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Deep Neural Network Based Continuous Blood Pressure Estimation with Data Mining Techniques

Dola Das, Nawshin Tabassum, Mahmudul Hasan and M.M.A Hashem
Department of Computer Science and Engineering
Khulna University of Engineering & Technology, Bangladesh
Email: dolacse.16@gmail.com, tabassum1407024@stud.kuet.ac.bd,
mahmudul@cse.kuet.ac.bd, hashem@cse.kuet.ac.bd

***Abstract*—Cardiovascular disease (CVD) is a common disease nowadays, and hypertension is one of the predictors of it. For unobtrusive BP measurement, continuous blood pressure (BP) estimation using Pulse Transit Time (PTT) is a useful technique. The accuracy is a fact as it is feasible for a large number of phases in our life. So a Deep Neural Network (DNN) based blood pressure estimation, using data mining is proposed in this paper. Instruments were made by ourselves for collecting real data using an electrocardiogram (ECG) and photoplethysmogram (PPG) sensor as the real machine was so much expensive. Fourteen features were extracted, and best features were selected using a genetic algorithm. After this, DNN, Multivariate linear regression (MLR) and Support vector regression (SVR) models were constructed using these features. The accuracy and robustness were validated according to our equipment as the Pearson's R between referenced and estimated BP for the static experiment (SBP) were 0.90 and for dynamic (DBP) is 0.82 for DNN model. DNN model is compared with MLR and SVR. DNN gave comparatively good results than MLR and SVR and also better than the PTT-based model.**

***Index Terms*—Comparative blood pressure (BP), feature selection, deep neural network (DNN), support vector regression (SVR), multivariate linear regression (MLR).**

I. Introduction

Most of the time, CVD is caused by hypertension. The usual range of BP is 120/80 mmHg, where BP is equivalent to systolic blood pressure/diastolic blood pressure (SBP/DBP). If the SBP/DBP increases by 20/10 mmHg, then it creates a risk for health [1]. CVD can be predicted more reliably by using ambulatory blood pressure and related blood pressure variability than measuring BP by clinical settings [2], [3]. Traditional techniques for BP estimation usually uses 24-hour BP devices for monitoring BP through repeated inflation with a cuff at a regular interval. These processes are unsuitable and discontinuous for regular use as the cuff is used here. So if we can use an unobtrusive device for BP measurement, it will be reliable for CVD prevention [4].

In our work, ECG and PPG sensor with Arduino and biosensor pads were attached to the patient body to collect data. As the medical device was so expensive, we have tried to make our own device.

Data mining techniques are used here as it can control a vast number of data, and the pattern from data mining analysis is helpful for BP estimation. Real data from 75 people were collected in a static situation, from 36 people in a dynamic situation (after walking for 10 minutes) and from 31 people after one month of the static and dynamic experiment.

Here, the ECG signal and PPG signal were extracted from the collected data and gathered 14 features for each subject. All the features were not crucial for BP measurement, and so the best features were selected using a genetic algorithm.

Selected features were used to estimate BP using some models like DNN, MLR and SVR and their performance like accuracy, robustness, etc. were recorded. Finally, the results of each model were compared with one another, and DNN is found out to be more precise than MLR and SVR.

So our contribution to this paper is:

1) Making the data collecting device using an ECG and PPG sensor, thus the experiment was less expensive.
2) Using data mining to manage a large amount of data.
3) A genetic algorithm was used, which gave the best feature sets to estimate BP.
4) A new model DNN was proposed, which gave better results than MLR and SVR.

In this paper, we have tried to propose a new technique like data mining to control substantial data sets and new model like DNN to estimate BP more precisely. The result showed that the new technique is better, according to our device.

Following sections provide more details about BP estimation techniques. Section II explains some of the contemporary works on the BP estimation techniques authored by some of the researchers of this domain. The overall architecture of the proposed system, data collection technique, details of the features extraction processes, and description of the models used in this work is addressed in section III. Section IV speculates results obtained from different models used in various states like SBP and DBP. Section IV also presents a comparison study on the approaches as mentioned above. Finally, section V concludes the overall processes and plan for this work.

II. Literature Review

Several continuous and discontinuous techniques were implemented in many articles previously for BP measurement. Most of them worked with cuff, impractical, and manual.

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In the discontinuous technique, there are physiological models with finger cuff technology, which has given noninvasive and feasible BP measurement [5].

A good indicator of BP measurement is PTT, which can be generated by ECG and PPG [6]. PTT based techniques can be used as both Linear [7] (in 2001) and nonlinear [8] (in 2005) methods. For nonlinear method, the accuracy is 0.6 ± 9.8 mmHg for SBP and 0.9 ± 5.6 for DBP.

In the time of 2015, PPG intensity ratio (PIR) based technique was proposed [9]. By employing both PTT and PIR, this algorithm improved the estimation accuracy by -0.37 ± 5.21 mmHg for SBP and -0.08 ± 4.06 for mean BP and -0.18 ± 4.13 mmHg for DBP. In the correlational study of BP and PTT, it differs with respect to time such as day and night, and it is a drawback [10], [11].

Data mining is used widely over the past few decades to control a large amount of data set with a large number of features which overcome the limitation of the mechanism-driven models [12]–[14]. The accuracy of the mechanism-driven models can be improved by DNN, MLR, and SVR with data mining.

Another technique is random forest technique. In [15], it was studied if more features from ECG and PPG signal could be extracted to improve the accuracy of PTT-based arterial blood pressure (ABP) technique. Multi-parameter intelligent monitoring was used here.

A description of continuous BP estimation using DNN and data mining techniques is given in this paper.

III. Methodology

In this section, basic principles and feature extraction process, data collection, data pre-processing and model construction are explained briefly. Fig. 1 represents the overall processes of our proposed system.

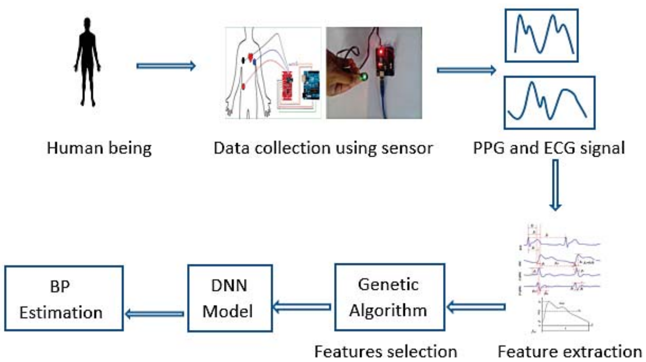

Fig. 1. Overview of our proposed system.

A. Basic Principles and Feature Extraction Process

Vascular elasticity, E can be expressed by mean BP P. When the pressure P is 0, vascular elasticity and correlation factor becomes E_0 and α. The relation between them is as following [16]:

$$P = \frac{1}{\alpha} ln \frac{E}{E_0} \tag{1}$$

In [17], the study says that arteriosclerosis can be achieved from 2nd derivative of PPG (2nd PPG) and it is the indicator of BP measurement. Here from Eq (1), it is clear that P depends on E/E_0 which specifies arteriosclerosis.

Again, the Moens-Korteweg (M-K) equation is another indicator of BP measurement named pulse pressure, PP, which indicates the difference between SBP and DBP is proportional to $1/PTT^2$ [8], [10], [18].

$$PP = PP_0 (\frac{PTT_0}{PTT})^2 \tag{2}$$

In Eq (2), PTT_0 and PP_0 are the initial conditions of PTT and PP. DBP and SBP are the two endpoints of PP. From the study of [19] following equations can be proposed.

$$DBP = DBP_0 \frac{PIR_0}{PIR} \tag{3}$$

$$SBP = SBP_0 \frac{PIR_0}{PIR} + PP_0 (\frac{PTT_0}{PTT})^2 \tag{4}$$

Eq (3) and (4) indicates the highly accurate estimation model with initial calibrated PIR_o. DBP_o which was proposed in the study of [9].

B. Data Collection

To collect real-life data for our experiment, three types of experiments were conducted named static, dynamic, and then a long term experiment is done after one month of the static and the dynamic experiment. 75 people (25 men and 50 women) for the static experiment, 35 people (18 men and 17 women) walked quickly for 10 minutes for the dynamic experiment, and 31 people (16 men and 15 women) gave their data after one month long to measure the correctness of previous BP estimation. On average the age is 22 to 35 years. AD8232 ECG sensor and PPG sensor connected with Arduino were used for collecting data, and the duration of collecting one data was about 10 minutes. Fig. 2 shows the experimental setup.

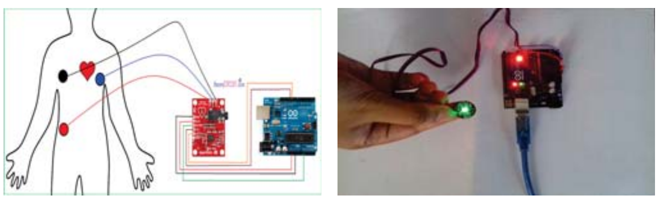

Fig. 2. Connection and data collection process with AD8232 ECG sensor and PPG sensor.

At the same time of collecting data for every experiment, referenced BP was collected to compare with the estimated value.

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TABLE I
NAMES OF THE FEATURES [21]

Features	Names
f1	Heart rate
f2	PTT_ppg_Bottom
f3	PTT_ppg_Peak
f4	PTT_Max_Deri
f5	Systolic time
f6	ppgFirstDeriHeight
f7	ppgFirstDeriWidth
f8	ppgSecondDeriHeight
f9	ppgSecondDeriPeakHeight
f10	ppgSecondDeriFootHeight
f11	ppgSecondDeriWidth
f12	PIR
f13	Diastolic time
f14	ppg_k

C. Data Pre-processing

From the collected data, features were extracted. From irrelevant and redundant features, essential best features were selected using Genetic algorithm as it finds out the near-optimal solution from a large number of feature set [20]. It also evaluates a fitness value to a satisfactory level. This process includes two steps like:

1) Feature Extraction: In this paper, 14 features were extracted for BP estimation. The definition of the features are mentioned in Table I, and they are depicted in Fig. 3. Feature 14 (f14) can be expressed as:

$$ppg\_k = \frac{p_m - p_d}{p_s - p_d} \tag{5}$$

where

$$p_m = \frac{1}{T}\int p_t dt \tag{6}$$

2) Feature Selection: From extracted feature sets, the essential features which are valuable for BP estimation were selected using a genetic algorithm. For selecting, there are two steps like:

I) Searching formula: It is the process of finding out the best one to generate new subset. Roulette wheel selection process is used here, which is familiar in the genetic algorithm.

II) Fitness function: For finding out the best feature set and skipping unnecessary feature set, the fitness function R is essential. The maximization of R was considered as an optimization problem. The overall technique for finding fitness are of two types named filter-based and wrapper-based. Filter-based selector ignores the classifiers and uses the intrinsic properties of the data, but the wrapper-based selector depends on the accuracy from the data mining process. Wrapper-based selector calls data mining technique repeatedly and so it is slower than a filter-based selector. Hence, filter-based feature selector was used in our experiment.

For calculating R, let, feature sets as n-dimensional independent variable be

$$X_1, X_2, X_3, ..., X_N$$

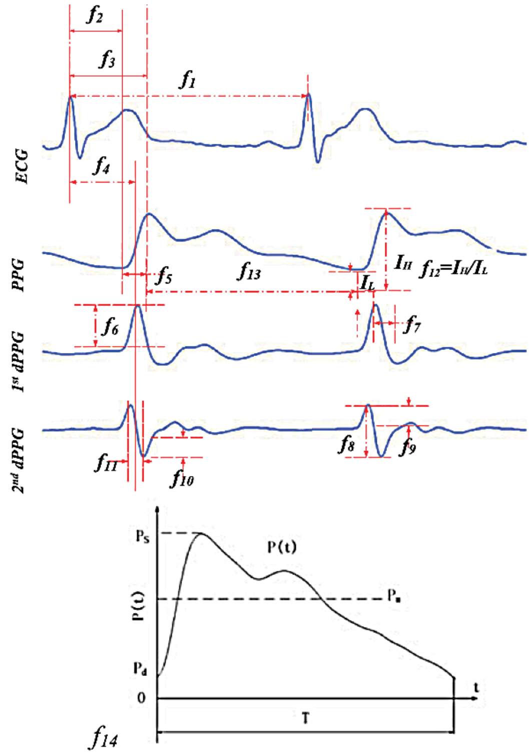

Fig. 3. Extracted features (Image Source: [21]).

and response variable are

$$y_1, y_2, y_3, ..., y_N$$

For each pair of y, Euclidean distance is:

$$D_y = d_{yi,yj} = y_i - y_j \tag{7}$$

Corresponding distance between independent variable is:

$$D = d_{Xi,Xj}$$

$$= \sqrt{\frac{(X_{i,1} - X_{j,1})^2 + (X_{i,2} - X_{j,2})^2 + ... + (X_{i,n} - X_{j,n})^2}{n}} \tag{8}$$

$$D_X = D, If\ D_y \geq 0, \tag{9}$$

$$D_X = -D, otherwise \tag{10}$$

The correlation coefficient R is:

$$R = \frac{S_{D_X D_y}}{\sqrt{S_{D_X D_y}}} \tag{11}$$

where,

$$S_{D_X D_y} = \frac{\sum_i (D_{X_i} - \overline{D}_X)(D_{y_i} - \overline{D}_y)}{n-1} \tag{12}$$

$$S_{D_X} = \frac{\sum_i (D_{X_i} - \overline{D}_X)^2}{n-1} \tag{13}$$

$$S_{D_y} = \frac{\sum_i (D_{y_i} - \overline{D}_y)^2}{n-1} \tag{14}$$

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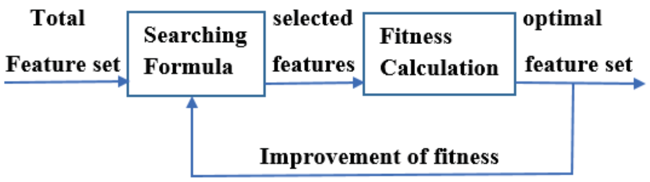

Fig. 4. Block diagram for selecting important features using genetic algorithm.

Fig.4 represents the block diagram of the overall feature selection process using genetic algorithm here.
Fig. 5 is an example of a feature selection process and demonstrates an individual's mean value and the highest correlation coefficient value. The overall increase in mean fitness tells that

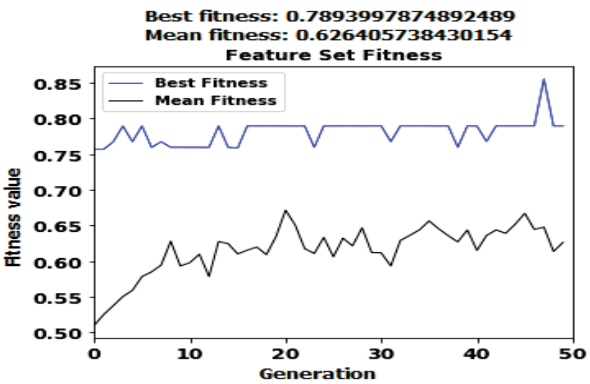

Fig. 5. Fitness improvement of feature set over time.

the high predictive features are selected and lower are avoided for genetic algorithm.
After finishing the part named data pre-processing, selected features were found to be same for the static and dynamic experiment. The dominant features for SBP were PTT_Max_Deri, systolic time, ppgSecondDeriFootHeight, ppgSecondDeriWidth, PIR, Diastolic time, ppg_k and for DBP were PTT_Max_Deri, ppgSecondDeriPeakHeight, ppgSecondDeriFootHeight, ppgSecondDeriWidth, PIR, ppg_k.

D. Model Construction

After extracting and selecting important features using a genetic algorithm, DNN, MLR, SVR with 5-fold cross-validation models were constructed. The models work as follows.

1) DNN: Deep neural network uses multiple hidden neurons to turn the input to the output calculating probability of each output to find out correct mathematical manipulation. In the neural network, each layer works by taking the previous layer's probabilities into consideration. It can work with both linear and non-linear relationships. Fig. 6 represents the architecture of DNN with our proposed layers.

2) MLR: It is a linear regression model which constructs the relationship between two variables named response and illustrative. In our paper, BP is a response variable, and the selected features are explanatory variables.

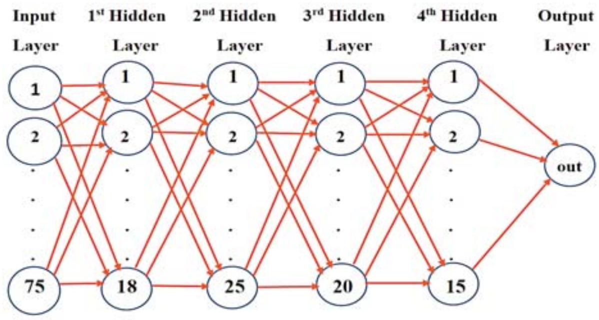

Fig. 6. DNN architecture with proposed layers.

3) SVR: It is a regression model which represents the non-linear relationship using kernel. Through non-linear mapping, feature f first mapped into m-dimensional space.

4) K-fold cross-validation is a technique of splitting data set into k groups.

IV. EXPERIMENTAL RESULTS

A. Evaluation Metrics of the Model

Unnecessary features are eliminated using a genetic algorithm to estimate a better BP model. Then the models were constructed using these selected features.

Accuracy of the estimated models was calculated according to Pearson's correlation coefficient (CC) which means measurement of consistency from the mathematical perspective, the mean distance (MD) which means the measurement of deviation from the real value that means the bias value in BP estimation, the difference in the standard deviation (SD) which means measurement of the variability of error with the referenced BP. Then MSE (mean squared error), MAE (mean absolute error), RMSE (root mean squared error) were used to calculate errors of every model and finally, the models were compared with one another. The results are here:
DNN-Based Model: As DNN consists of hidden network layers, so its performance is better than MLR and SVR as we found in our experiment. Statistical analysis of performance with the model DNN is in Table II:

TABLE II
STATISTICAL ANALYSIS OF PERFORMANCE WITH THE MODEL DNN

BP	DBP			SBP		
Term	Static	Dynamic	Long	Static	Dynamic	Long
Min CC	58.61	79.82	71.23	103.3	119.87	102.8
Max CC	98.79	102.37	98.58	135.5	140.44	124.84
MD	1.895	1.294	-1.39	0.488	1.159	-1.181
SD	5.553	10.029	14.43	12.92	10.064	13.615

Fig. 7 represents the comparison between estimated and referenced BP and Bland-Altman plots for static, dynamic and long term (after one month of the static and dynamic experiment) experiments. For DNN, the correlation coefficient between referenced and estimated BP are also represented in the figures like for DBP, correlation coefficient is 0.90 in the static situation, 0.82 for the dynamic situation, 0.71 for long

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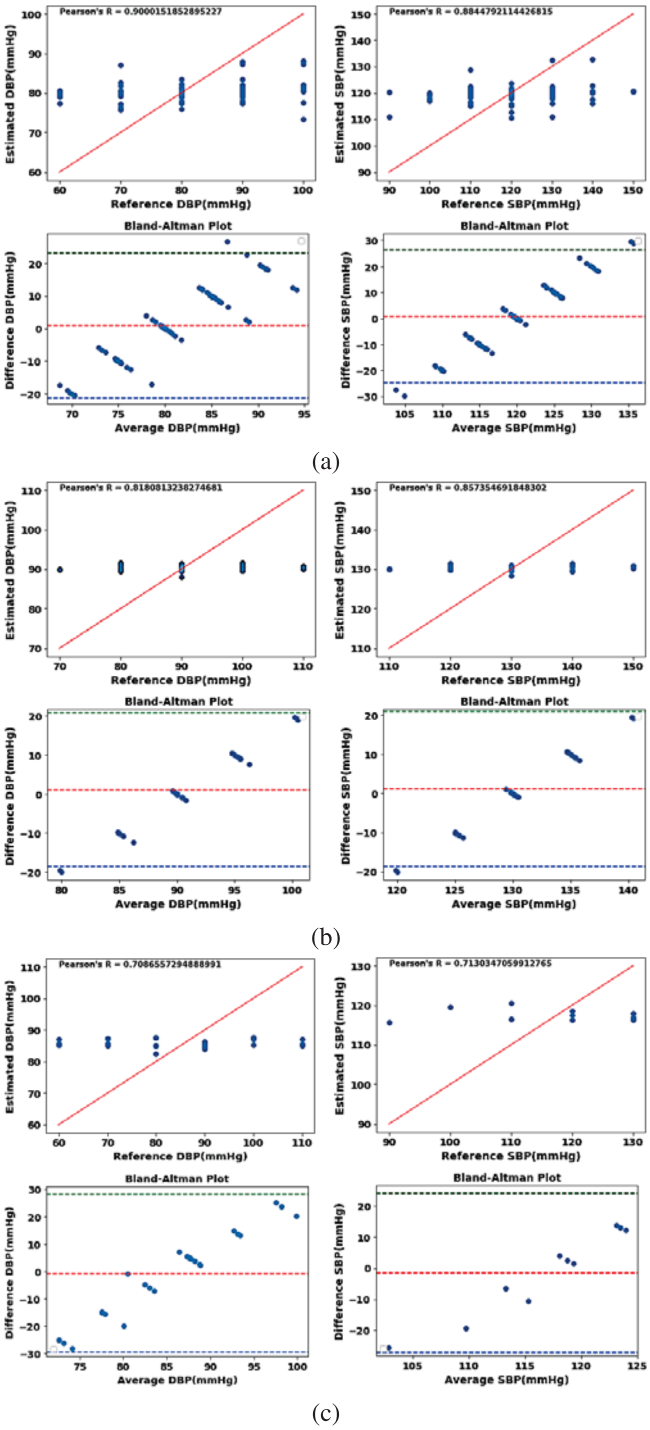

Fig. 7. Result analysis of DNN (a) Static (b) Dynamic (c) Long term.

term experiment and for SBP, the correlation coefficient is 0.88 in the static situation, 0.86 for the dynamic situation, 0.713 for long term experiment. The Bland-Altman plots indicate the estimated value approximated the referenced value for every experiment. From the results, it can be concluded that static and dynamic procedures are working well, but there are some limitations in long term processes.

Same procedures were followed for the MLR model and the SVR model. For both models, the validation is not too much high again, not too much low according to our devices, as stated above. However, DNN has the best result than these two in our experiment. K-fold cross-validation is used inside every model to make better results. Here, 5-fold cross-validation is used.

B. Robustness performance of the models

Our estimated blood pressure has not a higher level of accuracy, but according to our working environment, it is better. Same data, same methods were used to estimate the BP, and so the models MLR, SVR, and DNN were compared. Table III shows the result of the comparative study for static experiment, Table IV shows the result of the comparative study for dynamic experiment and Table, V shows the result of the comparative study for the long term (after 1 month) experiment.

TABLE III
COMPARISON OF ERRORS AMONG MODELS FOR STATIC EXPERIMENT.

BP	DBP			SBP		
Term	MSE	MAE	RMSE	MSE	MAE	RMSE
DNN	21.829	3.274	4.678	169.97	10.543	11.99
SVR	5883.89	76.641	76.713	13597.6	116.57	116.61
MLR	5920.36	77.522	76.94	13525.38	114.932	115.303

TABLE IV
COMPARISON OF ERRORS AMONG MODELS FOR DYNAMIC EXPERIMENT.

BP	DBP			SBP		
Term	MSE	MAE	RMSE	MSE	MAE	RMSE
DNN	133.7	8.601	11.61	134.67	8.645	11.648
SVR	7606.05	87.217	86.23	16188.98	128.23	127.24
MLR	8047.26	89.509	89.72	16806.8	129.49	129.64

TABLE V
COMPARISON OF ERRORS AMONG MODELS FOR LONG TERM(AFTER 1 MONTH) EXPERIMENT.

BP	DBP			SBP		
Term	MSE	MAE	RMSE	MSE	MAE	RMSE
DNN	221.013	11.59	14.87	163.53	10.992	11.827
SVR	7456.34	86.247	85.286	15953.8	127.28	126.304
MLR	6580.47	79.442	80.163	14427.02	118.79	121.108

For each of the experiment, DNN has a lower error rate that means higher accuracy than MLR and SVR experimented by ourselves. Three hidden layers were used in DNN, as stated previously in Fig 6. From this experiment, we can conclude that DNN has the most effect to estimate BP correctly using the same equipment in our experiment. However, if we compare the performance between another paper, who experimented MLR and SVR model using , SMART Medical, UK, the results are similar to ours. For static situation, our model acquired 169.97 MSE (DNN) value, but the paper has values in between the range -5 to +5. Moreover, we have found

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134.67 MSE (DNN) for the dynamic situation, but the paper has values in between the range -7/-8 to +7/+8 and 163.53 MSE (DNN) for long term (1 month) situation but the paper has values in between the range -10 to +5 for SBP. Again, we have 21.829 MSE (DNN) value for static situation, but the paper has values between the range -4/-5 to +4/+5, 133.7 MSE (DNN) for dynamic situation but the paper has values in between the range -4/-5 to +4/+5 and 221.013 MSE (DNN) for long term (1 month) situation but the paper has values in between the range -9/-10 to +5 for DBP. The considerable difference between the performance is due to equipment as we have our lower-priced sensor-based equipment only.

C. Discussion

In this paper, DNN, SVR, and MLR mechanism driven model with data mining techniques have been employed. Data mining technique is beneficial for a large amount of data for choosing important features and making patterns. However, it can be stated that DNN is better than the other two.

V. Conclusions

BP estimation is vital for predicting CVD. In this paper, data mining techniques with mechanism driven models are proposed. DNN, MLR, and SVR models were used to construct the BP model. Effectiveness of the models was checked by estimation accuracy and robustness accuracy. The performance is higher according to the experimental situation as the data could not be collected as needed. The comparison between models provides us a clear concept about the comparison of good and bad sides of the models.

In this paper, long term estimation is not entirely accurate due to inefficiency of equipments. In the future, other models will be used to estimate BP more accurately, and long term estimation will be tried to make perfect. Prediction of some diseases can be added with this experiment as the heart rate of an ill person is not the same as the average person.

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