Comparison of Artificial Intelligence Based Oscillometric Blood Pressure Estimation Techniques: A Review Paper

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***Abstract* - Accurate Blood Pressure (BP) measurement is an important physiological health parameter in the field of health monitoring, which is significant in determining the cardiovascular health of the patient under observation. Nowadays, automated blood pressure measurement systems are generally used by patients at home, and this requires less expertise to operate. The major requirement in the design of Automated Blood Pressure (ABP) measurement systems is the degree of accuracy and repeatability. There are various Artificial Intelligence (AI) based blood pressure estimation techniques and algorithms developed by various researchers in recent years and some of them are commonly employed by the BP monitoring market in the design of their automated blood pressure systems for accurate estimation of patient's systolic and diastolic blood pressures. In this review paper, various AI based Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) estimation techniques and algorithms are analyzed and compared in terms of their ability for accurate estimation of real time patient blood pressure. The performance of various AI based blood estimation techniques are analyzed in terms of their complexity, Mean Absolute Error (MAE) and Standard Deviation Error (SDE).**

Keywords - Artificial Neural Network (ANN); Adaptive NeuroFuzzy Inference System (ANFIS); Arterial blood pressure measurement; Principal Component Analysis (PCA).

I. INTRODUCTION

Accurate measurement of blood pressure plays an important role in the assessment and analysis of cardiovascular risk factors in clinical patient health monitoring because high blood pressure is a major risk for stroke or heart disease [1]. The accurate measurement of blood pressure is important for precise cardiovascular risk assessment, and for real time monitoring of the treatment effect by the doctors and health practitioners [1]. It has been repeatedly demonstrated in the studies carried out by various researchers that the blood pressure assessment in clinical practice is not precise, especially when the blood pressure is measured manually using the manual sphygmomanometer [2][3].

The deviations in blood pressure measurement techniques can lead to inaccuracy and misclassification of cardiovascular risk by the doctors and health practitioners [4]. For example, measuring the pressure manually with the arm positioned below the level of heart atria can lead to a blood pressure overestimation by 7-10/8-11 mm Hg [5]. In addition, leg crossing during manual blood pressure estimation also leads to the deviation in blood pressure by 8-10/4-5 mm Hg [6]. With the passage of time, the inaccurate manual blood pressure measurement systems have been replaced by Automated Blood Pressure (ABP) measurement systems which employs AI based BP measurement systems and digital display for the blood pressure readings. The digital blood pressure measurement systems suffer from the limitation of terminal digit preference i.e., rounding errors [7]. Thus, there is a need for accurate blood pressure measurement techniques and algorithms for the design of precise and accurate blood pressure measurement systems.

This review paper focuses on the study and comparison of various AI based BP estimation techniques and algorithms which have been developed by various researchers in the recent years for automated measurement of blood pressure precisely and accurately. Section II provides an introduction to blood pressure and various methods commonly employed for blood pressure measurement. Section III describes and compares the various non-invasive methods commonly used for the estimation and measurement of blood pressure. Section IV describes and classifies the various types of algorithms commonly used for the blood pressure measurement based on the stage at which the blood pressure estimation is carried out. Section V describes and goes into finer details of the various commonly employed AI based oscillometric blood pressure estimation algorithms for automated blood pressure measurement. Section VI compares the various AI based automated blood pressure estimation techniques and Section VII concludes this review paper.

II. BLOOD PRESSURE

In clinical terms, the *arterial blood pressure* is defined as the measure of pressure exerted by the blood against the walls of the brachial artery (the main artery in the upper arm of humans). The blood pressure is necessary to pump and circulate the oxygenated blood across the body in order to supply oxygen to the living cells, which is vital for the human survival. The blood is oxygenated through the lungs and circulated across the body via human heart at each cardiac cycle. The blood circulation system of the human body is shown in Figure 1 below.

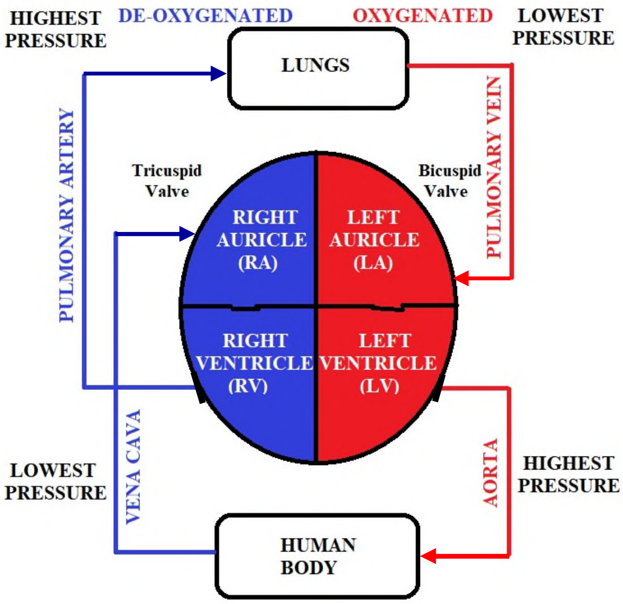

Figure 1. Human blood Circulation Model.

The heart operates like a pair of synchronized pumps and two pairs of valves (one between each auricle and ventricle and one between each ventricle and the blood vessel connected to it). The oxygenated blood is carried from lungs to the body by the left part of the heart, while the de-oxygenated blood is collected from the body and sent back to the lungs through the right part of the human heart. During the left ventricle contraction, the oxygenated blood is pumped into the aorta, which carries it to the various parts of body. During the left ventricle contraction, the blood pressure in arteries is highest and is known as arterial Systolic Blood Pressure (SBP), while the lowest pressure is established during ventricle relaxation period which is called Diastolic Blood Pressure (DBP) [8]. The arterial blood pressure as a function of time is shown in Figure 2.

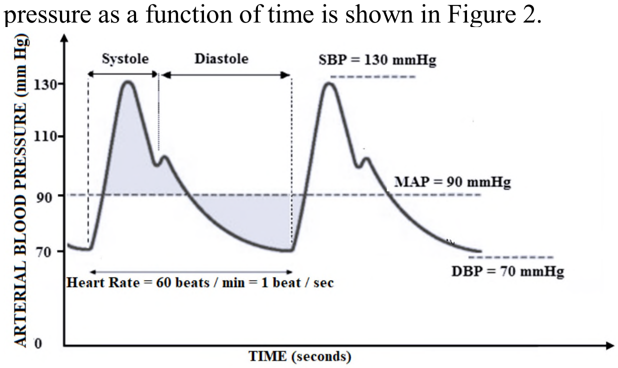

Figure 2. Arterial blood pressure as function of time.

The low blood pressure signifies that the force with which the blood is pushed from the aorta into the distributing arteries in human body will be quite low. In other words, it signifies that the blood could not be supplied in sufficient quantity throughout the human body if blood pressure is too low. Conversely, if the human blood pressure is too high, the blood vessels may be injured [8]. The blood pressure is generally measured in millimeters of Mercury (mm Hg) and the standard blood pressure of a healthy human is generally specified as 120/80 mm Hg, where the larger number (i.e., 120 mm Hg) signifies the Systolic Blood Pressure (SBP) and the smaller number (i.e., 80 mm Hg) indicates the Diastolic Blood Pressure (DBP).

There are two basic types of methods which have been generally employed for the measurement of blood pressure: [9]

(a) Invasive blood pressure measurement,
(b) Non-invasive blood pressure measurement

The invasive methods of blood pressure measurement are *in-vivo* methods, i.e. the blood pressure measurements are performed by inserting a pressure sensor inside the human body. The term '*in-vivo'* is a Latin word which means 'within the living'. Table I compares the two basic types of blood pressure measurement techniques.

TABLE I. COMPARISON OF INVASIVE AND NON INVASIVE BLOOD PRESSURE MEASUREMENT METHODS

S. No.	Invasive BP measurement	Non-Invasive BP measurement
1	The artery is punctured and pressure sensor is inserted inside the artery for pressure measurement i.e., the sensor is placed inside the human body for pressure measurement.	The blood pressure is measured by the sensor placed in close proximity to the human body and sensor is not inserted inside the human body by puncturing the artery carrying the human blood.
2	For example, placing the cannula needle inside the radial artery of patient for BP measurement [10]	For example, BP measurement using auscultatory or palpatory method [11]
3	Requires extremely high expertise as the sensor needs to be inserted into the punctured artery	Requires less expertise as the readings have to be noted by examiner or nurse from mercury manometer scale or from digital display.
4	The Blood Pressure is measured beat by beat	The Blood Pressure is not measured beat by beat
5	High accuracy	Comparatively less accurate
6	High complexity	Less complexity
7	Requires extensive overhead and time for measurement to be performed	Requires comparatively less overhead and time for measurement to be performed
8	Risk to the patient is involved	Safe for the patient and non-risky

III. NON INVASIVE BLOOD PRESSURE ESTIMATION METHODS

There are three common methods commonly employed for non-invasive blood pressure estimation:

(a) Palpatory method, (manual BP measurement)
(b) Auscultatory method, (manual BP measurement)
(c) Oscillometric method (automated BP measurement)

The above mentioned methods rely on sensing side effects generated on occluding an artery by inflating/ deflating a cuff around a subject's limb. It is to be noted that the palpatory and ausculatory methods of BP measurement are manual methods and involve the doctor or nurse to note the readings manually from the mercury scale, whereas the oscillometric method of BP measurement is an automated method which senses, measures and displays the BP magnitude on a digital display readout. It is also to be noted that the palpatory method was earlier used for measurement of SBP and was not considered suitable for measurement of DBP and Mean Arterial Pressure (MAP). However, a new palpatory technique for DBP pressure measurement has been proposed and is discussed in the following sections.

On the other hand, the auscultatory method is suitable for measurement of both SBP and DBP. It is because of this reason that the auscultatory method is more commonly used for BP measurement over the palpatory method. The palpatory method is limited for BP measurement by doctors in emergency situations [10]. However, the cuff based non-invasive manual BP measurement method requires the patient to position his arm above the level of heart atria and the mercury scale reading to be carefully observed by a nurse or observer for the accurate measurement of blood pressure.

The basic principles of various non-invasive BP measurement methods - auscultatory method, palpatory method and oscillometric method will be described below in detail.

A. Auscultatory method of BP Measurement

The most common blood pressure measurement method used by doctors and nurses in hospitals and clinics is the auscultatory method, which employs the usage of sphygmomanometer and stethoscope for blood pressure measurement [13]. A sphygmomanometer comprises of an inflatable cuff and mercury manometer. The inflatable cuff is placed around the subject's upper arm (around the brachial artery) and the subject's arm is placed above the level of heart atria for accurate pressure measurement, as shown in Figure 3 [14].

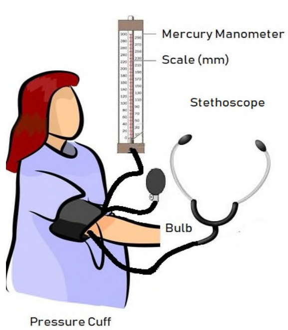

Figure 3. Auscultatory method of non-invasive BP measurement set up.

The cuff is inflated to suprasystolic pressure so that the artery is completely occluded. The cuff pressure is then slowly released and a trained nurse or doctor listens to the Korotkoff sounds with the help of a stethoscope placed between the arm and the cuff in order to identify the SBP and the DBP magnitudes, as shown in Figure 4.

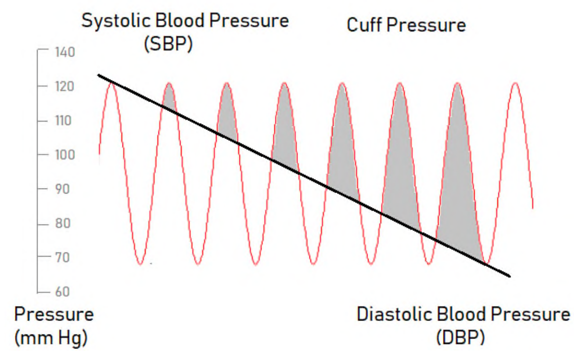

Figure 4. SBP and DBP measurements.

The cuff pressure at which the first Korotkoff sound is heard is the SBP and the pressure at which the sounds becomes muffled is the DBP. It should be noted that the auscultatory BP measurement method requires a trained health practitioner to note the accurate SBP and DBP magnitudes manually [14].

B. Palpatory method of BP measurement

In the palpatory method of BP measurement, the inflatable cuff is placed around the subject's upper arm (around the brachial artery) at the same height as the human heart for accurate pressure measurement [14]. The cuff is inflated to suprasystolic pressure. The cuff pressure is slowly released and a trained nurse or doctor senses the blood flow by placing a finger on the radial artery at patient's wrist, as shown in Figure 5 [12].

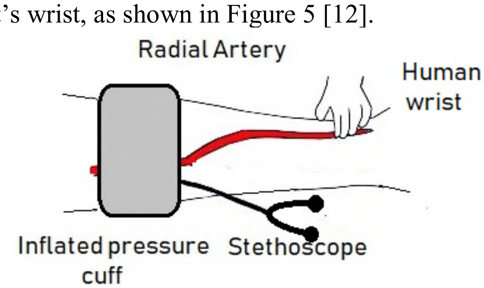

Figure 5. Palpatory method of non-invasive BP measurement set up.

The pressure at which the pulse disappears during inflation, and then subsequently, reappears during deflation is known as SBP. In a recent technique proposed for the measurement of DBP by palpatory method, the doctor places his first three fingers over the elbow bend and tracks the pulsating thrill over the elbow bend as he/she inflates and deflates the pressure cuff. The pressure measured on the manometer scale at which this pulsating thrill disappears is known as DBP [15]. Although it is a new technique for DBP

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measurement by using the palpation method, this method for BP measurement can lead to errors up to 25 percent and is commonly used by doctors and nurses during emergency medical situations [10].

C. Oscillometric method of BP measurement

The oscillometric method of BP measurement is one of the most common techniques for automated BP measurement and is suitable for the measurement of SBP, DBP and MAP [16]-[18]. The oscillometric principle of BP measurement is based on sensing the pressure pulses within a cuff wrapped over the brachial artery around the patient's arm or over the radial artery at the patient's wrist. The cuff wound around the patient's arm or wrist is inflated to a suprasystolic pressure. The cuff is then slowly deflated and the pressure oscillations are sensed by means of the pressure sensor in the cuff. Figure 6 clearly illustrates the principle used to sense the pressure pulsations by using the pressure sensor inside the cuff.

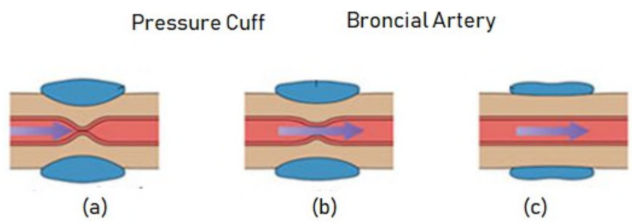

Figure 6. (a) Occluded brachial Artery with cuff pressure greater than 120mm Hg, (b) Blood flowing through relaxed brachial artery when cuff pressure is between 80mm Hg and 120 mm Hg, (c) Silent blood flowing when cuff pressure is below 80 mm Hg .

As the cuff is inflated to a suprasystolic pressure (i.e., greater than SBP), the cuff pressure leads to the occlusion of the artery and the blood flow within the artery stops, as shown in Figure 6(a). The cuff is then deflated slowly which leads to the flow of blood exerting pressure on the walls within the artery. The cuff is then deflated gradually to a subdiastolic pressure where the artery is no longer compressed and the blood starts flowing silently through the artery. During the deflation period (i.e., when the pressure is reduced in the cuff), the cuff pressure is recorded by means of the pressure sensor and the cuff pressure waveform is extracted at output of cuff pressure sensor. This extracted waveform is known as the cuff deflation curve, as shown in Figure 7.

The cuff deflation curve is comprised of two main components: (as shown in Figure 7)

(a) the slow-varying component due to the applied cuff pressure,

(b) pressure pulsations caused by arterial pressure (Oscillometric Waveform - OMW)

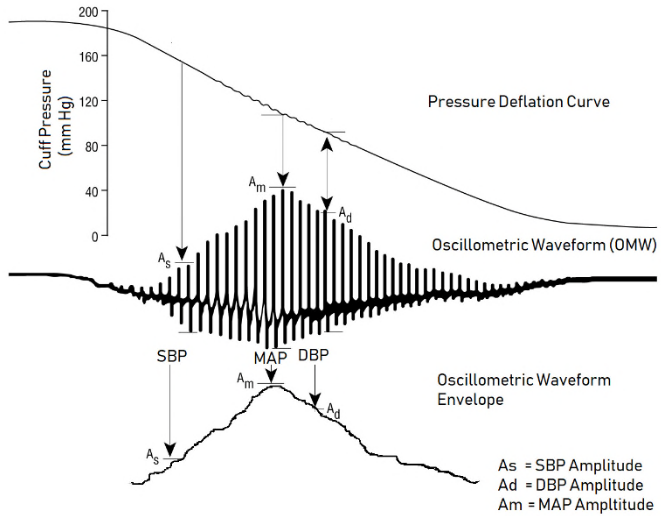

Figure 7. Oscillometric waveform for BP measurement.

The pressure pulsations, also known as Oscillometric Waveform (OMW) pulses, are extracted from the cuff deflation curve by extracting the slowly varying component through filtering techniques [19]-[21] or detrending techniques [22][23]. The filtering method is based on removing the cuff deflation frequency components using a bandpass filter [48]-[50]. The lower cut-off frequency of the filter is usually set to 0.1–0.5 Hz and the upper cut-off frequency of the filter is set around 20 Hz. In the detrending method, the trending curve is subtracted from the cuff deflation curve in order to obtain oscillometric waveforms OMW, as shown in Figure 7. The trending curve is basically a line of best fit which represents the decreasing cuff pressure [24]. It is to be noted that the BP information lies in the amplitudes of OMW and thus, the BP can be estimated from it. Most of the oscillometric algorithms proposed by various researchers for detection of BP are based on analyzing the Oscillometric Waveform Envelope (OMWE) [25]-[29].

The OMWE can be extracted and analyzed in terms of peak-to-peak [23] [31], baseline-to-peak [25], or the area of the oscillometric pulses during the cuff deflation period [33]. The peak-to-peak oscillometric waveform envelope ($OMWE_{p\text{-}p}$) is obtained by subtracting the consecutive peaks and troughs of oscillometric waveform (OMW). The baseline-to-peak oscillometric waveform envelope ($OMWE_{b\text{-}p}$) is obtained by subtracting the baseline from the peaks of the OMW where the baseline is the cuff deflation curve without the pressure oscillations. The computation of the area of the oscillometric pulses is based on the integration of the oscillometric pulses [29].

TABLE II. COMPARISON OF VARIOUS NON-INVASIVE BLOOD PRESSURE MEASUREMENT METHODS

S. No.	Parameter	Ausculatory method	Palpatory method	Oscillatory method
1	Working Principle	Detection of Korotkoff sounds by placing stethoscope over brachial artery with pressure cuff inflated and deflated slowly	Pulse detection by placing finger over radial artery with pressure cuff inflated and deflated slowly	Estimation of pressure from the oscillometric waveforms generated from cuff deflation or inflation waveform
2	Body target source employed for measurement	Brachial artery at upper arm	Radial artery at wrist	Brachial artery at upper arm or Radial artery at wrist
3	Output readout	Mercury Manometer	Mercury Manometer	Digital Display
4	Nature	Manual	Manual	Automated
5	Complexity	Less	Less	High

The oscillometric method of blood pressure measurement is more accurate than the auscultatory and palpatory methods of blood pressure measurement techniques. Table II compares the three non-invasive blood pressure measurement techniques. The various algorithms have been proposed by various researchers in the recent years for the estimation of SBP, DBP and MAP magnitudes from the OMWE. The various algorithms proposed by various researchers in the recent years for the detection of BP have been reviewed and compared in the following Section IV.

IV. CLASSIFICATION OF BP ESTIMATION ALGORITHMS

In the past few years, various BP estimation algorithms have been developed by various researchers. The BP estimation algorithms are usually applied on the signals recorded at the various stages which can be OMW, OMWE or ECG in BP measurement process. However, the BP estimation algorithms are generally applied on OMWE. Figure 8 below shows the basic flow process of automated BP estimation.

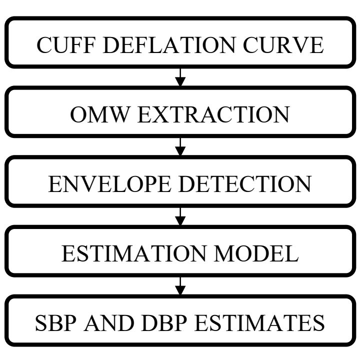

Figure 8. Basic flow process showing the process of BP measurement.

Table III shows the various blood pressure estimation algorithms and their principle of estimation.

TABLE III. VARIOUS BP ESTIMATION TECHNIQUES

S. No.	BP Estimation Algorithm	Principle of Estimation
1	Maximum Amplitude Algorithm (MAA)	Empirical coefficient detection from the peak amplitude of oscillometric waveform envelope
2	Derivative Oscillometry	Slope Estimation Detection
3	Neural Network Estimation	Machine learning approach
4	Model Based Algorithms	Mathematical modelling of envelope to estimate BP
5	Pulse Transit Time Estimation	Employ both cuff deflection curve and ECG (heart) signal for BP measurement

Figure 9 classifies the various BP estimation techniques based on the stage at which the BP estimation algorithm is applied.

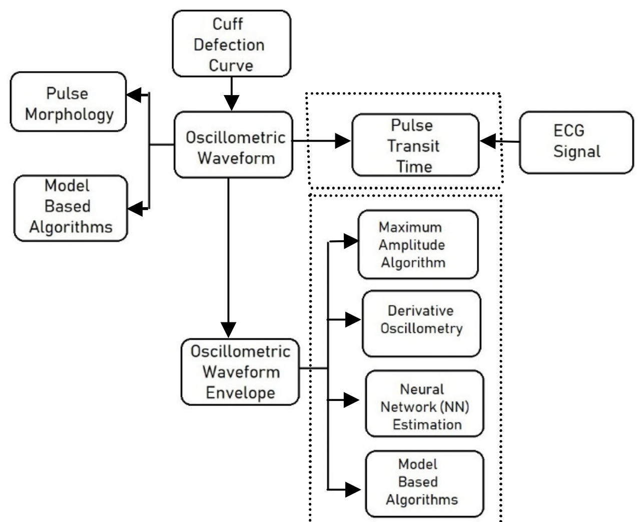

Figure 9. Classification of BP estimation algorithms based on stage at which BP estimation algorithm is applied.

This paper focuses on the comparison of various AI techniques, which are commonly employed for BP estimation applications. Section V focuses on the various AI based BP estimation techniques from OMWE in oscillometric method of BP measurement.

V. ARTIFICIAL INTELLIGENCE (AI) TECHNIQUES FOR BP ESTIMATION

In the recent years, artificial intelligence and deep learning algorithms have been employed by various researchers for blood pressure estimation from the OMWE. The most common AI technique employed in BP estimation is the artificial neural networks. The Neural Networks (NNs) are suitable for nonlinear physiological systems in the biomedical or instrumentation sector [34]-[37].

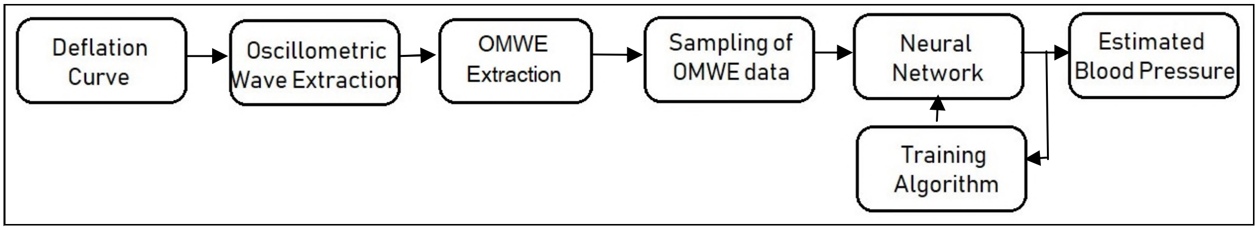

Figure 10. Feed Forward Neural Network (FFNN) based BP estimation using raw OMWE data.

The various NN algorithms that have been employed by researchers in the recent years in the field of BP estimation are listed and explained below.

A. Feed Forward Artificial Neural Network for BP estimation using raw OMWE data

The Artificial Neural Network (ANN) is a set of interconnected artificial neurons arranged in the form of layers forming a system, capable of learning in training mode, and providing the desired output according to the applied input in testing stage. The FFNN can be trained based on the nature and size of sample data and, once trained, the ANN can be tested by presenting different data sets for validating the results. The ANN can be trained and tested to estimate the SBP and DBP by presenting the raw OMWE data sampled at specific increments [38] [39].

Figure 10 shows the methodology to embed neural networks in the oscillometric BP estimation process. There are certain limitations of neural network based BP estimation technique, as mentioned below:

1. The performance of ANN is purely based on the nature of the data presented to the ANN when trained. The effective representation of data can lead to improved learning and the generalization of the network to be employed for estimation purposes. Since the neural network has to be trained for the specific OMWE data, it leads to a poor generalization network [40].
2. The redundant input data leads to a larger number of hidden layers in the neural network for better accuracy [41].
3. As the number of weights in the neural network increases, a large data set is required to train the neural network [43]. However, the collection of a large data set is time consuming and expensive.

Therefore, the raw sampled OMWE data leads to a neural network having more hidden layers and more weights and thus, it may lead to a large ANN network design. Therefore, the size of the ANN can be reduced by reducing the sample size of the OMWE or parameters that capture the essential features of the signal. Hence, the Principal Component Analysis (PCA) approach was introduced, which involves pre-processing of OMWE raw data before applying it to the ANN for training, as discussed in the following subsection.

B. PCA based Feed Forward Neural Network (PCA-FFNN) for BP estimation using raw OMWE data

The various features can be extracted from the envelope of oscillometric waveform, such as, the amplitude of the OMW pulses or height of OMWE, its derivative, width, etc. The basic principle behind the Principal Component Analysis (PCA) based FFNN approach for BP estimation was to reduce the dimensionality of the OMWE by discarding low-variance components that mainly reflect the noise. The compression of data set presented to the FFNN for training can be reduced by feature extraction. A subset of the extracted feature data set is used to train the ANN in PCA based approach, thus ensuring the requirement of small sized ANN for BP estimation since the input data set gets reduced because of the compression of input training data set [41]-[45]. The PCA based ANN approach implementation has been shown in the form of block diagram in Figure 11. The feature set of OMWE data is normalized before applying it to the ANN so that the data set should lie within the specified range, which reduces the chances of getting stuck at local minima [47]. The PCA based ANN approach derives a reduced feature set of OMWE instead of using the features for training the ANN. The optimal parameters of the Gaussian functions can be obtained by minimizing the least squares error between the model signal and the true signal by using the *Levenberg–Marquardt algorithm* (LMA) [45].

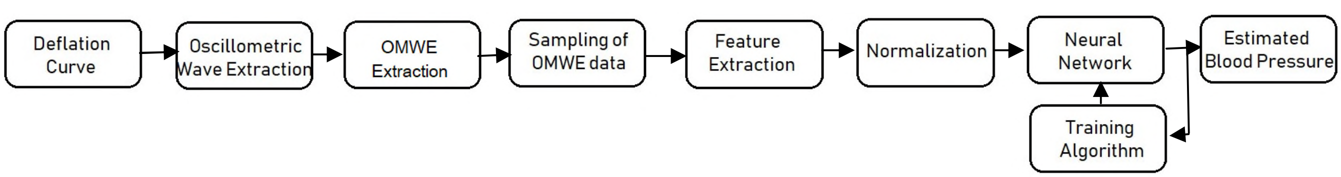

Figure 11. PCA based ANN approach implementation.

These optimal parameters have been considered as the features for training two separate Feed Forward Artificial Neural Networks using Resilient Backpropagation (RBP) learning algorithm [46] for estimation of SBP and DBP. The RBP algorithm introduced in year 1994 has been used to train the ANN instead of steepest decent algorithm [41] or steepest descent algorithm with momentum [39] introduced in year 1995 because the RBP has diverse advantages of fast learning rate, small learning data set, do not get stuck at local minima and is robust to noise. In [47], the PCA based ANN approach was implemented for BP measurement from the radial artery and the system was trained and tested using 425 BP readings (5 readings from each of 85 persons) and the range of BP data set ranged from 42-99 mm Hg for DBP and 78-147 mm Hg for SBP.

The number of hidden layers in the FFNN were chosen iteratively for minimum Standard Deviation Error (SDE) and Mean Absolute Error (MAE) by performing the experiments for minimal errors in the output during the training. It was observed that, by reducing the number of inputs from 48 to 5 and hidden layer neurons from 4 to 2, the first layer weight is reduced from 192 to 10. Figure 12 and Figure 13 compare the performance of PCA based SBP and DBP FFNN when tested with raw data for the first time and principal feature based data in terms of number of input layers, number of output layers required, hidden neurons, weight of first layer and weight of second layer [47].

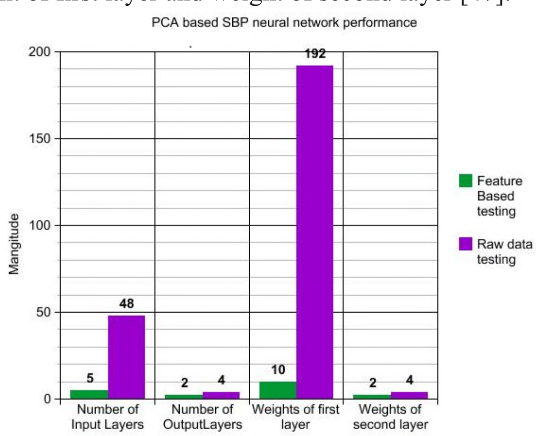

Figure 12. PCA based SBP FFNN performance when tested with raw and feature based data [47].

It can be concluded from Figure 12 and Figure 13 that principle feature based testing of feed forward neural networks[47]:

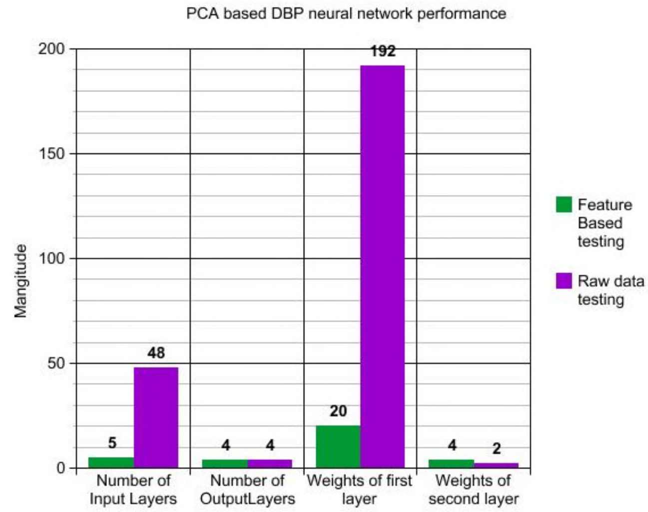

Figure 13. PCA based DBP FFNN performance when tested with raw and feature based data [47].

(a) employs a smaller number of input layers in both SBP and DBP estimation,
(b) employs fewer output layers in SBP estimation,
(c) employs lower weight magnitudes in the first layer in the network in SBP and DBP estimation, and
(d) employs lower weight magnitudes in the second layer in the network in SBP and DBP estimation,

C. Adaptive NeuroFuzzy Inference System for BP estimation

The ANFIS approach consists of three stages, as shown below in Figure 14. In the first stage, the oscillation amplitudes (OAs) of the oscillometric waveforms (OMW) has represented as a function of the cuff pressure. In the second stage, the Principal Component Analysis (PCA) has been utilized to reduce the size of the input training data set by extracting the most effective features from the oscillation amplitudes. In the final stage, the ANFIS has been employed to perform the BP estimation.

The proposed method was tested on the data feature set derived from the 85 patients in 1994 and the results of ANFIS approach was compared with the conventional maximum amplitude algorithm (MAA). It was found that the ANFIS achieved lower values of standard deviation of error (SDE) and Mean Absolute Error (MAE) as compared to MAA approach [48]. The ANFIS system employed the advantages of both ANN and fuzzy logic (FL) for BP estimation. It was observed by B. Kosko in 1994 that, under proper conditions, ANFIS can be used as an universal approximator [48].

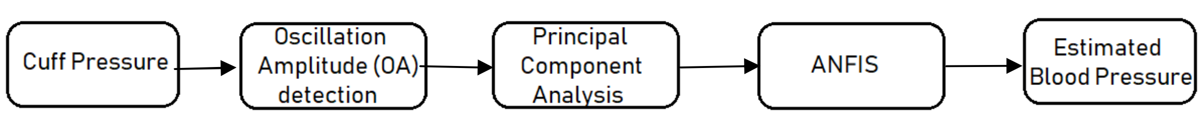

Figure 14. ANFIS approach based BP estimation process.

Figure 15 and Figure 16 show the performance of the ANFIS based SBP and DBP networks when tested with raw data and principal feature based data in terms of number of input layers and number of membership functions [47].

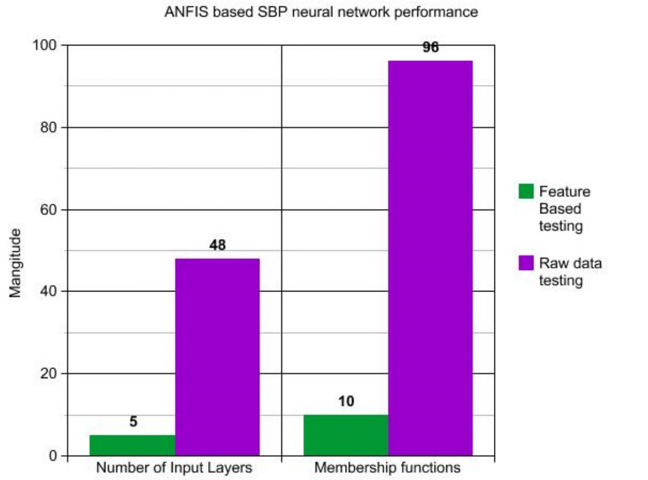

Figure 15. ANFIS based SBP network performance when tested with raw and feature based data [5].

It is to be noted that two separate ANFIS networks were designed for Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) estimation. The number of hidden layers was chosen by performing the random experiments for minimal Standard Deviation Error (SDE) and Mean Deviation Error (MAE).

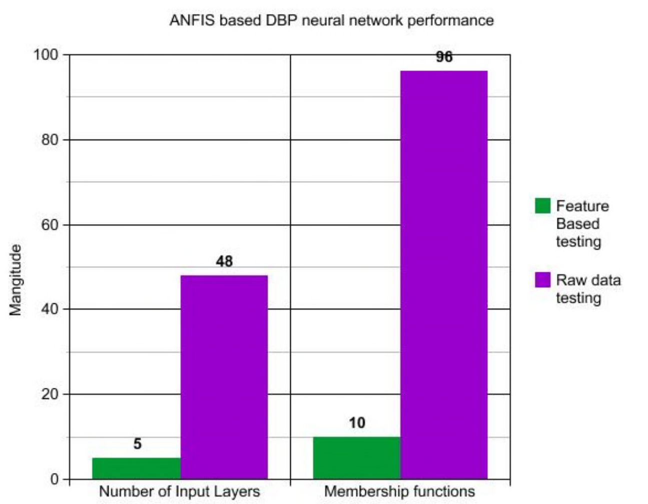

Figure 16. ANFIS based DBP network performance when tested with raw and feature based data [49].

It can be concluded from Figure 15 and Figure 16 that ANFIS employs:

(a) less number of input layers in both SBP and DBP estimation, and
(b) less number of fuzzy membership functions in both SBP and DBP estimation.

D. PCA based Cascade Forward Neural Network (CFNN) for BP estimation

In 2010, the PCA based Cascade Forward Neural Network (PCA-CFNN) for BP estimation was employed for BP measurement which was similar to the PCA based Feed Forward Neural Network discussed in sub-section B above but the difference lies in the fact that there existed a weight connection from input to each layer and from each layer to the successive layer. The experimentation was performed on 85 subjects and five readings were taken for each subject leading to 425 reading set and the principle parameter set was prepared from the subject data in order to constrain the input data train data set used to train the cascade forward neural network using gradient decent algorithm with momentum.

VI. COMPARISON OF VARIOUS AI BASED BP ESTIMATION TECHNIQUES

Figure 17 and Figure 18 show the comparison of various AI based BE estimation techniques discussed above in terms of the MAE and SDE [47]-[50].

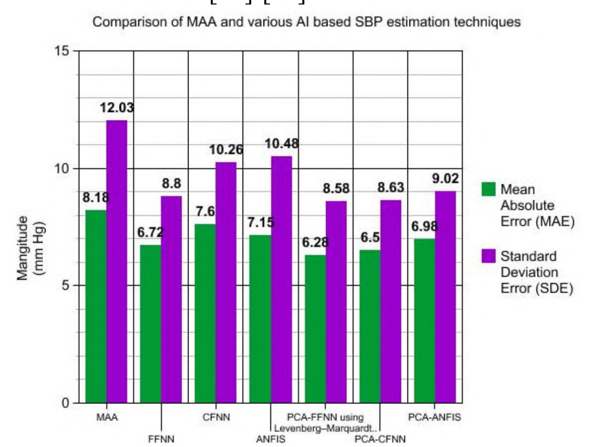

Figure 17. Comparison of various AI based SBP estimation techniques

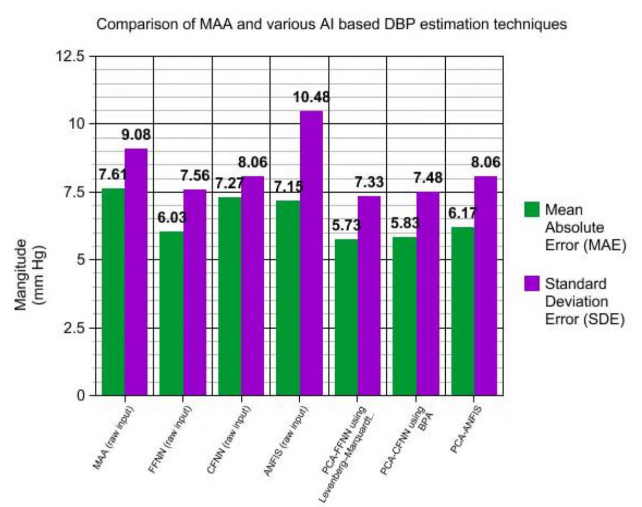

Figure 18. Comparison of various AI based DBP estimation techniques

It can be concluded from the above Figure 18 that the PCA-FFNN using Levenberg–Marquardt algorithm (LMA) has the least MAE and SDE followed by the PCA-CFNN using Back Propagation algorithm with momentum. It can also be observed that the using the PCA approach leads to lower MAE and SDE.

VII. CONCLUSION

In this review paper, the performance of various AI based BP estimation techniques have been analyzed and compared in terms of SDE and MAE. The effect of employing the PCA with the ANNs has also been reviewed in this paper. It has been concluded that the feature based testing of PCA-FFNN employs:

a) less number of input layers in both SBP/DBP estimation,
b) less number of output layers in SBP estimation,
c) lower weights in the first layer in the network for SBP/DBP estimation, and
d) lower weights in the second layer in the network for SBP/DBP estimation in comparison to the raw testing of the feed forward neural testing.

Therefore, it has been concluded that the complexity of the system gets reduced when using the principle features. It has also been analyzed and concluded from the above discussion that using the PCA approach with ANNs leads to a reduction in MAE and SDE. Further, the PCA-FFNN using Levenberg–Marquardt algorithm (LMA) has the least MAE and SDE in comparison with the other AI based algorithms.

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