The IoT based PPG Signal Classification System for Acute Audio-Visual Stimulus Induced Stress

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Abstract

Mental stress causes a great impact on our autonomic nervous system. Pulse rate variability (PRV) is a method which measures the changes in the autonomic nervous system of an individual. This study aims to acquire PPG signals in real time from a single spot Pulse sensor and then PRV analysis is performed on Pulse signal to determine perceived stress from the subject caused due to nerve-wracking audio-visual stimulus. PPG signal is then transferred wirelessly over an Android app. Also this work incorporates several Machine Learning models to organize the stress level of the subjects as average stress or high stress. Non-linear model gives best average classification precision, sensitivity and specificity of 90%, 100% and 82% respectively. With the advancement of portable PPG monitoring device acts as a substitute to Heart rate variability (HRV) even during the moving conditions. Also PPG signal is compared with ECG signal and a close precision is obtained with average percentage error of 8% for BPM and 3% for RR interval. PPG sensors offer more comfortness to the users which can be positioned on fingertip and wrist. By means of the improvement of android app provides feasibility to monitor stress by providing an alert to the mobile users whenever the stress exceeds the normal limits.

Keywords

Audio-Visual Stimulus, Autonomic Nervous System, Heart Rate Variability, Photoplethysmography, Pulse Rate Variability.

Introduction

The Excessive mental pressure is allied to numerous health problems, for example, nervousness, depression disorders, heart disease, cancer and infectious illnesses. Perceived stress is one of the outcomes that can be caused due to nerve-wracking audio-visual stimulus. A number of parameters like blood pressure, pulse rate variability and electroencephalograph, among others have been found sensitive towards any changes occurring in psychological stress level. Pulse rate variability (PRV) is a very reliable display of stress, it is used to measure the changes in the autonomic nervous system of an individual and it measures fluctuation in the time interval of Pulse signal. PRV can be used as an alternative to HRV which offers more comfortness to the user as the sensor can be placed on wrist and fingertip. Also PRV can be monitored even during moving conditions. The primary method of deriving the PRV is to acquire the Photoplethysmography (PPG) signal. Photoplethysmography (PPG) is a cost effective photosensitive method used in estimating Pulse Rate Variability. To assess the influence of nerve-wracking stimulus on individuals a PPG monitoring system is designed. Here, PPG signal is acquired, PRV parameters are calculated and experiments are conducted in sequences to find the variation in time, frequency and geometric domain of PRV parameters under nerve-wracking stimulus state as compared to normal circumstances.

Literature Survey

Photoplethysmography finds various uses in medical devices and clinical set up. It is observed the heart rate by incorporating a wireless device which works on PPG technique. With the advancement of Android app the PPG signal was displayed on smart devices. By using Matlab program the peak R-R interval was noticed. The HRV analysis report will be generated by Kubios software with the PPG signal peaks fed to it (Mohammad Ghamari et al., 2016).

If psychological stress can be detected effectively in daily life, then stress management can be done well. Some researchers have described an alternate method to heart rate variability (HRV) (R. Logier et al., 2018 and Alexandru Constantin Podaru et al., 2021). The correlation between the two parameters are identified as 0.96. PRV parameters based on ECG signals are computed and it is observed that SDNN values more than 50 is referred as abnormal stress. RMSSD more than 10 denotes abnormal stress. SD2 is measured as the non-linear analysis parameter, SD2 value more than 64 are measured to be tensed (Arun Kumar M et al., 2016).

Literature describes how HRV (Heart Rate Variability) can be used for detecting daily mental stress levels. In their research work, PPG signals are used for estimating HRV. The artifacts are removed using the Hierarchical bandpass filter of 3 levels. J. Park et al. applied spectral domain analysis to HRV data to evaluate a anxiety level by using AR method (J. Park et al., 2017 and Yaru Yue et al., 2021)

In a study on assessment of stress, a variety of PPG characteristics using mathematical model of pulse wave transmission is utilized. PPG waves obtained from three potential simulation measurement sites are used to extract PPG features. Mann–Kendall monotonic trend test is used to identify the PPG features which are suggestive to mental stress (Peter Charlton et al., 2018)

The six stress levels are used for analysis instead of six simulations. The quantitative parameters are investigated between PRV and HRV in long-term pain patients in the experimental setting (Jing-Jhao Ye et al., 2015). R-waves of ECG signal are documented from an Ag/AgCl electrode and a T-type rejection filter of 60 Hz frequency is used to process the signal, the amplified gain was 1000. The Pulse detected by Pulse sensor is processed by a second-order Butterworth filter and using DAQ device the ECG and Pulse signals are linked and then transferred to a personal computer for recording. It has been shown how sensitive states caused by disturbing sounds can be efficiently documented through the evaluations of Autonomic Nervous System (ANS) dynamics. In this study, the affective sounds are used to detect emotions by the Russel's Circumflex model. In this model, each emotion defines as linear combinations of valence and arousal, the affective dimensions. With the continuum of pleasantness-unpleasantness, arousal dimension describes intensity of the emotion, while the valence dimension gives a measure of how positive or negative the subject is due to an emotion. With this study, the peripheral physiological measures allow to distinguish emotions due to variation of the ANS dynamics on the cardiac control areas in the nervous system of cardio vascular (Mimma Nardelli et al., 2021). Researchers have presented three different types for HRV - Time domain, Spectral, Geometrical. The proposed methods are more easy, reasonable and robust to compute HRV, and can also be analyze short RR sequences with artifacts and missing values (Marcus Vollmer et. Al., 2015).

Methodology

The objective of this research work is to study Pulse rate variability (PRV) which can judge the fluctuations in the autonomic nervous system of an individual. The primary method of deriving the PRV is to acquire the Photoplethysmography (PPG) signal. The overview of PPG acquisition, analysis and wireless transmission is shown in figure 1.

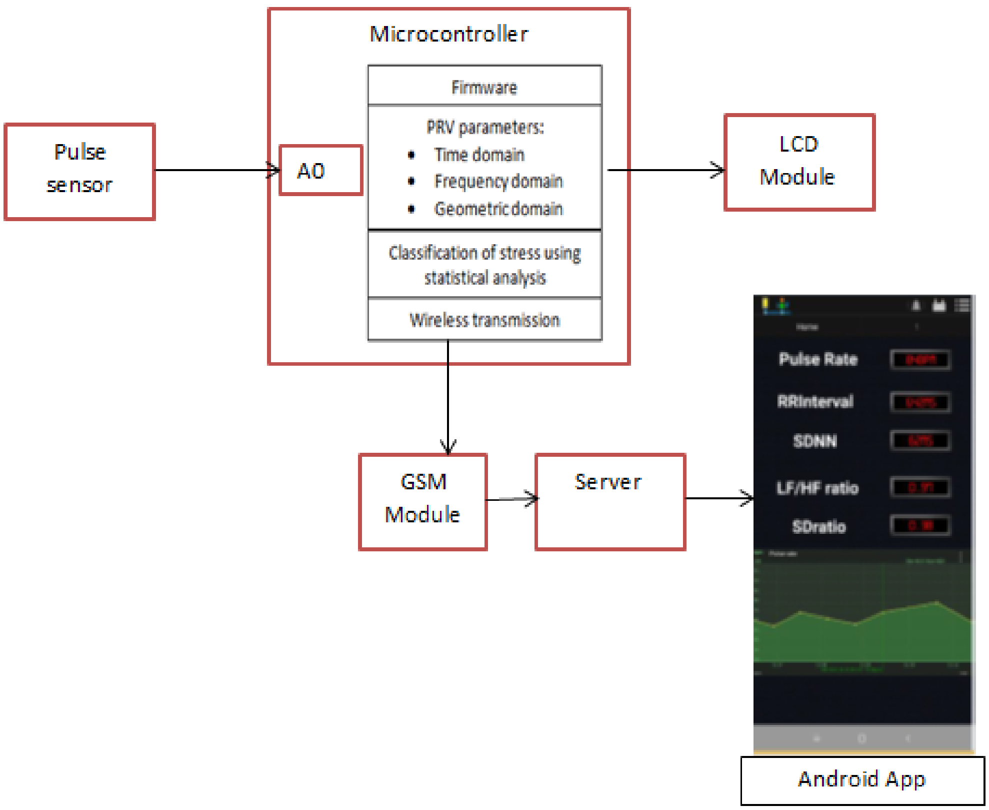


Figure 1 Photoplethysmography monitoring set up

The acquired pulse signal is validated with ECG signals to confirm that PPG monitoring device can be used as a substitute measuring tool for Heart rate variability (HRV). With the approval of Ethics Committee 35 subjects, apparently healthy males and females, aged from 18 to 24, took part in this study. Before the experiment general information about age, gender, height and weight of the subject was considered. Then PPG signal was procured using Pulse sensor. Later PPG signal and ECG signal are simultaneously monitored over a period of 30 minutes. A close accuracy was achieved between ECG and PPG signal with mean percentage error of 8% for BPM and 3% for RR Interval in contrast with ECG signal. This validation was performed for 10 subjects in Ramaiah Medical College, Bangalore. Also with various statistical models data is classified as normal or high stress depending on the PRV parameters dataset. The Photoplethysmography monitoring set up is shown in figure 1 consists of Pulse signal procurement unit and presentation unit.

Pulse Signal Procurement Unit

From figure 1 PPG signal is obtained by connecting pulse sensor to analog pin of the microcontroller. Pulse sensor converts analog to digital signal with built-in analog to digital converter. Once the pulse signal is procured, PRV analysis is performed in time, spectral and geometric domain to categorize the stress level as average or high stress. These constraints are transferred wirelessly to SIM800C module and the real time data is then transmitted to the server.

Display Unit

ThingSpeak server retrieves the parameter received from SIM800C module and ensures the ability to show the parameters in real time. The PRV parameters are then visualized using android app in real time.

PRV Parameters

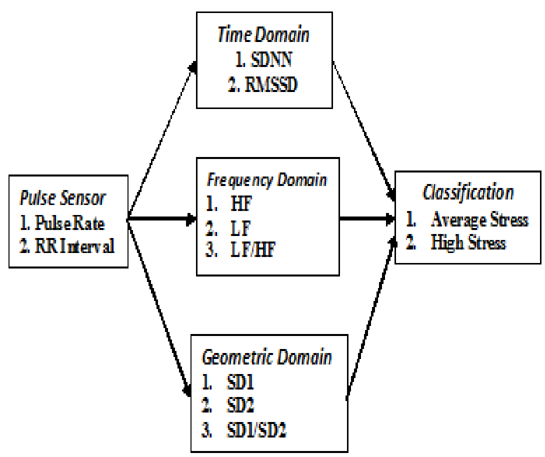


Figure 2 PRV analysis and classification

Time interval between two consecutive signal cycles of PPG signal is termed as RR Interval. Frequency domain, Geometric domain and Time-domain parameters computed from RR Interval as shown in figure 2. The stress is categorized as average or high stress by comparing the parameter readings with the standard values.

Computation of RMSSD and SDNN is done for time domain analysis. The evaluation of complete PRV and noticing the capability of the heart that responds towards stress is determined by SDNN. Below 20ms is a sign of long-lasting stress associated disease. Calculation of SDNN is shown in equation 1:

$$SDNN = \sqrt{\frac{1}{\mathrm{n}-1}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{RR_i} - \overline{\mathrm{RR}})^2} \tag{1}$$

RMSSD gives evaluation of periodic deviations in pulse rate present in RR readings. If RMSSD decreases less than 10ms, it is an indication of heart related disease. Calculation of RMSSD is shown in equation 2:

$$\mathrm{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{2}$$

LF/HF ratio gives frequency domain analysis and it measures the complete stability among sympathetic and parasympathetic systems. LF is seen to be from 0.04 to 0.15Hz while HF is seen to be from 0.15 to 0.40Hz. Calculations are done as shown in equation 3:

$$\frac{LF}{HF} = \frac{\int_{0.04}^{0.15} f(\lambda)d\lambda}{\int_{0.15}^{0.40} f(\lambda)\, d\lambda} \tag{3}$$

Geometric domain analysis is performed by calculating the ratio of SD2 and SD1 as shown in the equations 4 to equation 7:

$$SD_1 = \sqrt{Var(x_1)} \tag{4}$$

$$SD_2 = \sqrt{Var(x_2)} \tag{5}$$

Statistical Analysis

Tabulation of PRV parameters is done for all the participants when no nerve-wracking stimulus is given and this is considered as the values under normal condition. Similarly, PRV parameters are tabulated when the subject is shown the audio-visual clip for each of the 35 subjects. Also, for every subject, the time required for the PRV values during the audio-visual stimulus, to come back to their normal value is noted down. These observations are analyzed using statistical techniques such as regression, non-linear modelling and correlation. Seven variables ‘p’, ‘q’, ‘r’, ‘s’, ‘t’, ‘u’ and ‘v’ considered are pulse rate, RR interval, SDNN, RMSSD, LF/HF, SD2/SD1 and recovery time respectively. The samples considered for training and testing were in 70:30 ratio. Hence fourteen out of twenty average stress subjects were considered for training while the remaining six were used for testing. Similarly, out of fifteen high stress subjects, eleven were used for training and four were used for testing.

Nonlinear Modelling

The second method used for classification is a nonlinear model. The data are fitted by a method of successive approximations. After trial and error a nonlinear model of the type given in equation 6 was found to best fit the data.

$$Y = e^{B0} X_1^{\ B1} X_2^{\ B2} \qquad (6)$$

The model was trained with 20 data points and the remaining 15 were used as training input. An accuracy of 87%, sensitivity of 89% and specificity of 83% was obtained as shown in Table 1 by the confusion matrix [7]. This was repeated by changing the training data to 25 and test data to 10, as in Table 2. The accuracy was found to increase to 90%, sensitivity increased to 100% and specificity remained at 83%. It can be said that the obtained model is at least 83% specific, sensitive and accurate, and with increase in training data the accuracy improves. The best fit non-linear curve was found to be as in equation

$$y = \frac{19.5016 r^{1.05367} u^{0.172125}}{p^{0.0409398} q^{0.254762} s^{0.53331} t^{4.53724} v^{0.547898}} \qquad (7)$$

Parameters p, q, r, s, t, u and v represent the same values as in the case of regression.

Table 1 Confusion matrix before stimulus (20:15 ratio)

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	8	1
	High Stress	1	5

Table 2 Confusion matrix before stimulus (25:10 ratio)

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	5	1
	High Stress	0	4

During the stimulus the computed parameters, with the same test input to training input ratio, showed an accuracy, specificity and sensitivity of 90%,100% and 80% respectively, as calculated from confusion matrix of Table 3.

Table 3 Confusion matrix during stimulus

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	5	0
	High Stress	1	4

Regression

Our linear regression model when obtained for seven parameters yielded an accuracy of 80%, by considering six average stress subjects and four high stress subjects during testing. Sensitivity and Specificity were 83% and 75%respectively. Confusion matrix is shown in Table 4. The best fit curve for the training data was found to be as in equation 8.

$$Y = 109.87 - 0.21p - 0.021q + 0.23r - 0.17s - 60.4t + u - 2.4v \quad (8)$$

Where p, q, r, s, t, u and v represent the parameters as stated above and the coefficients are represented by column vector ‘b’. Y is the output binary quantity used to depict the two stress classes.

Table 4 Confusion matrix before stimulus.

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	5	1
	High Stress	1	3

Similarly a regression model was obtained for the parameters during the stimulus period. Accuracy, sensitivity and specificity were 91%, 100% and 75% respectively, as calculated from the confusion matrix of Table 5.

Where p, q, r, s, t, u and v represent the parameters as stated above and the coefficients are represented by column vector ‘b’. Y is the output binary quantity used to depict the two stress classes.

Table 5 Confusion matrix during stimulus

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	6	1
	High Stress	0	3

Correlation

The Spearman correlation among two variables, as depicted in equation 15, is equivalent to the Pearson correlation among the rank values of those two variables; while Spearman's correlation judges monotonic relations (whether linear or not), Pearson's correlation judges linear relationships [6].

Table 6 Correlation Coefficient values in Average Stress and High Stress subjects

	Correlation value	
Parameter	Average Stress	High Stress
Pulse Rate	0.8217	0.8363
RR Interval	0.468	0.9418
SDNN	0.713	0.8135
RMSSD	0.5041	0.9054
LF/HF	0.1041	0.1587
SD2/SD1	-0.069	-0.061

We examine the correlation between the respective parameters of the set of subjects categorized as having average stress before and after giving the audio visual stimulus. Similarly, the correlation between respective parameters for subjects categorized as having high stress is computed (Table 6). Before the stimulus the computed parameters, with the same test input to training input ratio, showed an accuracy, specificity and sensitivity of 80%,80% and 75% respectively (Table 7).

Table 7 Confusion matrix before stimulus (25:10 ratio)

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	5	1
	High Stress	1	3

During the stimulus the computed parameters, with the same test input to training input ratio, showed a decreased accuracy, specificity and sensitivity of 70%,80% and 60% respectively (Table 8).

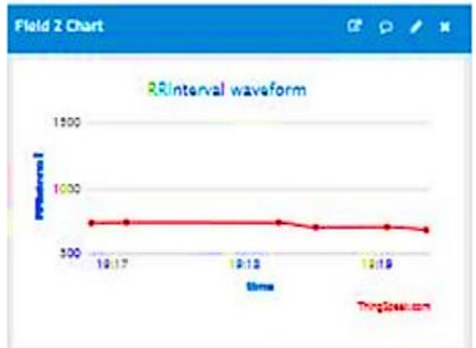
Table 8 Confusion matrix during stimulus

		Predicted	
		Average Stress	High Stress
Actual	Average Stress	4	2
	High Stress	1	3

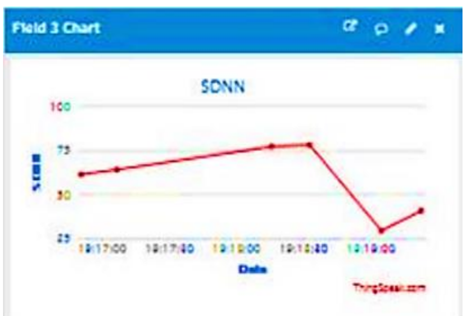
Results and Discussion

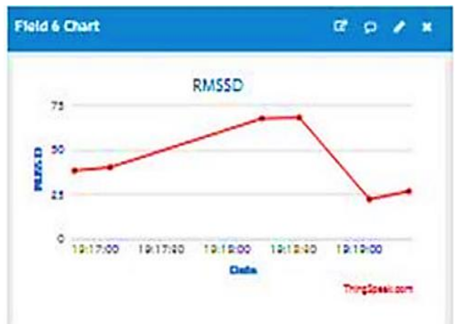
Server Output

The PRV parameters are retrieved from GSM module onto the server in real time. Thing speak server has the capability to display upto 8 field values. In this work 6 fields are used to display PRV parameter values.

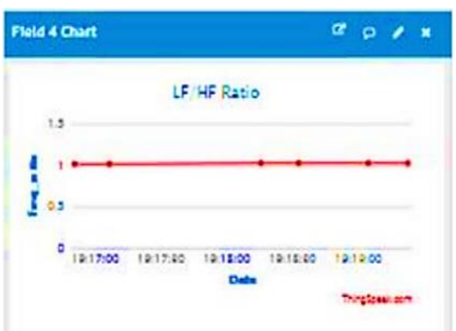


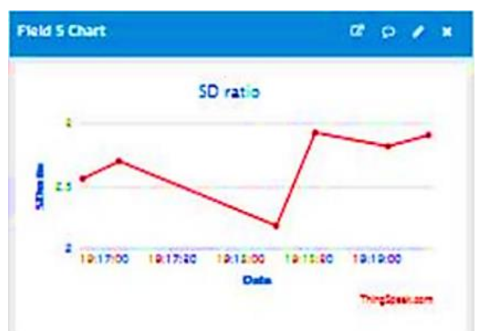
(a) Pulse Rate **b) RR Interval**





c)SDNN **d) RMSSD values**





e) LF/HF ratio **f) $SD2$ /$SD1$ ratio**

Figure 3 Display of waveforms in ThingSpeak Server

Field 1indicates the pulse rate waveform as shown in figure 3a. For every 15 seconds the data will be updated in the server based on strong internet connectivity. From the figure it is clear the pulse rate is within 70-75 BPM. Field 2 is an indication of RR Interval waveform. All the samples from the graph is within 500-1000 ms. This indicates that there is increase in PRV which is an indication of healthy condition as shown in figure 3b .Field 3 indicates SDNN waveform computed from RR Interval as shown in figure 3c . We can observe that first few samples are above 50-75 ms and only one sample is dropped to 25 ms. So overall it is an indication of normal condition. Field 4 indicates LF/HF Ratio waveform computed from RR Interval as shown in figure 3d. We can observe that all the samples are within 1 to 1.05. As the samples are within the standard range so it indicates normal healthy condition. Field 5 indicates SD2 /SD1 ratio waveform as shown in figure 3e. We can observe that the samples are within 2 to 2.9As it is in the standard range so it indicates normal condition. Field 6 indicates RMSSD waveform computed from RR Interval as shown in figure 3f. We can observe that the samples are within 25 to 75. These samples are within the normal range which is a sign of healthy condition. By connecting the android app with Thingspeak server the PRV parameters are displayed along with pulse rate waveform as shown in figure 4.

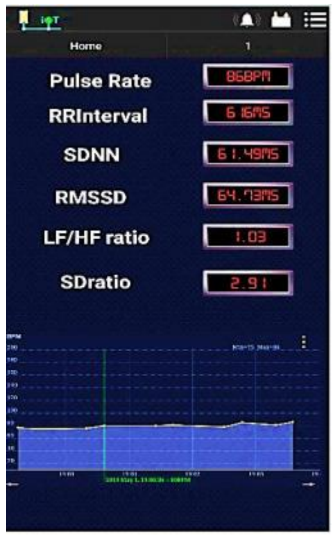


Figure 4 Demonstration of PRV parameters in Android app

Verification of PPG with ECG Signal

PPG signal obtained from pulse sensor is verified by comparing with ECG signal. ECG signal analysis is accomplished using RMS Vagus Software^{TM}. PPG signal analysis is accomplished using Arduino software. PPG and ECG readings were noted simultaneously for a duration of 5 min from the subject. A close precision is achieved with average percentage error of 8% for BPM and 3% for RR interval when matched with that of ECG signal as indicated in Table 9.

Table 9 Verification of PPG signal

Parameters	Computed from PPG (mean ± SD)	Computed from ECG (mean ± SD)
BPM	82.6 ± 3.43	89 ± 5.43
RR Interval (ms)	642 ± 35.18	677.28 ± 35.91
SDNN (ms)	38.55 ± 9.97	37.70 ± 6.61
RMSSD (ms)	26.98 ± 8.61	20.36 ± 6.62
LF/HF ratio	0.97 ± 0.005	2.19 ± 1.48
SD2/SD1 ratio	2.69 ± 0.49	3.72 ± 0.73

Assessment of Stress Levels during Pre Stimulus and Post Stimulus Conditions

On application of a nerve-wracking stimulus, SD2 and SD1 ratio was seen to be considerably increased while RMSSD, mean RR interval and SDNN were lowered considerably in comparison with normal condition. Table 10 indicates that there were no major changes in the LF/HF ratio. A major reduction in RMDDS, RR interval and SDNN values with an increase in SD1/SD2 ratio is seen due to the excitation of sympathetic system by the applied stimulus. During usual conditions, the sympathetic activity is low and effects in higher value of RR interval. But, during the application of stimulus, sympathetic activity becomes more and results in higher value of RR interval.

The lowering of RMSSD as well as SDNN during applied stimulus replicates a reduction in total pulse rate variability (PRV) and it is an indicator of effect of long-lasting pressure. Under ordinary circumstances, with increase in the values of RMSSD and SDNN, there is increase in PRV. Similarly, the substantial rise in SD2/SD1 ratio on application of nerve-wracking stimulus results in boosting of sympathetic activity with the result of increase in stress level while under ordinary circumstances it indicates a boost in parasympathetic activity.

Table 10 Mean values of PRV parameters for 35 subjects

Parameters	Under Normal Circumstances (Mean ± SD)	Due to Stimulus (Mean ± SD)	Ground Truth
RR Interval	724.26 ± 94.53	715.33 ± 99.65	Perceived Stress Scale (PSS) Questionnaire
RMSSD	49.55 ± 14.55	35.44 ± 10.85	
SDNN	57.24 ± 9.62	42.16 ± 9.44	
SD2/SD1 ratio	2.36 ± 0.47	2.60 ± 0.42	
LF/HF ratio	1.03 ± 0.016	1.04 ± 0.017	

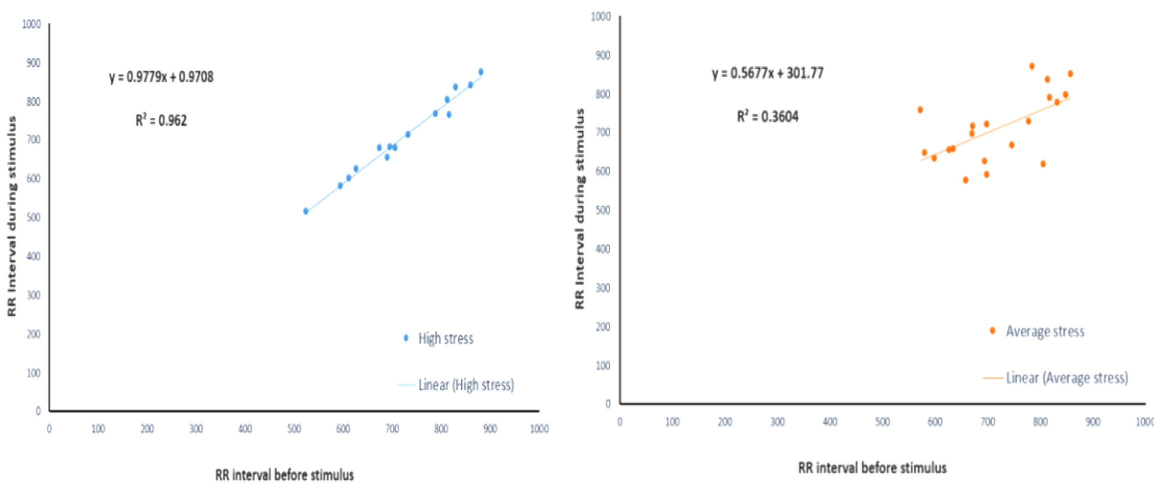
Hence, in the presence of stimulus, there is reduction of SDNN and RMSSD parameters and escalation in SD1 and SD2 parameters which is a sign of presence of psychological stress due to nerve-wracking stimulus and this is validated by PSS questionnaire. From PSS questionnaire, the stress levels are graded as follows: if the computed score level is in the range 13-19, it is categorized as normal stress level, if the score is more than 20 then it is categorized as greater stress level. From Table 10, it can be observed that after applying the stimulus, the individual having high stress level needs extra time to recover to the normal state.

Statistical Analysis Results

The analysis of results is done by the use of correlation in diagnosis, non-linear modelling and regression, and finally with general trends.

Use of Correlation in Diagnosis

Figure 5 depicts the plot for RR interval readings of average stress subjects with the initial readings on the X-axis and the readings during the stimulus on the Y-axis. The correlation coefficient for this is computed from Table 11 and is found to be 0.468. This value for high stress subjects as seen in Table 10 more than doubles to 0.9418. It drives to the conclusion that there is almost a linear relationship in the RR interval readings for high stress subjects before and during the stimulus period.



a) High Stress **b) Average Stress**

Figure 5 Depiction of variation of RR interval using the statistical model

With the current readings of RR interval, it is possible to estimate a straight line (Figure 10a) and interpolate new test readings of subjects in the normal condition, without having to give the audio visual stimulus. Indeed, if the interpolated value does not lie within the maximum residual of this linear curve, it is most likely that the subject belongs to the average stress category. The R-squared value of 0.36 as shown in Figure 10b, is highly dichotomous to the R-squared value of 0.962 attributed to figure 10a and the equations of both these lines of best fit is shown.

Table 11 Correlation Coefficient values in Average Stress and High Stress subjects

	Correlation	
Parameter	Average Stress	High Stress
Pulse Rate	0.8217	0.8363
RR Interval	0.468	0.9418
SDNN	0.713	0.8135
RMSSD	0.5041	0.9054
LF/HF	0.1041	0.1587
SD2/SD1	-0.069	-0.061

On superimposition of both the plots it was found that two out of twenty data points from the average stress category fell within the maximum residual of Figure 10a, hence yielding an accuracy of 90%. Similarly, there is a significant change in correlation values of RMSSD between average and high stress subjects. This reinforces the conclusion drawn on RR interval readings and further points towards a diagnosis in stress levels with the help of PRV parameters.

Use of Nonlinear modelling and Regression

With the introduction of the recovery time as an additional parameter a multivariate regression model was computed for both the normal state and the stress induced state. With a test to training data ratio of 10:25 acceptable accuracies of 80% and 90% respectively were seen, although these can only be considered reliable when similar results are produced for larger data sets. Various nonlinear models were tried out, but the type having its general form as shown in the previous section was found to be most useful. With a much larger test to training data ratio of 15:20 an accuracy of 83% was achieved and when this ratio decreased to 10:25 an accuracy of 90% was seen. The result of this analysis is simply that the plugging in of PRV parameters into the equations will yield reliable results for stress diagnosis, but at the expense of having to subject the patient to the audio visual stimulus. Therefore, the recovery time can be seen as a significant factor. Lower the recovery time higher the chances that the patient falls into the average stress category.

General Trends

By observing Table 12 a set of general trends can be seen and they are summarized.

Table 12 Comparison of performance

	Non-linear modeling		Regression		Correlation	
	Before Stimulus	After Stimulus	Before Stimulus	After Stimulus	Before Stimulus	After Stimulus
Classification Accuracy (%)	90	90	80	91	80	70
Sensitivity	100	100	83	100	80	80
Specificity	83	80	75	75	75	60

The decrease in SDNN and RMSSD values indicate the effect of long term stress. An increased reading of SD2/SD1 is also indicative of long term stress issues. Although many exceptions can be seen, the RR interval generally varies inversely with the pulse rate and it holds prominence in analysing sympatho-vagal balance [1][2]. The PSS questionnaire that every subject has to fill before the experiment helps to verify the presence of psychological stress caused by the stress inducing stimulus. It also offers a scaling system where the subject can either fall into the 13-19 point range (average stress) or above the 20 point range (high stress). This is helpful while classifying the subject based on PRV parameters [1][2][4]. From the observations in table 11, the average values of classification accuracy, sensitivity and specificity are highest for non-linear modelling at 90%, 100% and 82% respectively as compared to the results from Regression and Correlation.

Conclusion

This research work is conducted in three phases namely acquisition of PPG signals, computation of PRV parameters before and after stimulus and classification into different stress levels. All these values are transmitted wirelessly to the mobile App using IoT cloud server. The mobile App provides the graphs of measured and computed values obtained continuously over the monitored time period. Perceived Stress Scale (PSS) is used as the reference values to assess the performance of the statistical models considered. Non-linear model gives best average classification precision, sensitivity and specificity of 90%, 100% and 82% respectively. Also PPG signal is compared with ECG signal and a close precision is obtained with average percentage error of 8% for BPM and 3% for RR interval. Statistical analysis conducted also showed that with a more elaborate training data set more conclusions can be drawn in the form of increased accuracy for the nonlinear modelling schemes. Changes in correlation values of parameters other than RR interval and RMSSD is also something that can be explored with a larger data set.

This type of portable PPG checking devices can be used to evaluate HRV throughout the moving conditions. PPG sensors can be positioned either on fingertip and wrist which suggest more comfortness to users. Furthermore, with the advancement of Android app to exhibit PRV parameters, distantly monitoring the stress level becomes possible.

References

Mohammad Ghamari et al., 2016, Rapid Prototyping of a Smart Device-Based Wireless Reflectance Photoplethysmograph, *2016 32nd Southern Biomedical Engineering Conference (SBEC),* 175-176.

R. Logier et al., 2016, Comparison of Pulse Rate Variability and Heart Rate Variability for High Frequency Content Estimation, *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),* 936-939.

Podaru et al., 2021 On the Heart rate variability and Pulse rate variability evaluations based on electrocardiographic and photoplethysmographic signals. *2021 12th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*, 1-6.

M, ARUN et al., 2016 Concept of Measuring Pulse Rate Variability as a Tool for Determination of Stress in Healthy Individuals. *Journal of Evolution of Research in Human Physiology, 2,* 14-28.

J. Park et al., 2018. Prediction of Daily Mental Stress Levels using a Wearable Photoplethysmography Sensor, *TENCON 2018 - 2018 IEEE Region 10 Conference, Jeju, Korea (South),* 2018, 1899-1902, http://doi.org/10.1109/TENCON.2018.8650109

Yaru Yue et al., 2021 Heart Rate Variability as Classification Features for Mental Fatigue Using Short-Term PPG Signals Via Smartphones Instead of ECG Recordings. *2021 13th International Conference on Communication Software and Networks.* 370-376.

Charlton PH et al., 2018. Assessing Mental Stress from the Photoplethysmogram: A Numerical Study. Physiol Meas. 2018; 39(5):054001. Published 2018 May 15. doi:10.1088/1361-6579/aabe6a.

Chuang et al., 2015. Photoplethysmography variability as an alternative approach to obtain heart rate variability information in chronic pain patient. *Journal of clinical monitoring and computing. 29.* http://doi.org/10.1007/s10877-015-9669-8

M. Nardelli et al., 2021 Reliability of Pulse Rate Variability in Elderly Men and Women: An Application of Cross-Mapping Approach," *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC),* 2021, pp. 492-495. http://doi.org/10.1109/EMBC46164.2021.9630550.

Marcus Vollmer et al.,2015 Simple and Reliable Measure of Heart Rate Variability using Relative RR Intervals. *2015 Computing in Cardiology Conference (CinC),* 609-612, 6 September 2015.

P. Suma et al., 2019 Pulse Rate Variability for Detection of Autonomic Tone of an Individual. *2019 4th International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India*, 2019, pp. 1172-1177. http://doi.org/10.1109/RTEICT46194.2019.9016790

Cho Y et al. 2019. N Instant Stress: Detection of Perceived Mental Stress through Smartphone Photoplethysmography and Thermal Imaging, *JMIR Ment Health 2019; 6*(4): e10140.