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Design of a Highly Accurate PPG Sensing Interface via Multimodal Ensemble Classification Architecture

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Abstract: Photoplethysmogram (PPG) sensing is a field of signal measurement that involves accurate sensor design and efficient signal processing. Sensing interfaces have matured due to use of sophisticated nano-meter technologies, that allow for high speed, and low error sampling. Thus, in order to improve the efficiency of PPG sensing, the signal processing unit must be tweaked. A wide variety of algorithms have been proposed by researchers that use different classification models for signal conditioning and error reduction. When applied to blood pressure (BP) monitoring, the efficiency of these models is limited by their ability to differentiate between BP levels. In order to improve this efficiency, the underlying text proposes a novel multimodal ensemble classifier. The proposed classifier accumulates correct classification instances from a series of highly efficient classifiers in order to enhance the efficiency of PPG sensing. This efficiency is compared with standard classification models like k-nearest neighbors (kNN), random forest (RF), linear support vector machine (LSVM), multilayer perceptron (MLP), and logistic regression (LR). It is observed that the proposed model is 10% efficient than these models in terms of classification accuracy; and thus, can be used for real time BP monitoring PPG signal acquisition scenarios. This accuracy is estimated by comparing actual BP values with measured BP values, and then evaluating error difference w.r.t. other algorithms.

Index Terms: Blood pressure, PPG, sensing, ensemble, classifier.

1. Introduction

Sensing PPG data from human body is a multidomain signal acquisition and processing task. This task includes design of PPG sensor, capturing this data via a signal acquisition module, processing the captured data & converting them to digital signals, and post processing the converted data. In order to perform these steps a wide variety of instrumentation and signal processing expertise is needed. Design of such a sensor can be observed from figure 1, wherein relative intensity of capture functions is used for sensing signals from human body surface. These signals are given to the following processes for evaluation of PPG based variations,

- The input data captured is passed through a series of narrow band filters, wherein each filter is capable of accurately capturing data of a single frequency band.
- Individual filters are designed for the following wavelengths,
  - Wavelength between 450nm to 550nm
  - Wavelength between 600nm to 650nm
  - Wavelength between 920nm to 970nm
- Each of the wavelengths is decided as per intensity of the incoming signals, for instance, sensors on the corners are designed for minimum amplification; while sensors in the middle are designed for maximum amplification.
- All this data is given to an adaptive filter, wherein internal noise removal is performed.
- The internal noise removal process ensures that the system is free from any kind of vibrations, or harmonics that might occur due to internal processing by filters.

- The filtered signal is given to a signal processing unit, wherein the PPG data is converted into blood pressure values.
- Separate processing models are designed for systolic and diastolic values; and the accuracy of this evaluation is checked.
- If the accuracy is below a given threshold, then the filters and processing unit blocks are tuned; and their internal weights are adjusted for better performance.

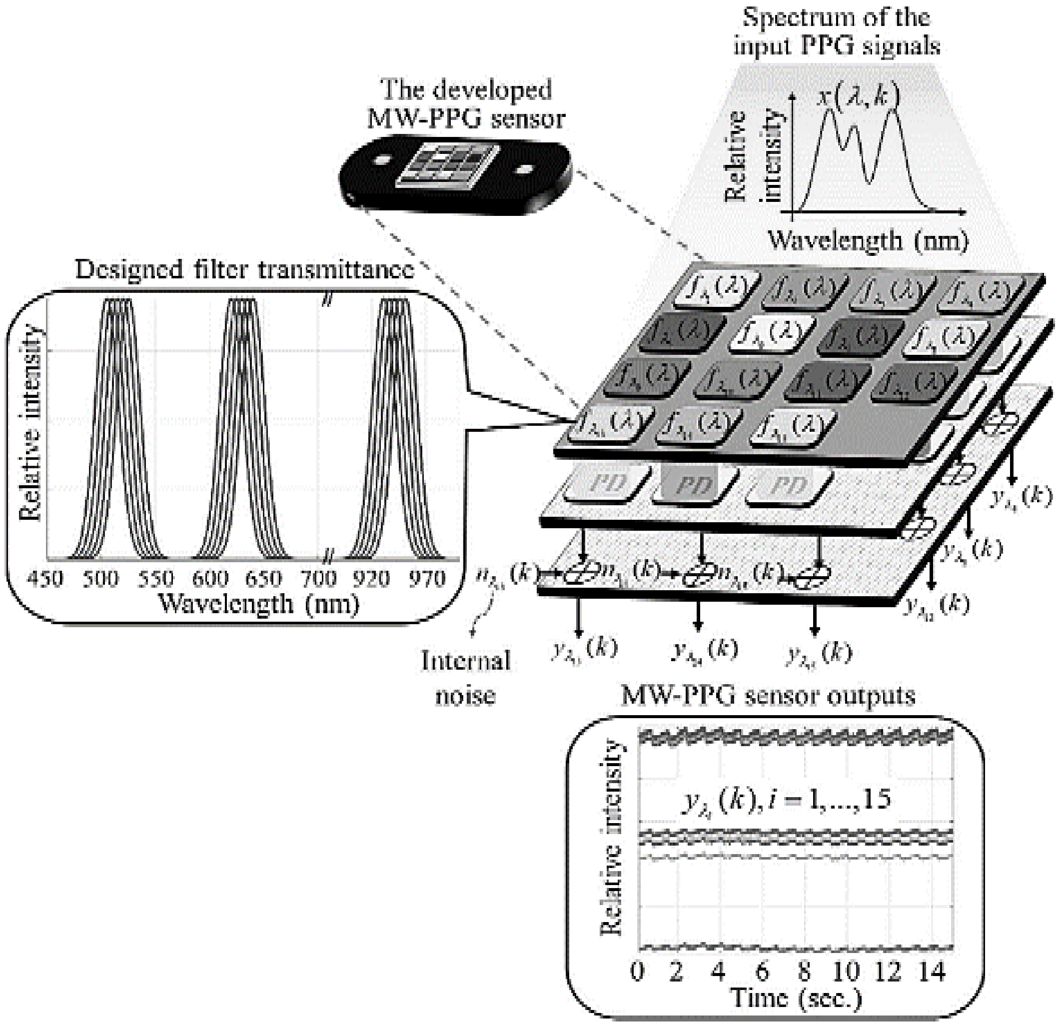

Fig.1. PPG Sensor design with internal processing units

Observing the sensing circuitry in figure 1, majority of noise reduction can be performed via intelligent signal processing. Thus, the main research objective of this text is to design a highly effective classification model that can denoise PPG data in order to improve accuracy of BP sensing. A survey of such PPG systems can be observed from the next section, which indicates that differential BP measurement [4] and CB-PDMS [11] are very effective in terms of accuracy of BP measurement. Moreover, from the survey it is evident that research in the area of sensor design & calibration has saturated, and can be infinitesimally improved. But the design of processing units of [4], [11] and other sensing circuits can be further tweaked in order to improve the accuracy of measurements. The existing accuracy of BP measurement using PPG is below 85%, this is the main limitation of existing sensors. Thus, following the literature survey; design of proposed multimodal, high accuracy, ensemble classification architecture for blood pressure monitoring is described. Design of the proposed classification architecture is the main novelty of this text, which assists in improving effectiveness of blood pressure measurements. This is followed be performance evaluation of the proposed classification model with existing state-of-the-art classifiers, wherein superiority of the proposed architecture can be observed. Finally, this text concludes with some interesting observations about the proposed model and recommends steps to improve it.

2. Literature Survey

Blood pressure measurement sensor setups can be classified into either one-time sensing, or continuous sensing setups. One-time sensing setups are designed to produce moderately accurate single readings via which the current blood-pressure values of the patient can be registered. These values are averaged over 3 different readings, and then presented either on a display device or wirelessly on the user's hand-held device. These sensors are used for home- based devices, wherein approximate blood pressure values are needed. Whereas, the continuous sensing setups are able to continuously monitor the blood pressure from the body with highest possible accuracy. The blood pressure sensed using the continuous monitoring setup is always instantaneous, and is generally used for monitoring blood pressure of hospital admitted patients. The work in [1] discusses a cuffless BP measurement system, which is based on micro-wave near-field communication (muNFC) protocol. The work presents a sensor design which is self- injection locked, and can be connected on the wrist of the user. The sensor is able to measure BP values with a high accuracy of more than 96%, with a standard deviation of less than 10%. The sensor is a combination of self- oscillating complimentary split-ring resonator, which is connected in series with a radio frequency amplifier. The self-oscillating complimentary split-ring resonator is able to capture pulse beats when the sensor is clipped perfectly on the wrist-nerves. These pulse-beats are amplified using the radio frequency amplifier and are later given to an amplitude-based demodulator, which consists of a micro- wave differentiator and an envelope detector. The micro- wave differentiator is able to remove any kind of noise from the pulse readings, while the envelop detector is able to remove any non-required frequency components from the system. The results from the envelop detector are given to a base-band amplifier, where the final amplification of signal takes place. This amplified signal is observed to have perfect pulse transit time (PTT) waveform symmetry when compared to a conventional Photoplethysmogram sensor. A simplified block-diagram of the sensor can be observed from figure 1, wherein a micro-controller unit is able to capture these signals, and send it to a signal processing unit for performing further analysis.

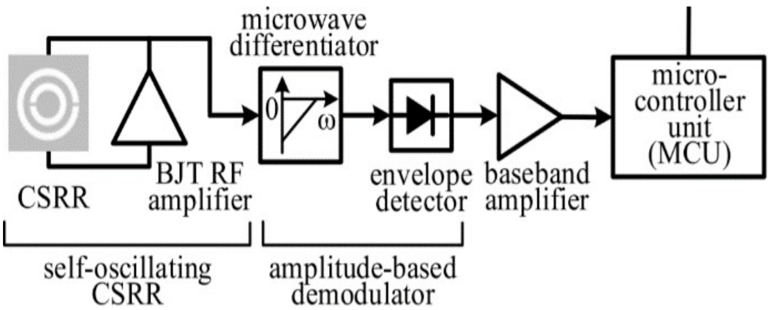

Fig.2. The cuffless BP sensor [1]

Results indicate that the sensor is observed to sense highly accurate continuous BP measurements for patients in the age group of 23 to 48 years, thereby limiting the use-cases of the sensor. It is recommended that this sensor be used for higher age groups, and be optimized for more accurate and faster response. This is done in [2], wherein the Photoplethysmogram (PPG) sensor's contact pressure is combined with the mentioned system in [1]. A combination of 3 sensors is taken in order to find the final BP values. These sensors are, The cuffless sensor mentioned in [1].

- PPG (loadcell-based sensor)
- Electrocardiogram (ECG) nodes

The results of all these sensors are combined together in order to evaluate the final pulse arrival time (PAT) values. These values are an indicative of the blood pressure levels, and are derived from the PTT values. This sensor is also based on continuous monitoring, and can help in reducing the overall measurements by 10%, and the variance to less than 5%. But the usage of this sensor requires manual intervention (pressing the PPG sensor whenever a pulse is incurred by the user), which reduces the accuracy of automatic detection for the system.

Another continuous BP monitoring system is mentioned in [3], wherein data from different sensors (like heart rate, coarse BP values, etc.) are taken from the user, along with the inertial measurement unit (IMU) data. All these data sources are combined and the data is classified into diastolic and systolic calibration values. This classification is done with the help of support vector machine and decision tree- based classification models, and the root mean squared error is evaluated as given in the following formula,

$$RMSE = \sqrt{\sum \frac{(x_{act} - x_{obs})^2}{n}} \tag{1}$$

Where in X_{act} is the actual values of BP, is the observed value of BP and 'n' is the number of readings taken over a period of time. Using these values, the final error is evaluated and it is observed that the final error is less than 10% when compared over a series of readings for the system.

A cuffless measurement system using smartphones is described in [4], wherein the PTT values between two different Photoplethysmogram values is used for estimating the systolic and diastolic BP values. For the purpose of PTT value acquisition, the NeXus-10 MK II kits were used. This is followed by a high pass filter, a smoothing device, a peak detector, PTT calculator, and finally a linear regression model is used in order to find the BPS and BPD (systolic and diastolic) values. A description of the given system can be observed from figure 3, wherein the OMRON10 series sensors are used for data acquisition followed by the given circuit for data cleaning and classification. Results indicate that the error values are reduced to less than 10%, and the standard deviation is reduced to less than 8% when compared to standard BP measurement equipment, thus making the system useful for real-time measurement of BP at home and at hospital premises. The theory behind estimation of BP values from the PTT and PAT values can be studied from [5], wherein 4 different types of models for BP measurement are studied.

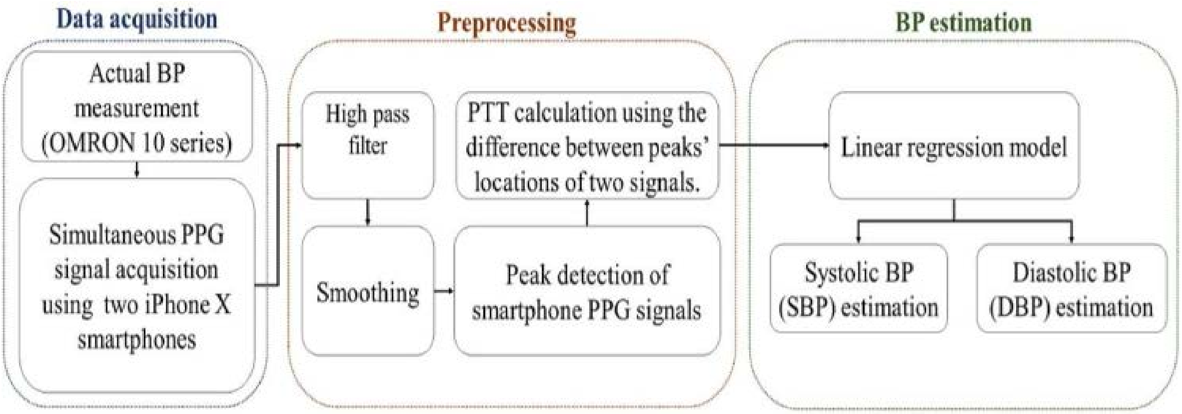

Fig.3. Differential BP measurement [4]

It is observed that the nonlinear MK-EE model outperforms L-MK, MK-BH, and dMK-BH models in terms of error performance and standard deviation performance, and thus should be used for any kind of BP measurement applications. All these models are based on the standard Kalman filter, and are developed using different mathematical modelling techniques. While these techniques provide the best estimation models, the work in [6] is able to demonstrate the fiducial point position which can be utilized for effective BP measurements. The work also suggests the use of Haar wavelet features in order to improve the accuracy of feature extraction of ECG signals for BP detection. They introduce an Adaptive Window Wavelet Transformation (AWWT) method for differentiating ECG values into different BP analysable pulses. Using this method, the overall error rate is reduced to 7%, while the standard deviation is reduced to 8%, which makes the system suitable for real-time application. The work also indicates the use of Tqrs (QRS Complex length), Tst (ST interval), Trr (RR interval), Tpr (PR interval), Tpt (PT interval), Tn1b (DN-EB interval), Tbb (EB-EB interval), Taa (DP-DP interval), Tn2b (SP-EB interval), Tn2n1 (SP- DN interval), Tn2a (SP-DP interval), Tab (EB-DP interval), Tia (duration between i peak and DP), Tin2 (duration between i peak and SP), Tpn (duration between i peak and DN), Tib (duration between i peak and EB), where 'i' is the P, Q, R, S and T peaks of ECG cycle. Using these features the overall accuracy of evaluating BP values can be improved. Another ECG-based sensor which utilizes differential data from 2 thumb sensors is described in [7]. As observed from figure 4, the data from these sensors is given to an instrumentation amplifier, followed by a high pass and a low pass filter. The final output of these units is a differentially amplified ECG-wave which is able to mimic the variations in BP for the patient.

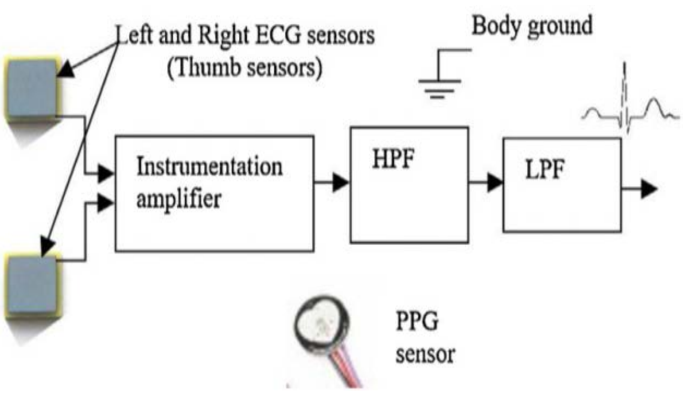

Fig.4. Differential ECG processing [7]

Results indicate that the differential ECG sensor is able to reduce the error rate of measurement to almost less than 8% and the reduction of standard deviation is almost less than 9%. Due to which the accuracy of detection is very high. This work can be super-seeded by with the research done in [8], wherein an Adaboost regression model which uses selected arterial pressure features is studied. This model is able to evaluate signals from radial and ulnar arteries in order to find the value of systolic and diastolic blood pressure. It is observed that the measurement errors are reduced to around 5% with the help of Adaboost regression. Usually, systolic BP measurements have more error than diastolic BP measurements, this can be confirmed from the research in [8].

The work in [9] introduces a portable BP measurement device, wherein a cylindrical and a rectangular shaped sensor design is proposed. Both the sensors are based on the piezoelectric principle and piezoresistive sensing. The testing of the proposed device is done on athletes, and an error rate of less than 5% is observed. For sensing a Foxboro/ ICT Model 1865 pressure sensor is used, in combination with machine learning prediction models to evaluate the value of systolic and diastolic BP. Another Plethysmography sensor for BP measurement is described in [10], wherein BP is estimated using Pulse Transit Time and Impedance. The values from photoplethysmography sensor (PPG values), and impedance plethysmography (IPG) are combined together in order to evaluate PTT values. The observed PTT values are compared with the impedance magnitude in order to find the final blood pressure using the following equation,

$$BP = P_0 + \rho * \frac{D^2}{PPT^2} \ln\left(1 + k\left(Z_0 - Z(t)\right)\right) \quad (2)$$

Wherein, P_0 is the initial PTT, ρ is the conversion constant, D is the pressure value, Z_0 and $Z(t)$ are the initial and current impedances of the system, while 'k' is the impedance constant for the system. Using equation 2, the BP measurement values are found to have an error less than 4%, while the standard deviation is less than 8%. An internal body sensor design is mentioned in [11], wherein flexible strain sensor that uses carbon black (CB) nanoparticles dispersed in polydimethylsiloxane (PDMS) sensor layer is described. It is an intrusive sensor, which needs to be placed on a vascular graft inside the body (as shown in figure 5), and works in tandem with an external measurement antenna.

Due to the internal placement of the sensor, the overall accuracy of detection is improved to around 99%, with an error rate of less than 2%, and standard deviation less than 4%. Due to the intrusive nature of this sensor, it is difficult to use, costly, and can only be applied in hospital environments, that too under the precautionary care of experts. Therefore, it has limited area of application in real- time measurement systems. The performance of non- intrusive systems can also be improved with the help of computational models like compressive sensing (CS), an example of which is described in [12]. Using the CS concept, existing cuffless BP measurement system errors can be reduced to less than 4%, which is a big performance improvement, due to the fact that even a 1% error reduction in systolic values reduces the error by almost 8 points, and for diastolic values it reduces the error by almost 10 points. In order to further enhance this performance, the study in [13] can be referred, wherein different non-intrusive sensor designs are studied and compared. It is observed that machine learning algorithms for estimation of BP values from PPG sensors outperform linear-regression methods, thereby suggesting the use of ML for prediction of BP values.

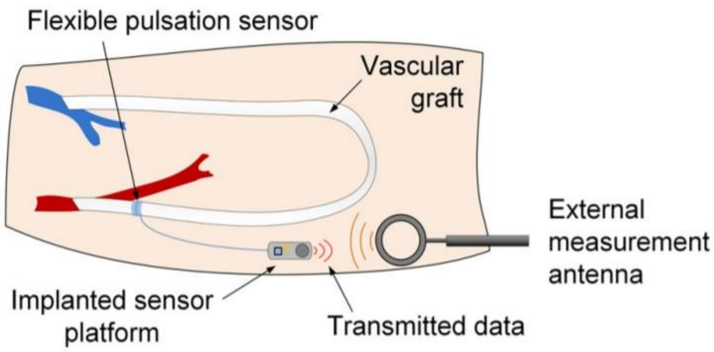

Fig.5. An implanted sensor based on CB-PDMS [11]

Another smartphone enabled sensor design can be observed from [14], wherein facial features are used for blood pressure monitoring. The system uses facial feature patterns in the RGB domain in order to train a convolutional neural network for estimation of BP values. The system can show very coarse values of BP, and can only be used as a hobby tool for estimating BP under perfect light conditions for a limited set of individuals. A micro-electromechanical system (MEMS) based capacitive pressure sensor for BP measurement is described in [15]. Here parameters like deflection of a diaphragm, Young's Modulus of Diaphragm, capacitance developed between two parallel square shaped plates and nonlinear capacitance variation are observed. Based on these parameters, the final BP values are evaluated. It is observed that the capacitive performance of the system is very high, and the sensitivity to blood pressure changes to the sensor output is consistent, due to which the error in BP measurement is reduced to nearly 8% under different real-time conditions. This accuracy can be improved with the help of high-order front-end filters as described in [16]. Using the high-order front-end filter and pulse width modulation dimming (PWM), along with transimpedance amplifiers, regulator, inversion gain amplifier, and programmable gain filter, the overall error in estimation of BP values is reduced to 4%. This is the lowest possible error rate for any cuffless sensor. The overall circuit diagram for the system can be observed from figure 6, wherein different circuit components are described. The system also has an ability to transmit the sensed signals wirelessly, thereby improving the user experience of the sensors, and also making it possible for application in remote sensing environments. The work in [14] is further extended in [17], wherein facial imagery data is converted into PPG values, and the final BP is estimated. The main cause of concern for facial BP measurement systems is the requirement of light-skinned images, with clear view of angle, which limits the application to strictly hobby level. The work uses concepts like region of interest detection, independent component analysis, etc. but is not able to detect BP values with an accuracy of more than 75% to 80%, which is very low for real-time purposes.

The application of continuous blood pressure monitoring can be extended to Ambient Assisted Living (AAL) as described in [18], wherein smartphone-based BP display and action activities are described. These activities assist the patients to have assisted living capabilities, wherein changes in BP levels are monitored by doctors, and based on these changes automatic lifestyle changing steps are prescribed. This claims to improve the long-term health of the patients, and assist them in living a disease-free life. A similar study is described in [19], wherein ambulatory BP measurements are done for intelligent health care. The only difference between the study in [18] and [19], is that in [19] actuator devices are pre-configured and connected to the patient's body. These devices react as soon as long temporal changes are observed in the BP values, and inject the patients with stabilizing medications. This improves the quality of life for the patients, with automatic medications, and reminders to change their personal habits for better life quality. In order to further extend the quality of BP measurement, the work in [20] can be referred, wherein discussions regarding cost, sensor placement, cuffless/cuff-based, smart-phone access, etc. are described. Researchers can use this study to evaluate different areas of analysis for their developed BP measurement device

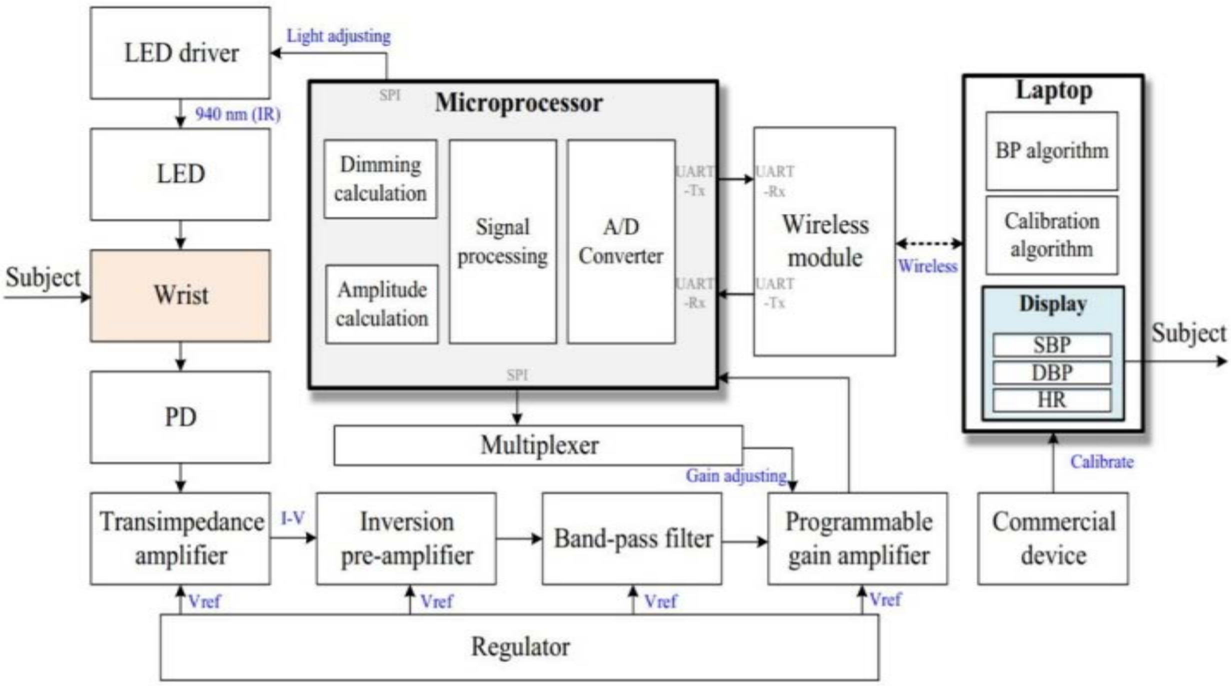

Fig.6. BP measurement using high-order front-end filter [16]

A similar study using chest-based cuffless BP is done in [21], wherein it can be observed that beat -to -beat and three -minute cuff sphygmomanometer readings are found to be most effective for BP measurements. A novel finger print based BP measurement system is described in [22], wherein a small chip is placed on the fingerprint of the patient, and then using similar principals of pressure-variation monitoring, the BP values are estimated. The sensor can be placed on top, middle or bottom of the finger, depending upon the heart beat presence on the patient's finger surface. Once the placement is fixated, the PTT values are evaluated similar to other cuffless measurement systems, and the final BP values are estimated. It is observed that the finger-based sensors are able to reduce the measurement error to less than 10%, but are highly portable, and thereby can be used in any kind of measurement environments. Another novel self-powered pressure sensing sensor that is able to evaluate BP signals from a cuffless arrangement is described in [23], wherein a flexible weaving constructed self-powered pressure sensor (WCSPS) is described. The sensor is able to measure BP with an error of less than 9%, which can be improved with the addition of compressive sensing processing techniques. These sensors require major alignment on the human body, which can be countered with the help of the work done in [24], wherein a Liquid-Capsule Pressure Sensor that is based on alignment free principle. The sensor is developed using a carbon decorated fabric, that interlocks the sensor onto the most effective pressure points on the cuff strapped to the hand. The device is able to reduce the measurement error to almost 8%, with an alignment free arrangement. Such tools are used in [25] to reduce hypertension and improve blood pressure control in patients. These tools are applied to specific geographies like China, and the effects of using these tools are described in [26],[28] wherein it is seen that the overall hypertension level of a selected group of population is reduced by 15%, and more than 50% people prefer cuffless systems over cuff-based systems. These concepts are combined in the work done in [27],[29] wherein a finger-based module for BP detection is described. It can be observed that almost 80% of these devices use the principles of photoplethysmography for improvement in the accuracy of BP detection.[30]

3. Research Methodology

From the literature survey it is evident that design of sensor interfaces has matured enough so that they can be used with high sampling rate, and consume low energy. But the design of signal processing units can be further ameliorated in order to improve overall performance of PPG based sensing devices. In order to perform this text, in this section an ensemble-based multimodal classification architecture is defined. This architecture is able to improve classification of acquired PPG signals into blood pressure values via instance-based analysis.

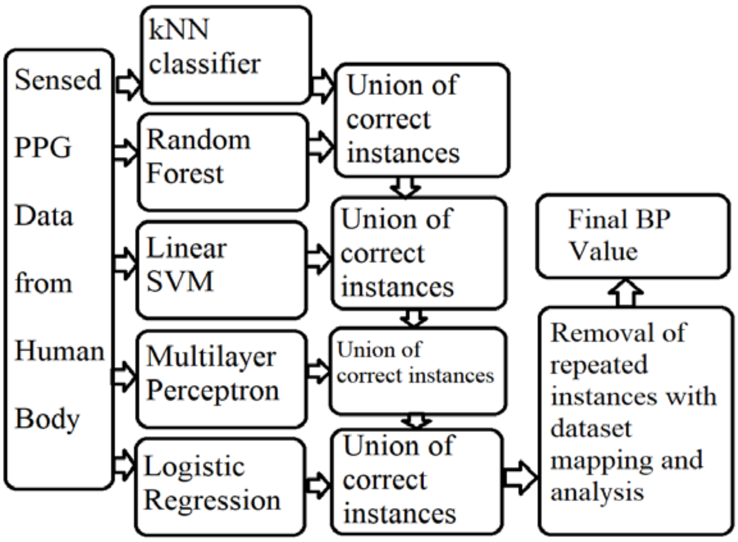

Fig.7. Architecture of the proposed multimodal ensemble classification model

It uses a combination of the following classification models in order to create an ensemble classification engine,

- k-Nearest Neighbors (kNN) for sample-to-sample comparison
- Random Forest Classifier (RF) for stochastic comparison
- Multilayer perceptron (MLP) for pattern analysis
- Logistic Regression (LR) for regression analysis
- Support Vector Machine (SVM) classifier for plane-based analysis

These models are trained using a PPG sensing dataset, which consists of respiratory information, Pleth Variability Index (PVI), voltage sensed from the PPG (V), average variability rate (AVR), and systolic to diastolic peak (II interval) for evaluation of blood pressure (BP) levels. Each of these signals are given to individual classification engines, and their instance results are evaluated. These results are further processed using a parameter tuned multimodal classification engine in order to obtain the final BP values. Architecture for the proposed model can be observed from figure 6, wherein all the classifiers, and ensemble learning process is described.

4. Proposed Model

From the architecture given in figure 6, it can be observed that PPG signals from human body are directly given to each of the classifiers. These classifiers are trained with existing PPG-to-BP mapped data, such that PPG signals are input features, while BP values are output classes. These classes are used in their unquantized state, which makes the classifier design very complex, but improves accuracy of classification. The results from each of these classifiers is given to a union block, which is governed via equation 3,

$$C_{out} = kNN_{out} \cup RF_{out} \cup SVM_{out} \cup MLP_{out} \cup LR_{out} \tag{3}$$

Where, *'out'* indicates class values of each classifier which are correctly classified. These correctly classified values are given to a mapping block, wherein all the duplicate values are removed. Upon removal of duplicates, the final resulting array can be represented using equation 4,

$$C_{final} = Unique(C_{out}) \tag{4}$$

The final classes are then mapped using testing dataset and accuracy values are evaluated. If the accuracy values are low, then internal hyperparameters of individual classifiers are sequentially tuned using the following steps,

- Value of 'k' for kNN is modified using the following equation 5,

$$\begin{gathered} k_{i+1} = k_i + 5; when\ A_{i+1} > A_i \\ else, k_{i+1} = k_i - 3; when\ A_{i+1} < A_i \\ else, k_{i+1} = k_i \end{gathered} \tag{5}$$

- Number of estimators (NE), and depth (D) of Random Forest are modified using equation 6 & 7,

$$\begin{gathered} NE_{i+1} = NE_i * 2; when\ A_{i+1} > A_i \\ else, NE_{i+1} = \frac{NE_i}{1.5}; when\ A_{i+1} < A_i \\ else, NE_{i+1} = NE_i \end{gathered} \tag{6}$$

$$\begin{gathered} D_{i+1} = D_i + 2; when\ A_{i+1} > A_i \\ else, D_{i+1} = D_i - 1; when\ A_{i+1} < A_i \\ else, D_{i+1} = D_i \end{gathered} \tag{7}$$

- Tolerance (T) of SVM is modified using equation 8,

$$\begin{gathered} T_{i+1} = T_i * 2; when\ A_{i+1} > A_i \\ else, T_{i+1} = \frac{T_i}{1.5}; when\ A_{i+1} < A_i \\ else, T_{i+1} = T_i \end{gathered} \tag{8}$$

- Iterations (I) of Logistic Regression are modified using equation 9,

$$\begin{gathered} I_{i+1} = I_i * 10; when\ A_{i+1} > A_i \\ else, I_{i+1} = \frac{I_i}{2}; when\ A_{i+1} < A_i \\ else, I_{i+1} = I_i \end{gathered} \tag{9}$$

Based on these hyperparameter tuning, accuracy of the proposed ensemble model is increased. The tuning steps when accuracy levels of more than threshold are obtained. The process continues for any new dataset values, and tunes ensemble performance. This performance is evaluated in terms of accuracy of classification and is compared with individual classification models. Analysis of this performance can be observed from the next section.

5. Practical Evaluation of the Proposed PPG Interface Model

The proposed model is trained on Beth Israel Deaconess Medical Center (BIDMC) PPG and Respiration Dataset, which consists of PPG data taken from 54 different users. Each of these users are scanned for 480 seconds, and 10 samples per second are stored. Due to machine error, some of these samples are not recognized properly, and are therefore replaced by normal systolic values of 120 beats per minute (bpm). The dataset can be downloaded from, https://physionet.org/content/bidmc/1.0.0/; and is free for research purposes. The model is evaluated on the entire dataset by taking different training and testing ratios. For each combination of training & testing samples, the train accuracy & test accuracy is evaluated. These accuracy values are compared for all the individual algorithms and are tabulated in table 1 (training) & table 2 (testing), wherein different train to test ratios are specified. It is recommended that the model must be trained on at least 60% samples in order to obtain good classification performance, because as the number of training samples increase, the probability of correct classification also increases.

Table 1. Training accuracy of different classifiers

Train: Test Ratio	kNN (%)	RF (%)	SVM (%)	LR (%)	MLP (%)	Proposed (%)
95:05	75.30	86.50	74.30	71.90	62.80	92.50
90:10	74.70	85.81	63.58	50.57	51.01	87.93
85:15	70.20	80.64	60.05	46.32	46.23	81.93
80:20	65.80	75.59	56.40	43.41	43.21	76.79
75:25	63.90	73.40	53.83	41.34	41.07	73.86
70:30	56.40	64.79	49.72	38.36	38.22	66.82
65:35	55.20	63.41	46.51	35.79	35.62	63.86
60:40	50.30	57.78	43.63	33.60	33.44	59.06
55:45	43.50	49.97	38.92	30.15	30.14	52.02
50:50	41.70	47.90	35.57	27.45	27.39	48.61
45:55	40.20	44.20	33.57	25.83	25.70	44.70
40:60	31.40	35.31	29.07	22.63	22.68	38.09
30:70	22.30	24.76	22.18	17.56	17.83	28.25
20:80	10.50	11.75	13.68	11.23	11.68	15.89
10:90	5.30	5.90	7.03	5.96	6.36	8.25

From the training accuracy, it can be observed that the proposed model outperforms all other models by over 8% at most, and 2% at minimum in terms of training accuracy. As the accuracy doesn't reach 100%, it indicates that model is not overfitting on the training samples. The performance of testing accuracy can be observed from table 2, wherein real-time evaluation capability of the models can be sees.

Table 2. Testing accuracy of different classifiers

Train: Test Ratio	kNN (%)	RF (%)	SVM (%)	LR (%)	MLP (%)	Proposed (%)
95:05	43.03	45.54	44.39	47.60	47.47	62.33
90:10	42.69	45.18	42.15	43.09	44.43	59.41
85:15	40.11	42.46	39.67	40.29	41.52	55.64
80:20	37.60	39.80	37.20	37.77	38.91	52.16
75:25	36.51	38.65	35.95	36.49	37.60	50.42
70:30	32.23	34.11	32.14	32.65	33.61	45.03
65:35	31.54	33.39	31.06	31.54	32.50	43.57
60:40	28.74	30.42	28.53	28.97	29.84	39.99
55:45	24.86	26.31	24.90	25.31	26.05	34.88
50:50	23.83	25.22	23.54	23.92	24.65	33.03
45:55	22.97	23.76	22.37	22.72	23.41	31.17
40:60	17.94	18.78	18.08	18.39	18.92	25.30
30:70	12.74	13.25	13.10	13.37	13.74	18.32
20:80	6.00	6.26	6.78	6.98	7.15	9.46
10:90	3.03	3.15	3.44	3.58	3.68	4.84

From the testing accuracy it can be observed that the proposed model is able to achieve 15% better performance than state-of-the art classification models; which makes it suitable for further analysis and usage. The testing accuracy can be further improved via use of better classification models like convolutional neural networks (CNNs), recurrent neural networks (RNN), etc.

6. Experimental Validation

In order to validate performance of the proposed PPG classification engine, the following experiment was performed,

- The PPG data taken from Physionet was given to different classification models as suggested in [4] and [11]
- Results of these models in terms of final BP values were estimated
- Error values were estimated for over 1000 patients, and error percentages were evaluated using equation 10 as follows,

$$E_{rr}(\%) = 100 * \frac{BP_{actual} - BP_{measured}}{BP_{actual}} \quad (10)$$

- These error percentages are tabulated in table 3, wherein number of patients, and the respective error percentage is shown,

Table. 3. Error in BP measurement for different algorithms

Num Patients	Err (%) [4]	Err (%) [11]	Err (%) [Proposed]
100	6.97	4.46	1.61
200	7.31	4.82	3.85
300	9.89	7.54	2.73
400	12.40	10.20	3.29
450	13.49	11.35	3.01
500	17.77	15.89	3.15
550	11.31	16.61	3.08
600	12.03	11.07	3.12
700	12.81	12.11	3.10
750	13.30	12.87	3.11
800	13.45	13.32	3.10
850	13.44	13.64	3.10
900	12.72	13.27	3.10
950	12.96	12.71	3.10
1000	13.12	12.99	3.10

From the error values observed in this experiment, it is evident that the proposed model outperforms other BP measurement systems by over 10%, thereby making it highly useful for clinical purposes. This can also be observed from the accuracy graph as indicated in figure 8, wherein an average accuracy improvement of 8% is observed. Doctors and other nursing staff can easily use this model for high accuracy and high efficiency BP measurement.

7. Conclusion & Future Scope

Use of singular classification models for obtaining PPG based blood pressure results into low testing accuracy. This is due to the fact that these models have limited training & pattern recognition capabilities when large datasets are used. In order to improve this accuracy, the underlying work defines a multimodal ensemble classification engine that can enhance accuracy of blood pressure classification via combining unique & correctly classified instances from the input dataset.

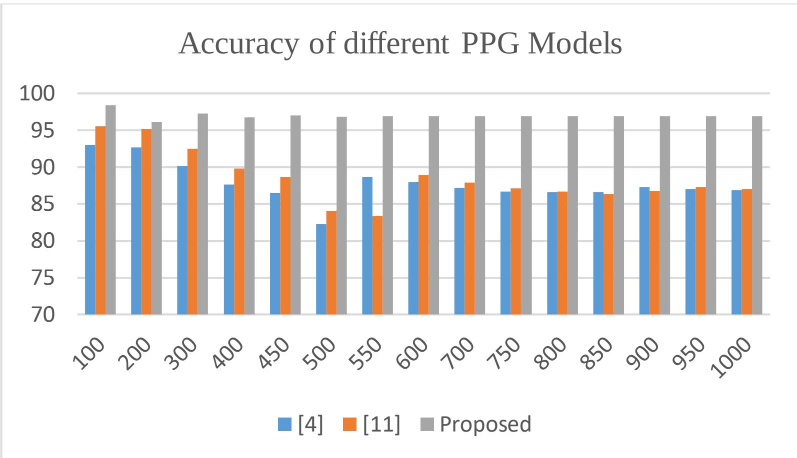

Fig.8. Accuracy of different PPG Models.

It is observed that the proposed model demonstrates 5% improvement in training accuracy, and 15% improvement in testing accuracy for various training to testing set ratios. The main reason for this accuracy improvement is use of multiple verification engines, and then combining their performance for highly accurate BP measurement. The main uses of this model are in clinical and critical BP measurement systems, where the number of sources for verification are limited. Future experiments can include real time patient monitoring, institute-level monitoring & validation of BP, etc. This accuracy performance can be further improved via use of deep learning models, and combining their architectures in order to have better pattern analysis capabilities. Moreover, this work can be extended by addition of larger and more complex PPG datasets, such that its clinical performance can be evaluated.

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