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Altered particle swarm optimization based attribute selection strategy with improved fuzzy Artificial Neural Network classifier for coronary artery heart disease risk prediction

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ABSTRACT

The application of soft computing in decision support system in disease prediction is one of the emerging interdisciplinary research areas in the field of computer science. Machine learning algorithms plays an important role in risk prediction of diseases. Attribute selection among the dataset is the key factor that influences prediction accuracy. Mathew's correlation coefficient performance metric is also taken into account. Particle swarm optimization algorithm is altered and applied for performing attribute selection. Improved fuzzy artificial neural network classifier performs the prediction task.

Keywords— *Soft computing, Attribute selection, Feature selection, Artificial Neural Network, Classification, Mathew's correlation coefficient, Particle swarm optimization*

1. INTRODUCTION

Ordinarily, the basic thoughts of conventional computing are precision, sureness, and carefulness. We perceive this as hard computing. Curiously, the essential idea in soft computing is that precision and sureness pass on a cost; sand that estimation, thinking, and fundamental initiative should abuse (wherever possible) the opposition for imprecision, vulnerability, surmised thinking, and deficient truth for getting insignificant exertion game plans. This prompts the magnificent human limit of understanding ruined talk, interpreting untidy handwriting, valuing the nuances of trademark language, gathering content, seeing and organizing pictures, driving a vehicle in thick surge hour gridlock, and, even more generally, settling on ordinary decisions in a space of vulnerability and imprecision. The test, by then, is to abuse the versatility for imprecision by coming up with methodologies for figuring that lead to recognize fit plan expecting practically no exertion. This, for the most part, is the fundamental belief of soft computing. There are persistent undertakings to fuse artificial neural networks (ANNs), fuzzy set hypothesis, genetic calculations (GAs), rough set hypothesis and different systems in the soft computing perspective. Hybridization abusing the characteristics of these hypotheses consolidate neuro-fuzzy, rough-fuzzy, neuro-genetic, fuzzy-genetic, neuro-rough, rough-neuro-fuzzy systems. In any case, among these, the neuro-fuzzy computing system has picked up many analysts' consideration nowadays. Coronary illness remains the main source of death throughout the world for as long as decades. In 2015, the World Health Organization (WHO) has evaluated that 17.7 million passing's have happened worldwide because of heart sicknesses. Heart infections are the essential driver of death universally: a greater number of individuals kick the bucket every year from CAHD than from some other causes. In the event that we can anticipate the CAHD and give cautioning already, a bunch of passing's can be forestalled. The utilization of soft computing conveys another measurement to CAHD risk prediction.

2. 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 an 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 a 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 an early stage. It calculated the coefficient of the 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 a feature selection concept, where the classifier omitted the important feature for classification. A modified version of Ant Colony Optimization [6] was proposed to increase the classification accuracy towards predicting coronary artery disease, where it uses the 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.

3. PROPOSED WORK

In the attribute selection problem, the problem space also contains valuable information that is not considered during the evolutionary process of the algorithm. By referring to the problem space, the store set can also determine the important attributes, which have been elected by store members. This research work aims to improve the existing PSO algorithm and make it fit for the attribute selection by grading them and uses this information to improve the searchability of algorithm. The working mechanism of the altered PSO mechanism is portrayed. The steps 4, 5 and 7 are the contributions of the altered PSO.

Training Dataset
Step – 1: Initialize the population and initialize the store set
Step – 2: Evaluate the aptness
Step – 3: 3. Update the store
Step – 4: Grade the attributes based on the current Pareto optimal set (current store)
Step – 5: Refine the store
Step – 5.1.: categorize attributes into subgroups based on the ordering of their grades
Step – 5.2.: choose attributes from subgroups and generate corresponding position vector as a new population member
Step – 5.3.: calculate the objective function of the new member and update the store
Step – 6: Update P_{best}, and G_{best} by using the crowding distance technique
Step – 7: Change the position of the particles
Step – 7.1.: Move the particles purposefully by updating their velocity
Step – 8: Mutate the particle
Step – 9: When the algorithm reaches the maximum number of iterations, stop; otherwise go back to step two.
Step – 10: Return the solutions of the store as train Pareto front.
Testing Dataset: Apply the obtained attribute subsets on test data,
Step – 1: Calculate and store the testing classification error rate.
Step – 2: Extract non-dominated solutions and store them as test Pareto front.

3.1. Encoding the particles

Each particle denotes the attributes of a dataset and each element shows the probability of an attribute being selected. For example, for a dataset with D attributes, i-th particle in t-th iteration is a vector named $X_i(t)$ with D dimensions as below:

$$X_i(t)=(x_{i1}, x_{i2}, \dots, x_{iD})x_{ij} \in [0,1], j=1,2,\dots,D \tag{1}$$

The probability of choosing *j-th* attribute is represented by $x_i \in [0,1]$. Each particle is decoded to binary elements and evaluated by aptness function. A threshold θ is considered. The j-th attribute is chosen and the related element is decoded to one if and only if its value is higher than θ. Other elements are set to zero. In this work, the value θ is set to 0.5. The decoded version $X(t)$ is considered as:

$$Z_i(t)=(z_{i1}, z_{i2}, \dots, z_{iD})z_{ij} \in \{0,1\} j=1,2,\dots.,D \tag{2}$$

3.2. Evaluating the aptness

Classification performance is calculated using (3) for i-th particle:

$$Error\_rate_i = (FP+FN)/(FP+FN+TP+TN) \tag{3}$$

TP, FP, TN and FN refer to true positives, false positives, true negatives, and false negatives of IFANN classifier, respectively. It is a fact that a smaller number of attributes reduces the computational cost yet increases the error rate. As normalized values of the objectives provide a uniform search of the problem space, it is based on the equation (4) for i-th particle:

$$Feature\_rate_i = f_i / D, f_i = \sum_{j=1}^{D} Z_{ij}(t) \tag{4}$$

Where D is the total number of attributes. In this way, both objectives are normalized in [0,1].

3.3. Updating the external store

The external store is used to store the non-dominated solutions found during the search. After calculating the aptness function in each iteration, the non-dominated solutions are extracted, and the store set is updated. The length of the store is limited. If store size is greater than a threshold of 0.5, extra members are removed.

3.4. Grading the attributes

The selected attributes by the store members (Pareto Optimal set) are more important than the other attributes. Therefore, the store is supposed to grade the attributes. They are graded based on equation (5).

$$AR = \sum_{k=1}^{|A|} Z_k(t), Z_k(t) \in A \tag{5}$$

The set A represents the store and $Z_k(t)$ is a decoded member of the store. In this way, FR is a vector with D dimensions as $AR = [r_1, r_2, \ldots, r_D]$ that, r_j , $j=1,2,...,D$, determines the grade of j -th attribute. The minimum value of r_j is zero when the j -th attribute is not selected by any member of store. The maximum value of r_j is equal to the length of the store when the j -th attribute is selected by all members of store.

3.5. Refining the store

The store not only provides the best solutions but also determines the trailblazer, which guides the entire swarm. Therefore, the refinement of the store by injecting a particle with high-grade attributes leads to high performance. In this step, the store can be improved by introducing a new solution (candidate subset) which is constructed from high-grade attributes. This strategy selects only the high-grade attributes and increases the elitism level of the algorithm. Consequently, the diversity of the algorithms is decreased and the probability of trapping to local optima is increased. To overcome this problem, selecting the candidate from high-grade attributes are restricted.

The attribute set is sorted into a hierarchy of subgroups based on the ordering of their grades. All attributes, which belong to the same subgroup, have equal grades and the first subgroup contains the attributes with the highest grade. Instead of choosing the high grade attributes an exponential distribution mechanism is used to choose the attributes from all subgroups. Equation (6) calculates n_i as the maximum number of allowed selected attributes from the i -th subgroup.

$$n_i = F\frac{1-u}{1-u^k}u^{i-1}, F = D/2 \tag{6}$$

Where, k is the number of subgroups and u is a number in [0,1], which controls the maximum number of attributes that are selected form high-grade subgroups. The smaller value of u means that more high-grade attributes are selected. Since F and n_i must be integer values, rounding function is applied to them. By so doing, each subgroup is allowed to have an exponentially reduced number of attributes.

3.6. Updating P_{best} and G_{best}

P_{best} is the personal best position of each particle that is used to guide the particle to the optimal solutions. In each iteration and for each particle, if the new position dominates the current best position, P_{best} is updated to the new position. G_{best}, on the other hand, is the global best position that is used as the trailblazer for all particles; therefore, it should be selected from the store set. To improve the diversity of the final solution set, this paper uses the defined crowding distance technique, along with binary tournament to determine G_{best}. In this way, the average distance of each solution in the store to two neighbouring solutions is calculated as crowding distances. Two members with larger crowding distance are selected; then one of them is determined as G_{best} by binary tournament selection.

3.7. Updating the position of particles

Grading the attributes means grading and weighing the dimensions. Therefore, the grade of the attribute (dimension) possibly will postulate the displacement rate or speed of particle along that attribute (dimension). At first, AR, which represents the grade of attributes, is normalized according to equation (7). Then, the normalized AR or NFR is used in equation (8) to tune the speed of particles.

$$NFR = \frac{FR - Min(FR)}{Max(FR) - Min(FR)} \tag{7}$$

$$v_i^u = NFR * v_i^t, x_{is}^t = x_{is}^{t-1} + v'^t_{is} \tag{8}$$

v_i^t is the speed vector of a particle i in all dimensions. Therefore, the particle movement is performed based on equation (8).

3.8. Applying the mutation operators

The swarm is divided into three equal parts, and the first sub-part is kept unchanged. The uniform operator is applied to the second sub-part to enhance the exploration ability of the algorithm. Non-uniform mutation is also applied on the third sub-part to increase the exploitation ability of the algorithm. The mutation rate is set to 1/D where D is the total number of attributes in the used dataset.

4. IMPROVED FUZZY ARTIFICIAL NEURAL NETWORK (IFANN) CLASSIFIER

IFNN is a supervised mechanism that performs incremental learning to build up information from available training samples. IFNN 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.

$$T_j = \frac{|A \wedge w_j^a|}{x_a + |W_j^a|} \tag{9}$$

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

$$p \wedge q := \left(\min\left(p_i, q_i\right)\right)_{2M} \tag{10}$$

and the norm $|\cdot|$ is the l_1 norm:

$$|p| := \sum_{i=1}^{2M} |p_i| \tag{11}$$

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

$$\frac{|A \wedge w_j^a|}{|A|} \geq \rho_a \tag{12}$$

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

$$\frac{|y^b \wedge w_j^{ab}|}{|y^b|} \geq \rho_{ab} \tag{13}$$

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

$$\rho_a = \frac{|A \wedge w_j^a|}{|A|} + \delta \tag{14}$$

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 has 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.

$$\left(w_J^r\right)^{new} = \left(w_j^r\right)^{old} + \frac{1}{N_J}\left[A - \left(w_J^r\right)^{old}\right] \quad (15)$$

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 for 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. 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 an attention test.

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 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 ART_b is adjusted using (7) by replacing the symbol a with b.

4.1. The TSK fuzzy inference mechanism applied in IFANN

A rule-based model needs to be established prior to the implementation of FIS. The rules are typically defined in this format: $R_i : if\ u_1\ is\ A_{i1}, \ldots, and\ u_n\ is\ A_{in}, then\ v_i = f_i^{O}(a; b_i), i = 1, 2, \ldots, I$ …(16) where R_i denotes the i -th rule; $u_{1,\ldots,u_n}$ denote the input variables; $A_{i1}, \ldots, A_{in}$ denote the fuzzy sets of the input variables; v_i denotes output value of the i -th rule; a is the input vector; $f_i^{O}(a; b_i)$ 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, $i.e.,\ f_i^{O}(a; b_i)$ is a constant, i.e. b_i. Hence, v_i is a discrete number where Eq. (13) is re-written as

$$R_i : if\ u_1\ is\ A_{i1}, \ldots, and\ u_n\ is\ A_{in}, then\ v_i = b_i, i = 1, 2, \ldots, I \quad (16)(17)$$

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.

$$\xi_i(x_k) := AND\left(F_1(u_1, x_{k1}), \ldots, F_n(u_n, x_{kn})\right) \quad (18)$$

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

$$\sum_{i=1}^{I} \xi_i(x_k)v_i \quad (19)$$

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

$$\hat{y}_k = \frac{\sum_{i=1}^{K} \xi_i(x_k)v_i}{\sum_{1=1}^{K} \xi_i(x_k)} \quad (20)$$

5. 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 a 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

6. 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 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 %)
TSK Fuzzy Classifier [7]	3156	339	392	442	87.72	46.37	80.73	33.21
ANN – GA Classifier [8]	3211	393	322	403	88.85	54.97	83.25	42.00
IFANN Classifier [9]	3352	385	266	326	91.14	59.14	86.32	48.51
ALC Classifier [10]	3416	376	255	282	92.37	59.59	87.60	51.07
Proposed APSO-IFANN	3470	375	231	253	93.20	61.88	88.82	54.27

Table 3: Performance results – Female patients

Classifiers	TP	TN	FP	FN	Sensitivity (In %)	Specificity (In %)	Accuracy (In %)	Mathews correlation coefficient (in %)
TSK Fuzzy Classifier [7]	2372	205	321	298	88.84	38.97	80.63	28.32
ANN – GA Classifier [8]	2263	360	303	270	89.34	54.30	82.07	44.48
IFANN Classifier [9]	2385	341	255	215	91.73	57.21	85.29	50.29
ALC Classifier [10]	2471	318	205	202	92.44	60.80	87.27	53.37
Proposed APSO-IFANN	2497	317	188	194	92.79	62.77	88.05	55.30

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.

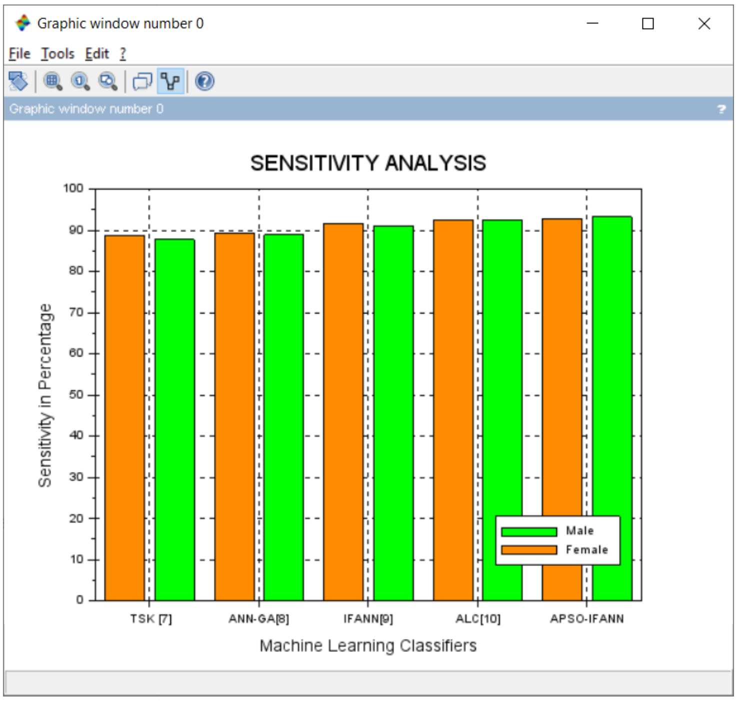

Fig. 1: Sensitivity Analysis of Classifiers

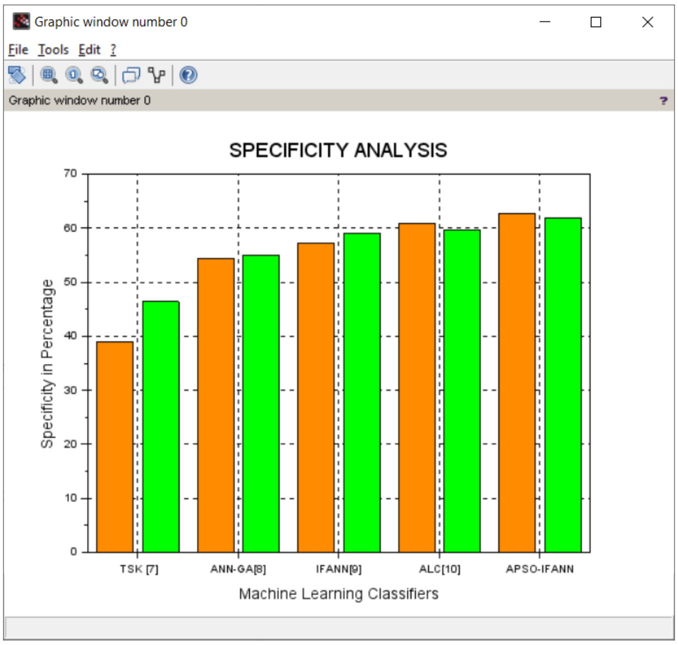

Fig. 2: Specificity analysis of classifiers

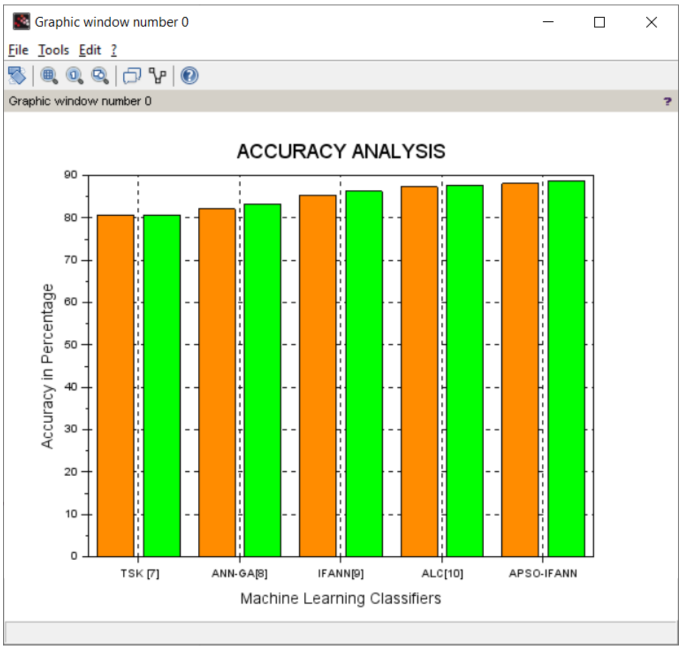

Fig. 3: Prediction accuracy analysis of classifiers

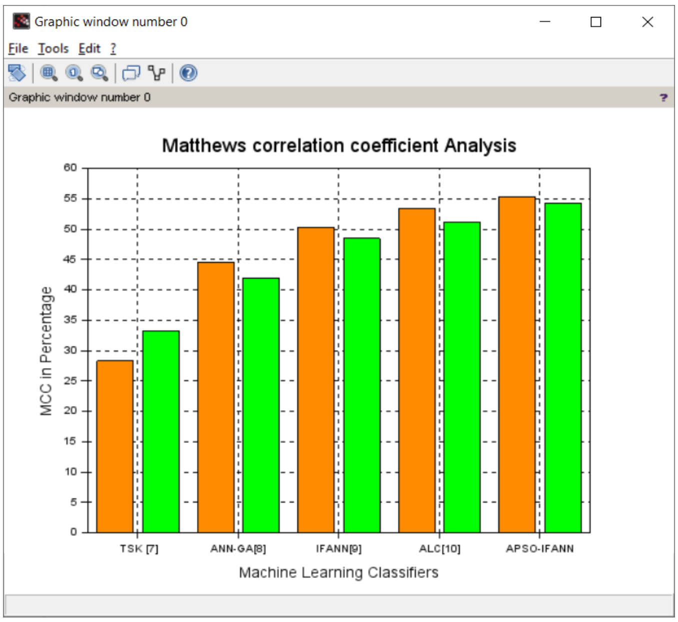

Fig. 4: Matthews correlation coefficient analysis of classifiers

The proposed research work is shortly coined as APSO – IFANN. From the experimental results, it is inferred that APSO – IFANN performs better than the rest of the chosen machine learning classifiers in terms of sensitivity, specificity, prediction accuracy and Mathew's correlation coefficient. The results are portrayed in table 2 and table 3 for male and female patients respectively.

7. CONCLUSION

This research work is the extension of our previous research works that are cited in [7], [9], [10]. Maximum accuracy of 88.82% and 88.05% is obtained for the male and female patients respectively. The proposed APSO-IFANN outperforms than other classifiers in terms of chosen performance metrics. Other optimization algorithms can also be applied for attribute selection and are considered for the further scope of research.

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