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Rhopalocera Optimization Algorithm Based Attribute Selection With Improved Fuzzy Artificial Neural Network (ROA - IFANN) Classifier for Coronary Artery Heart Disease Prediction in Diabetes Patients

B. Narasimhan[1*], A. Malathi[2]

[1,2]Department of Computer Science, Government Arts College, Coimbatore

Corresponding author: bnarasimhhan@gmail.com

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Abstract- Soft computing techniques and its applications extends its wings in almost all areas which includes data mining, pattern discovery, industrial applications, robotics, automation and many more. Soft computing comprises of the core components such as fuzzy logic, genetic algorithm, artificial neural networks and probabilistic reasoning. In spite of these, recently many bio – inspired computing attracted attention for the researchers to work in that area. Machine learning plays an important role in the design and development of decision support systems, applied soft computing and expert systems applications. Attribute selection is conducted by Rhopalocera optimization algorithm which mimic the features of butterfly optimization algorithm. After that an improved fuzzy logic based artificial neural network classifier for predicting coronary artery heart disease among diabetic patients is developed. Real time data are obtained and the built ROA - IFANN classifier is tested for performance in terms of prediction accuracy, sensitivity, specificity and Mathew's correlation coefficient. The significance of MCC is that to test the ability of the machine learning classifier in spite of other performance metrics. Implementations are done in Scilab and from the obtained results it is inferred that the built ROA - IFANN outperforms that that of other classifiers.

Keywords: soft computing, fuzzy logic, machine learning, CAHD, diabetes, artificial neural network, applications of soft computing**.**

I. INTRODUCTION

Typically, the essential contemplations of traditional computing are accuracy, sureness, and meticulousness. We recognize this as hard computing. Interestingly, the important thought in soft computing is that exactness and sureness convey a cost; sand that calculation, reasoning, and basic leadership should misuse (wherever conceivable) the resistance for imprecision, uncertainty, approximate reasoning, and incomplete truth for getting minimal effort arrangements. This prompts the wonderful human capacity of understanding mutilated discourse, translating messy penmanship, appreciating the subtleties of characteristic language, condensing content, perceiving and arranging pictures, driving a vehicle in thick rush hour gridlock, and, all the more for the most part, settling on normal choices in a domain of uncertainty and imprecision. The test, at that point, is to misuse the resilience for imprecision by concocting strategies for calculation that lead to an acknowledge capable arrangement requiring little to no effort. This, generally, is the core value of soft computing.

There are continuous endeavors to incorporate artificial neural networks (ANNs), fuzzy set theory, genetic algorithms (GAs), rough set theory and other strategies in the soft computing worldview. Hybridization misusing the attributes of these speculations incorporate neuro-fuzzy, rough-fuzzy, neuro-genetic, fuzzy-genetic, neuro-rough, rough-neuro-fuzzy methodologies. Notwithstanding, among these, neuro-fuzzy computing mechanism has gained may researchers' attention in these days.

Heart disease remains the number one cause of death throughout the world for the past decades. In 2015, the World Health Organization (WHO) has estimated that 17.7 million deaths have occurred worldwide due to heart diseases. Heart diseases are the primary cause of death globally: more people die annually from CAHD than from any other causes. If we can predict the CAHD and provide warning beforehand, a handful of deaths can be prevented. The application of soft computing brings a new dimension to CAHD risk prediction.

II. Related Works

In order to enhance the prediction of heart disease, optimized crow search algorithm [1] was proposed, where it made an attempt to predict the heart disease more accuracy to provide on-time treatment. The results showed that the proposed algorithm is not fit for dataset related to heart disease, where the classification accuracy becomes very low. Two Class Classification [2] was proposed with the framework of machine learning by utilizing artificial neural network classification concept. The classifier works by selecting the spectral features of sub-band. The results show that classifier could not perform well when there are noisy data more than the remarkable range, where the false positive gets increases. Disease Specific Feature Selection strategy [3] was proposed for the purpose of heartbeat classification in a automated manner towards predicting the cardiac attack. It holds 1-vs-1 features idea towards searching for the best feature, where it uses the support vector machine classification concept. The result showed that the feature selection is not suited for this classification, where the results came with false negative rate got increased. Multi Objective Classification method [4] was proposed with the ensemble of particle swarm optimization and genetic algorithms in order to predict the heart disease in a early stage. It calculated the coefficient of polynomial, also the limit of the threshold value which was set for the class and attributes. This calculation was made to decrease the error, but the misclassification error got increased a lot in classifying to the wrong class Automated Classifier based on Support Vector Machine [5] was proposed to classify the electrocardiograms towards predicting the heart disease. It depends on the time period of electrocardiograms, to train the support vector machine to select the feature. The results proved that the classification accuracy went down due to feature selection concept, where the classifier omitted the important feature for classification. Modified version of Ant Colony Optimization [6] was proposed to increase the classification accuracy towards predicting the coronary artery disease, where it uses least square model of regression. The correlation coefficients were calculated for checking the fitness level between the selected features. The result came with low classification accuracy.

Deep Learning Strategy [7] for the classification of ECG towards heart disease prediction was proposed. This strategy was proposed with the target of classifying in a automatic manner. The result showed that the results were not efficient when comparing with the existing algorithms in the term of sensitivity. Fuzzy Classifier [8] was proposed to perform classification on with dynamic electrocardiogram signals with the intention to predict the heart disease in a early stage. It has worked with the dynamic unknown features resulting with very low accuracy. It was also analyzed that the algorithm can work good with known features only. Identification of Heart Disease with a Embedded System [9] was proposed and analyzed viability. It takes the input as electrocardiogram signals for the initial stage clustering and finally used Gustafson Kessel based Fuzzy clustering algorithm for the purpose of classifying and correlating the signals. The result came with increased false negative rate. Hybrid Classifier [10], which was a ensemble of neural network and genetic algorithm, was proposed for the classification of coronary artery disease. Initially neural network was performed and then the genetic algorithm was used. The result showed that the this specific hybrid classifier was not fit for the prediction of coronary artery disease, where the results came with very low classification accuracy.

III. Rhopalocera Optimization Algorithms Based Attribute Selection with Improved Fuzzy Artificial Neural Network (ROA - IFANN) Classifier

3.1. Overview of Rhopalocera Optimization Algorithm (ROA)

ROA is the replica of a recently proposed bio-inspired algorithm that mimics the food foraging behavior of butterflies (Arora and Singh, 2018) [11]. ROA demonstrates competitive results in terms of exploration, exploitation, convergence and local optima avoidance. The underlying strength of ROA is its exploitation and high convergence rate which is because of the employed random walk and elitism. On the contrary, ROA is facilitated with high exploration owing to aroma attenuation which allows it search the attribute of patients' record space efficiently. Basically in the wrapper-based selection method, the classifier is utilized for training and assessed at every single rerun and subsequently, an intelligent optimization algorithm is employed to minimize the number of evaluations. Furthermore, the search space is anticipated to be extremely nonlinear with numerous local minima. Generally, continuous optimization algorithms are employed to find that combinations of attributes which maximize the performance of classifier and the search agents are utilized in d - dimensional search space at locations in [0, 1]. On the other hand, optimization algorithms are expected to demonstrate better performance, if properly utilized in a similar manner, because the search space is limited to only two values for each dimension {0, 1}. Moreover, the operators are considered to be more straightforward than continuous operators.

In the continuous version of ROA, the Rhopaloceras update their locations continuously to any location in the search space. The main motivation for making use of ROA is that in attributes selection problems, the attribute of patients' records are limited to the values {0, 1}. In the current research work, Rhopalocera optimization algorithm (ROA) is employed for attributes selection. It can be examined that every Rhopalocera is able to update its location using global search phase or local search phase. In the first phase, a Rhopalocera performs walk around the global best Rhopalocera with a suitable step size whereas, in the other phase, a Rhopalocera performs a random walk. As a result, the same search mechanisms are applied in ROA.

The concept is to vary the location of a Rhopalocera with the likelihood of its aroma. In order to achieve this, a relocation function is required to map the aroma values to the probability values of Rhopaloceras in order to update their locations. In alternative words, a relocation function characterizes the probability of changing a Rhopalocera location vector's elements from 0 to 1 and vice versa. Basically, the search space can be assumed as a hypercube in which the Rhopaloceras/search agents of ROA can shift only to the farther corners of the hypercube by flipping different numbers of the bits. The basic concept in the ROA is to update the location of a Rhopalocera with the probability of its aroma. To achieve this, a relocation function is mandatory which would map the aroma values to the probability values in order to update the locations of the Rhopaloceras. In other words, a relocation function provides the value of probability according to which the location vector will be changed from 0 to 1 and vice versa. In this research work, V-shaped relocation function is employed to for attributes selection. Traditionally in Butterfly optimization S – shaped relocation function is used. In this approach, instead of a S-shaped relocation function, a V shaped relocation function is proposed and in order to achieve this Eqs. (1) and (3) are utilized.

$$V\left(F_i^k(t)\right) = \left| erf\left(\frac{\sqrt{\pi}}{2} F_i^k(t)\right) \right| \quad \ldots (1)$$

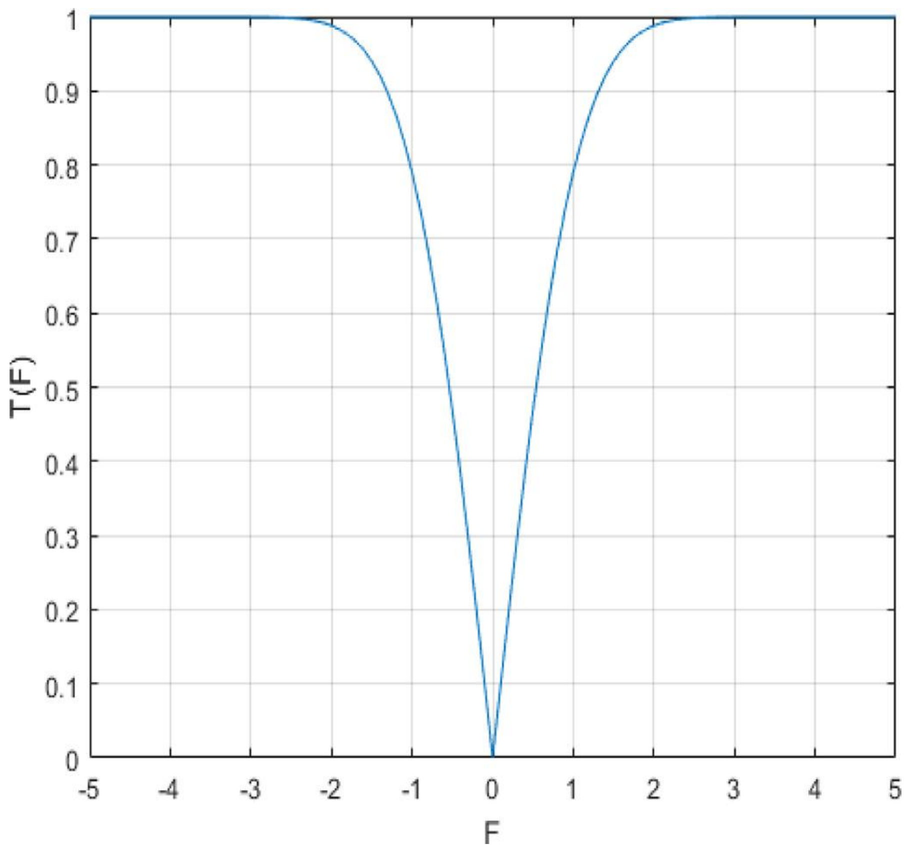

Fig. 1. V-shaped relocation function.

Hence the equation 1 is rewritten as

$$V\left(F_i^k(t)\right) = \left| \frac{\sqrt{\pi}}{2} \int_0^{\left(\sqrt{\pi}/2\right) F_i^k(t)} e^{-t^2} \, dt \right| \quad \ldots (2)$$

The threshold rules is derived as:

$$x_i^k(t+1)=\begin{cases}\left(x_i^k(t)\right)^{-1} & if \quad rand < V\left(F_i^k(t)\right)\\ \left(x_i^k(t)\right) & if \quad rand \geq V\left(F_i^k(t)\right)\end{cases} \quad \ldots (3)$$

where $x_i^k(t)$ and $F_i^k(t)$ indicate the location and aroma of i th Rhopalocera at rerun t in k th dimension, and $x_i^k(t)^{-1}$ is the complement of $x_i^k(t)$. In this ROA approach, eqn.1 is utilized as the relocation function with the aim to transform the aromas of Rhopaloceras to the probabilities of changing their location vectors' elements. Accordingly, the rules of Eq. (3) are employed to update the location vectors of Rhopaloceras. The benefit of V-Shaped relocation function is that it does not force Rhopaloceras to take 0 or 1 value. In other words, it encourages Rhopaloceras to switch to their compliments only when their aroma values are high otherwise the Rhopaloceras will stay in their current locations considering their low aroma values. The general steps of ROA are presented in Algorithm 1.

Algorithm 1. Working of ROA.

Objective function $f(x), x=(x_1, x_2, ..., x_d)$

Generate a population of n Rhopaloceras $x_i = (i = 1, 2, ..., n)$

Define sensor modality **c**, power exponent **a** and switch probability **p**

while stopping criteria are not met to **do**

  for each Rhopalocera ra in population **do**

    Calculate the aroma for **ra** using Eq.(1)

  end for

  find the best **ra**

  for each Rhopalocera ra in population **do**

    Generate a random number **rand** from [0, 1]

    if rand < p then

      Move towards the best Rhopalocera using Eq. (2) and (3)

    else

      Move randomly using Eq. (2) and (4)

    end if

    Calculate the value of relocation function using Eq. (5) or (7)

    Squash the attribute of patients' record using Eq. (6) or (9)

    Evaluate the new Rhopalocera

    If the new Rhopalocera is better, update it in the population

  end for

  Update the value of **c**

  Find the current global best Rhopalocera

end while

Output the best attribute of patients' record found.

3.2. Rhopalocera optimization algorithm for attributes selection

Attributes selection is one of the optimization problems in which the search agents are confined to {0, 1} values only. In this research work, every attribute of patients' record is characterized as a single dimensional vector in which the length of the vector depends on the number of attributes/ features in the dataset. Every cell of the vector can contain two values, i.e., 1 or 0, where the value 1 depicts that the corresponding attributes /attribute is chosen whereas the value 0 represents that the attributes/attribute is not selected.

Attributes selection problem can be considered as a multi objective optimization problem in which two opposing goals are to be accomplished; selecting minimum number of attributes and maximum classification accuracy. In attributes selection problem that attribute of patients' record is considered best which contains the minimal number of attributes along with the highest classification accuracy. Every attribute of patients' record is assessed by the proposed aptness function which relies on ROA - IFANN classifier in order to calculate its classification accuracy and on the number of attributes selected. Keeping in mind the end goal which is to find the balance between the number of attributes and classification accuracy, the aptness function in eqn. 4 is employed in all the optimization algorithms in order to evaluate the attribute of patients' records.

$$Aptness = \alpha\gamma_R(D) + \beta\frac{|R|}{|N|} \quad \ldots (4)$$

where $\gamma_R(D)$ is the classification error rate of the IFANN classifier. Furthermore, |R| represents the cardinality of the selected attributes subset and |N| represents the total number of attributes in the original dataset, α and β are two parameters corresponding to the importance of classification quality and subset length, $\alpha \in [0,1]$ and $\beta = (1-\alpha)$.

3.3. Improved Fuzzy Artificial Neural Network (IFANN) Classifier

IFANN is a supervised mechanism that performs incremental learning to build up information from available training samples. IFANN is composed by two fuzzy components namely ART_a and ART_b (ART stands for Adaptive Resonance Theory) that are connected using a map field named F^{ab}. Every available IFNN consists of three layers of nodes. The nodes are termed as normalization layer $F_0^a\left(F_0^b\right)$ where in an M - dimensional input vector, the input layer $F_1^a\left(F_1^b\right)$ where in its nodes receive A and the recognition layer $F_2^a\left(F_2^b\right)$ where in each node represents a group of information taken out from the recognized input category. The number of recognition nodes increases upon insertion of new nodes to $F_2^a\left(F_2^b\right)$ for encoding newly learned information. At the point of time when the training phase is initiated, ART_a obtains an input pattern whereas ART_b obtains the target class of the input pattern. The ART endures a similar pattern-matching cycle which has node selection, similarity test and category search processes. In ART_a , once when the input pattern vector is obtained it has been complement-coded as vector A (where A = (a ; 1 − a) where 1 is the vector of all entries being 1), it is forwarded from $F_1^a\left(F_2^a\right)$ where in the activation of each recognition node j is computed using a choice function.

$$T_j = \frac{|A \wedge w_j^a|}{x_a + |W_j^a|} \quad \ldots (1)$$

where $x_a \approx 0$ is the preference bound and w_j^a is the weight of node j . The fuzzy intersection $\wedge$ mentions

$$p \wedge q := \left(\min\left(p_i, q_i\right)\right)_{2M} \quad \ldots (2)$$

and the norm | · | is the l_1 norm:

$$|p| := \sum_{i=1}^{2M} |p_i| \quad \ldots (3)$$

The adaptive fittest rule is referred to identify a fittest node J that responses with the highest activation value. A attention test is conducted to compute the degree of similarity between the fittest prototype w_j^a and A , and compare the result with a attention stricture $\rho_a \in [0,1]$:

$$\frac{|A \wedge w_j^a|}{|A|} \geq \rho_a \ \ldots (4)$$

If the attention test is failed, a new search cycle will be commenced to find for the next fittest node. The search process is carried on until the identified fittest node could pass in the attention test. If no such node could be found, a new node will be introduced in F_2^a to include A . On the other hand, on presentation of the target vector, ART_b also goes through a similar pattern-matching process to find a node in F_2^b to represent the target class. A map-field attention test is then carried out to evaluate the correctness of the prediction between the two fittest nodes from F_2^a and F_2^b by using the below equation

$$\frac{|y^b \wedge w_j^{ab}|}{|y^b|} \geq \rho_{ab} \ \ldots (5)$$

where y^b refers to the output vector of $F_2^b; w_j^{ab}$ refers to the weight vector from F_2^a to F^{ab}; and $\rho_a \in [0,1]$ denotes the map-field attention stricture. Normally, ρ_{ab} is set to a value close to 1 , e.g., $\rho_{ab} = 0.95$. If the map-field attention test is failed, it denotes the fittest node in F_2^a has predicted incorrectly the target class in F_2^b. A match tracking is then operated to raise ρa from a baseline attention stricture $\overline{\rho a}$ (where $\overline{\rho a}$ is a user- defined parameter in a range [0,1]) to

$$\rho_a = \frac{|A \wedge w_j^a|}{|A|} + \delta \ \ldots (6)$$

where δ is a constant being defined as a small number close to 0 $(e.g. \delta = 0.0001)$. The purpose of match tracking is to avoid the current fittest node in F_2^a from passing in the ART_a attention test again so that another fittest node could be identified in a new search cycle. The search process is continued until both fittest nodes in F_2^a and F_2^b have made a correct prediction.

Each dimension d of a prototype p in F_2^a has either as $S_{pd} = 0$ or $S_{pd} = 1$. Initially all dimensions of a prototype are set to 0. When the prototype dimension is shrunk, its S_{pd} is updated to 1. Further, each F_2^a prototype consists of a reference vector w_j^r . Initially, w_j^r is a zero vector. When IFANN is in the resonance state, apart from the weight vector w_J^a of the J -th fittest node, its w_J^r is also updated iteratively using the below equation.

$$\left(w_J^r\right)^{new} = \left(w_j^r\right)^{old} + \frac{1}{N_J}\left[A - \left(w_J^r\right)^{old}\right] \ldots (7)$$

where N_J represents the latest number of input patterns categorized correctly by the J -th node, $N_J = N_J + 1$.

The prototypes of two fuzzy ARTs and their associations that are established in the map-field during the training phase are utilized to predict an output class on presentation of an unseen pattern during the test phase. The training procedure of IFNN is given below:

1. An M -dimensional input pattern $a \in [0,1]^M$ is complement-coded to a 2M -dimensional vector A in F_0^a; A is then forwarded to F_1^a.
2. A is forwarded to F_2^a through the weight vector, w^a. The activation of each node is calculated using Eq. (1) . The node with the highest activation value is selected as the fittest node J .
3. The prototype of node J is sent backward from F_2^a to F_1^a for evaluation by a attention test as in Eq. (4) .
4. If the attention test is not satisfied, go to Step 3 where a new search cycle for another fittest node is carried out (the same search cycle also happens in ART_b for finding a fittest node).
5. Upon receiving a prediction from $F_2^a \left(i.e., w_J^{ab}\right)$ and also from $F_2^b \left(i.e., y^b\right)$ at the map-field F^{ab}, a map-field attention test as in (5) is run.
6. If the map-field attention test is not satisfied, a match tracking as in (6) is exercised. Notably, match tracking only happens, in the ART_a module. Go to Step 3.
7. The weight vectors w_J^a and w^r are adjusted . Likewise, the weight vector w_J^b of the fittest node in ART_b is adjusted by replacing the symbol a with b.

IV. THE TSK FUZZY INFERENCE MECHANISM APPLIED IN ROA - IFANN

A rule-based model needs to be established prior to implementation of FIS. The rules are typically defined in this format:

$$R_i : if\ u_1\ is\ A_{i1}, ..., and\ u_n\ is\ A_{in}, then\ v_i = f_i^0(a; b_i), i = 1, 2, ..., I \quad \dots (8)$$

where R_i denotes the i -th rule; $u_{1,...,u_n}$ denote the input variables; $A_{i1},...,A_{in}$ denote the fuzzy sets of the input variables; v_i denotes output value of the i -th rule; a is the input vector; $f_i^0(a;b_i)$ indicates the O -th order of a polynomial function of a with a constant term b_i . For any $R_i, u_1, \ , u_n$ represent the antecedences whereas v_i the consequence of the rule.

Occasionally, a zero-order TSK model is defined for handling pattern classification problems. In this case (of zero order), the Consequence of R_i , i.e., $f_i^0(a;b_i)$ is a constant, i.e. b_i . Hence, v_i is a discrete number re-written as

$$R_i : if\ u_1\ is\ A_{i1}, ..., and\ u_n\ is\ A_{in}, then\ v_i = b_i, i = 1, 2, ..., I \quad \dots (9)$$

When a data sample x_k is presented to the model, the firing strength of the i -th rule R_i is computed using an AND operator (i.e. a T-norm operator such as min) that combines the membership values between the data sample and the antecedences of R_i , i.e.

$$\xi_i(x_k) := AND\left(F_1(u_1, x_{k1}), ..., F_n(u_n, x_{kn})\right) \dots (10)$$

where $\xi_i(x_k)$ is the firing strength of R_i given $x_k; F_1(.),...F_n(.)$ denote input membership functions. The qualified consequence of R_i on the firing strength is $\xi_i(x_k)v_i$. The qualified consequences of all rules based on firing strengths are aggregated, i.e.

$$\sum_{i=1}^{I} \xi_i(x_k)v_i \quad \dots (11)$$

The output of x_k is the weighted average of all rule outputs, as follows:

$$\hat{y}_k = \frac{\sum_{i=1}^{K} \xi_i(x_k) v_i}{\sum_{1=1}^{K} \xi_i(x_k)} \ \ldots (12)$$

ROA - IFANN is thus modeled for performing the classification task.

V. About the Dataset

The dataset is obtained from cardiac based medical centers. The dataset contains 7525 diabetic patients' records that have data from 4329 males and 3196 females. Totally 17 attributes including class label denoting whether the corresponding patient is likely to have CAHD risk or not. As far as 4329 male diabetic patients' records, 3911 patients owe the CAHD risk and 418 male diabetic patients' do not owe the CAHD risk. As far as 3196 female diabetic patients' records, 2808 patients owe the CAHD risk and 388 female diabetic patients' do not owe the CAHD risk. Scilab 6.0.2 has been utilized for implementation and experiments have been conducted on desktop personal computer with a 3.4 giga hertz Intel Core i7-6700 processor and 8 giga bytes RAM. Table - 1 shows the details of the dataset.

Table - 1. Dataset Details

Number of Attributes	**Total Number of patients**	**Male – 4329**		**Female – 3196**	
		Number of patients with risk of CAHD	**Number of patients with no risk of CAHD**	**Number of patients with risk of CAHD**	**Number of patients with no risk of CAHD**
17	Male 4329 + Female 3911 = 7525 patients	3911	418	2808	388

VI. Results and Discussions

Male patients and female patients' records are tested separately. Before that, 60% of the patient records (both male and female) are taken for training the classifier. 100% of the patient records are tested for performance evaluation in terms of sensitivity, specificity, prediction accuracy and Matthews correlation coefficient (MCC). The results are portrayed in the Table – 2 and Table – 3 for male and female patients respectively.

Table – 2. Performance Results – Male Patients

Classifiers	**TP**	**TN**	**FP**	**FN**	**Sensitivity (in %)**	**Specificity (in %)**	**Accuracy (in %)**	**Mathews correlation coefficient (in %)**
IFANN Classifier [13]	3352	385	266	326	91.14	59.14	86.32	48.51
ALC [12]	3416	376	255	282	92.37	59.59	87.60	51.07
Proposed ROA - IFANN Classifier	3617	359	182	171	95.49	66.36	91.85	62.39

Table – 3. Performance Results – Female Patients

Classifiers	**TP**	**TN**	**FP**	**FN**	**Sensitivity (in %)**	**Specificity (in %)**	**Accuracy (in %)**	**Mathews correlation coefficient (in %)**

IFANN [13]	2385	341	255	215	91.73	57.21	85.29	50.29
ALC [12]	2471	318	205	202	92.44	60.80	87.27	53.37
Proposed ROA - IFANN Classifier	2632	279	155	130	95.29	64.29	91.08	61.10

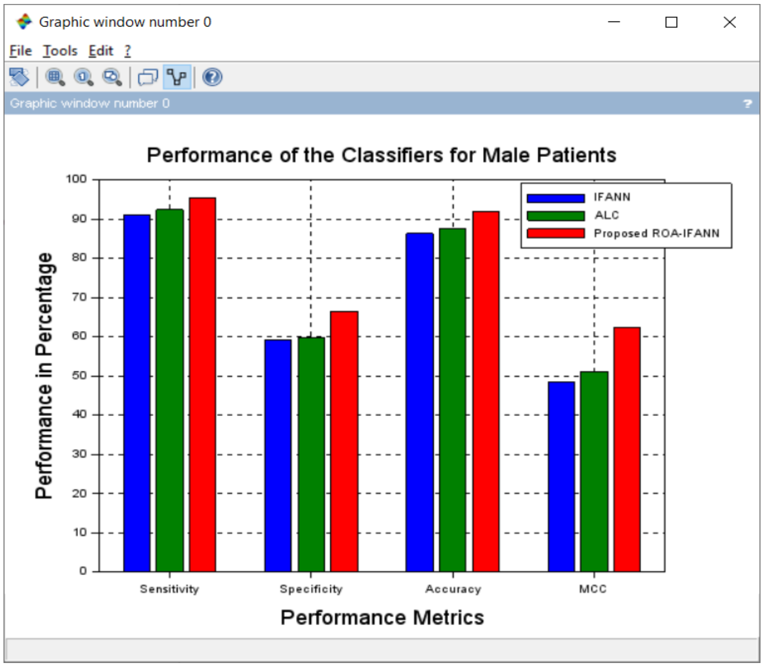

Fig.1. Performance of the Classifiers in Male Patients

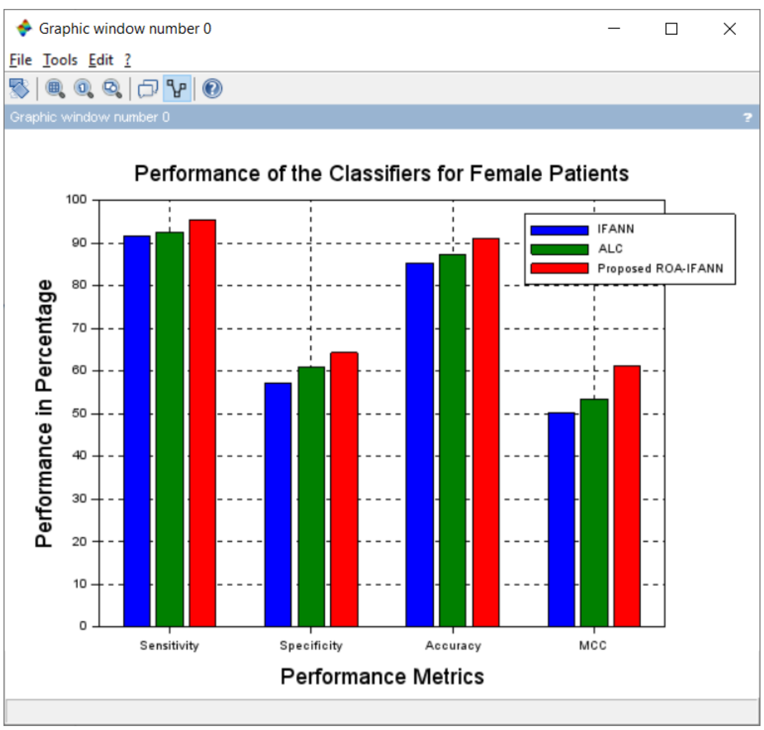

Fig.2. Performance of the Classifiers in Female Patients

This research work is the extension of the previous work named IFANN [13]. In this research work ROA mechanism is employed for feature selection. From the results it is inferred that ROA – IFANN outperforms than that of IFANN [13] and ALC [12] in terms of sensitivity, specificity, prediction accuracy and MCC.

VII. Conclusion

The usage of soft computing techniques in medical domain is more prominent and emerging area of research. Several decision support systems are built for diagnosing diseases among patients. In this research work the aim of the proposed ROA - IFANN classifier is to attain maximum prediction accuracy for CAHD among diabetic patients. Both male and female diabetic patient records are obtained from the reputed medical centers along with the class label of CAHD occurrence. The results are promising and it is inferred that 91.85% accuracy is obtained for male diabetic patients and 91.08% accuracy is obtained for female diabetic patients.

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