Communications in Mathematics and Applications
Vol. 15, No. 1, pp. 431–443, 2024
ISSN 0975-8607 (online); 0976-5905 (print)
Published by RGN Publications
DOI: 10.26713/cma.v15i1.2590

http://www.rgnpublications.com

Research Article

Prediction of Cardiovascular Disease on Transthoracic Echocardiography Data Using Artificial Neural Network

N. Chaithra*[1], S. Raviraja[2], S. Sunil Kumar[3] and V. Ranjini[3]

[1] *Division of Medical Statistics, School of Life Sciences, JSS Academy of Higher Education & Research, Mysuru, Karnataka, India*
[2] *Medical Informatics, Sri Siddartha Academy of Higher Education, Bangalore, Karnataka, India*
[3] *Department of Cardiology, JSS Medical College, JSS Academy of higher education and Research, Mysuru, Karnataka, India*
*__Corresponding author:__ chaithra.mstats@jssuni.edu.in

Received: February 12, 2024 **Accepted:** March 29, 2024

Abstract. According to World Bank Epidemiological modelling, India has the second highest rate of *Cardiovascular Disease* (CVD) mortality worldwide, at 2.5 million new cases occurring annually. Heart disorder is a condition that affects heart function. One of the main problems with heart conditions in estimating a person's risk of having insufficient blood supply to the heart. According to the World Health Statistics 2012 report, one in every three individuals in the world has high blood pressure, a condition that accounts for almost half of all fatalities from heart disease and stroke. Echocardiography is an ultrasound procedure that uses a projector to display moving images of the heart and is used to diagnose and assess a series of disorders. Authors have considered to analyse and review several recent research works on CVD and experimental models. The proposed retrospective experiment contained a total of 7304 patients *Transesophageal Echocardiography* (TTE) records with no missing values were chosen for the research in that 1113 patients were diagnosed with *Ischemic Heart Disease* (IHD) and 6191 normal patients were classified as the subject. 70% of patients' data were used to train the Neural Network and the other 30% of patients' data used to test the model. This research work estimates the efficiency of the Artificial Neural Network model to investigate the factors contributing significantly to enhancing the risk of IHD as well as accurately predict the overall risk using Machine learning software: WEKA 3.8.5. and SPSS modeler. The resulting model performance has a higher accuracy rate (97.0%) and this makes it a very vital techniques for cardiologists to screen patients at potential risk of developing the disease.

Keywords. Cardiovascular Disease, Transesophageal Echocardiography Data, Ischemic Heart disease, Artificial Neural Network

Mathematics Subject Classification (2020). 68T07, 92B20

1. Introduction

Cardiovascular Disease (CVD) is the major cause of mortality globally, as well as in India. One in three people worldwide have high blood pressure, which is a condition that contributes to over half of all deaths from heart disease and stroke, stated the 2012 World Health Statistics report (Ansarullah *et al*. [1]). CVD correspond to various diseases associated with the heart, lymphatic system and circulatory system of the human body. One of the main problems with heart conditions in estimating a person's risk of having insufficient blood supply to the heart. According to the World Bank epidemiological modelling, among the rest of the world India stood the second largest CVD mortality rate with two and a half million new cases reported each year (McAloon *et al*. [13]). As per the WHO survey, the recent data suggests that age-standardized mortality rates of CVD in India, per 100,000, among females and males, are 181-281 and 363-443 respectively [19]. In India, the age-standardized mortality rate of CVD being, 272 per 100,000 population is greater than the world average recorded as 235 for 100,000 population (Roman *et al*. [16]). The rapid urbanization in metropolitan cities in India has led to a range of concerns such as decreased physical activity, changed lifestyle, obesity, alcohol consumption, smoking and hypertension (Nag and Ghosh [14], and Singh *et al*. [21]). By 2025, India's National Health Policy 2017 seeks to minimise 25% of CVD-related premature deaths by screening and treating 80% of hypertension patients (Prabhakaran *et al*. [17]). Several additional medical illnesses and lifestyle choices have been identified as possible heart disease risk factors. Ischemic Heart Disease, Rheumatic Heart Disease, Congenital Heart Disease, Cardiomyopathy, Valvular Heart Disease and Atherosclerosis are the main categories of CVD (Kaddoura [8]). These are treated by cardiologists, thoracic surgeons, vascular surgeons, neurologists and interventional radiologists.

Ischemic Heart Disease (IHD) or coronary heart disease refers to a range of clinical disorders defined by myocardial ischemia. IHD develops when cholesterol particles in the blood begin to accumulate on the walls of the arteries that supply blood to the heart plaques or deposits may form over time and these deposits narrow the arteries, eventually obstructing blood flow (Malakar *et al*. [12]). CVDs are those disorders that affect cardiovascular function adversely, in the cardiovascular system and based on the tissue of the target, several causes may result in these diseases. Blood test, Echocardiogram, ECG, Holter monitor, Ambulatory blood pressure monitoring, Transesophageal echocardiography, Chest X-ray, Cardiac MRI & Catheterization, CT scan, Treadmill and Angiogram are commonly used diagnostic methods for CVDs [1] (Institute of Medicine [7], and Kaltman *et al*. [9]). *Transthoracic Echocardiography* (TTE) type is considered for the proposed research work. The TTE is the most common method for cardiac imaging which consists of the *Two-Dimensional* (2D) and M-mode view of the intrathoracic systems complemented by using non-stop and pulsed-wave spectral Doppler information and color float Doppler imaging (Lohr and Sivanandam [11]). Diagnosis is a difficult and essential function which must be accomplished efficiently and accurately (Ansarullah *et al*. [1]).

Heart disease diagnosis is a difficult and complicated task that is possible to automate to provide merely accurate prediction of the patient's heart condition, allowing for further to perform early effective treatments (Singh *et al*. [21]). Heart disease is typically diagnosed using the patients physical examination, signs and symptoms. Many data analytics techniques have been used to help healthcare professionals recognize several of the early signs of heart disease.

[1] *Rheumatic Heart Disease*, available online at: URL: https://www.hopkinsmedicine.org/health/conditions-and-diseases/rheumatic-heart-disease, accessed June 3, 2020.

The development of a medical diagnostic engineering science founded on *Machine Learning* (ML) for the prediction of heart disease offers a more precise diagnosis and lowers care costs than the conventional method. In order to achieve the above need, an automatic medical diagnostic method based on machine learning is proposed in this research article to predict early heart disease. ML technologies are gaining popularity as a way to reduce mortality rates and diagnosis costs by achieving maximum accuracy (Rahmani *et al*. [18]).

2. Literature Review

Following are the important recent research works which are considered to analyse and review work on CVD and experimental models.

The use of machine learning tools and techniques can assist in the detection and management of cardiovascular diseases. *Artificial Neural Networks* (ANN) are one of the popular ML techniques founded by McCulloch and co-workers beginning in the early 1940s (Hannan *et al*. [6]). The human brain, which has extraordinary processing capabilities due to its webs of interconnected neurons, is the inspiration for ANN. ANN has been regarded as one of the most powerful tools in recent decades, due to its ability to manage sizable amounts of data and can easily learn non-linear and complex relationships. NN have been effectively used to a range of real-world categorization problems including diagnostic aids, medicine, biochemical analysis, image analysis, and medication research (Gupta *et al*. [4], and Karayılan and Kılıç [10]). ANN refers to the act of searching for huge information stores automatically, to identify patterns and trends which go beyond simple analytical procedures. ANN makes use of complicated mathematical algorithms for the segments of data and predicts the likelihood of future events (Hamedi *et al*. [5], and Sayad and Halkarnikar [20]).

Singh *et al*. [21] developed an *effective heart disease prediction system* (EHDPS) employing neural networks to estimate the heart disease risk level. Two sets, the training set (40%) and the testing set (60%), each containing 303 items, were created from the dataset. The training algorithm was the *multilayer perceptron neural network* (MLPNN) with *backpropagation* (BP). Information about existent and prognosis classifications performed by a classification model, which is contained in a confusion matrix. The findings of using neural networks on the training dataset revealed that there are no FN or FP entries, indicating that the system can 100 % accurately forecast the risk level of cardiac illnesses.

Hannan *et al*. [6] presented this study is to investigate the applicability and capability of ANN methods, GRNN and RBF for prediction of medicine for the heart disease on the basis of symptoms. They collected 300 patients data from daily OPD session while doctor examining the patients. All the patients data is trained by using SVM and RBF and around 50 samples were tested with these two techniques. The analysis model by using SVM and RBF of ANN gives better result for medical prescription for heart disease patient. It is found that the result of testing data by using SVM is not satisfactory but the medicines prescribed by the RBF are satisfactory as per the result verified by the doctor.

Research on the effectiveness assessment of several machine learning methods for heart disease prediction was proposed by Dwivedi [3]. The dataset consists of 270 samples, 150 of which are free of heart disease (absence), and 120 of which are affected by it (presence). 13 different factors have been considered. Tenfold partitioning of the data samples was used; each fold was used for testing, and the rest of the folds were used for training during cross validation. The effectiveness of six machine-learning techniques such as ANN, SVM, Logistic

Regression, KNN, Naive Bayes and Classification Tree approaches, were evaluated using the receiver operating characteristic curve.

A decision support system for diagnosing a patient's cardiac illness was created by Chaitrali *et al*. [2]. The patients signs, symptoms and physical examination serve as the basis for the diagnosis and the forecast is made using a database of previous cases of heart disease. The dataset consists of 573 records overall, each having 13 attributes, and is split into two sets: the training set has 303 records, while the testing set has 270 records. *Multilayer Perceptron Neural Network* (MLPNN) with *Backpropagation Algorithm* (BP) is the technique utilised to construct the system and it achieves accuracy close to 100 percent. As the model performs realistically well even without retraining, it aids the domain experts in making plans for better diagnoses and delivering early diagnosis findings to patients.

3. Methodology

3.1 Data Sources and Study Design

A retrospective study contains a total of 7304 patients echocardiography records with one dependent variable and 15 independent variables were obtained from the echocardiography measurements was recorded at Cardiology Department, JSS Hospital in the year 2016. The Cardiology Department historically has generated a large scale of data, driven by record-keeping, compliance, regulatory standards and patient care. ECHO data are one of the large datasets that are available in the database recorded in BackBone software. The "diagnosis" attribute was recognized as a predicted variable with the value of "YES" for patients with IHD and the value "NO" for the patients with no IHD. The models were developed with an ANN using Machine learning software: WEKA 3.8.5. and SPSS modeler. The timely diagnosis of CVDs patients is the most challenging and complicated task for medical fraternity [17]. The prediction of heart disease is regarded as one of the most important subjects in healthcare. In this RESEARCH, TTE data were processed using ANN to provide a predictive model for the IHD shown in Figure 1.

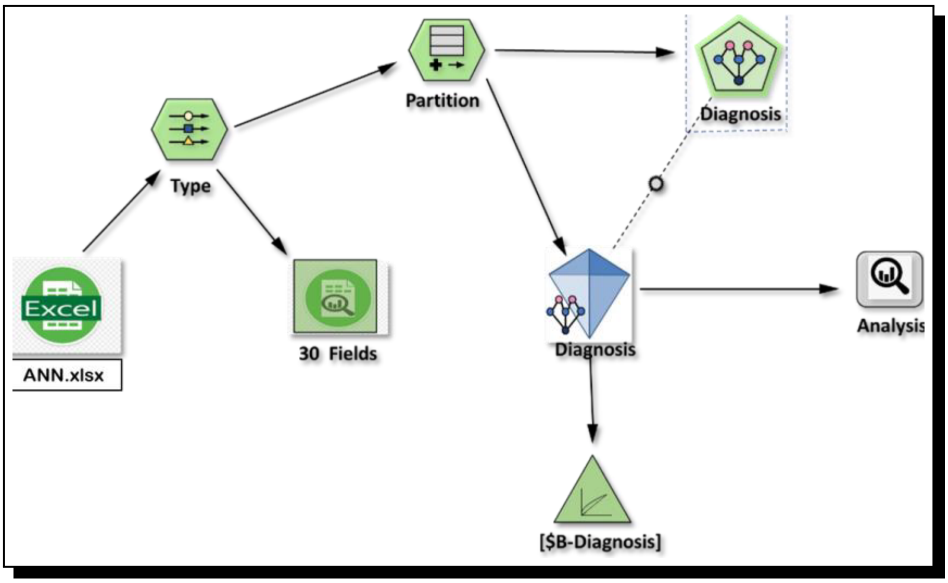


Figure 1. ANN algorithm stream for the diagnosis of the IHD

Table 1. ECHO parameters and their description

S. No.	Attributes	Description	Type
1	Age	Patient's Age in years	Numeric
2	AO (mm)	Aorta root	Numeric
3	LA (mm)	Left atrium	Numeric
4	RV (mm)	Right ventricle	Numeric
5	LVID_d (mm)	Left ventricular internal diameter end diastole	Numeric
6	LVID_s (mm)	Left ventricular internal diameter end systole	Numeric
7	IVS_d (mm)	Interventricular septum end diastole	Numeric
8	IVS_s (mm)	Interventricular septum end systole	Numeric
9	LVPW_d (mm)	Left ventricular posterior wall end diastole	Numeric
10	LVPW_s (mm)	Left ventricular posterior wall end systole	Numeric
11	EDV (ml)	End diastolic volume	Numeric
12	ESV (ml)	End systolic volume	Numeric
13	SV (ml)	Stroke volume	Numeric
14	EF %	Ejection fraction	Numeric
15	FS %	Fractional shortening	Numeric

The following datasets of individuals were included:

- Aged between 18 and 96 years.
- Normal adult patients.
- Ischemic Heart Diseases, Ischemic Cardiomyopathy.
- LV Diastolic Dysfunction.
- LV Systolic function
- Regional Wall Motion Abnormality.
- Myocardial infarction

Exclusion criteria: The following cardiovascular disease was excluded from participation in the research as these could have influenced their echo-cardiography data:

- Aortic Valve Sclerosis.
- Congenital Heart Disease.
- Concentric Left Ventricle Hypertrophy.
- Rheumatic Heart Disease.
- Degenerative Aortic, Mitral Valve Disease and other cardiovascular diseases

3.2 Mathematical Model of ANN

An ANN is a type of parallel computing system, distributed data processing structure made up of a large number of processing nodes connected by unidirectional signal channels. In ANN the perceptron theory plays an analytical function. It's utilized as an algorithm or a linear classifier to make binary classification supervised learning easier and it is a fundamental processing unit that is used to create ANNs (Gupta *et al*. [4]). One of the most successful ANN approaches for modeling and prediction is the multi-layer perceptron neural network (MLP) (Hamedi *et al*. [5]). Many perceptron are grouped to form MLPs which which were built using an input layer that receives the signal, an output layer that makes a decision or forecast and is utilized for modeling based on the input and a random number of hidden layers in between utilized for computing. Every hidden layer node must be connected to each input layer node and then each output layer node must be linked to every hidden layer node (Sayad and Halkarnikar [20]). These layers are used to solve a variety of issues on function-approximation, process-control, system-identification, optimization, and other such related applications. A synapse connects each neuron, and each synapse has a weight associated with it. The error may be measured in a variety of methods, such as root mean squared error and backpropagation is used to make those given weight and bias adaption relative to the error.

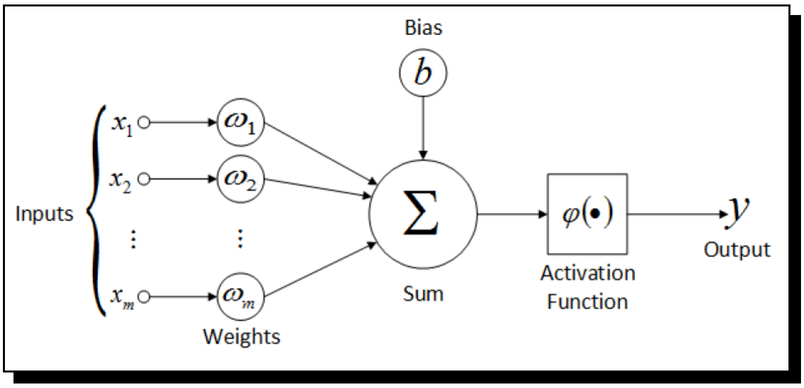


Figure 2. Computational model of artificial neuron[2]

The mathematical neuron calculates the m input signals weighted sum, x_i, $i = 1,2,\dots,m$, and generates an output of 1 if the total exceeds a certain threshold 'b'. Otherwise, a result of 0 is returned. Mathematically a binary threshold unit is being proposed as a computational model for an artificial neuron as shown in Figure 2.

$$y = \varphi\left(\sum_i (\omega_i x_i) + b\right),$$

where $\varphi(\cdot)$ at 0 is a unit-step-function, and ω_i is there a link between synapse weight and the ith input. Consider the threshold 'U' as an additional weight $\omega_i = -b$ linked to the neuron with a constant input of $x_0 = 1$. Excitatory synapses are represented by positive weights, while negative weights model inhibitoryones [15].

3.3 Algorithm for Perceptron Learning

The following are the steps of Perceptron Learning Algorithm (also shown in Figure 3):

I. To begin, set the weights and threshold to tiny random integers.

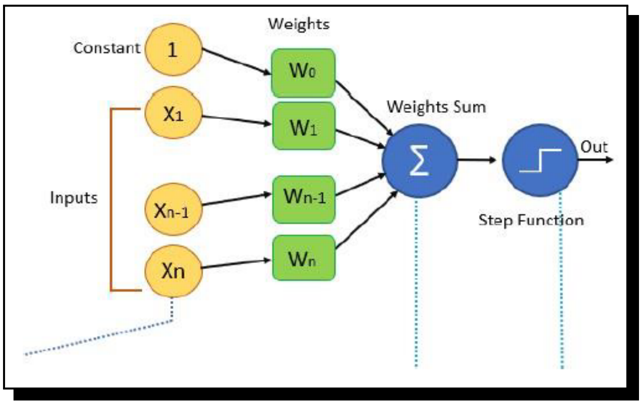
II. Present a pattern vector $(X_1, X_2, \dots, X_n)^t$ and assess the neuron output.

III. Update the weights as appropriate.

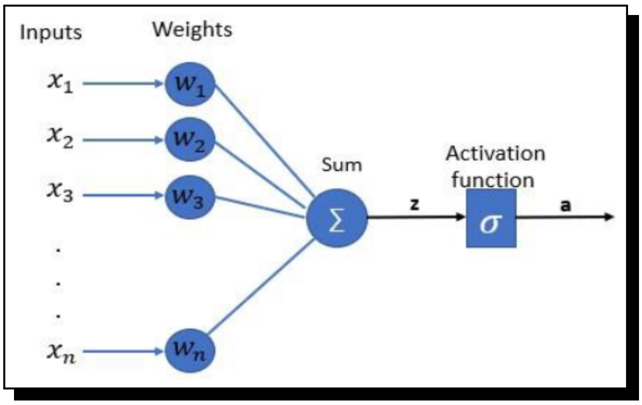
[2]URL: https://www.gabormelli.com/RKB/Artificial_Neuron

$$W_i(t+1) = W_i(t) + n(d-y)x_i,$$

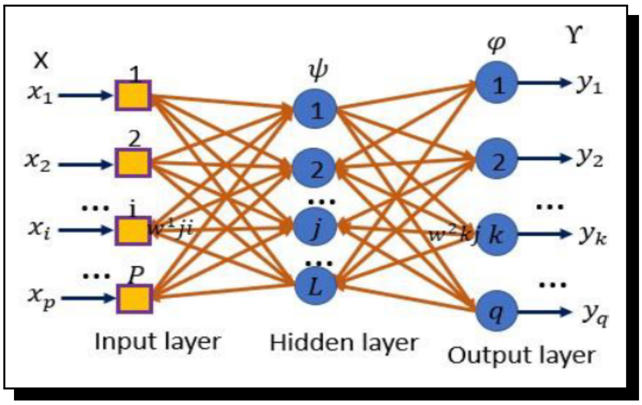
where d is the intended output, while the number of iterations is denoted by t and η $(0 < \eta < 1)$ is the gain.



(a) Perceptron Algorithm Block Diagram



(b) Single Layer Perceptron



(c) Multi-Layer-Perceptron

Figure 3. Algorithm for perceptron learning[3]

4. Results and Discussion

A total of 7304 cases with no missing values were chosen for the research in that 1113 patients were diagnosed with IHD and 6191 normal patients were classified as the subject. 70% of patients were used to train the Neural Network and once it was trained, the other 30% of patients were used to test the model. This prediction model can help physicians make accurate diagnoses far in advance and be valuable in making IHD diagnosis decisions.

Figure 4 displays the network structure, which gives the network information about the input layer which is the very beginning of the workflow for the ANN. The connections network layout the flow forward from the input layer to the output layer without feedback loops, is known as a *Feed-Forward-Network* (FNN) architecture. The hidden layer contains units which are also known as unobservable network nodes. Hence, the number of hidden layers here is 1 with 6 units or nodes attached to it, each hidden unit is a function of the weighted total of the inputs and there are 15 input layers or covariates are considered in this study. The output layer

[3]URL: https://www.javatpoint.com/perceptron-in-machine-learning

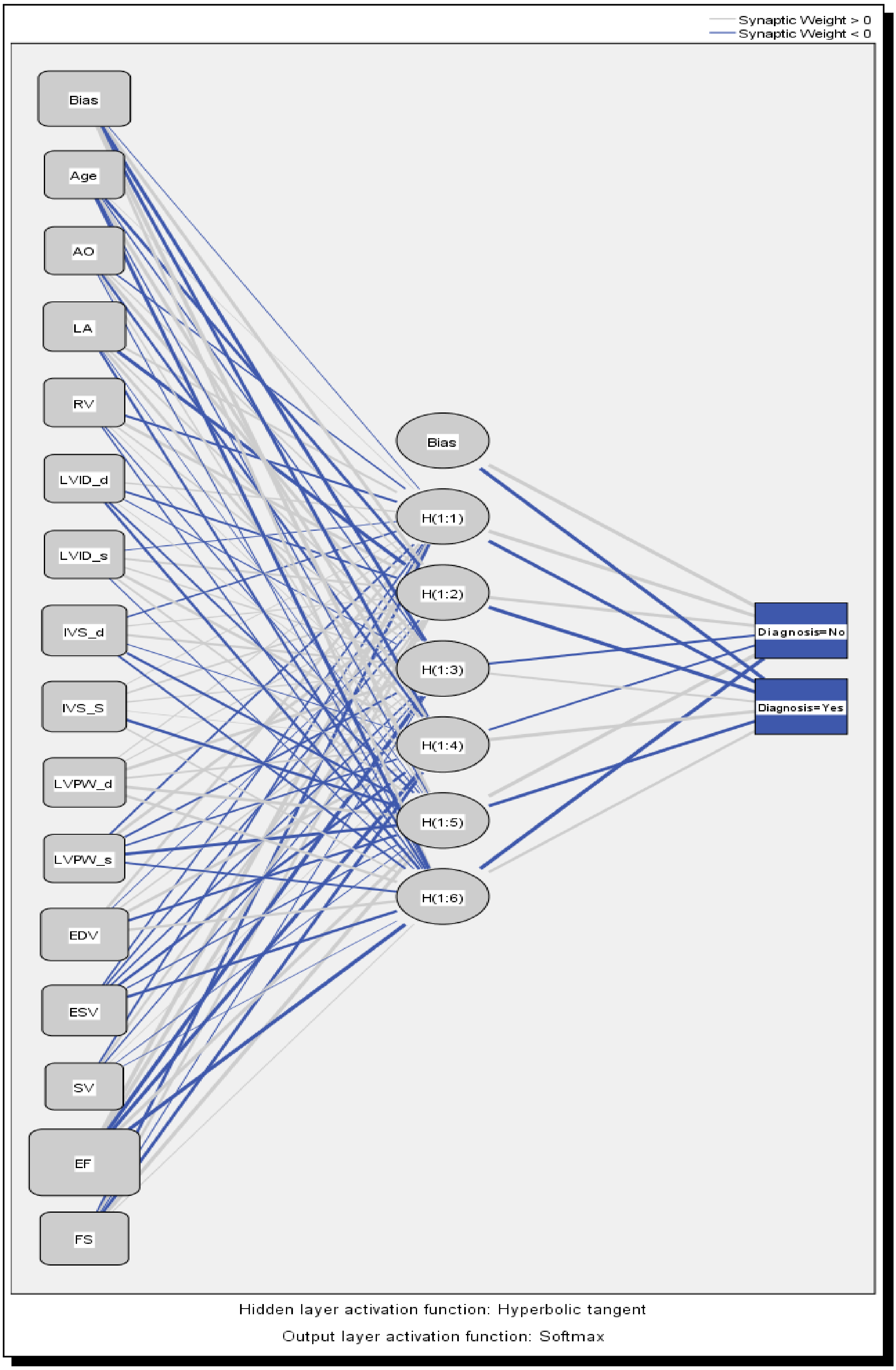


Figure 4. Structure of Artificial Neural Network [?]

is the final layer of neurons which consist of 1 dependent variable that is, diagnosis. The total number of units of output layers is 2 and which is normalized using the softmax function.

Table 2. Classification table

Sample	Observed	Predicted		
		No	Yes	Percent Correct
Training	No	4324	34	99.2%
	Yes	117	623	84.2%
	Overall Percent	87.10%	12.90%	97.0%
Testing	No	1813	20	98.9%
	Yes	48	325	87.1%
	Overall Percent	84.40%	15.60%	96.9%

Table 2 illustrates the number of instances classified correctly and incorrectly for each dependent variable category where the confusion matrix provides overall accuracy of classification in 'training sample' is 97 %. The Neural network model correctly classified 99.2% of cases where 4324 patients were rightly diagnosed and were predicted as free from disease but misclassified 34 patients were identified as having the disease but they were free from the disease. Model misclassified 117 patients were not having the disease but they had the disease and 623 patients were rightly classified as having disease and were predicted to be diseased, it correctly classified 84.2 % of cases.

In the 'testing sample', the overall accuracy of classification is 96.9% model correctly classifies and 1813 patients were rightly diagnosed and were predicted to be free from disease, but incorrectly classified 20 patients were having the disease but were free from disease and this classification achieved 98.9%. But the model misclassified 48 patients who were not having the disease but had the disease and correctly classified 325 patients are having the disease, and this classification achieved 87.1%.

Table 3. Prediction performance measures

True Positive Rate	0.84
True Negative Rate	0.98
Correctly Classified Instances	2136 (0.96)
Incorrectly Classified Instances	70 (0.03)
Kappa Statistic	0.87
F-score	0.87
Accuracy	0.97
Root Mean Squared Error	0.16
Mean Absolute Error	0.03
Relative Absolute Error	14.54%
Area under (ROC)	0.96

The result was obtained with 2136 correctly classified instances and 70 incorrectly classified instances which represent (0.96) and (0.03) respectively. the True-Positive and True-Negative were accurately classified positives and negatives, False Positive and False Negative is the incorrectly classified positives and negatives. overall True Positive Rate = 0.84, True Negative Rate = 0.98, Kappa Statistics = 0.87, F-score = 0.87, Root Mean Squared Error (RMSE) = 0.16, Mean Absolute Error = 0.03, Relative Absolute Error and AUC is 0.965 represents in the Table 3.

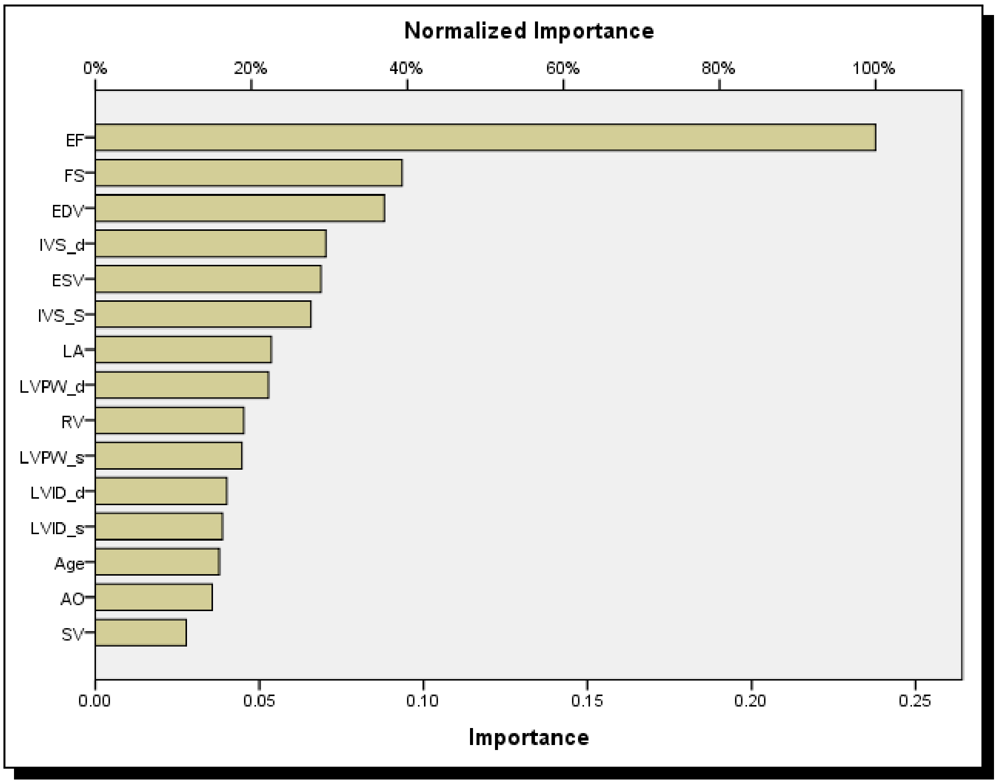


Figure 5. Independent variable importance chart

Figure 5 illustrate the input variable EF% was found to be a factor with importance of 0.238 which has been normalized into 100%, has very high importance in predicting our output variable and is the most influential factor for IHD and other attributes FS, EDV, IVS_d, ESV, IVS_s, LA, LVPW_d, RV, LVPW_s, LVID_d, LVID_s, Age, AO, SV are the key factors in determining patients with heart disease.

Figure 6 shows the Area under the *Receiver-Operating-Characteristic* (ROC) analysis approach is explored to assess the accuracy of medical diagnostics tests in differentiating between two patient states: "diseased" and "normal". The values of the area under the curve range from 0.5 to 1.0. AUC = 1.0 denotes a perfect test, whereas AUC of 0.9-0.99 suggest a excellent test, 0.8-0.89 a good test, 0.7-0.79 a fair test, 0.51-0.69 a poor test, and 0.5 imply no value at all. The AUC for this Artificial Neural Network model for predicting IHD using M-Mode 2D echocardiographic parameters was 0.976, with a 95 % class interval (0.97-0.98) indicating a good fit for the model.

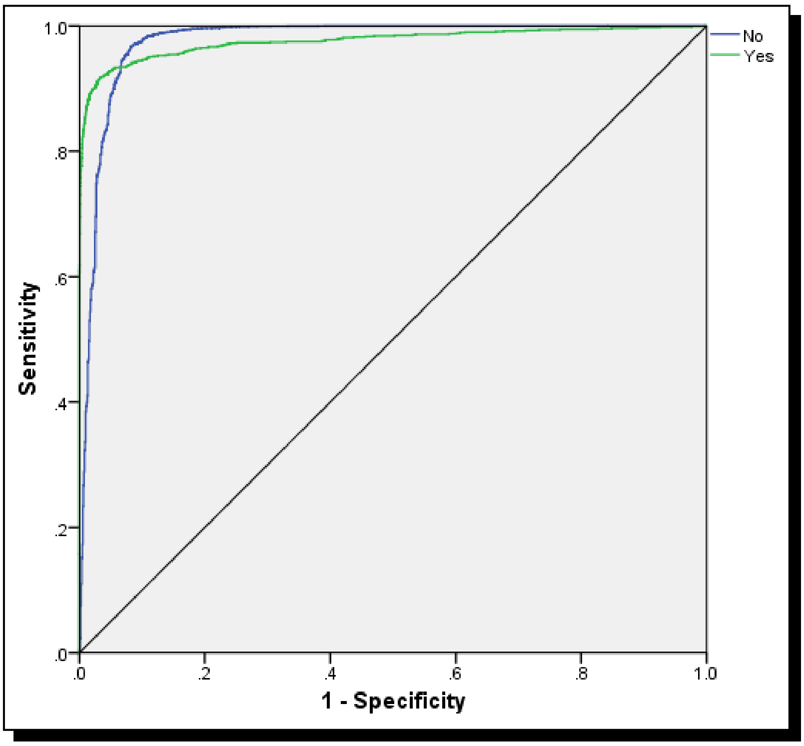


Figure 6. ROC curve for model

5. Conclusion

The retrospective experiment carried out contained a total of 7304 patients Transesophageal Echocardiography records with no missing values were chosen for the research in that 1113 patients were diagnosed with IHD and 6191 normal patients were classified as the subject. 70% of patients data were used to train and 30% to test the model. The proposed model estimates the efficiency of the ANN model to investigate the factors contributing significantly to enhancing the risk of IHD and accurately predict the overall risk using Machine learning technique. The model attains the higher accuracy rate that is 97.0% and EF% is the most influential factor, which is considered clinically important for diagnosing the likelihood of IHD. The resulting model proven to be a useful method for junior cardiologists and echo technicians to screen patients at potential risk of developing the disease.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

References

[1] S. I. Ansarullah, P. K. Sharma, A. Wahid and M. M. Kirmani, Heart disease prediction system using data mining techniques: A study, *International Research Journal of Engineering and Technology* **3**(8) (2016), 1375 – 1381.

[2] C. S. Dangare and S. S. Apte Sulabha, A data mining approach for prediction of heart disease using neural networks, *International Journal of Computer Engineering and Technology* **3**(3) (2012), 30 – 40.

[3] A. K. Dwivedi, Performance evaluation of different machine learning techniques for prediction of heart disease, *Neural Computing and Applications* **29**(10) (2018), 685 – 693, DOI: 10.1007/s00521-016-2604-1.

[4] R. Gupta, D. Srivastava, M. Sahu, S. Tiwari, R. K. Ambasta and P. Kumar, Artificial intelligence to deep learning: machine intelligence approach for drug discovery, *Molecular Diversity* **25**(3) (2021), 1315 – 1360, DOI: 10.1007/s11030-021-10217-3.

[5] S. Hamedi, Z. Kordrostami and A. Yadollahi, Artificial neural network approaches for modeling absorption spectrum of nanowire solar cells, *Neural Computing and Applications* **31**(12) (2019), 8985 – 8995, DOI: 10.1007/s00521-019-04406-3.

[6] S. A. Hannan, R. R. Manza and R. J. Ramteke, Generalized regression neural network and radial basis function for heart disease diagnosis, *International Journal of Computer Applications* **7**(13) (2010), 7 – 13, DOI: 10.5120/1325-1799.

[7] IOM (Institute of Medicine), *Cardiovascular Disability: Updating the Social Security Listings*, The National Academies Press, Washington, DC (2010), DOI: 10.17226/12940.

[8] S. Kaddoura, *Echo Made Easy*, International edition - 3rd edition, Elsevier, 294 pages (2017).

[9] J. R. Kaltman, K. M. Burns, G. D. Pearson, D. C Goff and F. Evans, Disparities in congenital heart disease mortality based on proximity to a specialized pediatric cardiac center, *Circulation* **141**(12) (2020), 1034 – 1036, DOI: 10.1161/CIRCULATIONAHA.119.043392.

[10] T. Karayılan and Ö. Kılıç, Prediction of heart disease using neural network, *2017 International Conference on Computer Science and Engineering* (UBMK), Antalya, Turkey (2017), pp. 719– 723, DOI: 10.1109/UBMK.2017.8093512.

[11] J. L. Lohr and S. Sivanandam, Introduction to echocardiography, in: *Handbook of Cardiac Anatomy, Physiology, and Devices*, P. Iaizzo (editor), Humana Press (2009), DOI: 10.1007/978-1-60327-372-5_20.

[12] A. K. Malakar, D. Choudhury, B. Halder, P. Paul, A. Uddin and S. Chakraborty, A review on coronary artery disease, its risk factors, and therapeutics, *Journal of Cellular Physiology* **234**(10) (2019), 16812 – 16823, DOI: 10.1002/jcp.28350.

[13] C. J. McAloon, L. M. Boylan, T. Hamborg, N. Stallard, F. Osman, P. B. Lim and S. A. Hayat, The changing face of cardiovascular disease 2000–2012: An analysis of the world health organisation global health estimates data, *International Journal of Cardiology* **224** (2016), 256 – 264, DOI: 10.1016/j.ijcard.2016.09.026.

[14] T. Nag and A. Ghosh, Cardiovascular disease risk factors in Asian Indian population: A systematic review, *Journal of Cardiovascular Disease Research* **4**(4) (2013), 222 – 228, DOI: 10.1016/j.jcdr.2014.01.004.

[15] R. M. S. de Oliveira, R. C. F. Araújo, F. J. B. Barros, A. P. Segundo, R. F. Zampolo, W. Fonseca, V. Dmitriev and F. S. Brasil, A system based on artificial neural networks for automatic classification of hydro-generator stator windings partial discharges, *Journal of Microwaves, Optoelectronics and Electromagnetic Applications* **16**(3) (2017), 628 – 645, DOI: 10.1590/2179-10742017v16i3854.

[16] D. Prabhakaran, P. Jeemon and A. Roy, Cardiovascular diseases in India: Current epidemiology and future direction, *Circulation* **133**(16) (2016), 1605 – 1620, DOI: 10.1161/CIRCULATION-AHA.114.008729.

[17] D. Prabhakaran, P. Jeemon, M. Sharma, G. A. Roth, C. Johnson, S. Harikrishnan, R. Gupta, J. D. Pandian, N. Naik, A. Roy, R. S. Dhaliwal, D. Xavier, R. K. Kumar, N. Tandon, P. Mathur, D. K. Shukla, R. Mehrotra, K. Venugopal, G. A. Kumar, C. M. Varghese, M. Furtado, P. Muraleedharan, R. S. Abdulkader, T. Alam, R. M. Anjana, M. Arora, A. Bhansali, D. Bhardwaj, E. Bhatia, J. K. Chakma, P. Chaturvedi, E. Dutta, S. Glenn, P. C. Gupta, S. C. Johnson, T. Kaur, S. Kinra, A. Krishnan, M. Kutz, M. R. Mathur, V. Mohan, S. Mukhopadhyay, M. Nguyen, C. M. Odell, A. M. Oommen, S. Pati, M. Pletcher, K. Prasad, P. V. Rao, C. Shekhar, D. N. Sinha, P. N. Sylaja, J. S. Thakur, K. R. Thankappan, N. Thomas, S. Yadgir, C. S. Yajnik, G. Zachariah, B. Zipkin, S. S. Lim, M. Naghavi, R. Dandona, T. Vos, C. J. L. Murray, K. S. Reddy, S. Swaminathan and L. Dandona, The changing patterns of cardiovascular diseases and their risk factors in the states of India: the Global Burden of Disease Study 1990–2016, *The Lancet Global Health* **6**(12) (2018), e1339 – e1351, DOI: 10.1016/s2214-109x(18)30407-8.

[18] A. M. Rahmani, E. Yousefpoor, M. S. Yousefpoor, Z. Mehmood, A. Haider, M. Hosseinzadeh and R. A. Naqvi, Machine Learning (ML) in medicine: Review, applications, and challenges, *Mathematics* **9**(22) (2021), 2970, DOI: 10.3390/math9222970.

[19] W. P. Roman, H. D. Martin and E. Sauli, Cardiovascular diseases in Tanzania: The burden of modifiable and intermediate risk factors, *Journal of Xiangya Medicine* **4**(33) (2019), 1 – 14, DOI: 10.21037/jxym.2019.07.03.

[20] A. T. Sayad and P. P. Halkarnikar, Diagnosis of heart disease using neural network approach, *International Journal of Advances in Science Engineering and Technology* **2**(3) (2014), 88 – 92.

[21] P. Singh, S. Singh and G.S. Pandi-Jain, Effective heart disease prediction system using data mining techniques, *International Journal of Nanomedicine* **13** (2018), 121 – 124, DOI: 10.2147%2FIJN.S124998.