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A Novel Hybrid Framework for Cuff-Less Blood Pressure Estimation based On Vital Bio Signals processing using Machine Learning

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ABSTRACT

Blood Pressure is one among the most important physiological parameters for assessing the overall well being of an individual. It plays pivotal role in the detection of many cardiovascular diseases specially Hypertension. Traditional Cuff-Based BP measurements techniques have several drawbacks and they are significantly inconvenient to patients, moreover continuous BP measurement is difficult. Lot of research is currently going on for Cuff-Less BP Estimation and several techniques are researched out in the researcher's community. However, most of the existing approaches lack the required level of accuracy, generality and they are not experimented out on a large population of having heterogeneous subjects with varied demographic features. In this paper we propose a novel hybrid signal processing approach using machine learning for continuous estimation of BP without the need for calibration. Our proposed framework has reached satisfactory results in terms of Mean Absolute Error (MAE) for mean arterial pressure (MAP) Estimation.

Key words: Cuff-Less BP, ECG, Machine Learning, PPG, Signal Processing.

1. INTRODUCTION

Continuous BP measurement will certainly improve the overall healthcare monitoring of individuals at all stages of life leading to increased mortality rate among the population. Most of the cardiovascular disease remains undetected due to lack of awareness about healthcare in individuals. Hypertension, specially is a giant and silent killer according to WHO's report [1]. Most of the youngsters today are also suffering with Hypertension and are vulnerable to Heart attacks. Even recently released report of the WHO-China Joint Mission on Coronavirus Disease (COVID-19) stated persons with conditions such as hypertension, diabetes and cardiovascular diseases are at high risk of severe disease and death [33]. In purview of this situation continuous Blood Pressure estimation can act as early warning signs of most of these medical conditions.

Traditional Cuff-based BP measurement techniques are highly inconvenient to patients as the cuff is to be wrapped around the arms of the subject. Moreover the subjects may get conscious while taking such measurements. The Cuff Band may get germy while used in public hospital settings. To overcome these problems Cuff-Less BP Estimation techniques by means of Vital Bio Signals and there processing was attempted. The origin of the solution lays in the Kortis-Moeg Equation [2]-[5].

Several approaches are present in the literature to estimate BP in Cuff-Less manner, however most of the approaches has still limitations and fosters more research in this hot research arena. Some of these approaches attempted to make it a solution without the need for calibration [6], [7]. Machine Learning provides the potential to classify most of the medical conditions with state-of-the art accuracy and provided the most efficient assistance to medical community.

Looking at the exiting literature broadly speaking there are two different approaches found:-

1. Simultaneous processing of ECG and PPG signals [8]-[14].
2. Extraction of only PPG signals Time and Frequency-Domain features and processing them without the need for ECG signals [15]-[17].

This paper proposes a novel kind of Hybrid proof-of-the concept framework for processing of ECG and PPG signals, extracting their respective features and training the machine learning algorithms for Continuous Blood Pressure estimation without the need for Calibration.

2. METHODOLOGY

The proposed framework is shown in Figure. 1. The working of the framework is explained in the steps below:-

1. Obtaining the ECG Signals and the PPG signals.
2. Pre-processing of the raw signals.
3. Extraction of Features of ECG Signals.
4. Extraction of Features of PPG Signals.
5. Application of Machine Learning Algorithms.

2.1 Obtaining the ECG Signals and PPG Signals

We have downloaded the data from UCI repository containing 12,000 patient records processed by Mohamad et.al. [6] Originally obtained from MIMIC [18]. The dataset is arranged in the form of cell array of matrices where every cell is 1 record and every row of the matrix is signal channel namely PPG obtained from fingertip, ABP in mmHG and ECG from Channel II all at 125HZ.

2.2 Pre-processing of the raw Signals

Since the data is already preprocessed by Mohamad et.al. [6], no separate processing is required. The 12,000 patient records are available in 4 .mat files containing 3,000 patient records each. From the Part_1 File we chose few Sample Records for our experimentation purpose.

2.3 Extraction of Features of ECG Signals

Vital Bio Signals such as ECG contains significant information about the overall functioning of the Heart and are somehow correlated with the Flow of Blood in the vessels.

2.4 Extraction of Features of PPG Signals

PPG Signals has been found to have high correlation with the Flow of Blood in the vessels and could be used as significant indicators of Blood Pressure.

Following is the List of Important Parameters considered from the Signals:-

Time Domain Features:-

1. beats per minute (BPM)
2. interbeat interval (IBI)
3. standard deviation of intervals between adjust beats (SDNN)
4. standard deviation of successive differences between adjacent R-R intervals (SDSD)
5. root mean square of successive differences between adjacent R-R intervals (RMSSD)
6. proportion of successive differences between R-R intervals above 20ms (pNN20)
7. proportion of successive differences between R-R intervals above 50ms (pNN50)
8. median absolute deviation of RR intervals (MAD)
9. standard deviation perpendicular to identity line (SD1)
10. standard deviation along identity line (SD2)
11. area of ellipse described by SD1 and SD2
12. SD1/SD2 ratio

Frequency Domain Features:-

1. low-frequency component (LF)
2. high-frequency component (HF)
3. the ratio high frequency / low frequency (HF/LF)

Some Other Important Features:-

1. breathing rate
2. PIR
3. PBMax Frequency
4. PTT

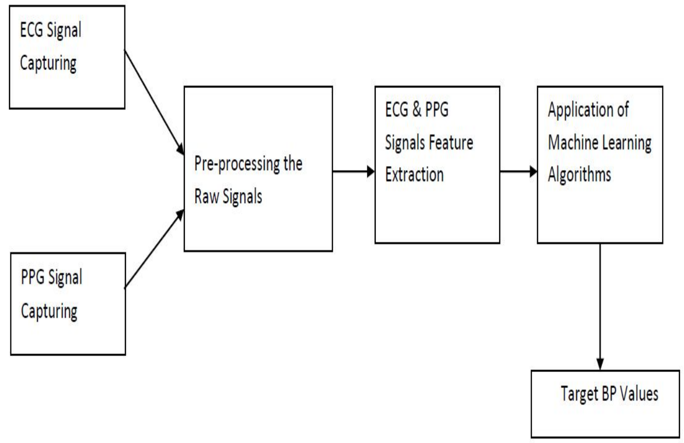

Figure 1: Proposed Cuff-Less BP Estimation Framework

Special PPG Signal Parameter List:-

Since we are going to propose a Hybrid framework we have also taken out exclusive PPG Signal Parameters as proposed by Kurylyak et. al. [24] as listed in Table 1. As characterized by Kurylyak et. al. [24], Specific amplitude of the Pulse [31] and Specific height of the Pulse [32] are important indicators as PPG Pulse components.

C.El-Hajj et.al. [25] presented a review of Cuff-Less BP estimation methods using machine learning based on PPG Signals. The authors have explained the Pulse Wave Analysis and explained the PPG Features mentioned in Table-1 diagrammatically represented in Figure 2.

Table 1: KURYLYAK ET AL. FEATURES [24]

Feature	Description
CP, ST, DT	Stipulated difference of Time as shown in Figure 2
10% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two
25% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two
33% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two
50% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two
60% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two
75% Width	At 10% Diastolic Width, At 10% Systolic Width, Sum and Division of the two

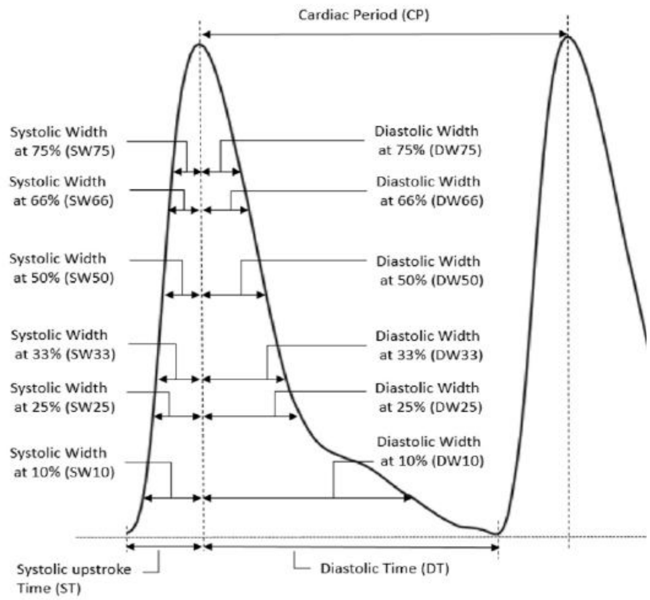

Figure 2: PPG Signal Features for BP Estimation [24], [25]

2.5 Application of Machine Learning Algorithms

In our earlier paper Santosh et.al. [19], we have reviewed machine learning applications in Healthcare Risk Predictions. Machine Learning techniques encourage improvement of the insight into a machine, with the goal that it can perform better later on utilizing the educated understanding. Machine Learning explores the potential to predict certain classes of problems based on earlier experiences [34], [35]. We make use of machine learning algorithms in estimating the most accurate Blood Pressure values that too continuously without the need for calibration. Moreover we have also referenced M. Supriyamenon et. al. [26] who had presented a Review on Mining Techniques and Dr. P. Raja Rajeswari et.al. [28].

Specifically we have implemented following 3 Machine Learning Algorithms:-

1. Linear Regression
2. Adaboost
3. Decision Trees

- **Linear Regression :-**

Earlier research in Blood Pressure estimation suggests that the Problem of BP Estimation is that of a Time Series and its best tackled with Linear Regression [20]-[22]. Hence we decided to experiment Linear Regression first on the given dataset.

- **Adaboost :-**

Adaptive boosting makes an expectation by consolidating the yields of various weak learners into a weighted entirety that predicts the target value. In the most general case, it is a non-linear classifier. While AdaBoost linearly combines the outputs of the base hypotheses, the base hypotheses themselves could be non-linear. Then, the overall prediction function is a direct blend of non-linear functions. These functions in turn are non-linear function of the inputs.

- **Decision Tree Algorithm :-**

Decision trees fabricate models as Tree structure. They comprises of number of nodes that each chooses a branch dependent on a trained condition.

3. RESULT ANALYSIS

We have implemented 3 Machine Learning algorithms and evaluated their performance. We have considered Prediction Accuracy, MAE, MSE and RMSE parameters for MAP (mean arterial pressure) values.

A. Performance Comparison of the Algorithms:-

Table 2 shows the comparison of the performance of the 3 machine learning algorithms namely Linear Regression, Decision Tree Algorithm and AdaBoost.

Though Linear Regression demonstrated higher prediction accuracy as compared to the other 2 algorithms (Figure 3) it significantly falls behind in terms of MAE (Mean Absolute Error), MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) (Figure 4). AdaBoost Algorithm exhibits promising results in terms of Mean Absolute Error (MAE) (Figure 5), Mean Squared Error (MSE) (Figure 6) and Root Mean Squared Error (RMSE) (Figure 7) among all. These observations are in line with Mohammad Kachuee et. al. [7] and Amirhossein Esmaili et.al. [23], who have confirmed the hypothesis that states BP Estimation using Non Linear Models outperforms the Linear Regression and the relationship of BP with these signal parameters is Non Linear.

B. Comparative Analysis Graphical Representation

Further Computational optimization might be achieved by leveraging the use of the next generation of Computing as proposed by Yanish Pradhnanaga et.al. [27] and T. Ganesan et.al. [30]. In Future we envision increasing the accuracy of the system using Neural Network Architectures and use some CNN architectures, Navya Krishna et.al. [29].

Table 2: Comparison of the Performance using different Machine Learning Algorithms

Classifier	**Prediction Accuracy**	**MAE**	**MSE**	**RMSE**
Linear Regression	79.68%	6.92	51.59	7.18
Decision Tree	71.03%	1.90	4.98	2.23
AdaBoost	72.42%	1.08	1.68	1.29

Where:-

MAE - Mean Absolute Error

MSE - Mean Squared Error

RMSE - Root Mean Squared Error

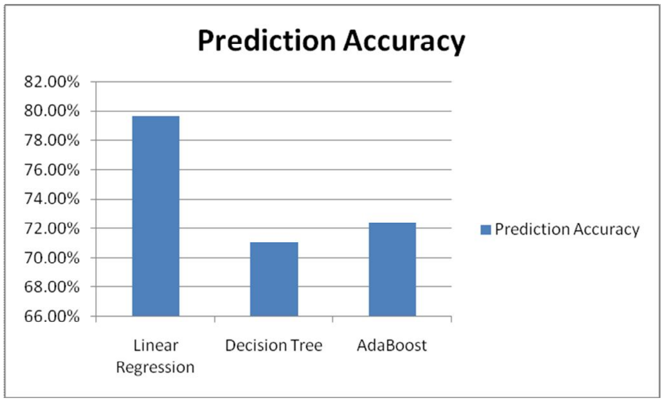

Figure 3: Comparative Analysis of Prediction Accuracy

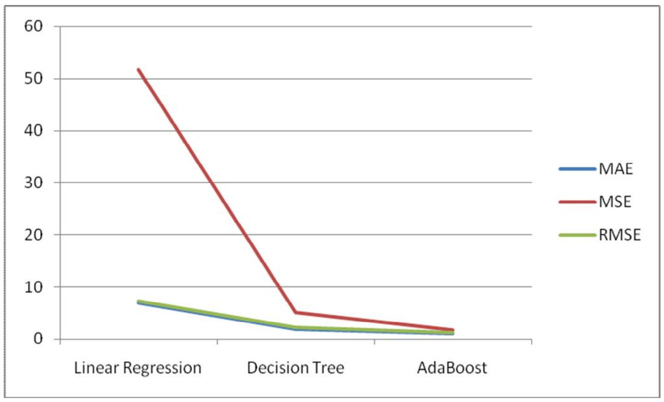

Figure 4: Comparative Analysis MAE, MSE and RMSE

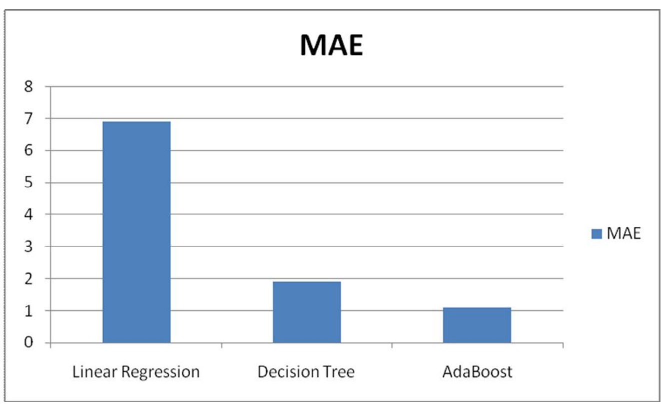

Figure 5: Comparative Analysis of MAE

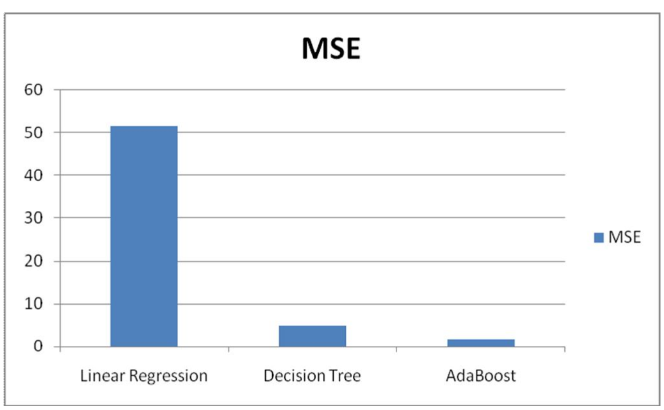

Figure 6: Comparative Analysis of MSE

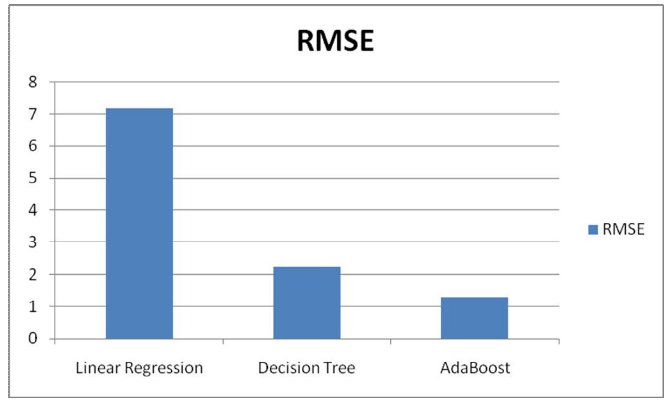

Figure 7: Comparative Analysis of RMSE

4. CONCLUSION

In this paper we have presented a new kind of Proof-of-the Concept Framework for Cuff-Less BP Estimation using Machine Learning. Our framework is tested with 3 machine learning algorithms namely Linear Regression, Decision Tree and AdaBoost. Our work has obtained satisfactory results in terms of BP Estimation especially AdaBoost algorithm has outperformed in terms of Mean Absolute Error (MAE).

This work has given a new insight into the arena of Cuff-Less measurement of Blood Pressure using machine learning with several future work directions to overcome the existing limitations. This work has been tested with only 3 machine learning algorithms and more Machine Leaning algorithms might improve the results. Moreover this framework is evaluated on a standard dataset obtained from UCI Repository and it's a candidate for evaluating on a larger dataset obtained in real Time. The dataset has its own limitations that it does not contain heterogeneous subjects of varied age ranges and hypertension categories. Normal Subjects are not considered in this dataset. We plan to extend this work on more real time samples with heterogeneous subjects, normal people, pre and post exercise effects on BP and demographic features.

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REFERENCES

1. A Global Brief on Hypertension: SilentKiller, Global Public Health Crisis. World Health Organization, Geneva, Switzerland, 2014.
2. Federico S. and Harinath Garudadri. Noninvasive Cuffless Estimation of Blood Pressure from Pulse Arrival Time and Heart Rate with Adaptive Calibration, *in Proc. IEEE BSN Conf.*, Cambridge, 2009, pp.114-115.

3. Soo-young Ye, Gi-Ryon Kim, Dong-Keun Jung, Seong-wan Baik, and Gye-rok Jeon. Estimation of Systolic and Diastolic Pressure using the Pulse Transit Time, *J. World Academy of Science, Engineering and Technology*, vol. 43, 2010, pp.726-731.
4. R. A. Payne, C. N. Symeonides, D. J. Webb, and S. R. J. Maxwell. Pulse transit time measured from the ecg: an unreliable marker of beatto- beat blood pressure, *J. Appl. Physiol.*, vol. 100, pp. 163–141. https://doi.org/10.1152/japplphysiol.00657.2005
5. Heiko Gesche, Detlef Grosskurth and Gert Kuchler. Continuous blood pressure measurement by using the pulse transit time: comparison to a cuff-based method, *J. J. Appl. Physiol.*, 2011, pp.726-731.
6. M. Kachuee, M. M. Kiani, H. Mohammadzade and M. Shabany. Cuff-less high-accuracy calibration-free blood pressure estimation using pulse transit time, *2015 IEEE International Symposium on Circuits and Systems (ISCAS)*, Lisbon, 2015, pp. 1006-1009. https://doi.org/10.1109/ISCAS.2015.7168806
7. M. Kachuee, M. M. Kiani, H. Mohammadzade and M. Shabany. Cuffless Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring, *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 4, pp. 859-869, April 2017.
8. S. Kumar and S. Ayub. Estimation of Blood Pressure by Using Electrocardiogram (ECG) and Photo-Plethysmogram (PPG), in *Proc. 2015 Fifth International Conference on Communication Systems and Network Technologies*, Gwalior, 2015, pp. 521-524. https://doi.org/10.1109/CSNT.2015.99
9. Andreas Patzak, Yuri Mendoza, Heiko Gesche and Martin Konermann. Continuous blood pressure measurement using the pulse transit time: Comparison to intra-arterial measurement, Blood Pressure, 2015, 24:4, 217-221, DOI: 10.3109/08037051.2015.1030901
10. N. Kumar, A. Agrawal and S. Deb. Cuffless BP measurement using a correlation study of pulse transient time and heart rate, in *Proc. 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, New Delhi, 2014, pp. 1538-1541.
11. A. Jadooei, O. Zaderykhin and V. I. Shulgin. Adaptive algorithm for continuous monitoring of blood pressure using a pulse transit time, in *Proc. 2013 IEEE XXXIII International Scientific Conference Electronics and Nanotechnology (ELNANO)*, Kiev, 2013, pp. 297-301. https://doi.org/10.1109/ELNANO.2013.6552042
12. X. He, R. A. Goubran and X. P. Liu. Evaluation of the correlation between blood pressure and pulse transit time, *2013 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Gatineau, QC, 2013, pp. 17-20.
13. I. c. Jeong and J. Finkelstein. Potential value of electrocardiogram and photoplethysmogram for non-invasive blood pressure estimation during exercise, in *Proc. 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, 2013, pp. 230 4-2307.
14. F. S. Cattivelli and H. Garudadri. Noninvasive Cuffless Estimation of Blood Pressure from Pulse Arrival Time and Heart Rate with Adaptive Calibration, *2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks*, Berkeley, CA, 2009, pp. 114-119. https://doi.org/10.1109/BSN.2009.35
15. N. Bersano and H. Sanson. Non-invasive blood pressure estimation from photoplethysmography signals using artificial neural networks, in *Proc. 2018 20th International Conference on Advanced Communication Technology (ICACT)*, Chuncheon-si Gangwon-do, Korea (South), 2018, pp. 1-1.
16. Y. Zhang and Z. Feng. Blood Pressure Prediction Based on Pattern Classification, in *Proc. 2017 Ninth International Conference on Advanced Computing (ICoAC)*, Chennai, 2017, pp. 174-178. https://doi.org/10.1109/ICoAC.2017.8441501
17. S. N. Shukla. Estimation of blood pressure from non-invasive data, in *Proc. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Seogwipo, 2017, pp. 1772-1775.
18. A. L. Goldberger *et al.* PhysioBank, PhysioToolkit, and PhysioNet : Components of a new research resource for complex physiologic signals, *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.
19. Santosh A. Shinde and Dr. P. Raja Rajeswari. Intelligent Health Risk Prediction Systems using Machine Learning: A Review, *International Journal of Engineering and Technology*, Vol. 7, Issue 3, pp. 1019-1023, 2018. https://doi.org/10.14419/ijet.v7i3.12654
20. F. S. Cattivelli and H. Garudadri. Noninvasive cuffless estimation of blood pressure from pulse arrival time and heart rate with adaptive calibration, in *Proc. 6th Int. Workshop Wearable Implant. Body Sens. Netw. (BSN)*, Jun. 2009, pp. 114–119. https://doi.org/10.1109/BSN.2009.35
21. V. Chandrasekaran, R. Dantu, S. Jonnada, S. Thiyagaraja, and K. P. Subbu. Cuffless differential blood pressure estimation using smart phones, *IEEE Trans. Biomed. Eng.*, vol. 60, no. 4, pp. 1080–1089, Apr. 2013.
22. S. Kumar and S. Ayub. Estimation of Blood Pressure by Using Electrocardiogram (ECG) and Photo-Plethysmogram (PPG), in *Proc. 2015 Fifth International Conference on Communication Systems and Network Technologies*, Gwalior, 2015, pp. 521-524. https://doi.org/10.1109/CSNT.2015.99
23. A. Esmaili, M. Kachuee and M. Shabany. Nonlinear Cuffless Blood Pressure Estimation of Healthy Subjects Using Pulse Transit Time and Arrival Time, in *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 12, pp. 3299-3308, Dec. 2017.

24. Y. Kurylyak, F. Lamonaca, and D. Grimaldi. A Neural Network-based Method for Continuous Blood Pressure Estimation from a PPG Signal, in *Proc. 2013 IEEE International Instrumentation and Measurement Technology Conference*, Minneapolis, MN, pp. 280–283, May 2013.
25. C. El-Hajj and P.A. Kyriacou. A Review of Machine learning techniques in photoplethysmography for the non-inavasive cuff-less measurement of blood pressure, *Elsevier*, *Biomedical Signal Processing and Control,* 2020, pp.1-14. https://doi.org/10.1016/j.bspc.2020.101870
26. M. Supriyamenon and Dr. P. Rajarajeswari. A Review on Association Rule Mining Techniques with Respect to their Privacy Preserving Capabilities, *International Journal of Applied Engineering Research,* July 2017 ,ISSN 0973-4562 Volume 12, Number 24 (2017), pp. 15484- 15488.
27. Yanish Pradhananga and Dr. Pothuraju Rajarajeswari. Tiarrah Computing: The Next Generation of Computing, *International journal of Electrical and Computer Engineering*, 81(2),pp. 1247-1255. 2018.
28. Dr. P. RajaRajeswari and Supriyamenon. M. A contemporary way for enhanced modeling of context aware privacy system in PPDM, *Journal of Advanced Research in Dynamic and Control systems*, Vol.10, 01-issue, July 2018.
29. Navya Krishna and Dr. Rajarajeswari P. Recognition of Fake Currency Note using Convolutional Neural Networks, *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* ISSN: 2278-3075, Volume-8 Issue-5 March, 2019.
30. T. Ganesan and Dr. Pothuraju RajaRajeswari. Genetic Algorithm Based Optimization to Improve the Cluster Lifetime by Optimal Sensor Placement in WSN's, *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* , ISSN: 2278-3075, Volume-8 Issue-8, June, 2019.
31. X. F. Teng and Y. T. Zhang. Continuous and noninvasive estimation of arterial blood pressure using a photoplethysmographic approach, in *Proc. of 25th Annual Inter. Conf. of the IEEE Engineering in Medicine and Biology Society*, Cancun, Mexico, 2003, pp. 3153–3156.
32. S. Linder, S. Wendelken, E. Wei, and S. McGrath. Using the morphology of photoplethysmogram peaks to detect changes in posture, *Journal of Clinical Monitoring and Computing*, vol.20(3), pp.151–158, June 2006. https://doi.org/10.1007/s10877-006-9015-2
33. Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19), 16-24 February 2020, https://www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf (Accessed on 07/04/2020).
34. Munya A. Arasi and Sangita Babu. Survey of Machine Learning Techniques in Medical Imaging, International Journal of Advanced Trends in Computer Science and Engineering, Volume 8, No.5, pp. 2107-2116, September - October 2019. https://doi.org/10.30534/ijatcse/2019/39852019
35. Mohammad Ashraf Ottom, Noor Aldeen Alawad and Khalid M. O. Nahar. Classification of Mushroom Fungi Using Machine Learning Techniques, International Journal of Advanced Trends in Computer Science and Engineering, Volume 8, No.5, pp. 2378-2385, September - October 2019. https://doi.org/10.30534/ijatcse/2019/78852019