Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

An Intelligent Hybrid Inference System For Monitoring Of Heart Disease

Janpreet Singh[1], Dalwinder Singh[2]

[1,2]*School Of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India*

***Abstract:* -** In the healthcare system, the most crucial and vital issue is the procedure of heart disease diagnosis as the patient's life is only dependent on it, and it can reduce the disease at a particular level. However, in many cases, the selected procedure results in wrong and unexpected results or even lead to a patient's death. Hence, the most challenging task in the medical domain is a diagnosis of heart disease done by medical professionals. In this technical era, the role of artificial intelligence in the healthcare system is considerable and appraisable. Therefore, this study introduced a model which has the capability to monitor heart disease by using a hybrid methodology of machine learning, i.e., neuro fuzzy approach. In the developed intelligent hybrid inference system, there are total input variables which are utilized to classify the disease into different stages. The system generates the output, which provides the three different stages or levels of the disease. Moreover, according to this generated outcome, professional doctors of the heart can make a wise decision for the patient and also can choose the best procedure for the treatment corresponding to the disease's stage. The k-fold cross validation method is utilized to do the partitioning of the dataset and for testing purposes. The performance of the system is also calculated, and according to those results, the presented inference model accurately forecasts the stage of the heart disease from which a patient is suffering with an accuracy of 98.90 percent.

Keywords: *Heart disease, classification, artificial intelligence, fuzzy inference system (FIS), medical diagnostic system, neuro fuzzy method, ANFIS.*

1. Introduction

All over the world, the greatest reason for high mortality is heart disease, also referred to as cardiovascular disease or CVD [1]. Also, it is found that one out of three fatalities is attributable to these diseases as per the new investigation done by World Heart Federation [2]. Moreover, according to W.H.O., stroke, as well as heart failure, will account for the majority of the 23.6M deaths due to heart diseases worldwide by 2030 [3]. In India, the percentage of these disorders is 2 to 3 times higher as compared to western nations [4]. Throughout the previous few decades, even though deaths due to heart diseases were greater in developing nations, however, heart disorders were more common in developed nations [5]. Various risks that are associated which can be blamed for the high burden of heart disease are excessive alcohol intake, poor diet, hypertension, inactivity, obesity and diabetes [6], [7], [8]. Furthermore, these diseases not only lower life quality and expectancy but also it is placing a financial burden significantly on healthcare systems around the world [9].

Now, the biggest question arises whether the prediction of heart disease is possible before it reaches its worst stage or not. The utilization of advanced computer technology and intelligent algorithms as well as models has become a life saver for patients and plays a crucial role in various uncertain and difficult tasks of the healthcare system [10]. The use of computed assisted tools and programmes to diagnose and treat patients appears to be an increasingly emerging subject of focus [11]. Additionally, as medical diagnoses are rife with uncertainty, medical professionals are also adapting such technology for their assistance in making wise decisions [12]. However, the perfect technologies that can deal with these uncertainties in an effective way are neural networks and fuzzy logic [13], [14]. These methodologies use their certain advantages when there is ambiguous data or prior information is involved and also perform better than traditional approaches [15], [16], [17].

If these two approaches are used separately, then some drawbacks may result from both methodologies. But, the integration of neuro-fuzzy offers an intelligent model that blends the strengths of neural networks and fuzzy logic, such as the neural network's connectionist structure and similar style of reasoning like a human from fuzzy logic [18], [19], [20], [21]. Additionally, the ANFIS utilizes Takagi Sugeno type FIS which is a hybrid neuro fuzzy model created in 1993 [22], [23]. With the help of the ANFIS approach, the procedure of fuzzy modelling is able to get knowledgeable data for the identification of parameters of membership functions that the linked to FIS, which needs to keep track of the provided output as well as input data [24], [25], [26]. During the training phase, it automatically creates the values and rules for the membership function [27]. The rules are written in a set of IF, and THEN statements and the synaptic weights are not employed [28]. This approach is utilized used to forecast the onset, categorize, and provide the best treatment for a diagnosis of certain illnesses [29]. This methodology has five layers as shown in figure 1.

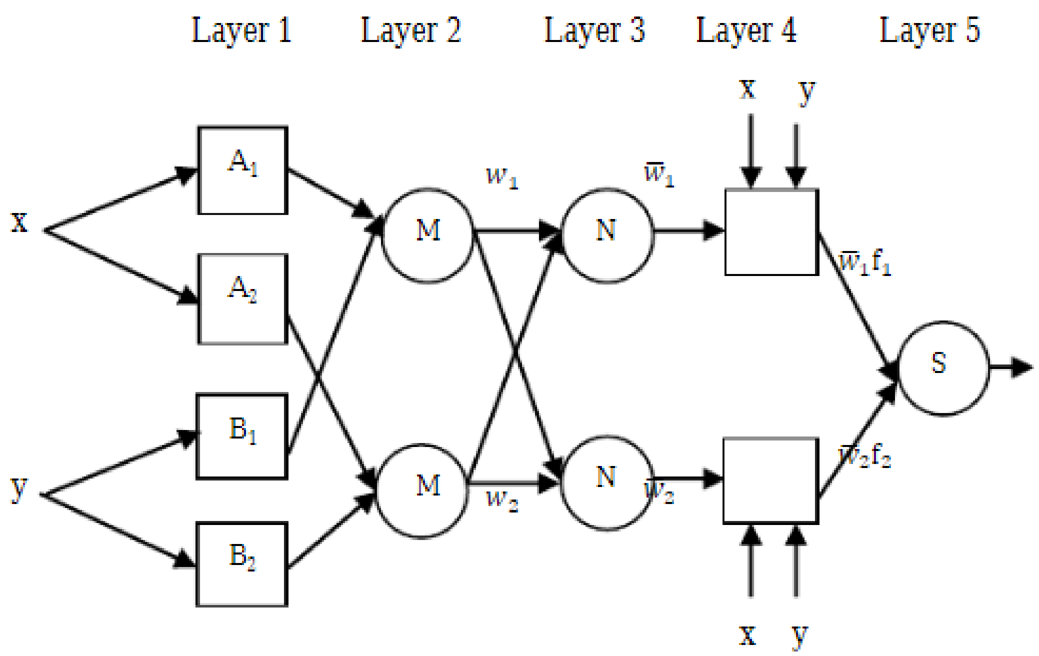

Figure 1 ANFIS layers [30]

This study introduced a model which has the capability to monitor heart disease by using a hybrid methodology of machine learning, i.e. neuro fuzzy approach. In the developed intelligent hybrid inference system, there are total input variables which are utilized to classify the disease into different stages. The system generates the output, which provides the three different stages or levels of the disease. Results show that the ANFIS technique is a reliable and adaptable mechanism for predicting heart diseases.

This paper is categorized into 4 sections, in which 1st is all about the introduction of the topic; 2nd section demonstrates the flow of the executed methodology, 3rd is experimental results in which the performance of the developed hybrid model is calculated by using some performance parameters and at least the 4th section sum up the whole research study into a paragraph known as the conclusion.

2. Methodology

The two most effective and beneficial approaches of machine learning have collaborated in order to construct an intelligent hybrid method. This methodology uses the benefits or pros of fuzzy logic as well as neural networks to produce the final results hence named as a neuro-fuzzy method. Additionally, the profit of utilizing these two methods together is that the limitation of one approach is overpowered by the advantage of the other approach. Hence both approaches help each other to generate highly accurate outcomes. This paper also introduces an intelligent hybrid system which assists in the monitoring of different stages of heart diseases. Cholesterol, blood pressure, diabetes, irregular heartbeat, smoking, shortness of breath and age are seven different input variables provided to the intelligent model. Likewise, the different stages, such as the normal stage, early stage and advanced stages, are the different outputs that are provided by the system after processing the given input values. The flow of methodology used in the implementation of the developed model is provided in figure 2.

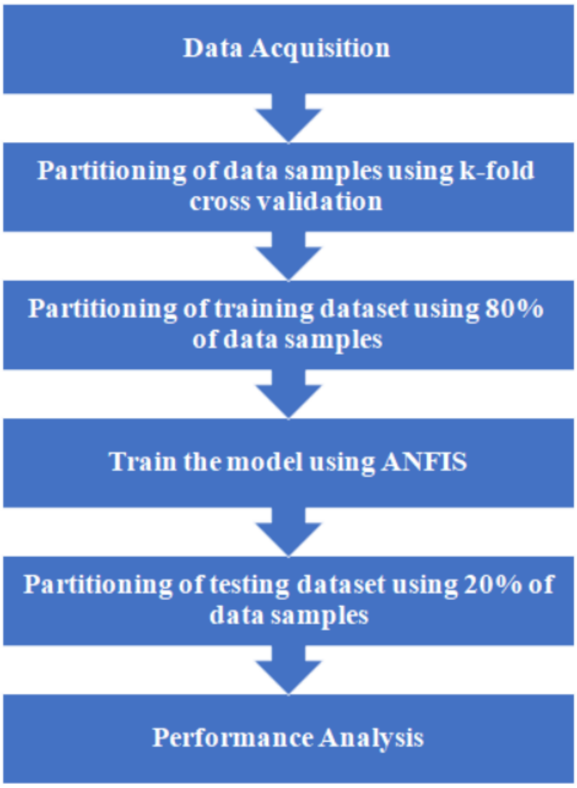

Figure 2 Flow of used methodology

2.1. Membership Functions

In this study, for input and output variables, the used membership functions are triangular membership functions. There are different numbers of membership functions for each input variable, such as 4 MFs for input 1, i.e., cholesterol, 3 for input 2, i.e., blood pressure, 2 from input 3 to 6, which are diabetes, irregular heartbeat, smoking and shortness of breath and 4 for input 7, i.e., age. The structure of ANFIS is illustrated in table 1 and figure 4. Moreover, the FIS properties of the ANFIS model are also demonstrated in figure 3. The representation of all 7 inputs is shown in figure 5 to 11, respectively.

Table 1 Structure of ANFIS

Structure of ANFIS	
No of layer of ANFIS	5
Number of input variables	7
Name of input variables	• Cholesterol as input 1 • Blood Pressure as input 2 • Diabetes as input 3 • Irregular Heartbeat as input 4 • Smoking as input 5 • Shortness of breath as input 6

	• Age as input 7
Type of membership function	Triangular
Number of rules	768
Number of outputs	1
Number of stages of disease	3
Name of stages	• Normal stage • Early stage • Advanced stage

The table above shows the architecture and settings of an ANFIS designed for medical diagnosis problems but, in particular, solving the problem of determining stages of the disease. It is categorized into five layers: input nodes, rule nodes, average nodes, consequent nodes, and the output node. There are seven system inputs, which include Cholesterol, Blood Pressure, Diabetes, Irregular Heartbeat, Smoking, Shortness of Breath, and Age. Such fuzzification of inputs is through the membership function of triangles for each input. The 768 fuzzy rules are then implemented to allow the model to map inputs to a sole output efficiently. The output from this ANFIS model classifies the disease into three stages: Normal stage, Early stage, and Advanced stage. This classification helps identify the severity of the condition based on the input variables. It uses membership functions in triangles and a vast number of fuzzy rules to allow the system to handle complicated and diverse input data, thus giving highly reliable and accurate diagnostic results. Through this structured approach, a detailed analysis of the patient's status of health is realized, providing support for early detection with adequate intervention.

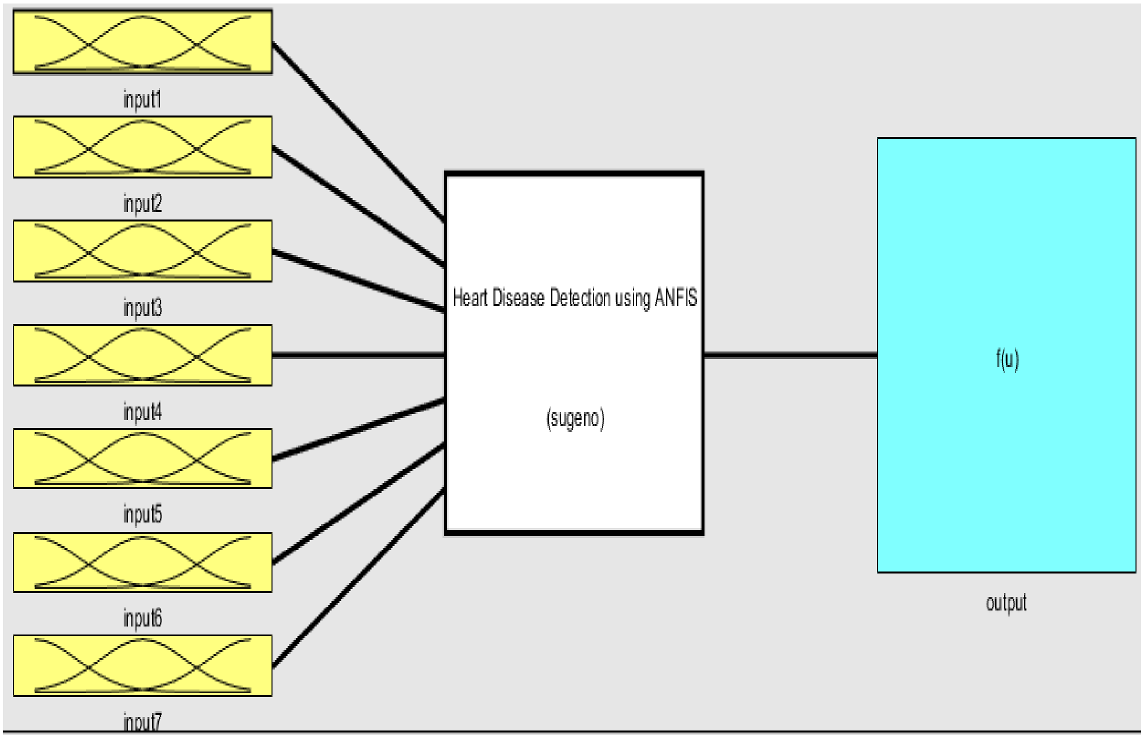

Figure 3 FIS properties of developed intelligent hybrid model

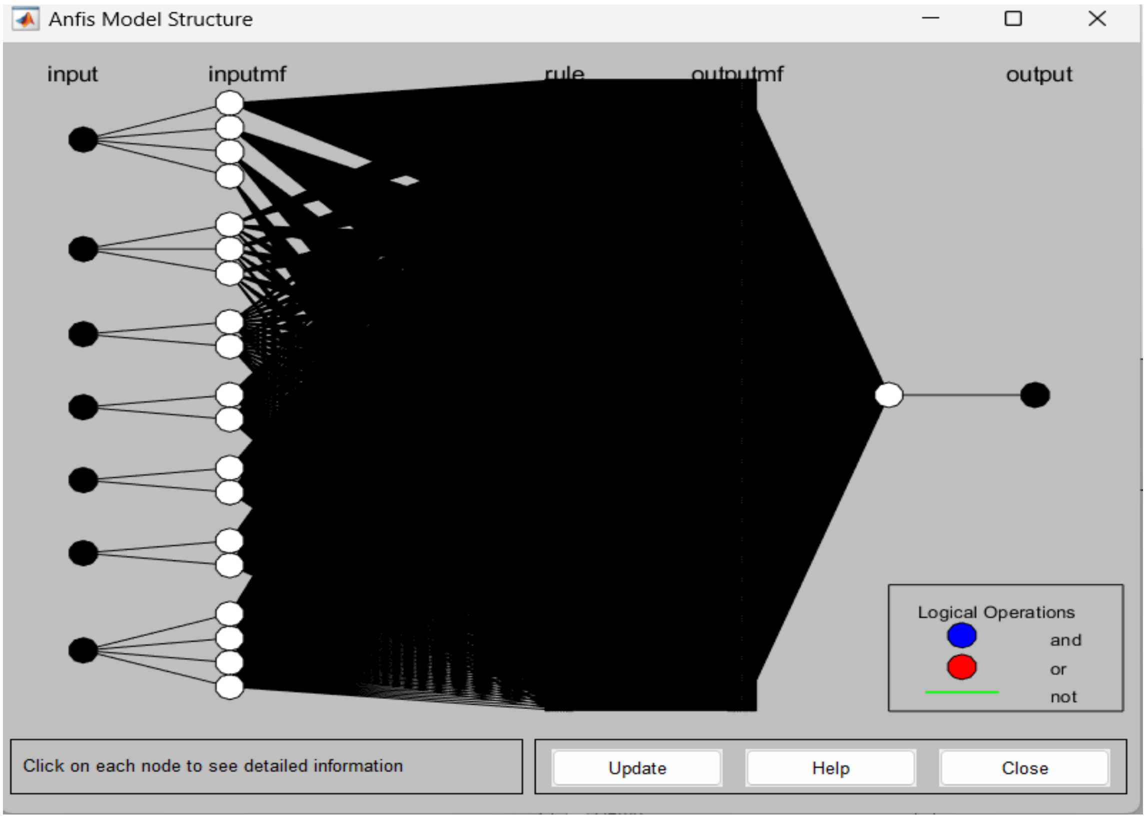

Figure 4 ANFIS model structure

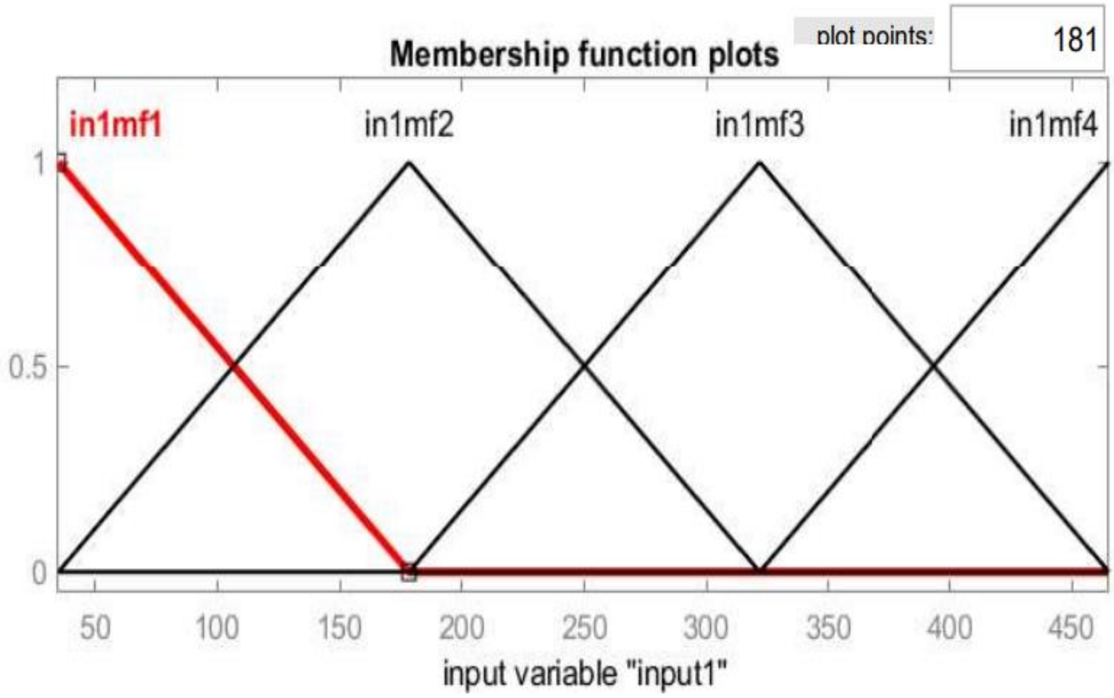

Figure 5 MF plot of input 1

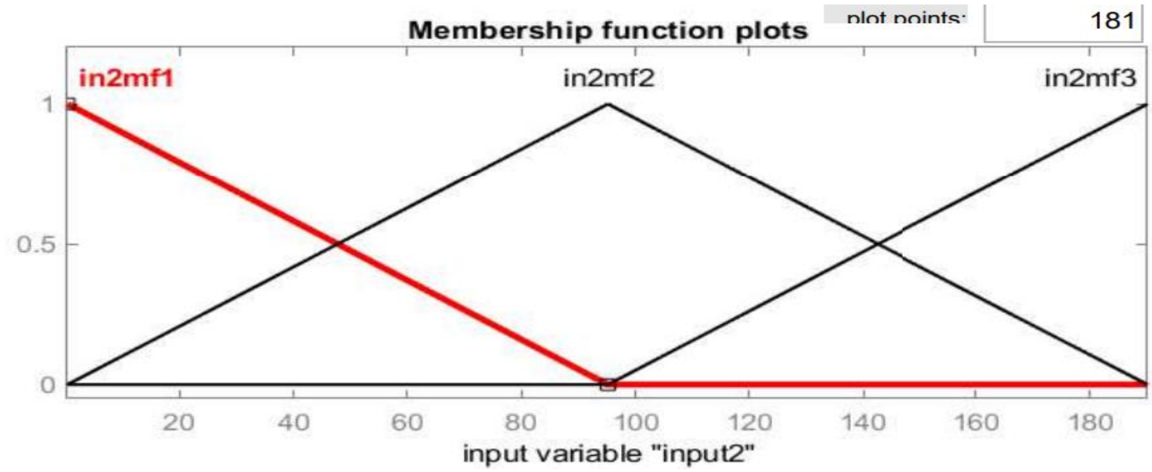

Figure 6 MF plot of input 2

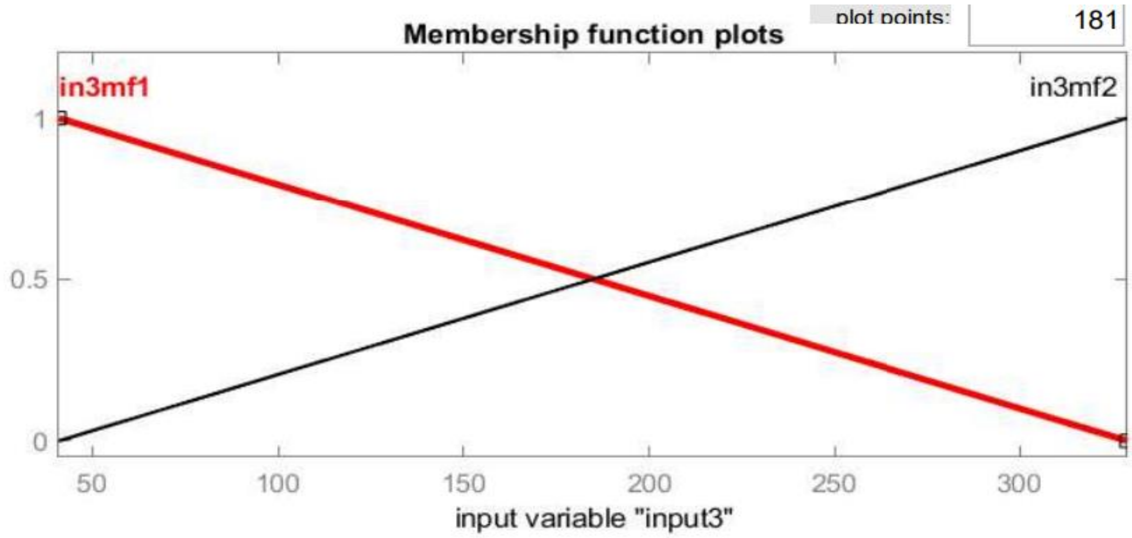

Figure 7 MF plot of input 3

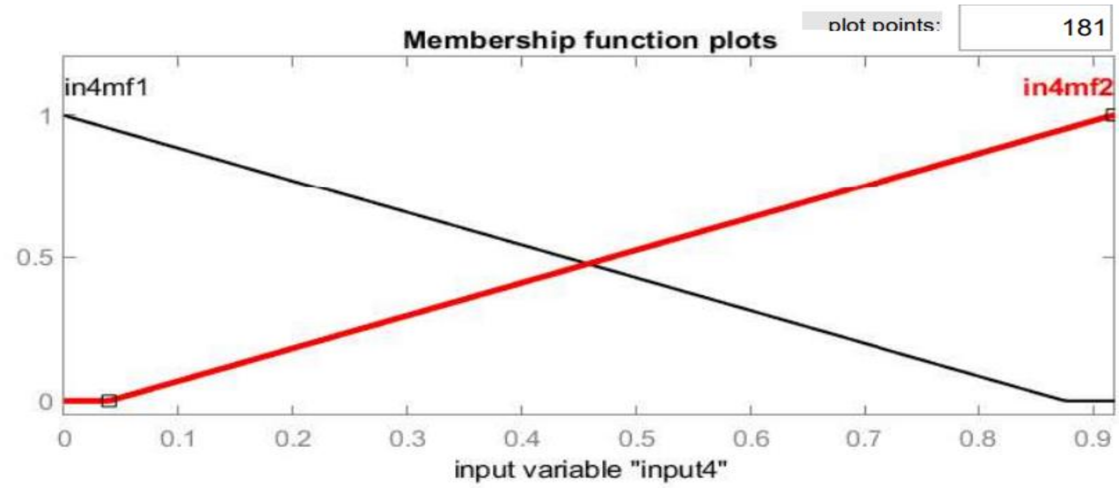

Figure 8 MF plot of input 4

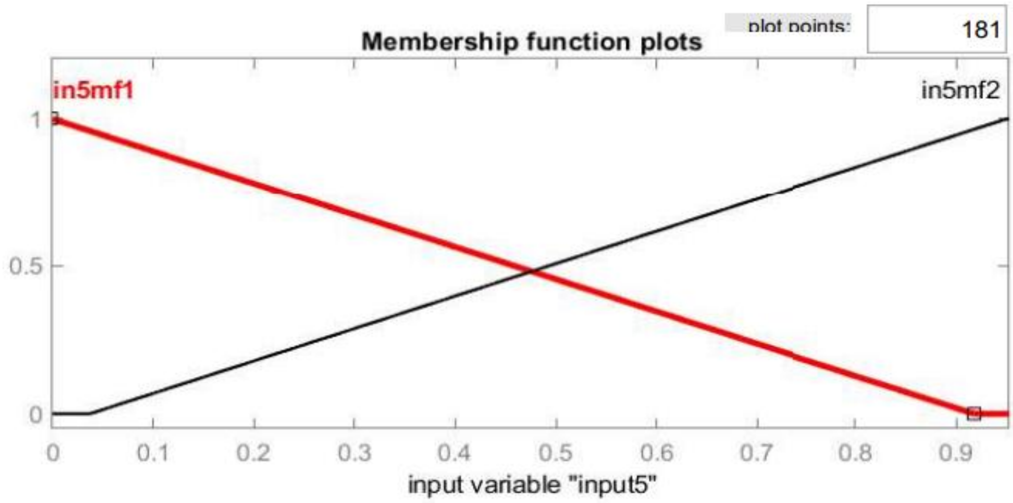

Figure 9 MF plot of input 5

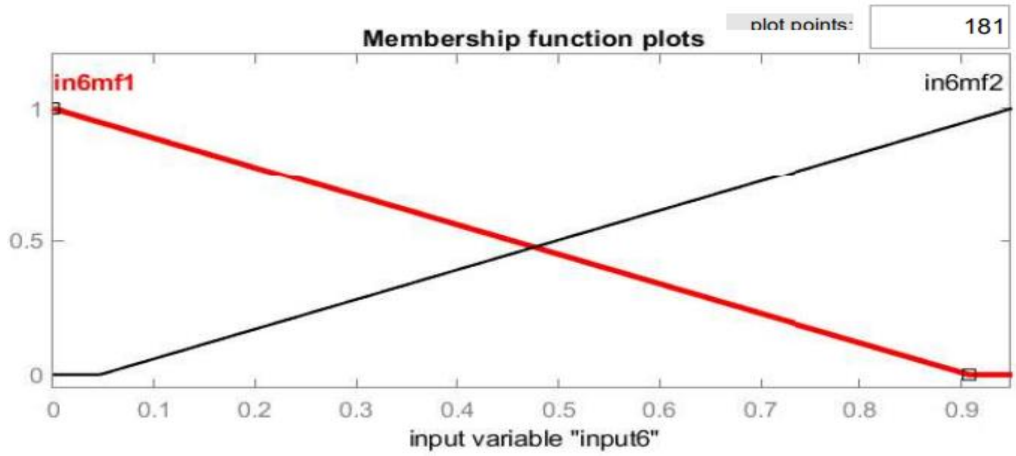

Figure 10 MF plot of input 6

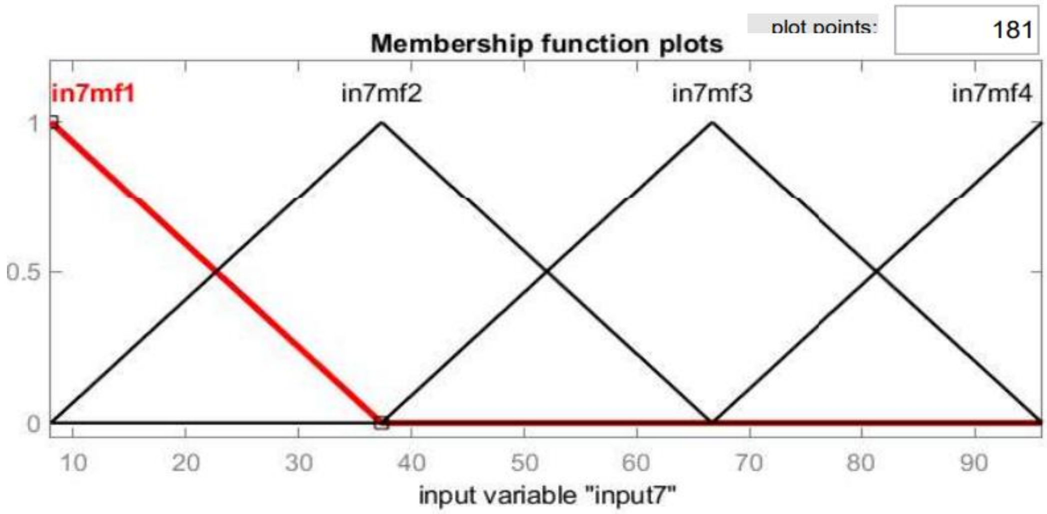

Figure 11 MF plot of input 7

2.2. Rules

The system uses all possible combinations of the provided input data to automatically build the rules for this methodology during the training phase in order to identify the stage of heart disease. The developed hybrid model generates the rules utilizing the training data set shown in Figure 12. The put-forward intelligent hybrid model employs 768 rules in total. The number of MFs utilized for each of the system's input variables can be multiplied to determine the number of rules. Hence, total rules = 4x3x2x2x2x2x4 = 768.

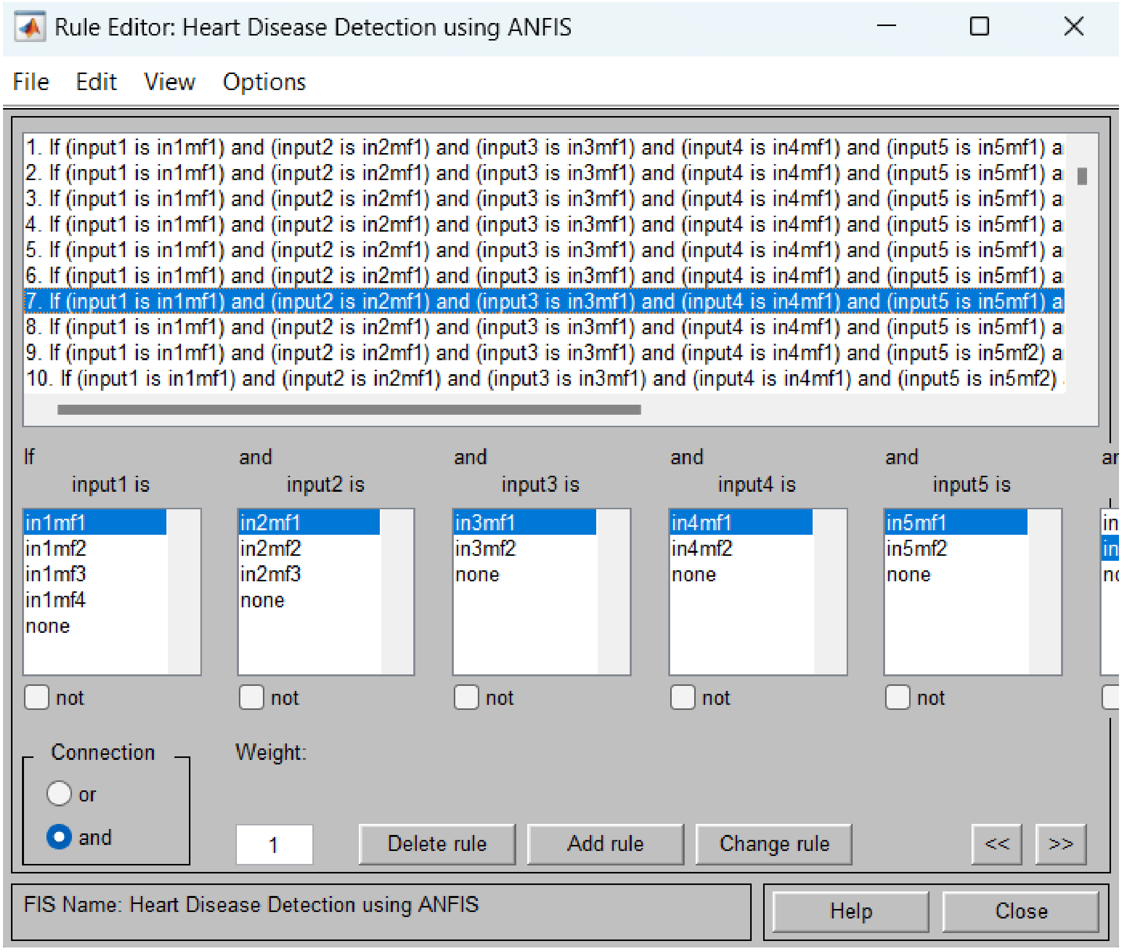

Figure 12 Rules generated by the model

2.3. Training phase and Testing phase

During the implementation of the hybrid system, the training and testing phase of the system is most crucial. The data is initially obtained from the heart specialist. After the acquisition of data, the gathered data is partitioned using k-fold cross validation. There are 800 data samples in the used dataset. The k-fold cross validation is utilized to divide this dataset into different parts corresponding to the value of k. For instance, in this study, the value of k is considered as 4, and hence the dataset is categorized into four sections. Also, 4-fold cross validation is the term used to describe the cross-validation process when k = 4.

Now, as the data is partitioned into 4 parts, the 3 sections of data samples are used for the training phase, and the other 1 section is utilized in the testing phase. It might be clarified by saying that the dataset is divided into four pieces, namely 1st part, 2nd part, 3rd part, and 4th part. The 1st part serves as testing, while the remaining sections serve as training data in the first iteration. Similar to the first iteration, the 2nd part of the dataset is used to test the system in the second iteration, and the remaining parts, i.e., 1st part, 3rd part, and 4th part, will be utilized as training data. These iterations go on until the 4th iteration, and in each iteration, the testing and training instances will be different. Out of 800 data samples, 640 instances are utilized in the training phase and the rest 160 sample instances are utilized in the testing phase. Hence, it can be said that 80 percent of the dataset is utilized in the training phase and 20% of the dataset is utilized in the testing phase of the developed system. 10 epochs are used to train the developed intelligent hybrid system. The validation is also performed to see if the proposed system could correctly distinguish patients with different stages of heart disease. Figure 13 demonstrates the training error following the training phase.

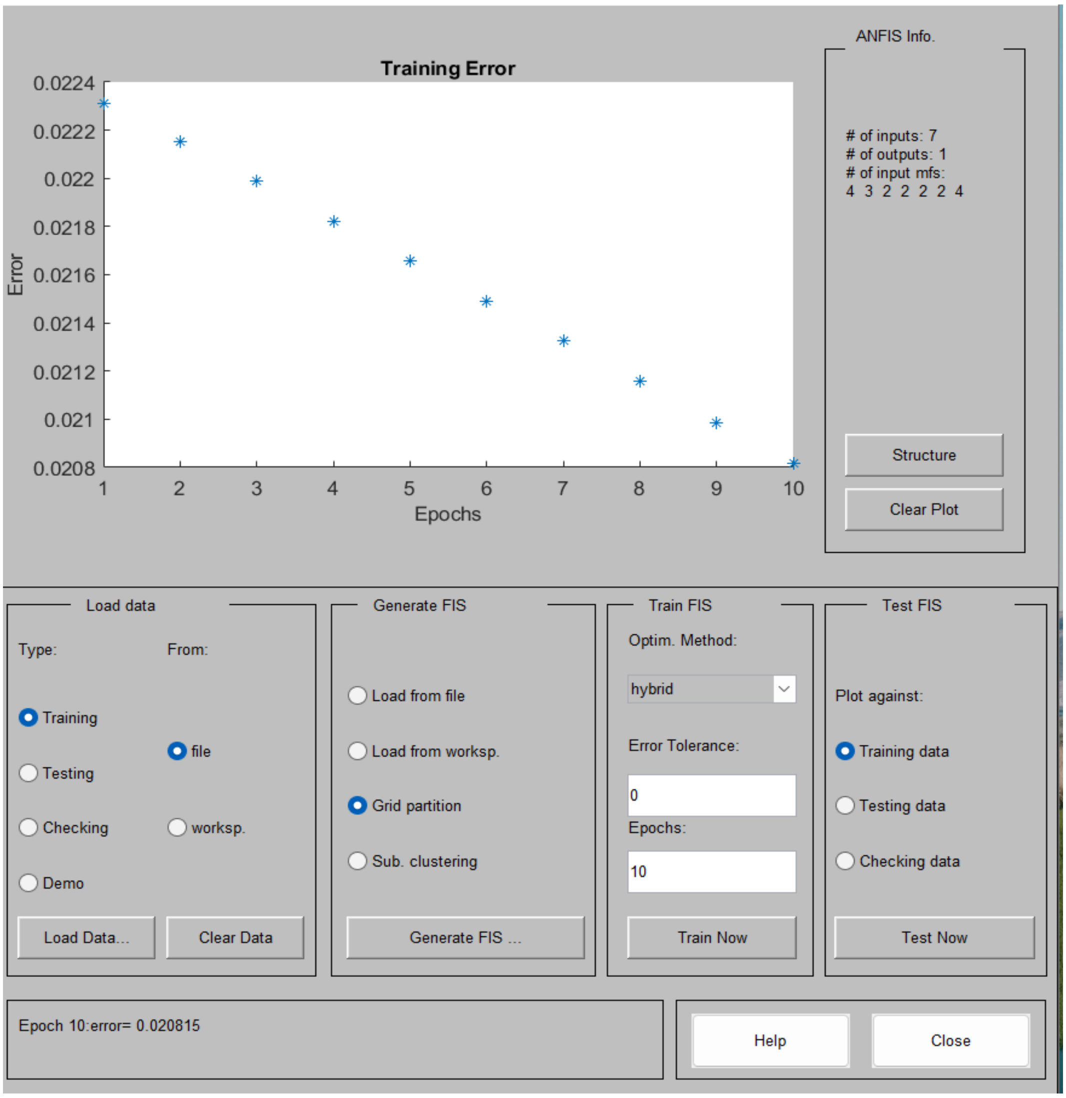

Figure 13 Training error at 10 epochs

3. Results

The proposed technique is thought to be accurate if the observed value and the goal value are identical or nearly identical; otherwise, they do not accurately classify patients having different stages of heart disease. After examining the system's ability to accurately identify the heart disease stage, it was found that the input is correctly classified by the system. Table 2 to table 5 display the confusion matrices for each fold.

Table 2 Confusion matrix for fold 1

Normal Stage	Early stage	Advanced Stage	Class Name
52	01	00	**Normal stage**

02	48	00	**Early stage**
00	00	57	**Advanced stage**

Table 3 Confusion matrix for fold 2

Normal Stage	Early stage	Advanced Stage	Class Name
53	00	00	**Normal stage**
00	49	01	**Early stage**
00	00	57	**Advanced stage**

Table 4 Confusion matrix for fold 3

Normal Stage	Early stage	Advanced Stage	Class Name
52	01	00	**Normal stage**
00	50	00	**Early stage**
00	00	57	**Advanced stage**

Table 5 Confusion matrix for fold 4

Normal Stage	Early stage	Advanced Stage	Class Name
53	00	00	**Normal stage**
02	48	00	**Early stage**
00	00	57	**Advanced stage**

The dimensionality of above given confusion matrix is reduced to 2 by considering the first column, “normal stage” as “No”, and 2nd and 3rd columns, which are “ early stage” and “advanced stage” as “Yes”. The confusion matrices with reduced dimensionality is displayed in table 6 to 9.

Table 6 Decreased dimensionality of a confusion matrix for k = 1

No	Yes	Class Name
52	01	**No**
02	105	**Yes**

Table 7 Decreased dimensionality of a confusion matrix for k = 2

No	Yes	Class Name
53	01	**No**
00	106	**Yes**

Table 8 Decreased dimensionality of a confusion matrix for k = 3

No	Yes	Class Name
52	01	**No**
00	107	**Yes**

Table 9 Decreased dimensionality of a confusion matrix for k = 4

No	Yes	Class Name
53	00	**No**
02	105	**Yes**

By using the values of true positive, true negative, false positive and false negative from the above four tables that are from tables 6 to 9, the performance of the model for each fold is calculated. The several parameters used to measure the performance of the developed intelligent hybrid system for monitoring heart disease, along with their values, are shown in table 10. Additionally, the bar chart of measured performance is displayed in figure 14.

Table 10 Measured performance of the model

Parameters	k = 1	k = 2	k = 3	k = 4	Overall Performance
Classification accuracy	98.12	99.37	99.37	98.75	98.90
Specificity	96.29	100	100	96.36	98.16
Sensitivity	99.05	99.05	99.07	100	99.29
Precision	98.13	100	100	98.13	99.06

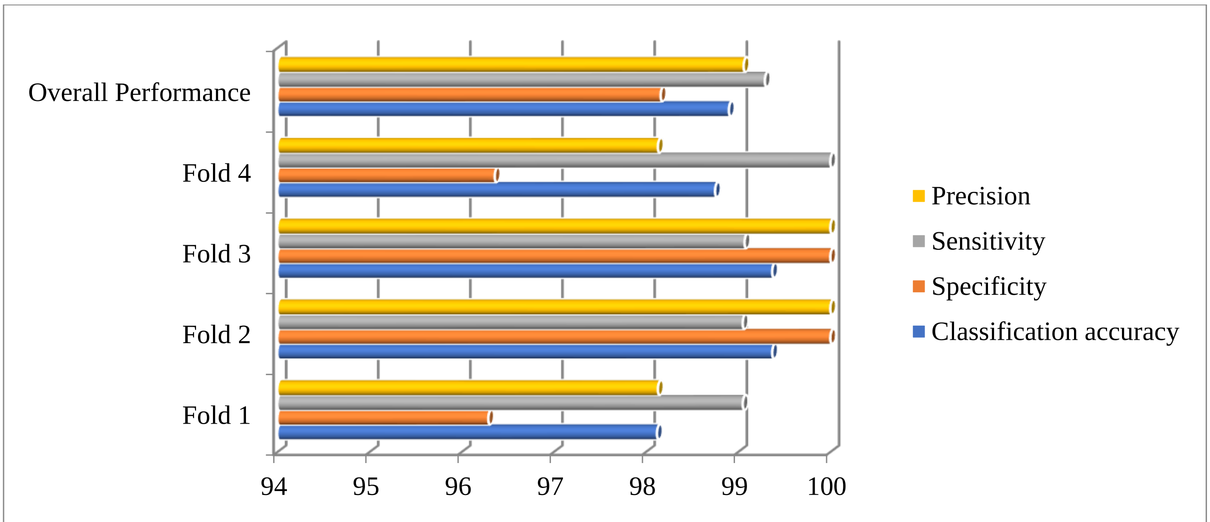

Figure 14 Graphical representation of calculated performance parameters at each fold and overall performance

4. Conclusion

The created model, which uses an adaptive neuro-fuzzy inference method to identify stages of heart disease, can help medical professionals, as well as unaware individuals, recognize the illness on their own. The system can help doctors maintain the patient's health. During the training phase, the introduced intelligent hybrid system is initially trained by utilizing the pertinent dataset. The system has since undergone testing and validation in order to assess the observed output provided by the intelligent hybrid system. Additionally, the model's output is used to calculate the performance parameters, and as a result, it is found that the model is 98.90% accurate. This performance evaluation found that the created hybrid system employing ANFIS provided results that were accurate and appropriate for usage within healthcare facilities for monitoring heart diseases.

Future research may uncover other biomarkers, and other machine learning approaches may be used to create a decision-making model that helps experts and novices in monitoring heart diseases at their early stages more accurately.

Refrences

[1] Abdellatif, H. Abdellatef, J. Kanesan, C.-O. Chow, J. H. Chuah, and H. M. Gheni, “Improving the heart disease detection and patients’ survival using supervised infinite feature selection and improved weighted random forest,” IEEE Access 10 (2022), 67363–67372.

[2] R. T. Selvi and I. Muthulakshmi, “Retracted article: An Optimal Artificial Neural Network based big data application for heart disease diagnosis and classification model,” Journal of Ambient Intelligence and Humanized Computing 12(6) (2020), 6129–6139.

[3] G. Andreoni, E. G. Caiani, and N. Castaldini, “Digital Health Services Through Patient Empowerment: Classification, Current State and Preliminary Impact Assessment by Health Pod Systems,” Applied Sciences 12(1) (2021), 359-359.

[4] A. Sreeniwas Kumar and N. Sinha, “Cardiovascular disease in India: A 360 degree overview,” Medical Journal Armed Forces India 76(1) (2020), 1–3.

[5] Y. G. Tefera, T. M. Abegaz, T. B. Abebe, and A. B. Mekuria, “The changing trend of cardiovascular disease and its clinical characteristics in Ethiopia: Hospital based observational study,” Vascular Health and Risk Management 13 (2017), 143–151.

[6] G. Musinguzi, R. Ndejjo, I. Ssinabulya, H. Bastiaens, H. van Marwijk, and R. K. Wanyenze, “Cardiovascular risk factor mapping and distribution among adults in Mukono and Buikwe Districts in Uganda: Small area analysis,” BMC Cardiovascular Disorders 20(1) (2020).

[7] Y. Ruan, Y. Guo, Y. Zheng, Z. Huang, S. Sun, P. Kowal, Y. Shi, and F. Wu, “Cardiovascular disease (CVD) and associated risk factors among older adults in six low-and middle-income countries: Results from sage wave 1,” BMC Public Health 18(1) (2018).

[8] D. S. Arsyad, J. Westerink, M. J. Cramer, J. Ansar, Wahiduddin, F. L. Visseren, P. A. Doevendans, and Ansariadi, “Modifiable risk factors in adults with and without prior cardiovascular disease: Findings from the Indonesian National Basic Health Research,” BMC Public Health 22(1) (2022).

[9] M. Amini, F. Zayeri, and M. Salehi, “Trend analysis of cardiovascular disease mortality, incidence, and mortality-to-incidence ratio: Results from Global Burden of Disease Study 2017,” BMC Public Health 21(1) (2021).

[10] P. Vadamodula, B. S. Satwika, and A. Swamy, “An Ensemble Approach to Predict the Presence of Cardio Vascular Disease using Machine Learning and Deep Learning.,” Journal of Emerging Technologies and Innovative Research (JETIR) 9(10) (2022), 559–563.

[11] N. Shahid, T. Rappon, and W. Berta, “Applications of artificial neural networks in health care organizational decision-making: A scoping review,” PLOS ONE 14(2) (2019).

[12] R. T. Sutton, D. Pincock, D. C. Baumgart, D. C. Sadowski, R. N. Fedorak, and K. I. Kroeker, “An overview of clinical decision support systems: Benefits, risks, and strategies for Success,” npj Digital Medicine 3(1) (2020).

[13] Ł. Apiecionek, R. Moś, and D. Ewald, “Fuzzy neural network with ordered fuzzy numbers for Life Quality Technologies,” Applied Sciences 13(6) (2023), 3487-3487.

[14] P. Keikhosrokiani, A. B. Naidu A/P Anathan, S. Iryanti Fadilah, S. Manickam, and Z. Li, “Heartbeat sound classification using a hybrid adaptive neuro-fuzzy inferences system (ANFIS) and Artificial Bee Colony,” DIGITAL HEALTH 9 (2023).

[15] O. Taylan, A. S. Alkabaa, H. S. Alqabbaa, E. Pamukçu, and V. Leiva, “Early prediction in classification of Cardiovascular Diseases With Machine Learning, neuro-fuzzy and statistical methods,” Biology 12(1) (2023), 117-117.

[16] T. Kasbe and R. S. Pippal, “Design of heart disease diagnosis system using fuzzy logic,” 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS) (2017).

[17] K. Balasubramanian and N. P. Ananthamoorthy, “Improved adaptive neuro-fuzzy inference system based on modified glowworm swarm and differential evolution optimization algorithm for medical diagnosis,” Neural Computing and Applications 33(13) (2020), 7649–7660.

[18] K. V. Shihabudheen and G. N. Pillai, “Recent advances in neuro-Fuzzy System: A survey,” Knowledge-Based Systems 152 (2018), 136–162.

[19] G. Zhang, S. S. Band, S. Ardabili, K.-W. Chau, and A. Mosavi, “Integration of neural network and fuzzy logic decision making compared with bilayered neural network in the simulation of Daily Dew Point temperature,” Engineering Applications of Computational Fluid Mechanics 16(1) (2022), 713–723.

[20] K. Damodara and A. Thakur, “Adaptive Neuro Fuzzy Inference System based prediction of chronic kidney disease,” 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (2021).

[21] J. Singla and B. Kaur, “A medical intelligent system for diagnosis of chronic kidney disease using adaptive neuro-fuzzy inference system,” Nature-Inspired Optimisation Algorithms (2021), 19–32.

[22] J. Feng, Q. Wang, and N. Li, “An intelligent system for heart disease prediction using adaptive neuro-fuzzy inference systems and genetic algorithm,” Journal of Physics: Conference Series 2010(1) (2021), 012172-012172.

[23] J.-S. R. Jang, “ANFIS: Adaptive-network-based Fuzzy Inference System,” IEEE Transactions on Systems, Man, and Cybernetics 23(3) (1993), 665–685.

[24] M. Kabir and M. M. Kabir, “Fuzzy membership function design: An adaptive neuro-fuzzy inference system (ANFIS) based approach,” 2021 International Conference on Computer Communication and Informatics (ICCCI) (2021).

[25] S. Chidambaram, S. S. Ganesh, A. Karthick, P. Jayagopal, B. Balachander, and S. Manoharan, “Diagnosing breast cancer based on the adaptive neuro-fuzzy inference system,” Computational and Mathematical Methods in Medicine 2022 (2022), 1–11.

[26] B. Paul and B. Karn, “ANFIS based diabetes mellitus prediction,” 2021 IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) (2021).

[27] N. Jindal, J. Singla, B. Kaur, H. Sadawarti, D. Prashar, S. Jha, G. P. Joshi, and C. Seo, “Fuzzy logic systems for diagnosis of renal cancer,” Applied Sciences 10(10) (2020), 3464-3464.

[28] D. Singh, S. Verma, and J. Singla, “A neuro-fuzzy based medical intelligent system for the diagnosis of hepatitis B,” 2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM) (2021).

[29] Nikita, B. Kaur, D. H. Sadawarti, and D. J. Singla, “A Neuro-Fuzzy Based Intelligent System For Diagnosis Of Renal Cancer,” International Journal of Scientific and Technology Research 9(1) (2020), 3699–3705.

[30] N. Ziasabounchi and I. Askerzade, “ANFIS Based Classification Model for Heart Disease Prediction,” International Journal of Engineering & Computer Science IJECS-IJENS 14(2) (2014), 7–12.