needs to be connected to the ‘error in’ inputs of the sub Vis, and the ‘error out’output generated from the subVI is given to the next subVI. Also, the front panel object properties are set using their respective property nodes and a TDMS file is opened for storing the signals using the TDMS open function. This is the initialization part of the main VI.

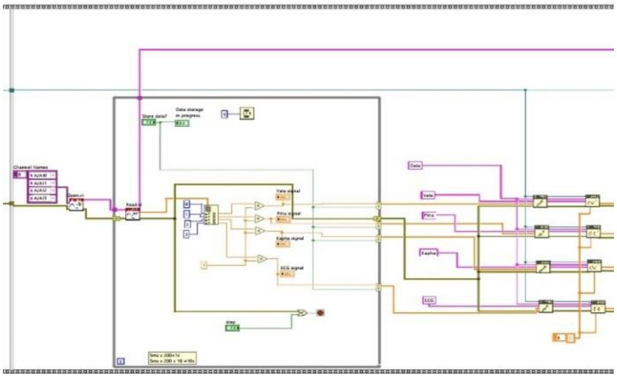

Fig. 6. Block Diagram of the main VI showing signal acquisition and storage

In the block diagramindicated in figure 6, signals are read by opening references to the channels of the myRIO device connected to the computer by using the Open.vi function and specifying the channel names. The reference created by the Open.vi function is then used to read the signals using Read.vi function. The Read.vi outputs a two dimensional array of values read from the respective channels. This array is indexed to give Vata, Pitta, Kapha and ECG signals which are displayed in real time using a waveform window and the signals are stored onto the TDMS file.

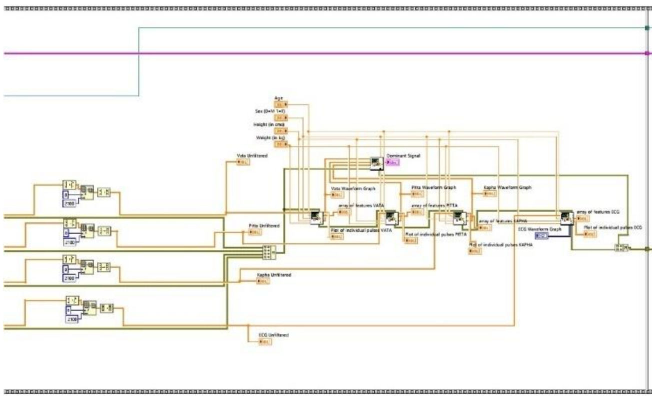

Fig. 7. Block diagram of the main VI designed to process the acquired signals

In the block diagramindicated in figure 7, the signals are given to the sub Vis individually which filter and perform statistical analysis which includes computing the mean, standard deviation, kurtosis, RMS value, median, mode and skewness. Also, the number of cycles, means cycle time and the mean pulse area is computed. A separate sub VI for finding out the dominant signal is also included. In the block diagramindicated in figure 8, the block diagram is terminated by closing the TDMS file and resetting the mtRIO.

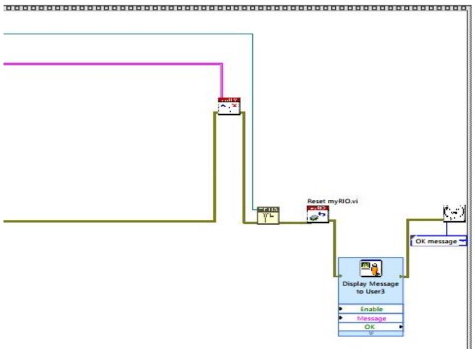

Fig. 8. Block diagram of the main VI showing termination

Filtering and Feature extraction

The signals are filtered by examining their FFT spectrums. The FFT is computed using the equation (1)

$$X_k = \square\square x_n e^{-i2\pi kn/N} \quad k=0 \text{ to } N-1;\ n=o \text{ to } n-1;$$

□□□

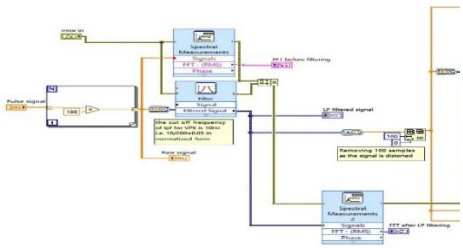

Fig. 9. Block diagram of the filtering and feature extraction subVI showing filtering

In the block diagram indicated in figure 9, the signal is amplified by a factor of 100. Also, the FFT of the signal is calculated before and after filtering. The filtered signal, as well as the FFTs can be viewed by connecting the graphical indicators to the signal outputs.

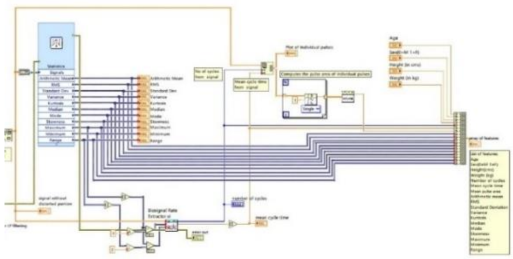

Fig. 10. Block diagram of the filtering and feature extraction subVI showing stastical analysis and feature extraction

In the block diagram indicated in figure 10, statistical analysis is performed on the filtered signal. Parameters such as mean, RMS, standard deviation, variance, kurtosis, median, mode, skewness, maximum, minimum and range along with the number of cycles, mean cycle time, and the mean pulse area are computed and are assembled into an array of features.[7]

Applying machine learning algorithms

Machine learning is a field of study of algorithms and statistical models that computer systems use to perform a specific task without being explicitly programmed, and rather rely on patterns and inferences instead. Machine learning encompasses 3 learning schemes i.e, supervised, unsupervised, and semi-supervised learning algorithms. From a comparison of the learning schemes keeping in mind the medical field, the supervised learning approach proves to be a better choice as the model is developed using train data, collected and evaluated by medical professionals, and given appropriate classifications. The results predicted by supervised learning models are more accurate and trustworthy as compared to unsupervised or semi supervised learning models.

The K-nearest neighbor algorithm

The KNN algorithm is a simple algorithm that stores all available cases and classifies new cases based on similarity measure. A new case is classified based on a majority vote of its neighbors, measured by a distance function given in equation (2).

$$\sqrt{\Sigma(x_i - y_i)^2};\text{i=1 to k} \qquad (2)$$

If K=1, then the case is simply assigned to the class of its nearest neighbor. The accuracy of the predictions increases with the value of K but is also associated with an increase in the computation costs.[8]

Support Vector Machine

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms. It is used for classification as well as regression problems. However, it is best suited for regression. The SVM algorithm creates a decision boundary also called a hyperplane(s) in n-dimensional space, where n refers to the number of input features. This hyperplane(s) segregates the n-dimensional space into classes so that a new data point can be easily assigned to the correct category.[9]

Naïve Bayes

The Naïve Bayes algorithm is a supervised learning algorithm based on Bayes Theorem and is mainly used in classification problems involving text that includes a high-dimensional training dataset. It is one of the most simple and effective classification algorithms. This algorithm is based on the Bayes theorem which is used to determine the probability of a hypothesis based on previous evidence or knowledge. This is also referred to as conditional probability. The formula for Bayes theorem is given in equation (3).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (3)$$

Where P(A|B) is the posterior probability, P(B|A) is the likelihood probability, P(A) is the prior probability and P(B) is the marginal probability.[10]

Results and Discussions

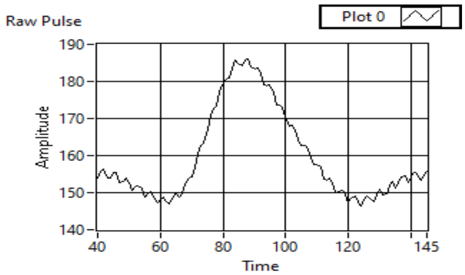

Fig. 11. Noisy waveform of Vata pulse

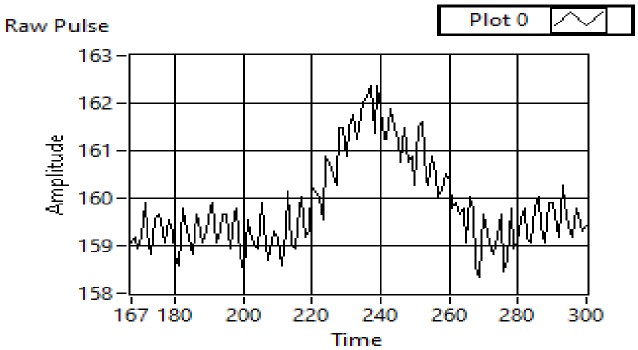

Fig. 12. Noisy waveform of Pitta pulse

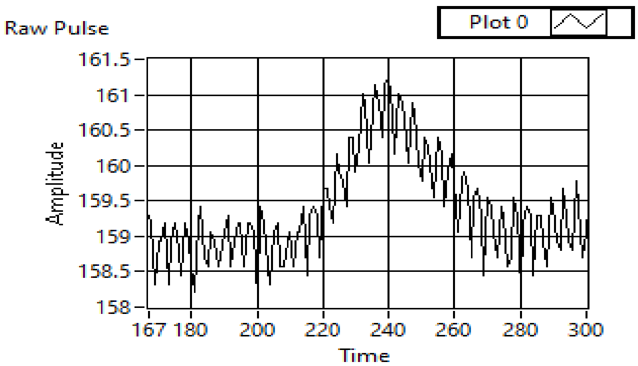

Fig. 13. Noisy waveform of Kapha pulse

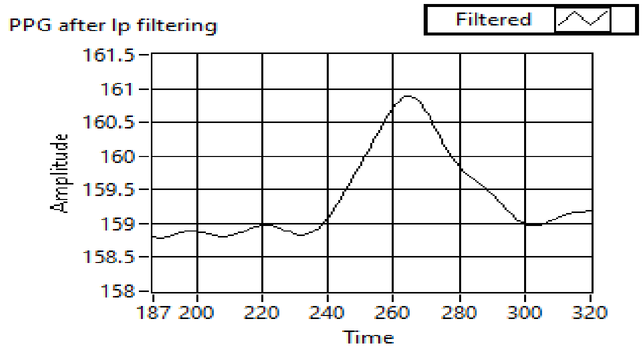

Fig.14. waveform of Kapha pulse. After filtering

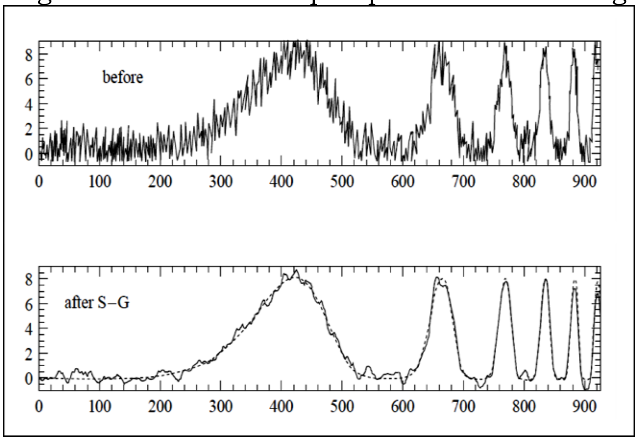

Fig.15. waveform of PPG pulse. After filtering S-G filter

From the FFT plots of Vata, Pitta, and Kapha signals, the dominant frequencies are found to occur in the range of 1 to 6 Hz, hence a low pass Butterworth filter of order 12 with a cut off frequency of 10 Hz was used and smooth signals were observed post filtering as can be seen .[12]. From the FFT plot of the raw PPG signal shown in figure 12, the dominant noise frequency caused by powerline interference was found to occur in the range of 45Hz to 60Hz, which was successfully eliminated by using a Butterworth low pass filter of order 12 with a cut off frequency of 20Hz.[13] The baseline wander, which is a low frequency noise was reduced by using a similar high pass filter with a cut off frequency of 5Hz. A much smoother version of the PPG signal was finally obtained as indicated in figure 13.

Savitzky in addition with Golay proposed a technique for information smoothing in light of neighbourhood least squares polynomial estimate. They appeared that fitting a polynomial to an arrangement of information tests and afterward assessing the subsequent polynomial at a solitary point inside the guess interim is identical to discrete convolution with a settled motivation reaction. The deterioration of a polynomial to $n_L + n_R + 1$ samples around a section of k, then valuing for all k from 1 to M, where M is the degree of the polynomial

$$P(x) = a_0 + a_1(x - x_k) + a_2(x - x_k)^2 + . + a_M(x - x_k)^M \ldots 1$$

The Savitzky-Golay (SG) smoothing and differentiation filter is a well studied simple and efficient technique for noise eliminating problems.[11]

Table 1
Showing the extracted features each from Vata, Pitta, Kapha and ECG signals

Features	Vata	Pitta	Kapha
No of cycles	11	12	12
Mean cycle time	144	133	134
Mean pulse area	22889.1	21113	21200.6
Arithmetic mean	160.221	159.939	159.393
RMS	160.665	159.941	159.395
Standard deviation	11.9359	0.7917	0.6161
Variance	142.466	0.6268	0.3795
Kurtosis	3.40211	3.6073	3.4994
Median	154.758	159.612	159.119
Mode	152.778	159.402	158.954
Skewness	1.2939	1.3357	1.3254
Maximum	194.809	162.319	161.341
Minimum	147.317	158.947	158.644
Range	47.4921	3.3718	2.2.6967

Table 2
Showing the comparison of features for a normal vs diabetic vs heart patient

Features	Normal	Heart	Diabetes
Mean pulse area_Vata	63965	62539.5	60673.75
Arithmetic mean_Vata	250.871	245.229	237.935
RMS_Vata	250.973	245.568	238.087
Standard deviation_Vata	7.195	12.929	8.517
Variance_Vata	51.766	167.169	72.545
Kurtosis_Vata	1.948	2.992	4.912
Median_Vata	247.775	238.021	235.058
Mode_Vata	243.927	236.16	232.043
Skewness_Vata	0.735	1.191	1.756
Maximum_Vata	264.693	275.798	263.065
Minimum_Vata	243.394	233.853	231.247
Range_Vata	21.298	41.946	31.817
Mean pulse area_Pitta	62308.9	63898.2 4	62211.64
Arithmetic mean_Pitta	244.368	250.571	243.952
RMS_Pitta	244.418	250.618	244.013
Standard deviation_Pitta	4.969	4.864	5.456
Variance_Pitta	24.689	23.656	29.773
Kurtosis_Pitta	3.108	3.256	5.694
Median_Pitta	243.053	248.605	242.027
Mode_Pittta	241.152	246.788	240.529
Skewness_Pitta	0.879	1.224	1.9
Maximum_Pitta	265.519	262.283	261.241

Minimum_Pitta	236.165	245.349	239.324
Range_Pitta	20.354	16.935	21.917
Mean pulse area_Kapha	62272.65	64431.47	61784.05
Arithmetic mean_Kapha	244.217	252.667	242.297
RMS_Kapha	244.233	252.754	242.41
Standard deviation_Kapha	2.824	6.667	7.386
Variance_Kapha	7.973	44.448	54.559
Kurtosis_Kapha	2.091	4.108	4.48
Median_Kapha	243.134	249.485	239.894
Mode_Kapha	241.351	249.308	238.391
Skewness_Kapha	0.721	1.547	1.551
Maximum_Kapha	249.81	270.848	263.423
Minimum_Kapha	240.952	246.781	234.146
Range_Kapha	8.858	24.067	29.277

Table 3
Showing accuracy of ml algorithms for the ppg and ecg dataset

ML algorithm	Accuracy for PPG dataset	Accuracy for ECG dataset
KNN	0.8421	0.5466
SVM	0.8421	0.5266
Naïve Bayes	0.6315	0.4733

Conclusion and Future Enhancement

A module development with respect to primeval medical therapy based on wrist throb analysis is implemented which includes the data acquisition from the optical sensors connected to human wrist. A case study of diabetics depiction is done and variation of wrist signals is plotted and compared with normal person wrist signals. Further to have a friendly interaction using LabVIEW we built a Graphical User Interface (GUI) indicating wrist throb signals and mean, maximum amplitudes od individual wrist throb signals and their individual percentage contribution. Finally an electronic instrumentation module to analyze the human health status depending on wrist throb signals is developed. PPG signals provides more detection capabilities for various machine learning algorithms.[14]. The future scope of this work can be to develop a portable module to analyze accurately the human health status depending on three elements of wrist throb signals. Also the project can be enhanced to predict various wide variety of diseases and their intensity of disease.

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