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Others Section

Original Article

Assessment and Evaluation of Diabetic Foot using Biothesiometry and Artificial Neural Networks

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ABSTRACT

Introduction: Diabetes is a common disorder that is prevalent in the general population. As it advances, it causes a multitude of consequences, some of which are fatal. Diabetic Neuropathy (DN) is one such illness that causes nerve damage, and it is quickly recognised and diagnosed using a technique known as biothesiometry.

Aim: To create an assessment tool based on an Artificial Neural Network (ANN) that evaluates diabetic foot based on Vibration Perception Threshold (VPT) values.

Materials and Methods: This experimental and predictive study was done using VPT values for 696 controlled and diabetic groups selected by purposive sampling. The VPT was measured by a biothesiometre. A metal probe was placed under the foot of the person and the voltage was increased gradually from zero and the transition from no vibration to the point of vibration is marked as VPT. Average of three measurements were taken to calculate the VPT value of the given patient. This involves the VPT value which helps in the assessment of severity of the condition. The recorded data was fed as an input to the ANN model which predicted the average VPT value of the left and right foot. Furthermore, the ANN model was assessed my means of statistical measures and parameters.

Results: The results of the study confirmed the correlation between the values of VPT acquired at different points of the foot and the coefficient for the left and right foot was found to be 0.99549 and 1.0000 respectively. Furthermore, the efficiency of the proposed ANN model was assessed using statistical measures like Mean Square Error (MSE), Mean Absolute Error (MAE), Square Sum Error (SSE) and Coefficient of determination (R^2). The predicted values were very close to the experimental VPT results, and the correlation coefficient R are 0.99549 and 0.99975 for the left and right foots respectively, which shows the best settlement.

Conclusion: The study concluded that VPT acquired from the foot of diabetic patients is useful in categorising the level of severity of DN. Furthermore, the results of ANN model proved that there exists a strong correlation between the average VPT values of left and right foot and those that are acquired from different points of the foot such as Great Toe, First metatarsal, Third metatarsal, Fifth metatarsal, In step and heel which concluded the study to be effective in the assessment and diagnosis of DN.

Keywords: Diabetes, Vibrometre, Vibration perception threshold

INTRODUCTION

Diabetes is common in the general population, particularly among people aged 40-60 years. According to Saeedi et al., the incidence of diabetes would rise to 537 million by 2030 [1]. In such people with diabetes, damage to nerves in foot and legs can occur which can range from severe to fatal. The condition is called Diabetic Neuropathy (DN), this condition has numerous complications associated with it such as foot ulcerations, leg amputation and pain and it is mostly identified in the later stage [2]. The early diagnosis of such conditions can be done using the procedure known as biothesiometry. A biothesiometre is an electromechanical device that is used to measure the VPT values that serves as a simple technique to diagnose peripheral neuropathy in people [3]. In most cases DN is detected by using VPT values wherein it gives a quantitative measure of the vibration that is being perceived by a patient. Aruna BM and Haragopal R, conducted a study on 60 people, 30 of whom were diabetic and 30 of whom were not; the findings were reached by calculating the mean VPT between the two groups, and there was a statistical significance between the groups [4]. In a related study based on VPT, Dash S and Thakur AK; Kaur J and Batra AP found no significant difference between individuals with clinical neuropathy and those without clinical neuropathy, concluding that the severity of the condition cannot be detected by biothesiometry [5,6]. Furthermore, in a study conducted by Ashok BH et al., it was discovered that obtaining thermal images in addition to VPT data proved to be effective in producing an accurate diagnosis report for plantar lesions in the foot [7].

The presence of neuropathy is a crucial factor in evaluating if a foot is particularly prone to painless damage, which can progress to a persistent and spreading ulcer. This has major ramifications and might result in massive amputations below or above the ankle and knee. Neuropathy can be qualitatively assessed by means of using a tuning fork, hot and cold sensation and pricks. But quantitative assessments of the protective sensation in the foot should be done in order to report any incremental risks and damage. Many procedures, such as nerve conduction investigations, are available but unfeasible due to their high cost [8]. Hence, simple techniques like using vibration perception prove very useful and effective. The device that produces vibration at specific voltage levels is known as a Vibrometre/ Biothesiometre.

In this work, VPT values were acquired from various point of the foot of diabetic and non diabetic individuals with the help of a biothesiometre and an ANN model based on the Levenberg Marquardt algorithm was constructed with the acquired VPT values as input and the average VPT value as output. ANN is increasingly being used as a method to diagnose DN, but many algorithms remain untested. Hence, this work proposes the adoption of a new ANN model and the proposed ANN was tested for its performance based on parameters such as MSE, MAE, SSE, and R^2.

MATERIALS AND METHODS

The present experimental and predictive survey was conducted among 696 volunteers at Sri Sivasubramaniya Nadar College of Engineering, Chennai, Tamil Nadu, India, from January 2022 to March 2022. The subjects were selected by purposive sampling technique. The subjects who attended the HCL health camp for VPT measurement were both diabetic and non diabetic. Out of the 696 volunteers 78 were normal subjects where the maximum VPT value for both the foot was found to be less than 15. The minimum age of the participant involved in the study was 35 years and the majority consisted of participants above the age of 50 years. The measurements were made from the subjects as shown in [Table/Fig-1a,b].

[Table/Fig-1]: a) Placement of vibrometre probe on the right foot to acquire data; b) Placement of vibrometre probe on the left foot to acquire data.

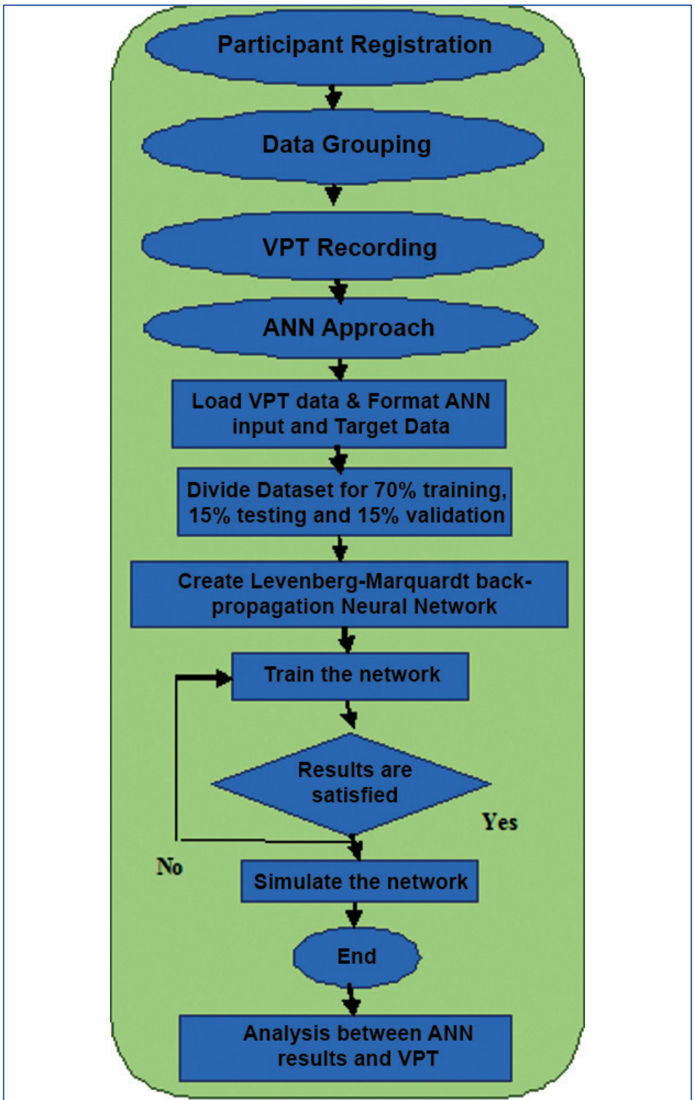
Vibration Perception using Biothesiometre

The vibrometre model that was used in the study is the Vibrometre VPT by Diabetik Foot Care India Pvt Ltd. The technical specifications of the device are shown in [Table/Fig-2] [9]. The overall framework of the work involved in the present study is illustrated in [Table/Fig-3].

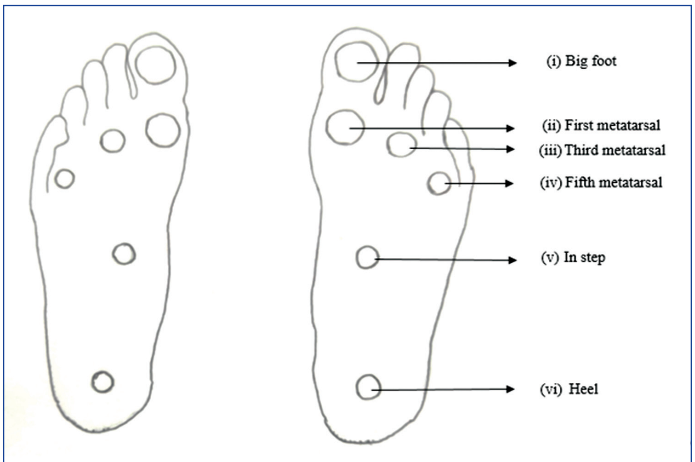
Features	Specification
Power supply	230 V
Frequency	50 Hz
Fuse rating	100 mA
Operating temperature	15-45°C
Humidity	15-90% condensing
Operating pressure	523 mmHg
Vibration frequency	120 Hz
Vibration output range	0-50 V
Computer interface	RS232C
Display	LED

[Table/Fig-2]: Technical specifications of vibrometre.

Data generation: In this study, a health camp was organised in a hospital and the data was collected from 696 volunteers using the aforementioned model of vibrometre. All the volunteers were informed about the procedure and an informed consent was obtained from the all the participants involved in the study. The subjects were then asked to sit in a relaxed position. The vibrometre probe was initially placed on the hands in order to provide a sense and impression of vibration. Then the probe was applied at six points on the foot as illustrated in [Table/Fig-4] and the voltage level was simultaneously increased. The points shown in the figure represent the parts of foot namely the (i) big foot, (ii) 1st metatarsal, (iii) 3rd metatarsal, (iv) 5th metatarsal, (v) In step and (vi) heel respectively. The level of severity was classified and assessed by using the voltage perception range as shown in [Table/Fig-5] [5,10]. which led to categorising the subjects into right mild loss, left mild loss, right moderate loss, left moderate loss, right severe loss and left severe loss as shown in [Table/Fig-6]. The procedure was stopped immediately if the volunteer felt any slight discomfort. Several trials were conducted, and the data generated was transmitted via the RS23C serial interface to the PC.



[Table/Fig-3]: Workflow diagram.



[Table/Fig-4]: Foot diagram illustrating the placement of biothesiometre probe [5].

Voltage perception range (V)	Frequency of vibration (Hz)	Level of severity
<15	4-225	Normal study or level 1
16-20	256-625	Mild loss of vibratory perception or level 2
21-25	256-625	Moderate loss of vibratory perception or level 3
>25	>625	Severe loss of vibratory perception or level 4

[Table/Fig-5]: Allocation for biothesiometre values [5,10].

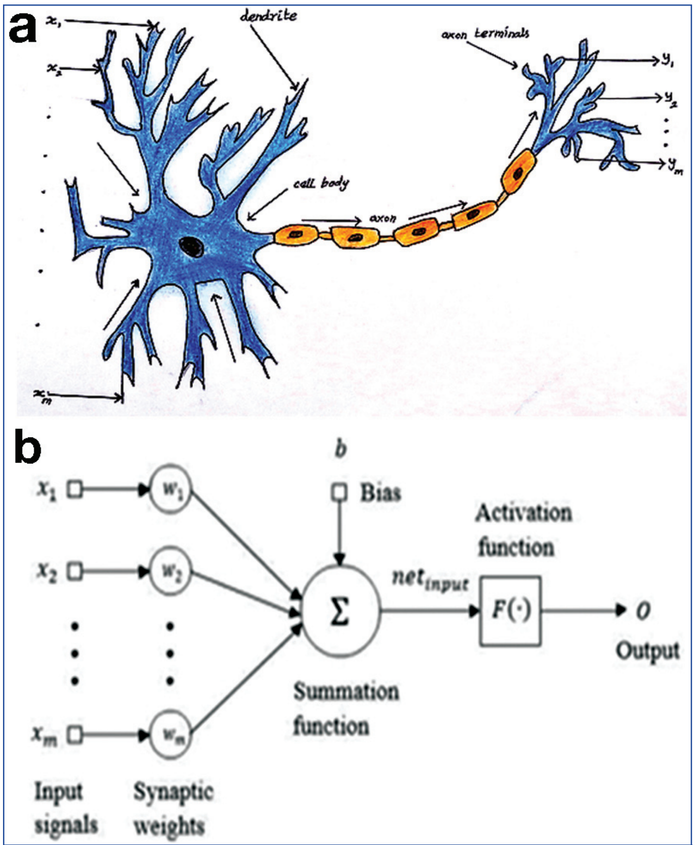
Artificial Neural Network (ANN) Approach

ANN is a data-driven modelling tool that is used to imitate the structure and functional abilities of a biological neural network, as shown in

Category based on severity	Number of subjects
Right mild loss	124
Left mild loss	124
Right moderate loss	112
Left moderate loss	112
Right severe loss	112
Left severe loss	112

[Table/Fig-6]: Category of subjects according to severity.

[Table/Fig-7a] [11,12]. ANN is a parallel distributed processor made up of basic and highly linked processing components known as neurons that process data. The brain network learns and stores that knowledge in the interneuron connection strengths known as synaptic weights [13]. The neural model has a set of connecting channels, an adder, and an activation function. The synaptic weights *w*1, *w*2,...,*wm* are multiplied by the input signals *x*1, *x*2,...,*xm*. In order to determine the neuron's net input, the weighted inputs are summed and multiplied by bias (b) (net input). The net input is then passed via an activation function (*F*(·)), which generates the output (*0*) of the neuron as shown in [Table/Fig-7b]. The bias term is used to improve network performance by adjusting the net input of the activation function. The activation function limits the amplitude range of a neuron's output to a limited value [14].



[Table/Fig-7]: a) Single biological neuron; b) Schematic of Artificial neural.
a) and b)- Sri Sivasubramaniya Nadar College of Engineering

The net input (net_{input}) and output (*0*) of the neuron are expressed as

$$net_{input} = \sum_{k=1}^{m} w_k x_k + b \tag{1}$$

$$0 = F\left(\sum_{k=1}^{m} w_k x_k + b\right) \tag{2}$$

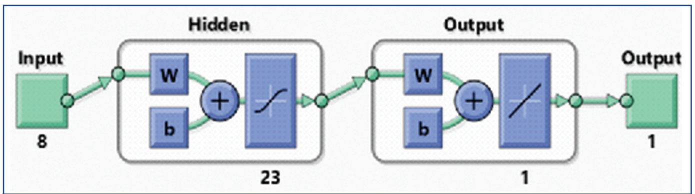
The most widely used activation functions are the sigmoid and linear functions, and they are described in equations (3) and (4), respectively.

$$F(net_{input}) = \frac{1}{1 + e^{-net_{input}}} \tag{3}$$

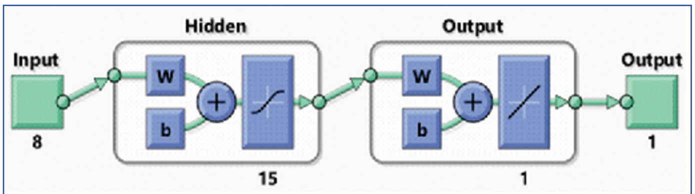
$$F(net_{input}) = net_{input} \tag{4}$$

The multilayer feed forward neural network with the back propagation training technique is the most often used ANN. A Multilayer Perceptron (MLP) is made up of an input layer, one or more hidden layers of linear threshold units, and an output layer. The Back Propagation (BP) technique computes the difference between expected and actual outcomes and propagates the mistake back to the network. The BP algorithm modifies the network's weights and biases at each iteration to decrease error, and the process is repeated until a particular level of accuracy is attained.

Artificial Neural Networks (ANN) application in diabetic foot: In this work, authors have imported an ANN model onto a database of diabetic foot occurrences in order to show the reliability of neural networks in the biomedical sector. Hence, an ANN model with one hidden layer and 25 neurons was built utilising the VPT values of diabetic and non diabetic measured using a biothesiometre. The chosen network design includes eight neurons in the input layer that represent the age, big toe, first metatarsal, third metatarsal, fifth metatarsal, instep, and heel, as well as one neuron in the output layer. The number of hidden neurons that was selected was 23 and 15 in one hidden layer for the left and right foots which is demonstrated in [Table/Fig-8,9] respectively. The coefficient of determination (R^2) for the left and right foots were 0.990963 and 0.974916 respectively. This selection process was made upon experimenting all the probability of growing hidden neurons from 1 to 25, R^2 from 0.1 to 0.9 for each. Levenberg–Marquardt BP was used as a training function and sigmoid was used as a transfer function. The coefficient of determination was estimated based on network performance, with different modifications to connection weights made throughout training. The input data set was distributed as 70% for training, 15% for testing, and 15% for validation, respectively. The correlation coefficient (*R*) captured for training, testing, validating, and overall data for left foot (LF) and right foot (RF) ANN models are shown in [Table/Fig-10].



[Table/Fig-8]: Architecture of neural network (Left foot).



[Table/Fig-9]: Architecture of neural network (Right foot).

ANN model	Correlation coefficient (*R*)			
	Training	Testing	Validating	Overall data
Left foot ANN	0.99848	0.98913	0.9894	0.99549
Right foot ANN	1.00000	1.00000	1.00000	1.00000

[Table/Fig-10]: Correlation coefficients values for left and right foot ANN models.

RESULTS

Based on an analysis of [Table/Fig-8,9], it can be observed that the proposed Levenberg-Marquardt BP neural network, which has one hidden layer with 23 hidden neurons for the left foot and one hidden layer with 15 neurons in the hidden layer for the right foot, shows superiority in terms of reduced standard statistical errors and decreased overall error rates [Table/Fig-11]. As a result, the Levenberg-Marquardt BP neural network has been proposed as the best structural framework for the proposed ANN model. It has eight inputs, one hidden layer, 23 and 15 hidden neurons in the hidden layer for the left and right feet, respectively, and one output layer with one output neuron. The convergence of the VPT value of a diabetic using a biothesiometre and ANN model in terms of MSE, states of convergence, Error Histograms (EH) and the correlation coefficient (R) are depicted in [Table/Fig-12-19]. From [Table/Fig-12,13], it can be observed that the best validation performance of left and right foots was accomplished at 37 and 52 epochs with the value of MSE around 0.032724 and $1.2021e^{-10}$ respectively. The corresponding gradients are [0.12792 and $9.5743e^{-0.8}$] while the step size *Mu* for left and right foots are [$1e^{-06}$ and $1e^{-14}$] and at epochs 43 and 52 respectively as displayed in [Table/Fig-14,15]. Furthermore, the bins near to apt zero line having EH values for the aforementioned cases are 0.03727 and $1.14e^{-07}$, respectively are illustrated in [Table/Fig-16,17]. To scrutinise the capability of the developed ANN model, the regression analysis between the numerical and predicted results were plotted for the stated cases that can be seen in [Table/Fig-18,19]. The values of R, is always closer to 1, for training, validation, testing, and overall dataset, which confirms that a good agreement lies between the actual and the targeted numerical value. Hence, the proposed Levenberg–Marquardt BP neural network modeling approach is reliable, effective, accurate, fast, and alternative tool particularly in healthcare sector.

where $\hat{E}_i$ measured output using biothesiometre, $\hat{P}_i$ predicted value by ANN model, $\overline{E}$ = average measure and N_d number of input data set, respectively.

$$MSE = \frac{1}{N_d}\sum_{i=1}^{N_d}(\hat{E}_i - \hat{P}_i)^2 \quad (5)$$

$$MAE = \frac{1}{N_d}\sum_{i=1}^{N_d}|\hat{E}_i - \hat{P}_i| \quad (6)$$

$$SSE = \sum_{i=1}^{N_d}(\hat{E}_i - \hat{P}_i)^2 \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N_d}(\hat{E}_i - \hat{P}_i)^2}{\sum_{i=1}^{N_d}(\hat{E}_i - \overline{T})^2} \quad (8)$$

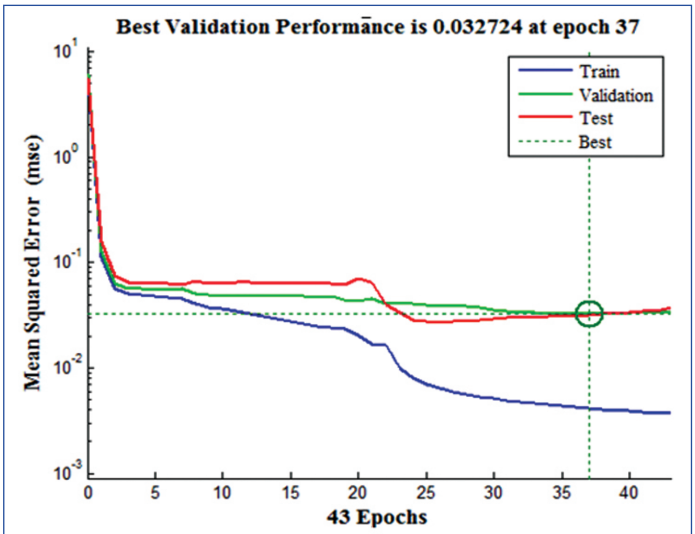
The error calculations such as MSE, MAE, SSE and the coefficient of determination (R^2) of developed ANN model of one hidden layer with 25 neurons are presented in [Table/Fig-11]. It should be noted that the suggested ANN model produced better results, and the predicted levels of diabetes severity were in close agreement with data obtained using a biothesiometre, with correlation coefficients of 0.99096 (LF) and 1.0000 (RF) for each.

DISCUSSION

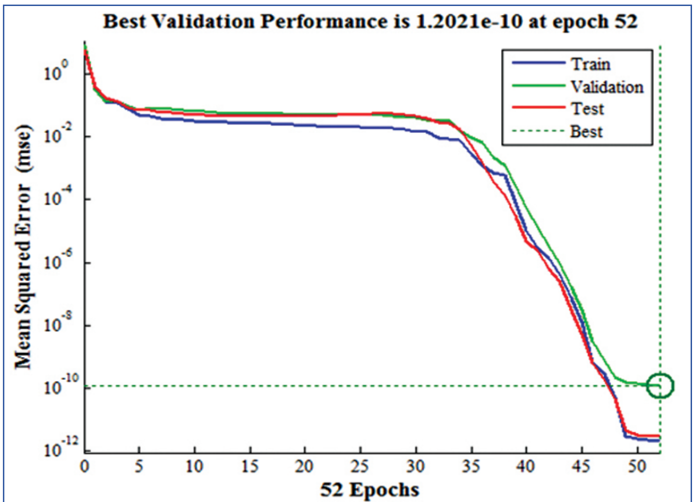
ANN was chosen since it offers an effective and credible solution and has been widely employed in a variety of engineering and science disciplines [15-18]. In the health industry, ANN is a suitable tool for prediction of illness such as Malaria and Cancer, widely employed in image processing in the medical profession, and finds its application in Decision Support Systems (DSS) [19-22].

Number of neurons	MSE(%)		MAE%		SSE%		R^2	
	LF	RF	LF	RF	LF	RF	LF	RF
1 neuron	0.05422	0.06203	0.18142	0.19923	37.7380	43.1762	0.96086	0.95358
5 neurons	0.05362	0.05452	0.17917	0.17866	37.3193	37.9480	0.96129	0.95920
9 neurons	0.05590	0.05645	0.18976	0.18548	38.9069	39.2935	0.95965	0.95775
15 neurons	0.04923	**1.99E-11**	0.16640	**1.17E-06**	34.2684	**1.39E-08**	0.96446	**1.00000**
20 neurons	0.04296	0.05674	0.14337	0.18618	29.9027	39.4911	0.96898	0.95754
23 neurons	**0.01252**	0.03352	**0.06227**	0.12323	**8.71384**	23.3313	**0.99096**	0.97491
25 neurons	0.04878	0.05460	0.16650	0.16710	33.9563	38.0069	**0.96898**	0.95913

[Table/Fig-11]: The performance analysis of the ANNs models using standard statistical measures.

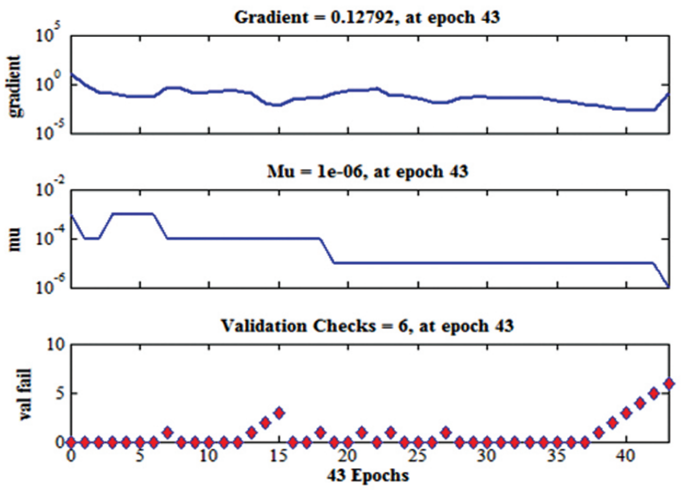


[Table/Fig-12]: Performance plot of MSE.

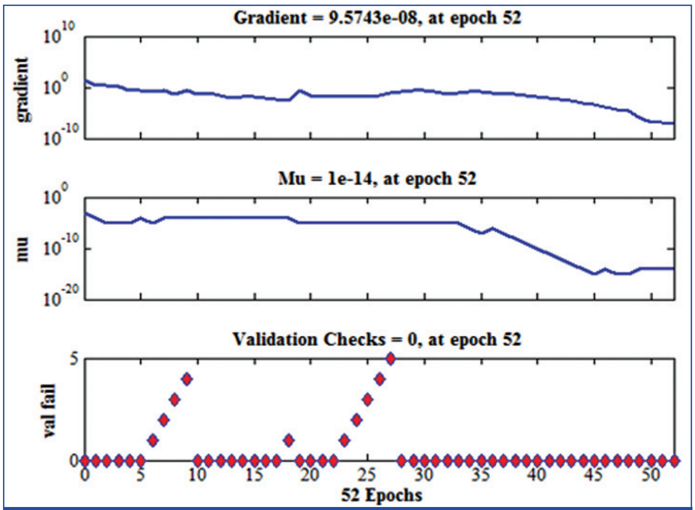


[Table/Fig-13]: Performance of MSE for right foot.

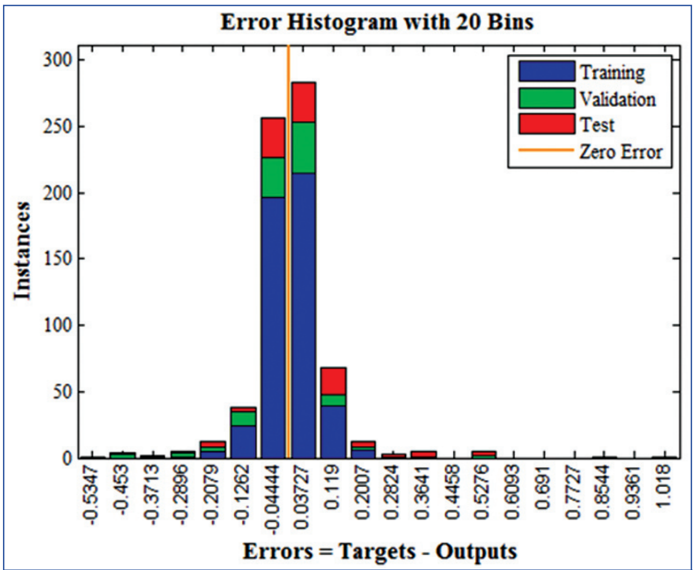
Furthermore, to estimate the performance of this ANN configuration, the following standard statistical measures such as MSE, MAE, SSE and coefficient of determination (R^2) were adopted.



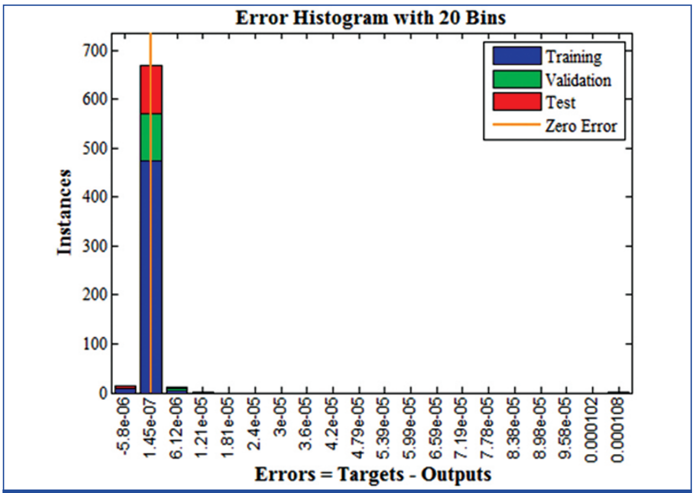
[Table/Fig-14]: Training states for the left.



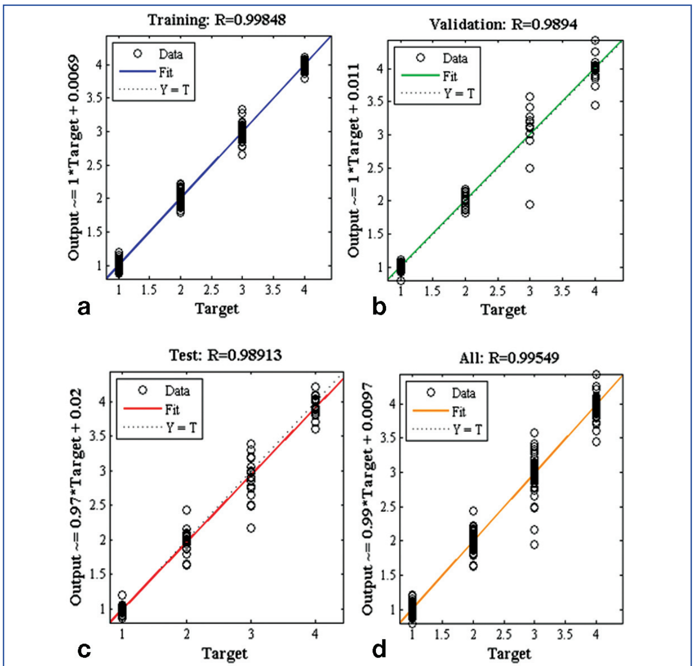
[Table/Fig-15]: Training states for the right.



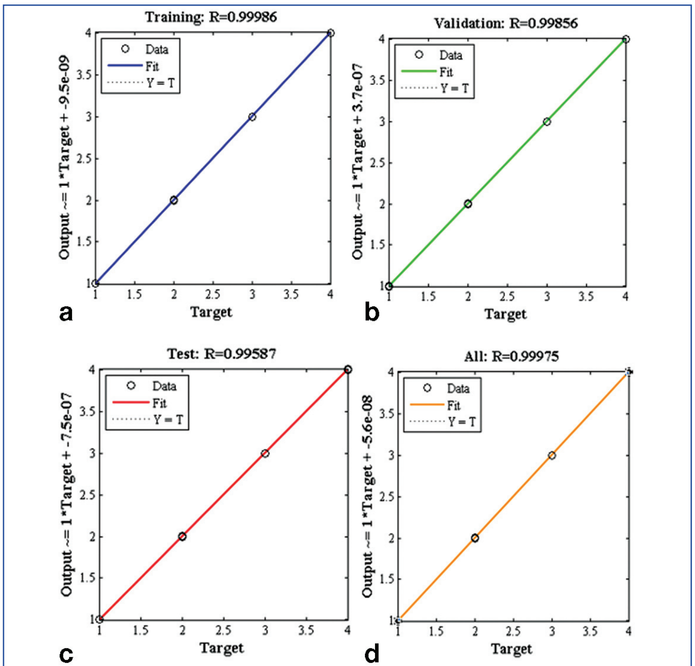
[Table/Fig-16]: Error histogram for the left foot.



[Table/Fig-17]: Error histogram for the right foot.



[Table/Fig-18]: Illustration via regression plots for left foot with a) R=0.99848 for training data; b) R=0.9894 for validation data; c) R=0.98913 for testing data; d) R=0.99549 for overall data.



[Table/Fig-19]: Illustration via regression plots for right foot with a) R=0.99986 for training data; b) R=0.99856 for validation data; c) R=0.99587 for testing data; d) R=0.99975 for overall data.

Several studies have also demonstrated that ANN is an appropriate method for predicting early diabetes [23-25]. A research work on ANN introduced a network trained with BP to study the inadequate accuracy in diagnosis of diabetes mellitus [26]. Another work was conducted using ANN to identify appropriate factors that disturb the health conditions and to also assess their impact on diabetes [27]. A few investigators did the timely prediction of diabetes using a hybrid neural network and logistic regression model [28]. Many studies have recently investigated the application of machine learning and deep learning algorithms for diabetes prediction in the early stages, such as the artificial BP scaled conjugate gradient neural network (ABP-SCGNN) algorithm, deep learning model, and ANN algorithms [26-28].

Limitation(s)

To efficiently handle big data is one limitation of the proposed Levenberg–Marquardt BP neural network model. Thus, the authors plan to implement the newly developed prediction models like Gaussian process regression, and Gradient boosted regression trees via Bayesian inference in future work.

CONCLUSION(S)

In this work, it can be concluded that biothesiometry is an effective technique and tool that can be used to assess diabetic foot and evaluate the same by means of VPT values. The subjects were categorised into groups based on the severity of DN and the range of VPT which helped in further analysis and provided information for the construction of the ANN model. The ANN based on the Levenberg-Marquardt algorithm was utilised to predict the average VPT values of the left and right foot and the value of (R^2) determined for both the foot were found to be highly correlated. The performance of the ANN was tested using the performance validation plot, state of convergence and error histograms which also showed appealing results thereby proving the reliability and efficiency of the proposed ANN model.

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