PP-Net: A Deep Learning Framework for PPG based Blood Pressure and Heart Rate Estimation

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***Abstract*— This paper presents a deep learning model 'PP-Net' which is the first of its kind, having the capability to estimate the physiological parameters: Diastolic blood pressure (DBP), Systolic blood pressure (SBP), and Heart rate (HR) simultaneously from the same network using a single channel PPG signal. The proposed model is designed by exploiting the deep learning framework of Long-term Recurrent Convolutional Network (LRCN), exhibiting inherent ability of feature extraction, thereby, eliminating the cost effective steps of feature selection and extraction, making less-complex for deployment on resource constrained platforms such as mobile platforms. The performance demonstration of the PP-Net is done on a larger and publically available MIMIC-II database. We achieved an average NMAE of 0.09 (DBP) and 0.04 (SBP) mmHg for BP, and 0.046 bpm for HR estimation on total population of 1557 critically ill subjects. The accurate estimation of HR and BP on a larger population compared to the existing methods, demonstrated the effectiveness of our proposed deep learning framework. The accurate evaluation on a huge population with CVD complications, validates the robustness of the proposed framework in pervasive healthcare monitoring especially cardiac and stroke rehabilitation monitoring.**

***Index Terms*— Heart Rate, Blood pressure, Deep learning, Long-term Recurrent Convolutional Network (LRCN), Photoplethysmography (PPG), Times-series prediction.**

I. INTRODUCTION

BLOOD pressure (BP) and Heart Rate (HR) are the most important biomarkers as well as risk indicators for stroke and cardiovascular diseases [1-3] which are the leading causes of mortality and morbidity worldwide [4]. The accurate measurement of these physiological parameters, plays a major role in preventing and predicting stroke and cardiac diseases, hypertension screening, tracking of clinical progress of ill-subjects (e.g. post-operative subjects, rehabilitated subjects and patients inside the intensive care units) [5-7]. The existing methods for BP (Sphygmomanometery and oscillometry) and HR (electrocardiography), require inflatable cuff and multiple electrodes attached to the body surface respectively, which are obtrusive and inconvenient for continuous and pervasive monitoring [8-10].

The recent technological advancement and development in sensor technology have enabled a way to monitor the physiological parameters unobtrusively anytime, anywhere [11-12]. In this context, photoplethysmogram (PPG), an electro-optical technology has emerged as a key factor for monitoring the physiological parameters without the need of reference signal and laboratory conditions [13]. It utilizes the low-cost, portable pulse oxi-meter which illuminates the skin and measures the volumetric variations in the blood caused due to light absorption during the cardiac cycle [6]. It encloses various information about the body systems including cardiovascular system, respiratory system and nervous system [14], attracting the researchers towards accurate measurement of physiological parameters. The simplicity, portability and low-cost of PPG, facilitate the ability to be integrated on mobile and wearable devices, providing an alternative for pervasive monitoring [7-8]. Despite these advantages, susceptible nature of PPG technology towards noise and motion artifacts induced by finger or hand movement, causes widening of gap between sensor and skin of the user, distorting the signal fidelity [15-16]. This impede the robust evaluation of physiological parameters, making them inefficient for clinical applications [17].

A number of studies related to HR [18-26] and BP [27-35] are performed, utilizing the signal processing and feature-engineering based learning algorithms to eliminate/attenuate the motion artefacts (MA). Although, these methods were successful in measuring the BP and HR but employed motion reference from external sensor, heuristic thresholds or different tuned parameters and a number of features for successful estimation of physiological parameter in presence of MA which prevent the accurate evaluation of these methodologies for different conditions and users [25]. Further, these techniques [18-35] have mainly focused on monitoring the single physiological parameter i.e. either BP or HR.

In this paper, we have developed a deep learning framework for simultaneous estimation of HR and BP using a

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single channel PPG data, collected from diverse population with cardiovascular disease (CVD) complications in intensive care unit. The convolutional neural network and long short term memory network, are the most widely used deep neural networks, emerged as key benefits for classification and prediction task respectively [36]. The inherent capability of these deep networks in extracting the useful features from the data while learning phase, provides not only accurate results but also cost effective solution compared to conventional signal processing and machine learning algorithms [37, 38]. The performance evaluation of deep learning algorithms, is also examined in our preliminary work for biometric identification, heart rate estimation, and rehabilitation monitoring, which resulted in accurate performance [39-41] for sensory data.

The proposed framework is developed with customized Long-term Recurrent Convolutional Network (LRCN) model, utilizing the convolutional neural network (CNN) and long short-term memory (LSTM). The joint framework of CNN-LSTM, leverages the advantages of both the networks with the data driven feature extraction, providing an efficient and light-weight model. The novelty of this work lies in developing an efficient deep learning framework *PP-Net* with generalized, light-weight and customized LRCN model, having multi-score output capability to estimate three parameters i.e. diastolic blood pressure (DBP), systolic blood pressure (SBP) and heart rate (HR) simultaneously using a sensor unit i.e. PPG sensor. The proposed framework *PP-Net*, is successfully tested on 'MIMIC' dataset which is the publically available largest dataset, consisting intensive care data of patients with diverse CVD complications. We have performed the validation on 1557 patient's data wherein we achieved an average normalized mean absolute error (NMAE) and normalized root mean square error (NRMSE) of 0.059 and 0.090, and a correlation coefficients of 0.9902 for simultaneous estimation of DBP, SBP and HR, demonstrating the importance of LRCN in inferring physiological information from time-series data collected through PPG technology. These results reflect the robustness of *PP-Net,* in spite of having much larger population with diverse CVD complications, indicating the potential usage in pervasive healthcare monitoring of cardiac and stroke rehabilitated subjects, elderly subjects, post-operative subjects. Further, efficiency of the proposed methodology is also validated in comparison with the existing methodologies for BP and HR estimation.

The rest of the paper is structured as follows: Section II discusses about background details and motivation behind this research, section III provides the brief details of proposed methodology, section IV presents the obtained results and analysis and section V presents the discussion whereas section VI concludes the paper with future plans.

II. Background And Motivation

The role of PPG technology in clinical field was first presented by Alrick Hertzman in 1937 [42]. With the advancements in semiconductor technology, PPG got popularization in the clinical applications [43]. It is considered as one of the best method, allowing simple, unobtrusive and inexpensive way of monitoring the physiological parameters ubiquitously [44] which is also observed in recent research [8, 14].

The majority of the studies related to HR estimation have evaluated their methodologies on IEEE signal processing cup (SPC) dataset which contains 23 healthy subjects' data. The studies by [18-20] have presented signal processing based algorithms for successful evaluation of HR estimation. However, these algorithms involved a number of signal processing step, optimized and heuristic thresholds which are highly parameterized for specific conditions, preventing the generalization of these methods. Further, these studies [18-24], [26], have included accelerometer along with PPG signal for HR estimation. A few studies [24-26], have applied the machine learning and deep learning based algorithms to overcome the limitations of existing signal processing based algorithms. The study by [24], has applied the feature-engineering before the estimation of physiological parameter, which involves selection and extraction of a number of features, making more compute and time intensive. Another study by [25], has developed a deep learning based personalized method without any need of feature-engineering and shown robustness of deep learning algorithm for sensory data. The development of personalized model necessitates data collection followed by training of model for the each new user who wants to use in real-time. A very recent study by [26], also applied the deep learning algorithm but performed the time-frequency spectral of PPG and then used with the accelerometer data as inputs. The usage of two input signals in these studies [18-24], [26] increases the processing and computational complexity which directly affects the power requirement, which is a paramount for enabling the long-terms monitoring on mobile applications. Furthermore, all these studies have validated their methodologies on a small and healthy population. Therefore, validation on diverse population with CVD complications is a very important and necessary step to facilitate the usage in clinical applications especially for critically-ill patients, post-operative, cardiac and stroke monitoring. On the other side, researchers also explored about the relationship between BP and PPG [27-35] for cuff-less BP estimation. The most of the studies mainly focused on utilizing the different machine learning algorithms wherein they have employed handcrafted feature-engineering before estimating the BP, which is a cumbersome and compute-intensive task.

The inherent capability of deep learning algorithms to perform the data-driven feature extraction, precludes the necessity of handcrafted feature engineering, making them preferred choice for many biomedical applications [36-41]. Motivated from the advantages of PPG technology and limitations of the existing studies, we focused on developing an efficient deep learning framework with generalized, light-weight and customized model, having multi-score output capability to estimate HR and BP (SBP, DBP).

The proposed deep learning framework is tested on University of California, Irvine (UCI) Machine learning Repository dataset, derived from publically available largest database 'Multi-parameter Intelligent Monitoring in Intensive

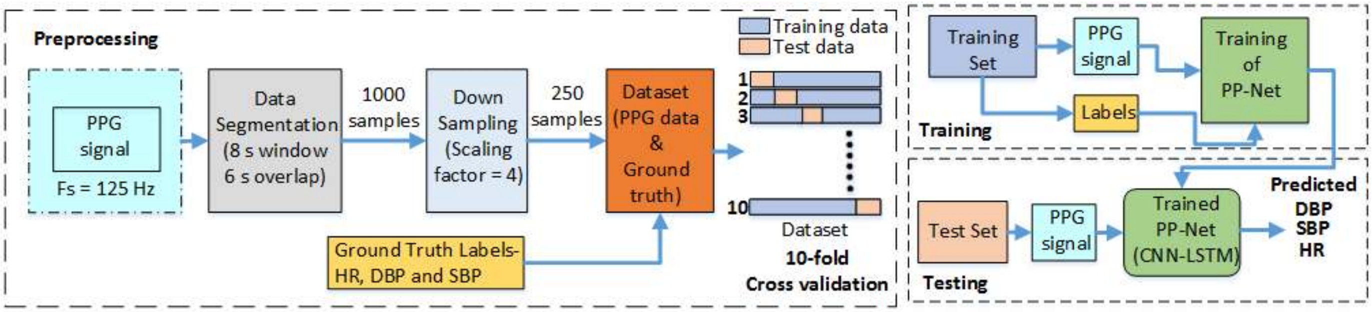

Fig. 1. Overview of the proposed *PP-Net* methodology.

Care (MIMIC-II)' which is available at Physionet repository [45]. This database consists simultaneous recordings of multi-parameters of Intensive care unit (ICU) patients which include physiological signals as well as physiological parameters. We extracted simultaneous recordings of electrocardiogram (ECG), photoplethysmograph (PPG) and arterial blood pressure (ABP) of 12000 subjects for this study which are provided in UCI repository. The sampling frequency for these signals are 125 Hz. The ground truth scores for SBP and DBP are calculated using the ABP signal, applying the approach used in the existing studies [37-35]. For HR scores, pantompkin algorithm is used from the BioSigKit Toolbox (Matlab) [29], [46].

III. PROPOSED DEEP LEANING FRAMEWORK

The proposed framework is designed for estimating the physiological parameters: BP and HR simultaneously from the PPG sensor to enable the pervasive healthcare monitoring. The overview of the proposed deep learning framework is illustrated in Fig. 1 which includes three stages: 1) Pre-processing; 2) Model development; 3) Training and Evaluation, which are detailed below.

A. Stage 1: Pre-processing

First, PPG and ECG data are pre-processed to eradicate the data of insufficient duration (less than 8 minutes recording), resulted in approximately 83% reduction in the dataset. Then, data segmentation is performed by taking 8 seconds window with 75% overlapping which is considered enough to capture the useful information about cardiac activity, observed in the existing studies [18-26]. Further, unreliable signals such as missing data (Nan), and very high/low BP and HR values (SBP $\geq$180, SBP $\leq$ 80, DBP $\geq$130, DBP $\leq$ 60, HR < 40, HR > 220) are excluded from the dataset [33], reduced the remaining data by approximately 20%. These pre-processing steps result in reduction of total subjects from 12000 to 1557. Now, final data of approximately 1557 subjects were included for evaluation. Further, PPG data are down-sampled with the aim of reducing the computational complexity of the LRCN model which is suggested in many previous studies [19-21]. The down-sampling is performed by scaling factor of 4 while preserving the important information, similar to the technique applied in [40]. Further, complexity reduction can be useful for implementing the model on resource-constrained platforms such as mobile phone. Lastly, PPG data and their corresponding scores (HR, SBP, and DBP) are normalized.

B. Stage 2: LRCN Model

The proposed deep learning framework, *PP-Net*, involves CNN-LSTM which is jointly called LRCN model. The network architecture is designed for multi-score output which means it has capability to estimate DBP, SBP and HR simultaneously from a PPG signal. Fig. 2 shows the topology of the *PP-Net* model, designed by stacking the CNN, LSTM and fully connected layer. In this, CNN is working as a feature extractor consisting two 1D convolutional layers, each interleaved with ReLU activation, max-pooling and drop-out layers. The output features obtained from the previous layer, are passed through the LSTM model and then, fed to the fully connected layer for predicting the physiological parameters. The LSTM model is constructed with two LSTM layers, each using tangent activation and dropout layer. The architectural information about the proposed model is discussed below.

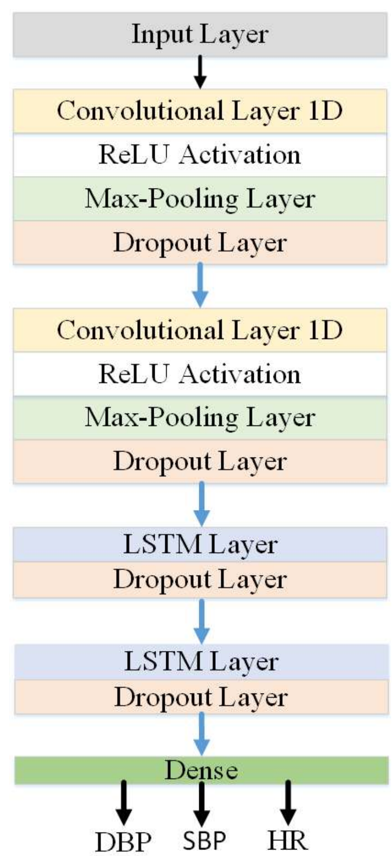

Fig. 2. Topology of the proposed *PP-Net* Model.

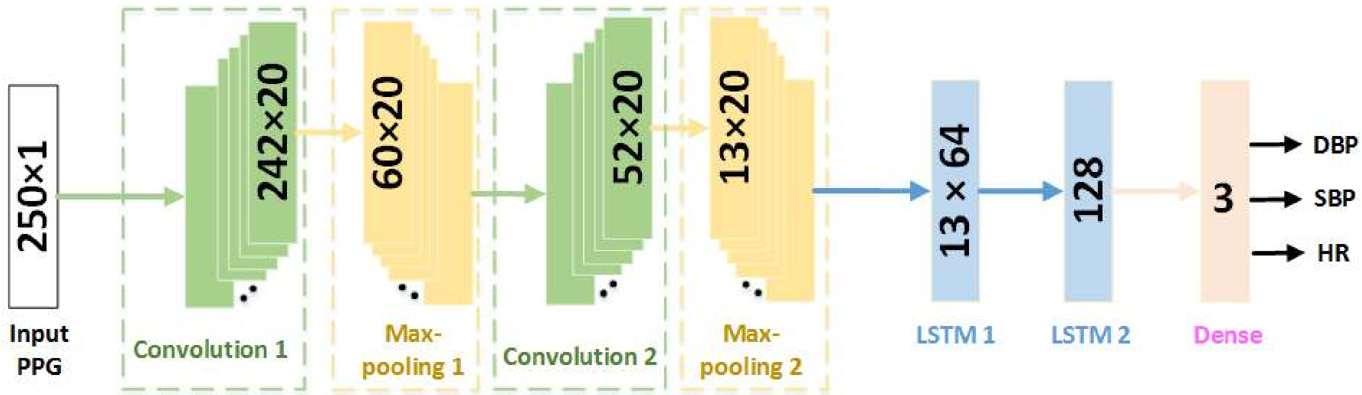

Fig. 3. Architecture of the proposed *PP-Net* model.

Fig. 3 shows the architecture of the proposed *PP-Net* model, which is a hybrid architecture. It consists two 1D convolutional layers which are core building blocks of a CNN. Each convolutional layer consists of a set of 20 learnable filters of size 9×1 sliding across the width by 9 and height by 1 of the input volume, computing dot product between their weights and a small 9×1 region they are connected in the input volume. This produces the 20 activation maps, providing the responses of corresponding filters at every spatial position where each feature map captures different low-level features. Subsequently, pooling is applied along the spatial dimensions (width, height) by 4×1 using the max operation. This step progressively reduces the spatial size of representation by 75% while keeping the depth dimension unchanged. The intuitive idea behind using this layer is once the features are known then their exact location doesn't matter as much as relative location to the other features. This serves two main purposes- 1) amount of parameters/weights are reduced, thus, lessening the computational cost; 2) control the over-fitting.

Next, two LSTM layers of 64 and 128 memory cells using hyperbolic tangent, are united with CNN model for use case of regression problem. Lastly, one fully connected layer with 3 output neurons are introduced to find the final prediction scores using the linear function where DBP, SBP and HR are predicted together through each of the output neuron. These architectural parameters are selected using the heuristic grid search method similar to [40]. To assure the proposed model is not getting too fitted to the training data, dropout layer with 0.1 probability factor is used after each pooling layer which forces the network to be redundant and helps to alleviate the over-fitting problem.

C. Stage 3: Training and Evaluation

For training the LRCN model, 100 epochs with batch size of 100 are used initially wherein it is found that there is no improvement in performance beyond the 50 epochs, therefore, 50 epochs are fixed for further analysis. The optimization during the training is performed by Adam optimizer [44] and mean squared error (MSE) are used as the loss function to evaluate the performance of proposed framework. The LRCN model is validated based on testing performance using the k-fold cross-validation approach owing to the fact that it always provides less optimistic and less biased estimation compared to simple train/test split method [45]. For this experiment, k is set to 10 following the existing studies analysis and experimental observation found in [45], stated that k fixed to 10 generally results in low bias with modest variance. The performance evaluation for the PP-Net is done by averaging the model scores of all the k testing sets wherein NMAE, NRMSE and correlation coefficients are considered as effective metrics for prediction tasks [8],[33-35],[18-26].

IV. Results and Experimental Analysis

The proposed *PP-Net* framework is realized in Keras 2.0.5 platform using Theano 1.0.4 as backend engine where execution of training and testing are performed utilizing Nvidia Quadro P4000 GPU with 8GB dedicated memory, deployed in a workstation with a 64- bit Ubuntu operating system (18.04), an Intel Xeon Processor @1.80 GHz x 32 and 64 GB of RAM.

A. Performance assessment

One of the main aim of this work is designing an efficient yet light-weight model which can be deployed on resource constrained platforms (e.g. mobile phone) to enable long-term monitoring. Therefore, at algorithmic level, the LRCN model architecture is designed in such a way that it is capable of estimating the three parameters: DBP, SBP and HR simultaneously from the same network without the need of separate model for each parameter. This will help in reducing the time and computational complexity for real-time analysis as compared to the other existing algorithms which have used the same network but performed the separate training [29], [35]. Further, input PPG signal is also compressed by applying the down-sampling to reduce the data processing complexity which will directly affect the computational load of the LRCN model. This results in reduction from 1000 samples to 250 samples in the input data for the proposed LRCN model.

Table I depicted the performance of the proposed methodology for 10 fold test validation method wherein an average NMAE of 0.059 and NRMSE of 0.090 are achieved for estimation of DBP, SBP and HR simultaneously, highlighted in bold [50]. Further, a comparison study between the reference and estimated scores of DBP, SBP and HR, are conducted and depicted in Fig. 4. In this, (a) and (b) represent the graph of reference and estimated scores for approximately twenty thousand test windows wherein DBP, SBP and HR are depicted with blue, red and yellow color respectively.

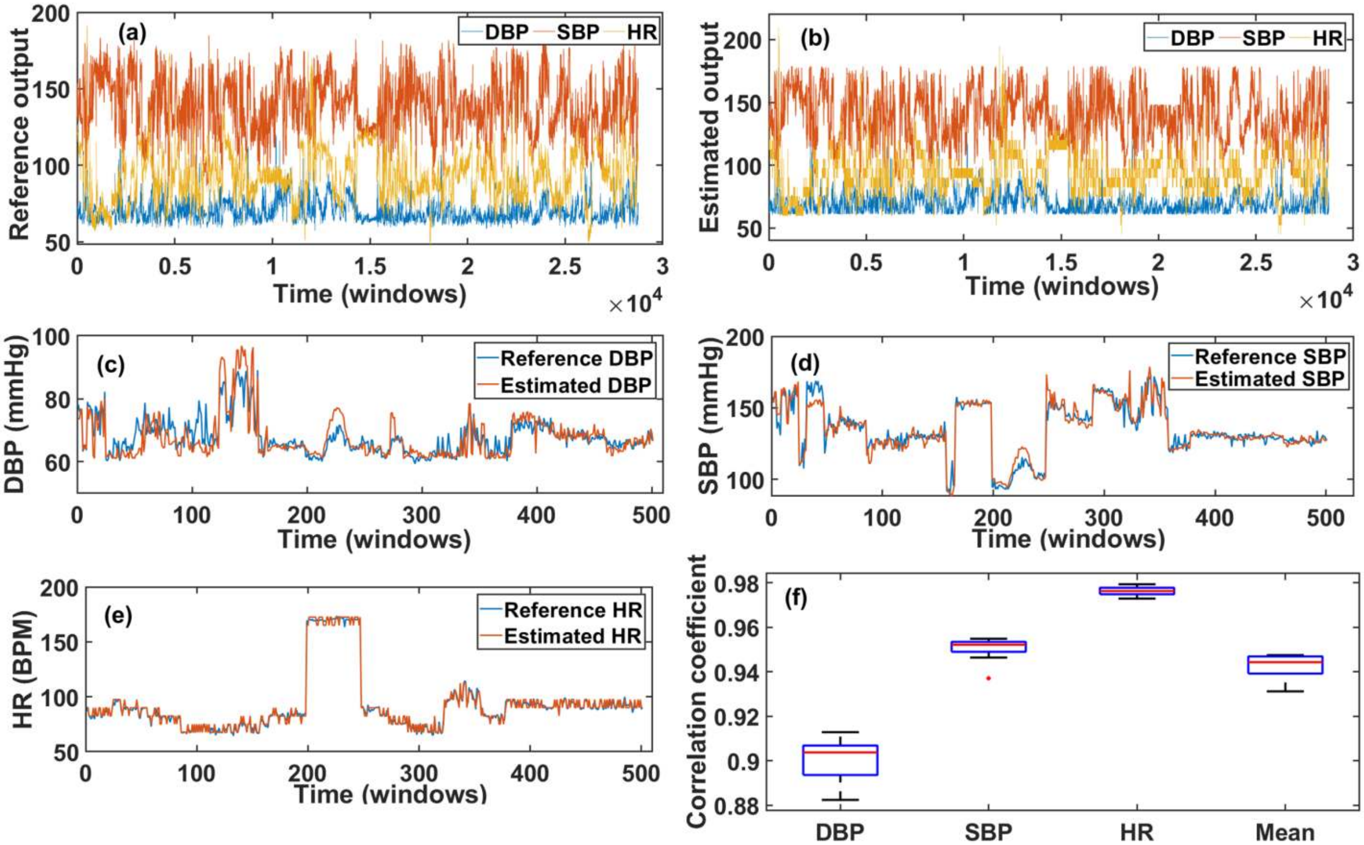

Fig. 4. Comparison between reference and estimated output scores where (a) and (b) represent the difference between the reference and estimated DBP (Blue), SBP (Red) and HR (Yellow) scores respectively; (c), (d) and (e) show the individual graphical analysis for DBP, SBP and HR respectively for reference and estimated scores for 500 test windows; (f) represents the box plot for the correlation coefficients.

It can be clearly visualized from the Figs. 4 (a) and (b) that both the graphs exhibit the similar pattern which is also demonstrated through the correlation coefficient. Fig. 4(f) measures the correlation between the reference and estimated scores of DBP, SBP and HR, having correlation coefficient of 0.9902. Further, we have also performed the comparison analysis of reference and estimated scores of DBP, SBP and HR separately, illustrated in Fig 4. (c), (d) and (e) for 500 test windows (lesser data) for better visualization of the performance. The exact error difference between reference and estimated output scores for each test window, are provided using the histograms which are shown in Fig. 5.

Furthermore, we have also performed a study to show the impact of dataset size on the performance of the proposed model wherein we have considered three different datasets, created by including subjects having minimum 8 minutes, 6 minutes and 4 minutes data. These results are reported in Table I-B. Since, a previous study by [33] has used the same dataset for BP estimation, considering the 10 minutes recording. However, our study mainly focused on utilizing the dataset created with subject having data of minimum 8 minutes to include more number of subjects while keeping the sufficient duration.

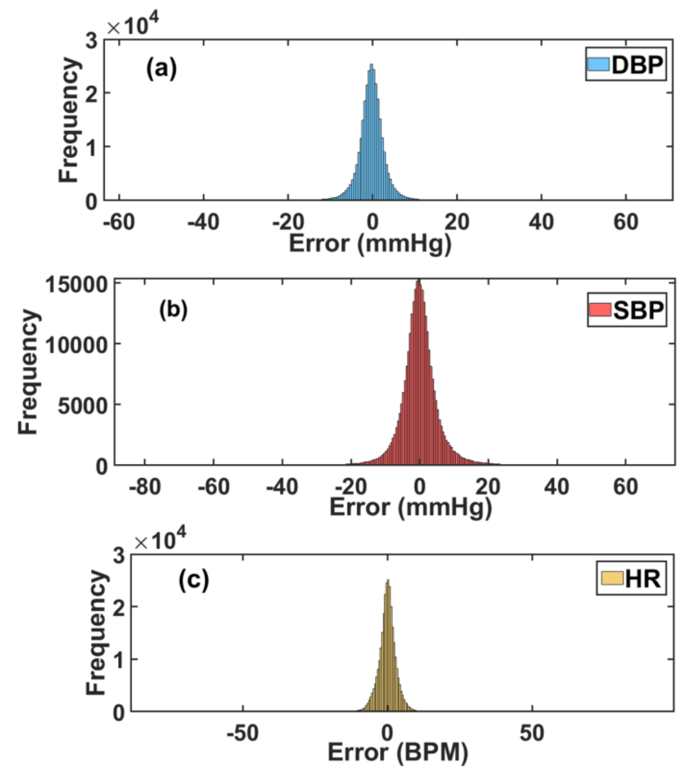

Fig. 5. Histogram of errors between reference and estimated outputs for DBP, SBP and HR depicted in (a), (b) and (c) respectively.

TABLE I: PERFORMANCE ANALYSIS OF PROPOSED METHODOLOGY (where measurement units of error for BP and HR estimation are mmHg and bpm respectively)

Table I-A

Parameter	**Performance**	
	NMAE	**NRMSE**
DBP	0.090	0.139
SBP	0.040	0.061
HR	0.046	0.069
Total	**0.059**	**0.090**

Table I-B

Minimum Data-length Per subject (minutes)	**Performance**	
	NMAE	**NRMSE**
8	0.059	0.090
6	0.083	0.127
4	0.091	0.139

Table I-C

Model type	**Performance**	
	NMAE	**NRMSE**
Proposed (CNN-LSTM)	0.059	0.090
CNN	0.127	0.198

TABLE II: SIGNIFICANCE OF INPUT DATA COMPRESSION (where measurement units of error for BP and HR estimation are mmHg and bpm respectively)

Table II-A

Parameter		**Performance**		**Trade-off** (absolute difference)
		Pre-processed 250 samples	Without pre-processing 1000 samples	
Performance	NMAE	0.059	0.054	0.005
	NRMSE	0.090	0.083	0.007
Layer		**Multiplication**	**Operations**	**Difference**
		250 samples	1000 samples	
Conv layer 1 (C1)		43560	178560	135000
Conv layer 2 (C2)		187200	892800	705600
Total		230760	1071360	840600

Table II- B

Parameter		Pre-processed 250 samples (**Input Compression**)	Without pre-processing 1000 samples (**Inherent Down-sampling**)	Absolute difference
Performance	NMAE	0.059	0.076	0.017
	NRMSE	0.090	0.114	0.024
Complexity Multiplication operations	C1	43560	44640	1080
	C2	187200	194400	7200
	Total	230760	239040	8280

B. Significance of CNN-LSTM over CNN

This study shows the comparative analysis between CNN-LSTM and CNN model, which is highlighted in Table I-C. The CNN model is designed by replacing the LSTM layers in the proposed architecture with dense layers having 64 and 128 number of neurons. It can be seen from Table I-C that CNN-LSTM model performs better compared to CNN model. This is because CNNs suffer from the long chain problem (vanishing gradient) wherein information from previous computations is rapidly attenuated as it progresses through the data flow. To analyze time series data often necessitates inferring the sequential/time-variant information wherein LSTM proved to be an effective choice. The proposed hybrid network leverages the advantages of both the networks where CNN helps in extracting the silent features from the raw data and LSTM captures the sequential dependency in historical trend developed from PPG signals, making the model robust for spatial and temporal variance. The similar observation is also examined in our previous studies [25, 41].

C. Significance of Input compression over inherent down-sampling

As discussed earlier in this section, we have performed the input compression through down-sampling to reduce the data processing complexity which directly affects the complexity of the LRCN model. Thus, a comparative analysis is done by considering the compressed (down-sampled) and un-compressed PPG data as input to analyze the impact of down-sampling on the performance and complexity of the model. It can be noted from Table II-A that the total error difference of 0.005(NMAE) and 0.007 (NRMSE) between compressed (250 samples) and un-compressed PPG signal (1000 samples) is obtained to reduce the 4 times input data complexity which directly impacted the LRCN model complexity. This is shown with respect to convolutional layers of the model wherein approximately 4 times reduction can be seen in total number of operations and similar analogy can be seen for other layers. This can be beneficial for real-time deployment on mobile platforms having power constraint.

Further, it can also be noted that by applying the appropriate stride rate, down-sampling can be achieved inherently which can eliminate the need of down-sampling during the pre-processing step. However, input data compression is providing better results in terms of performance as well as complexity for the same down-sampling factor which can be seen from Table II-B. This shows input data compression is better option for this particular problem in terms of performance as well as complexity.

D. Comparison with Existing Studies

1) BP estimation

To validate the effectiveness of the proposed methodology, comparative analysis is performed with the existing works. Table III shows the comparative analysis of the proposed methodology with the recent studies which have evaluated their methodologies on MIMIC database. It can be noted that all these existing studies performed the separate training for estimation of DBP and SBP which resulted in development of separate models for DBP and SBP estimation for real-time execution in inference phase. Also, these existing studies listed in Table III, involved feature selection and extraction steps before estimation of the corresponding scores which increase the complexity and make the system less responsive. Moreover, our proposed methodology doesn't involve any feature selection and extraction steps and also performs DBP and SBP estimation simultaneously from the same model. This reduces the computational complexity and makes the model responsive for real-time analysis. Further, our proposed *PP-Net* achieved an average $\mathrm{MAE} \pm \mathrm{SD}$ of 3.14 ± 0.13 mmHg for 1557 subjects on BP estimation which are better compared to the existing methods. These results demonstrates the

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effectiveness of our proposed methodology for real-time usability in clinical applications.

Table IV depicts the existing works which have performed the BP estimation using the PPG but evaluated their methodologies on different datasets. Since, these studies have used different datasets and/or smaller number of subjects for evaluation than the proposed methodology, therefore, fair comparison can't be performed for BP estimation. The studies performed by [30-31] have utilized the University of Queensland Vital Signs Database (32 surgical persons) and their own datasets [32], [34] respectively , wherein our proposed methodology performed better compared to these studies despite of having much larger and diverse population with CVD complications.

2) *HR estimation*

The performance analysis for HR estimation is depicted in Table V along with the exiting studies. It can be noted that the existing studies [18-25] have used the SPC dataset which is consisting 12 healthy subject's data while performing exercise. The recent study by [26] has involved their own dataset (PPG-DaLiA) and other publically available dataset to evaluate their methodology. Whereas, our study includes intensive care data of 12000 subjects with CVD complications, thereby, fair comparisons cannot be made. Further, SPC and PPG-DaLiA datasets, do not include the BP measurement information which restricts the usage in our methodology. However, it can be applied for only estimating HR by training with HR data which suppresses the novelty of the proposed methodology for estimating multi-physiological parameters simultaneously. Thus, we have performed the analysis with MIMIC database and tabulated the results wherein we have obtained MAE±SD of 2.32±0.11 BPM on 1557 subjects, showing effectiveness for real-time usability.

Further, main novelty of the proposed methodology lies in having capability to estimate DBP, SBP and HR simultaneously from the same network without any need of individual training for each parameter (DBP, SBP and HR). All the existing studies, utilizing the MIMIC database for BP estimation are using the same network architecture for DBP and SBP but require separate training for DBP and SBP which means there are two different networks with same architectures for each parameter (DBP and SBP). Thus, for real-time analysis, two separate models are required to estimate the DBP and SBP simultaneously or one model with twice the time complexity. This shows the tradeoff between time and resources for real-time analysis. Similarly, for HR estimation, another network or model is require, augmenting the time and computation complexity further. Based on the aforementioned facts, *PP-Net* model shown in Fig. 3 is considered as less-compute intensive design compared to the existing works for implementation on resource constrained platforms (mobile phone) for the given application.

E. Comparison with AAMI and BHS standards

We have performed the comparative study of the proposed methodology with the standard criteria defined by Association for the Advancement of Medical Instrumentation (AAMI) and British Hypertension society (BHS) for validating the effectiveness of the proposed methodology for BP estimation. According to AAMI standard, evaluation methodology should include minimum 85 subjects and it validates the algorithm if mean error (ME) and standard deviation (SD) are within the range of 5 mmHg and 8 mmHg. Whereas, BHS standard considers performance accuracy in terms of percentage of cumulative error which is divided in three categories based on the performance, shown in Table VI. The results of the proposed model is validated on 1557 subjects which is listed in Table VII and Table VIII for BHS and AAMI standards respectively. We have obtained ME±SD of -1.25±5.65 mmHg and 1.55±5.41 mmHg in AAMI standard for estimation of DBP and SBP respectively and grade A in BHS standard for both DBP and SBP, which are within the limits of their defined criteria. Further, we have presented the correlation and Bland-Altman plots for DBP and SBP scores in Fig. 6 wherein blue and red color indicate the results of DBP and SBP analysis respectively.

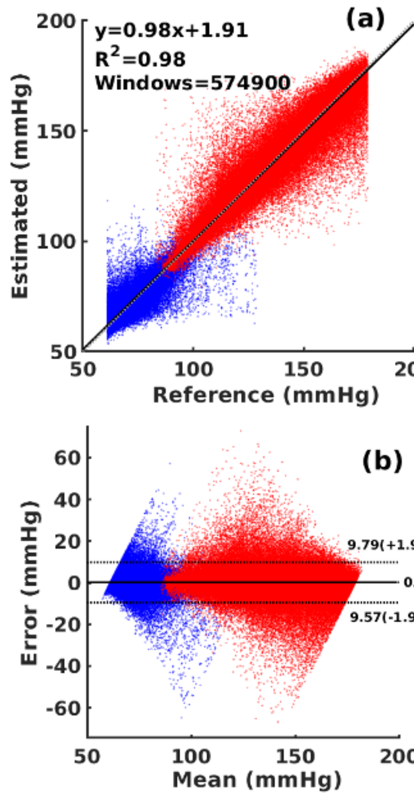

Fig. 6. (a) and (b) represent the correlation coefficient and Bland-Altman graph respectively for DBP (Blue) and SBP (Red) estimation.

F. Complexity analysis

Deep-learning algorithms mostly involve power-consuming MAC operations and intensive-memory which may restrict the deployment on resource-constrained platforms such as mobile and wearable devices for deeper networks. Therefore, we have performed the algorithmic optimization and designed the less-complex model *PP-Net* in this methodology. Further analysis includes the exploration on complexity of the proposed model to keep an eye towards hardware implementation for the real time execution during the inference phase which is shown in Table IX. The complexity analysis is performed in terms of number of MAC operations and memory blocks needed for the real-time execution in inference phase.

TABLE III: PERFORMANCE ANALYSIS OF THE PROPOSED *PP-NET* FOR BP ESTIMATION ON MIMIC DATABASE
(* number of subjects before eradicating the insignificant record of subjects)

Work	Subjects	Method	No. of Models	Validation Method	Performance ($MAE \pm SD$) mmHg	
					DBP	SBP
EMBC'16 Gaurav *et. al* [29]	3000 subjects*	Feature extraction (46 features) and Artificial Neural Network (ANN)	2	Conventional method	3.21 ± 4.72	4.47 ± 6.85
TBME'16 Kachuee *et. al* [33]	1000 subjects	DWT, PCA, whole based and physiological feature extraction and conventional regression algorithms	2	10 fold validation	5.35 ± 6.14	11.17 ± 10.09
BSPC'18 Mousavi *et. al* [35]	441 subjects	FFT, FFT^{-1}, Feature extraction, PCA and conventional regression algorithms	2	10 fold validation	2.43 ± 4.173	3.97 ± 8.901
This work	1557 subjects	LRCN deep learning algorithm	1	10 fold validation	2.30 ± 0.196	3.97 ± 0.064

TABLE IV: PERFORMANCE ANALYSIS OF THE PROPOSED *PP-NET* WITH EXISTING WORKS

Work	Database	Subjects	Method	Validation Method	Performance ($MAE \pm SD$) mmHg	
					DBP	SBP
EMBC' 16 Gao et. al [32]	Own dataset	65 healthy subjects	DWT, Feature extraction and SVM	10 fold validation	4.6 ± 4.3	5.1 ± 4.3
EMBC' 16 Duan et. al [30]	University of Queensland Vital Signs Database	32 Surgical persons	Feature extraction and Support vector regression	10 fold cross-validation	3.67 ± 5.69	4.77 ± 7.68
ICMLC'17 Zhang et. al [31]	University of Queensland Vital Signs Database	32 Surgical persons	Feature extraction and Support vector machine (SVM)	Conventional method	7.61 ± 6.78	11.64 ± 8.22
BSPC'18 Radha et. al [34]	Own dataset	90 healthy subjects	Feature extraction and LSTM	Conventional method	4.95	5.95
This work	UCI machine learning repository (MIMIC II)	1557 subjects	LRCN deep learning algorithm	10 fold validation	2.30 ± 0.196	3.97 ± 0.064

Table IX illustrates the total number of multiply-and-accumulate (MAC) operations and weight parameters required for each layer. Furthermore, we have also conducted the comparison with our preliminary work [25], utilized the CNN and LSTM algorithm for HR estimation which is listed in Table IX (last two column). Our proposed model shown 52.89% and 51.36% improvement in terms of total number of MAC operations and memory blocks for estimation of BP and HR simultaneously. Despite the huge improvement in complexity of the model, further research is necessary to eliminate the number of multipliers involved in the deep learning algorithms. Current trends of implementing these deep learning algorithms on mobile and wearable devices, made possible to perform real-time analysis [49]. Further, we have also performed the timing analysis wherein our proposed *PP-Net* model takes approximately 1 *ms* time to estimate DBP, SBP and HR.

TABLE V: PERFORMANCE ANALYSIS OF THE PROPOSED PP-NET FOR HR ESTIMATION

Work	Database	Subjects	Method	Validation Method	Performance ($MAE \pm SD$) BPM
TBME'15 Zhang et. al [18]	SPC dataset	23 subjects	Signal processing method (signal decomposition, temporal difference, sparse signal reconstruction, spectral peak tracking)	-	2.34±2.47 1-12 subjects 3.19±3.61 13-23 subjects 2.77± 3.04 23 subjects
TBME'15 Zhang [19]	SPC dataset	23 subjects	Signal processing method (Joint sparse spectral reconstruction, spectral subtraction and peak tracking)	-	1.28±2.61 1-12 subjects 3.05±3.35 13-23 subjects 2.17±2.98
TBME'16 Khan et. al [20]	SPC dataset	12 subjects	Signal processing method (Ensemble empirical mode decomposition, adaptive filtering, decision making processing)	-	1.02±1.79 1-12 subjects
TBME'17 Tempko [21]	SPC dataset	23 subjects	Signal processing method-WFPV algorithm (pre-process, de-nosing phase decoder and post processing)	-	1.02±1.25 1-12 subjects 2.95±3.71 13-23 subjects 1.99±2. 48 subjects
Sensors letters' 19 Zhu et. al [24]	SPC dataset	12 subjects	Neural network, linear regression, post processing	-	1.03±1.82 12 subjects
BSPC'19 KR et. al [22]	SPC dataset	12 subjects	Signal processing method (Cascaded three stage adaptive filters and FFT)	-	0.92±1.17 1-12 subjects
TBioCAS'19 Biswas et. al [25]	SPC dataset and Own dataset	25 subjects (23+2)	CNN and LSTM	5 fold validation	1.99±4.64 12 subjects 0.86±1.86 13-23 subjects 1.47±3.37 23 subjects
This work	UCI repository database	12000 subjects	LRCN	10 fold validation	2.32±0.095

V. Discussion

The advantages of being unified with wearable and mobile devices, recent success and promising results obtained in recent research, indicate the significance of PPG technology in pervasive healthcare monitoring [8], [18-35]. Our results and performance analysis validate the effectiveness of our proposed deep learning framework for simultaneous estimation of physiological parameters: BP and HR using the minimal number of PPG sensors. The accurate estimation on larger and diverse population are very essential for proving the effectiveness of any algorithm in clinical applications. Our proposed methodology achieved the good performance on much larger population of CVD complications than the existing studies, validates the potential usability in clinical applications. Further, extensive analysis on algorithmic optimization and pre-processing offered an efficient and light-weight architecture for *PP-Net* having low computational complexity while achieving good performance.

TABLE VI: BHS GRADING SCALE FOR BP MEASUREMENT

Grade	Cumulative error percentage		
	$\leq$ 5 (mmHg)	$\leq$ 10 (mmHg)	$\leq$ 15 (mmHg)
A	60	85	95
B	50	75	90
C	40	65	85

TABLE VII: COMPARATIVE ANALYSIS WITH THE BHS STANDARD

Method	Physiological parameter	$\leq$ 5 (mmHg)	$\leq$ 10 (mmHg)	$\leq$ 15 (mmHg)
This work	DBP	90%	98%	99%
	SBP	75%	91%	96%

TABLE VIII: COMPARATIVE ANALYSIS WITH THE AAMI STANDARD (Where ME represents mean of errors between reference and estimated scores)

Method	Physiological parameter	ME (mmHg)	SD (mmHg)	Subjects
This work	DBP	-1.25	5.65	1557
	SBP	1.55	5.41	1557
AAMI	BP	≤ 5	≤ 8	≥ 85

TABLE IX: COMPLEXITY ANALYSIS OF THE PROPOSED *PP-NET*

Layers	Multipliers Operations	Adders operations	Weight parameters
Conv-1	43560	38720+20	200
Conv-2	187200	166400+20	3620
LSTM-1	327680	326400+256	21760
LSTM-2	4194304	4186112	98816
Dense-1	384	381+3	387
Total	4753128	4718013	124783
Proposed	9.47 M		124783
[25]	20.1 M		256578

This study is a step towards developing an efficient yet light-weight generalized solution for estimating the multi-physiological parameters simultaneously in unobtrusive way to enable the pervasive monitoring in health-care applications. The proposed methodology can be applied for continuous monitoring of ICU patients and remote-health monitoring including elderly care, cardiac and stroke rehabilitation, hypertension screening, post-operative subjects monitoring in home environment. The proposed methodology can be extended for estimation of physiological parameters (HR, BP) in ambulant environment as well as for other physiological parameters (SpO2, HR, BP, and RR) but requires the corresponding dataset for designing the deep learning model for the specified applications. Moreover, our proposed deep learning framework achieved the following goals: 1) The proposed *PP-Net* model is able to predict HR, SBP and DBP simultaneously, providing three in one solution with minimal number of sensor units, making it cost effective solution; 2) The development of generalized framework, eliminates the need of training the model for each new user before their use, thereby, making the proposed methodology more robust.; 3) The proposed methodology estimates physiological parameters from minimum number of sensor units, in a very simple and unobtrusive way, hence, offering a safer and potentially more convenient mode of health monitoring which enable practical usability for real-time analysis; 4) Continuous measurement increases the potential for early detection of patient deterioration, leading to improved outcomes; 5) The capability of estimating BP and HR simultaneously, utilizing the same network architecture and same parameters, facilitate the implementation on resource constrained platform for real time execution such as mobile and embedded platforms (wearable devices); 6) An average NMAE of 0.059 and NRMSE of 0.090 are achieved for BP and HR estimation on larger population, illustrate the effectiveness of our proposed methodology.

VI. CONCLUSION

This paper presents a deep learning framework *PP-Net* for simultaneous estimation of HR and BP (DBP, SBP) using a single channel PPG data. The obtained results of an average NMAE of 0.059 and NRMSE of 0.090 with correlation coefficients of 0.9902 for estimation of DBP, SBP and HR, simultaneously on a larger population of CVD complications, showing the efficiency of the proposed model in pervasive healthcare monitoring. The multi-score output capability of proposed *PP-Net* framework provides a less-complex solution than the existing methodologies which have estimated HR and BP by utilizing the different methodologies and neural models. In addition, the proposed model performed the data driven feature extraction during the training which eliminated the cost effective steps of feature selection and extraction separately. Moreover, *PP-Net* is a light-weight (low-complex) model providing many in one solution in unobtrusive way using a sensor, offering a cost effective, safer and convenient mode of health monitoring in/out of clinical setting. In future, we plan to extend this work by including the other physiological parameters such as respiratory rate (RR) and SpO2 and targeting the mobile platforms for the inference mode.

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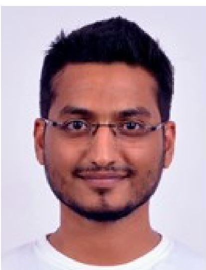

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