Original Article

Study of Fuzzy and Artificial Neural Network (ANN) Based Techniques to Diagnose Heart Disease

Raj Kumar Bhagat[1], Anil Yadav[2], Yogendra Kr. Rajoria[3], Sandeep Raj[4], Rahul Boadh[5*]

[1], [3], *[5]Department of Mathematics, School of Basic and Applied Science, K. R. Mangalam University, Sohna Road, Gurugram, Haryana, India-122103
[2]Department of Chemical Engineering, Deenbandhu Chhotu Ram University of Science and Technology, Murthal, Sonipat, Haryana, India – 131027
[4]School of Engineering, Ajeenkya D Y Patil University, Pune, Maharashtra- 412105

***Corresponding author:** - Dr. Rahul Boadh (Assistant Professor), Department of Mathematics, School of Basic and Applied Science, K. R. Mangalam University, Sohna Road, Gurugram, Haryana, India-122103, E-mail:- rboadh.iitkgp@gmail.com
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Abstract

Cardiovascular disease and cardiac arrest causes millions of fatalities worldwide each year. Heart disease depends upon various physiological parameters. These parameters need constant monitoring to know the condition of heart in real time. Accurate and appropriate analysis of these parameters can timely diagnose the problem and can save life of the people. But continuously generated data by wearable health device and clinical data related with these parameters, needs smart algorithm for analysis. Also, huge and dynamic nature of data requires special attention. In recent years, FL and ANN are being used to diagnose the heart related problems. This paper reviews various algorithms and techniques related FL and ANN to diagnose heart related problems.

Keywords: - Artificial Neural Network, Fuzzy Logic, Smart Algorithm, Heart Disease, Wearable Health Device;

I. INTRODUCTION

Heart is a major organ of any species. Cardiovascular disease (CVD) and cardiac arrest causes millions of fatalities worldwide each year. The term "CVD" refers to a variety of heart and blood vessel conditions. It comes in a variety of forms, including CAD, congenital, peripheral arterial, rheumatic, and pulmonary embolism. One-third of the 17.9 million CVD fatalities every year, according to statistics, occur in those under the age of 70. Even new born child has prenatal ventricular septal defect, it is the most common coronary heart problem and approximately 2 % newborns have this problem [1]. Risk factors for CVDs include elevated lipids, abnormal glucose levels, high blood pressure (BP), overweight, smoking, obesity and inactivity. According to the WHO, at least until 2030, heart disease (HD) will remain most covert human killer [2]. A very popular proverb being used by doctors is that “prevention is better than cure”. Heart conditions include hypertension, heart attacks, and strokes are the leading causes of death in America. In order to treat cardiac patients efficiently and prevent heart attacks and strokes, early detection of heart disease is crucial [3]. Therefore, continuous monitoring of mental and physical health parameter can prevent unhealthy habits and lifestyle and save life [4].

Medical knowledge is growing tremendously and it is assumed that it doubles in every six to eight years [5]. Also, huge amount of health-related data generated in healthcare sector every year. These data can be analyzed for prediction, diagnosis and treatment of various diseases [6]. Various DMT have been evolved and that can be used for disease predictions by applying various immersive technology [7]. Although many smart algorithms have been developed for disease prediction, but still, we are facing many challenges in terms of the efficiency of prediction and information protection [8].

In India and other developing countries have economic and regional disparities in terms of health care services, especially in rural areas [9]. Therefore, we need to develop a good remote healthcare management and disease prediction system. IoT is an innovative technology, which is changing the lives of people with the help of medical devices connected with internet. It is a worldwide internet-based network, which collect and analyze data on real time. This architect popularly known as IoMT and extensively being used in medical and healthcare sector [10],[11],[12]. Demographic and economic factors like aging population and limited health care infrastructure can be addressed with the help of IoMT [13].

Wearable health devices, wireless body area network and mobile app based medical services are growing rapidly and have potential to address these problems [14],[15]. Smart Watches and Fitness Trackers are most popular wearable health devices to monitor steps covered, calorie burned, sleep quality and heart beats and it can be integrated with smart phone. These parameters are powerful indicator of health problem [16]. This structure is multidimensional and complex in nature. Wearable health sensor or device collects data of the patients and send it to health service provider through internet. Therefore, using internet of things (IoT) technology, real time physiological data of vital parameters of a heart

patients can be recorded and sent to a remote healthcare management center [17]. Young people are also affected by heart disease and WHD are popular among them [18]. WHD can be used to continuously monitor the vital parameters of youth [19]. Remote surveillance of elderly people suffering from heart ailment is necessary and can also be done with IoT [10].

Healthcare data collected through wearable senor and transmitted, via internet might have some error. Error can be in terms of missing values, incorrect values and outliers. These errors occur due to unstable internet signals and bad sensor quality. Therefore, comparing wearable sensors data with electronic medium records (EMRs) is a difficult task when observing heart patients. Medical data involves many features which might not be useful for heart disease prediction and diagnosis. Those irrelevant data need to be removed to strengthen, efficiency and precision of the disease forecast model. Hence, smart algorithm for feature selection, classification and clustering needs to be developed for better performance of heart prediction model [3]. Accuracy of prediction depends upon smart algorithm and fast computing devices. Fuzzy and ANN techniques being widely used as smart algorithm for prediction and diagnosis of heart disease. FIS [20] and ANFIS are two widely used techniques in various fields.
Since the area of Artificial Intelligence (AI), Machine Learning (Ml), and Data Analytics are very wide and have application in various fields. Therefore, a list of abbreviations of various tools and techniques are given below for the convenience of readers.

Table I Table of Abbreviations

S. No.	Techniques/Terminology	Abbreviation
1	Adaptive Neuro Fuzzy Inference System	ANFIS
2	Analytic Hierarchy Process	AHP
3	Artificial Neural Network	ANN
4	Beetle Swarm Optimization	BSO
5	Cardio Vascular Disease	CVD
6	Clinical Decision Support system	CDSS
7	Congenital Heart problem	CHP
8	Coronary Heart Disease	CHD
9	Data Mining Techniques	DMT
10	Decision Tree	DT
11	Electronic Medical Record	EMR
12	Ensemble Deep Learning	EDL
13	Ensemble Learning Method	ELM
14	Fourier Transform	FT
15	Fuzzy Inference System	FIS
16	Fuzzy Logic	FL
17	Fuzzy Set Theory	FST
18	Genetic Algorithm	GA
19	Heart Disease	HD
20	High Blood Pressure	HBP
21	Information and Communication Technology	ICT
22	Internet of Medical Things	IoMT
23	Internet of Things	IoT
24	Laplacian Gaussian Mutation based Moth Flame Optimization	LGM-MFO
25	Linear Discriminant Analysis	LDA
26	Modified Dynamic Multi-Swarm	MDMS
27	Modified Slap Swarm Optimization	MSSO
28	Multi-Layer Perceptron	MLP
29	Multiple Kernel Learning	MKL
30	Multiple Logistic Regression	MLR
31	Multivariate Adaptive Regression Splines	MARS
32	Naïve Bayes	NB
33	Neural Network	NN
34	Particle Swarm Optimization	PSO
35	Principal Component Analysis	PCA
36	Random Forest	RF
37	Recurrent Fuzzy Neural Network	RFNN
38	Self-Organizing Map	SOM
39	Smart Clinical Decision Support System	SCDSS
40	Smart Clinical Support system	SCSS
41	Special Vector Machine	SVM
42	Supervised Machine Learning	SML
43	Tuned Neuro Fuzzy Inference System	TANFIS
44	Wavelet Transform	WT

A. Motivation

All existing tools and techniques of fuzzy & ANN to diagnose HD needs through investigation. Due to revolution in the area of IoMT, lots of medical data available and various DMT helps us to get valuable information out of it [21]. Every year millions of people die due to inappropriate treatment and inaccurate diagnosis of diseases. Hence, reliable and efficient smart clinical support systems (SCSS) can save time, effort and money and can improve the accuracy of diagnosis [22].

In country like India, where there is huge disparity in terms of income and healthcare facilities, SCSSs can play an important role. Before performing any expensive test, preliminary non expensive examination can be done with the help of SCSSs [23]. If it confirms then further procedure can be performed. Also, uneven distribution of healthcare facilities can be overcome by using IoT. IoT combines ICT to provide better medical services. Even in remote areas, patients' health conditions can be improved by using the IoT. Through IoT, medical information can be transferred from one location to another, to identify disorders and arrange for the right drugs. Time and resources can be efficiently used in this way [24].

B. General procedure of FL and ANN

FST and FL have wide use in the area of medical science for disease prediction, diagnosis and treatment. In knowledge-based structure of medical science, problem can be transformed into linguistic if and then statement [20].

FL is effective at explaining decisions, but it cannot automatically learn the rules that were used to make the decision. NN are efficient at identifying patterns, but poor at explaining how they make decisions. These constraints serve as a fundamental motivating factor in the development of hybrid algorithms, in which two or more approaches are merged in an appropriate way to overcome the weaknesses of individual techniques. A hybrid algorithm, such as NF, which combines FL with ANN, is extremely effective in dealing with complicated data structure [20]. Therefore, in last few years ANN and FL is being widely used as an important tools to develop an intelligent information/data processing systems [25].

General architecture of FL system and ANN consist following steps:

1) **Fuzzification:** It the process of converting crisp input values into linguistic values with the help of membership function. This is the process of inductive learning or rule generation. This step is basically for structure identification.

2) **Fuzzy Neural Network:** In this step fuzzified value is used to train ANN for parameter identification and classification. This is important steps as it applies intelligence to detect problem.

3) **Defuzzification:** It converts classified data into different decision i.e., conversion of fuzzy values to crisp value.

II. LITERATURE REVIEW

The Concept of Fuzzy set theory was first introduced in 1965 by professor Zadeh. He was professor at University of California, Berkeley. This concept widely used as control methodology and data processing. But now it is widely used to implement ML techniques [26]. ANN mimics human brain in processing the data. This concept was first introduced by McCulloch and Walter Pitts in 1943. They created a computational techniques-based algorithm for NN called threshold logic. In 1950s, Frank Rosenblatt working at Cornell Aeronautical Laboratory designed a single layer neuron called Perceptron to classify an image of few hundred pixels. This was the beginning of first modern neural network [27]. Over last few years, hybrid techniques like Neuro-Fuzzy have been evolved to simulate the human reasoning ability with great accuracy. Researchers are developing systems which have high level of flexibility, adaptability, and autonomy to evolve their structure and knowledge [28].

Around 60 research papers selected from Scopus and Web of Science to study Fuzzy and ANN techniques to predict heart disease. The purpose of this study is to discuss various techniques related with fuzzy and ANN, their accuracy and limitations. We critically discussed around 22 research papers, which exclusively used latest tool and techniques to diagnose heart disease. Details presented in tabular form for better understanding.

Table II: Application of Fuzzy Logic, Artificial Neural Network and other techniques to detect heart related diseases

S. No	Methodology/Techniques	Conclusion
1	DMT consists two stages in which PSO technique is used to categorize and cutting the assets, and ANFIS classifies the statistics consuming Adaptive Group based K-Nearest Neighbour (AGKNN [29].	This algorithm is better than traditional methods and found to classify data more effectively. Accurate prediction lowers the expense of unneeded medical testing, and patients can take preventative actions on time.
2	Fuzzy expert system in which defuzzification being done by centroid techniques. MATLAB used for this purpose [30].	It is an easy expert system in terms of usability but gives better performance than any other previous methods. This method gives highest accuracy of 93.33%.
3	GA based trained RFNN [31]	Provide the good agreement as compare to ANN-Fuzzy.
4	MLP structure on ANN and ANFIS) approach [32].	The NF system has better performance than ANN system.
	LDA and Adaptive ANFIS being used in three stages. WT and short-time FT used for feature extraction in second stage. Wavelet entropy was also applied. [33]	Better results with compared the previous studies.
6	The NF & Genetic Algorithms for feature collection.[34]	The projected NF rule-based classification system found to be an effective and efficient method than any other classifiers.
7	The mobile cloud computing technology is used to integrate ECG tele-monitoring and risk assessment for CHD [35].	According to the classification result, it provides the maximum precision.
8	The proposed MSSO and ANFIS improve the search capability using the Levy Flight Algorithm. [17]	The proposed MSSO-ANFIS integrated with IoMT worked well for continuously monitoring patients' heart conditions.
9	A novel efficient IoT based the TANFIS classifier has been suggested for precise heart disease prediction. Through LGM-MFO, the tuning parameters of the proposed TANFIS are optimised and grasshopper optimization algorithm [36].	The proposed TANFIS-LGM2G method compared with various optimization algorithms attains 99.76% of accuracy.
10	The IoT, which includes NF self-learning technology. The suggested system tracks the physiological characteristics of the patients and aids in the earliest possible disease diagnosis for the medical personnel [24].	The suggested monitoring system accurately identifies any anomaly while also keeping track of the patient's vital signs including temperature and ECG.
11	For the design of the prediction system NN, FIS, and ANFIS—are taken into consideration. MATLAB software was used to put all the techniques into practise [37].	The ANFIS has showed good performance.
12	A hybrid NN that includes ANN and FNN was developed and k-fold cross validation was used for performance analysis [38].	The suggested techniques attained precision values of 84% and 86% respectively.
13.	GA created skilled RFNN to verdict of heart diseases [39].	This study achieved truth of 97.78 percent and an inclusive truth of 96.6 percent.
14.	The proposed model evaluates the classification performances of two discrete ANFIS_LSLM and ANFIS-LSGD in MATLAB's [40].	Even though the conventional ANFIS_LSGD took slightly less time to compute than the ANFIS-LSLM, the results of the latter surpass those of the former.
15.	This paper presents comparative study of three SML algorithms FIS, ANFIS and NN to predict patients' health condition [41].	The FIS achieved the highest classification accuracy of 87 percent, the ANFIS achieved 83 percent, and NN achieved just 78 percent.
16	The performance of ANN is determined by used NS. The proposed model's initial NN weights were selected using GA, and the NN was learnt using training data [42].	By modifying weights using GA, the performance of the proposed NN was improved by about 10%, 97 percent, and 92 percent, respectively, were reached using the suggested technique.
17	NN, DNN, and fuzzy C-means clustering with deep neural network [43].	In comparison to the NN and DNN approaches, the suggested FCM-DNN technique consumes the highest exactness degree of 99.91 percent besides the lowest incorrect degree.
18.	Three ML approaches were examined in the suggested model: ANN, DT, and NB. The uncertain constructed model deposited in the haze was used to retrieve real-time patient data.[44]	The findings showed that the suggested fuzzy-based model is 91.30 percent accurate.
19.	Heart problems and multiple illness detection using the BSO-ANFIS modelling system [6].	The suggested BSO-ANFIS model has an overall accuracy of 96.08 percent, which is greater than the ANN, SVM, and traditional ANFIS models.
20.	Fuzzy logic, ANN and Deep extreme machine learning are used.[50-51]	The DCD-SL-MFIS, DCD–ANN and DCD–DEML framework draws out the 87.05 percent, 89.4 percent precision, and 92.45 percent precision respectively.
21.	A deep learning approach based on MKL and ANFIS is proposed [52-53].	The suggested MKL-ANFIS method's findings for high compassion as well as a low Mean Square Error were demonstrated.
22.	A subset of relevant features is chosen using Fisher Discriminant Ratio (FDR) analysis when seven distinct features extraction algorithms are being applied. Lastly, the chosen characteristics are used to construct ANFIS [47].	The TA cardiac defect has never been discovered using 2D US pictures before the proposed CADSS. The suggested CADSS has been designed with a variety of image processing tasks that often produce accurate diagnostic outcomes.

After going through around 22 research paper published between from 2008 to 2021.We observed following Characteristics;

a. Around the world people are working on disease prediction using hybrid techniques.

b. Most popular hybrid technique is based on FL and ANN. These two techniques are very powerful because they

complement each other. ANFIS, GA based trained RFNN and IoT based TANFIS are three most frequently used techniques.

c. Different classification, clustering, learning and training optimization techniques being used with FL and ANN.

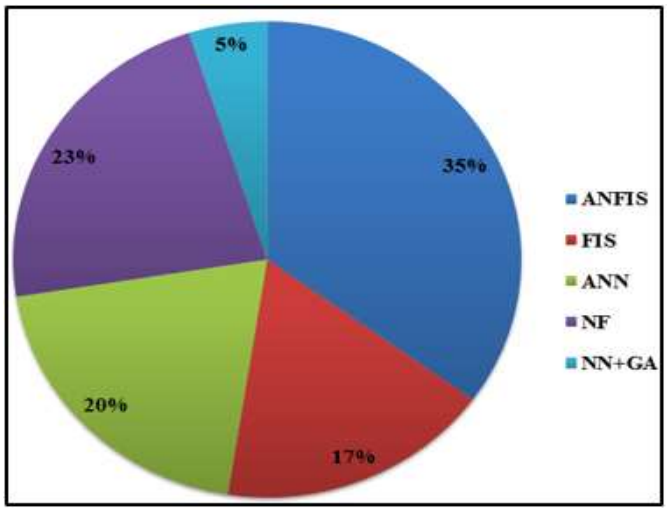

Fig. 1 Different smart algorithms used to diagnose various types of heart diseases.

d. In this study, it has been observed that maximum studies are done by using ANFIS and it follows by NF, ANN, FIS and NN with GA respectively shown in Fig. 1.
e. Most of the authors had taken the data from MIT-BIH Database Distribution, UC Irvine, Machine Learning Repository and Kaggle. All these data collected from or deposited by authentic source.
f. All the proposed algorithms claimed accuracy in between 85 to 98 percent. This can be considered as good in comparison with human error in clinical diagnosis.
g. Few authors tried to develop a dynamic model by integrating clinical data with actual period data. The data of actual period is being composed with the help of wearable health device integrated with internet (Internet of Things) [48]. Though it is in nascent stage due to data complexity, but it has tremendous potential. Across the world people are working on smart algorithm. It will revolutionize the entire health sector and health infrastructure.

All smart algorithms based on machine learning techniques needs reliable datasets to train themselves for better predictions. There are few data depository available online. UC Irvine, Machine Learning Repository is a data depository supported by National Science Foundation. Kaggle is another data depository. It is a subsidiary unit of Google.
Fuzzy and ANN Techniques have been widely used for developing smart algorithm for heart disease diagnosis. Various software is available to perform simulation and develop smart algorithm. MATLAB is licenced based multi-platform software developed by MATHWORK. Software is Weka developed by University of Waikato, New Zealand. This is free software under general public licence.

III. LIMITATIONS

Although many data depository like Kaggle, UC Irvine and Machine Learning Repository are available. But for reliability and validation of the model, real time data or current data has been used. Getting real time data is not easy to procure due to following reasons:

a) For privacy and safety of patients/user of wearable health devices [49],[50].
b) Data collection through wearable health device (fitness tracker/smart watch/smart phone) is essential for dynamic modeling. But getting consent of individual user is not easy task [51]. No person will be ready to share their personal physiological data due to various reasons. Because data can be misused by vested interest [52]. Therefore, people are very much conscious about their privacy and safety [53].
c) These days many companies are providing specialized and customized health services using wearable health data [54],[55]. They have accessibility of huge real time data but either they will charge money for data or will not share at all [56].

IV. CONCLUSION

Since Neuro-Fuzzy model can process dynamic data in real time and predict heart disease. Therefore, this method is being widely used across the world by various researcher and medical service provider. WHD is getting popularity among people and it collects data in real time. Deloitte Global predicts that 320 million consumer health and wellness wearable devices will ship worldwide in 2022 [54].
Many new techniques based on Neuro Fuzzy have been developed to process these data. After reviewing various relevant literatures on FL and ANN to diagnose heart diseases, we found that an accurate algorithm can save millions of lives across the world. Remote care of critical patients will be possible. Also, it will save time and money. In country like India,

where health care facilities/infrastructure is unevenly distributed, it can be very helpful. Real time update about heart related parameters will improve the quality of life and reduce the chance of heart disease.

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