INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 4.295
(Volume 5, Issue 2)
Available online at: www.ijariit.com

Artificial Lampyridae Classifier (ALAC) for coronary artery heart disease prediction in diabetes patients

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ABSTRACT

Soft computing techniques and its applications extend its wings in almost all areas which include 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. This research work aims to build an artificial Lampyridae classifier and also compared with Takagi Sugeno Kang fuzzy classifier and ANN classifier in terms of prediction accuracy, sensitivity, specificity, and Mathew's correlation coefficient. The significance of MCC is 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 ALC outperforms that that of TSK fuzzy classifier and ANN classifier.

Keywords— *Soft Computing, Fuzzy logic, Machine learning, CAHD, Diabetes, Artificial neural network, Applications of soft computing*

1. 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 acknowledging capable arrangement requiring little to no effort. This, generally, is the core value of soft computing.

There are continuous endeavours 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, the neuro-fuzzy computing mechanism has gained may researchers' attention 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.

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.

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 an automatic manner. The result showed that the results were not efficient when compared with the existing algorithms in the term of sensitivity. Fuzzy Classifier [8] was proposed to perform classification with dynamic electrocardiogram signals with the intention to predict the heart disease in an early stage. It has worked with the dynamic unknown features resulting in very low accuracy. It was also analyzed that the algorithm can work well with known features only. Identification of Heart Disease with an 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 an increased false negative rate. Hybrid Classifier [10], which was an ensemble of the neural network and genetic algorithm, was proposed for the classification of coronary artery disease. Initially, the neural network was performed and then the genetic algorithm was used. The result showed that this specific hybrid classifier was not fit for the prediction of coronary artery disease, where the results came with very low classification accuracy.

3. ARTIFICIAL LAMPYRIDAE CLASSIFIER (ALC)

3.1. Overview of Artificial Lampyridae algorithm

The Lampyridae algorithm is encouraged by the pattern of firefly insect behaviour. Lampyridae insect use to interrelate and pass certain vital information among themselves by rhyming flashing lights. It is well known that the flashlights are emitted from their bodies. The emitted light is made use to appeal to other Lampyridae insects. Based on the distance between the Lampyridae insects, the emitted light or intensity differs. By the pattern by which Lampyridae insects behaviour, the algorithm is developed based on three statutes: The first statute is that Lampyridae is a unisex by which all the Lampyridae insects will be attracted to each other regardless of its gender (either male or female) The second statute is that attractiveness is proportionate to brightness, and henceforth for any flash lighting between two Lampyridae insects, the less bright Lampyridae insect will move on to the brighter Lampyridae insect. At the point of time when the attractiveness decreases as the distance increases between two Lampyridae insects, the Lampyridae insects will move in a random fashion where there is no brighter Lampyridae. The third statute is that Lampyridae brightness is determined based on the aptness function.

Two important non - static values in the Lampyridae algorithm administer the pattern of the algorithm processing, the light intensity, and attractiveness between Lampyridae insects. Light intensity differs from each source based on the brightness of the Lampyridae. This is done with the help of aptness function. The aptness function is calculated using the formula (1).

$$\beta(r) = \beta_0 \, e^{-\gamma r 2} \tag{1}$$

Where β_0 denotes the attractiveness at distance *(r)=0* and sometimes for mathematical computation is said to be 1, and γ denotes the value of the light absorption in the air. r is the distance between Lampyridae i location and Lampyridae j location. The distance between Lampyridae insects is the degree of how two Lampyridae insects are attracted to each other. Lampyridae insects keep moving status from one location to another location. According to the fact that attractiveness between Lampyridae insects is related to the distance between them, Euclidean distance is used to calculate the distance between any two Lampyridae insects i and j is given in equation (2).

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k} \right)^2} \tag{2}$$

Where d denotes the dimensionality and $X_{i,j}$ is the k^{th} component of the location of Lampyridae i. Once after measuring the distance between the two Lampyridae insects, at a point of time when the Lampyridae i is less brightness than Lampyridae j, so the attractiveness between them happens while moving the Lampyridae i to the Lampyridae j. The control movement is denoted in equation (3):

$$x_i^{1+1} = x_i^t + \beta_0 \, e^{\left(\gamma r_i \, j^2\right)} * \left(x_j^t - x_i^t\right) + \alpha * \left(rand - 1/2\right) \tag{3}$$

Where t denotes the number of reruns, the coefficient α denotes a random number managing the size of the random walk behaviour, and rand denotes a random number generator. The Lampyridae with low brightness keeps moving on to the higher one based on three criteria. The first one is the current location of the low brightness Lampyridae. The second is the movement toward the Lampyridae with higher brightness by the attraction coefficient β. The third is a type of random walk calculated by a random generator multiplied by α.

3.2. Proposed lampyridae classification mechanism
The idea behind the proposed Lampyridae classification algorithm is to utilize the pattern of Lampyridae insects to develop a classifier as well as an attribute selection tool. The proposed classification algorithm includes three different steps as follow:

First step: Attribute selection.
Second step: Prototypical construction.
Third step: Prototypical usage/prediction.

At the first step, dimensionality is reduced from an available number of attributes. After that prototypical construction step is responsible for dividing the dataset into a set of existing class labels, where each class is processed individually using the Lampyridae algorithm. In this step, a set of Lampyridae class markers are produced to denote existing class labels, where Lampyridae class markers are the most informative Lampyridae in their class labels. Subsequently, in prototypical usage/prediction step, testing or unseen data has been compared with different class markers produced from the prototypical construction step to select the nearest and the most fitting class. Datasets are divided into two sets: training subset and testing subset. As stated above, the proposed Lampyridae algorithm is a supervised learning technique. Therefore, the learning prototypical will be built based on training/testing patient records and training/testing class labels.

The attribute selection step that produces a subset of informative Attributes, then passing these selected subsets of attributes to the prototypical construction step. In prototypical construction step, the reduced subset of attributes is used to extract Lampyridae class markers, while the prototypical usage/prediction step plays the role of allocating each test Lampyridae to its related class using class markers. Lampyridae class markers are passed in parallel with the testing Lampyridae insects to the prototypical usage/prediction step in order to categorize each testing patient record to its class, if the classification accuracy is acceptable, then the prototypical is considered a successful prototypical in categorizing any future unknown data. Otherwise, the process is repeated by selecting another subset of informative Attributes, then create class presenter and so on. In the next sections, the three steps of the proposed algorithm are discussed in details.

3.2.1. Attribute selection step based on Lampyridae algorithm: The attribute selection process is used to reduce the dimensionality of datasets and eliminate undesirable Attributes. The Attribute selection process was implemented using the Lampyridae algorithm, by considering each Attribute as a Lampyridae. Lampyridae insects were filtered and selected for classification. The output of this step is a subset that includes the most informative Attributes/Lampyridae insects.

3.2.2. Lampyridaeprototypical construction step: In this step each class $C = \{c_1, c_2\}$ in the dataset will be considered as a kind of Lampyridae insects, where c_i is the class or kind of Lampyridae insects, $i = \{1,2\}$ and j is the number of existed class labels. All Lampyridae insects/patient records of class c_i have been set in a separate group and processed individually, where each class or swarm has a number n_i of Lampyridae insects or patient records, in which $c_i = \{s_1, s_2, s_3, \ldots, s_{ni}\}$, n_i is divided into 75% training n_{tri} patient records and 25% testing n_{tei} patient records. Suppose we have j class labels/kinds of Lampyridae insects and each class c_i contains n_{tri} training patient records. This step needs to extract Lampyridae f_i class presenter for each class c_i through applying Lampyridae algorithm for obtaining the most informative Lampyridae insects/patient records from the training patient records n_{tri}, where Lampyridae presenter for each class has to denote this class. It is worth noting that the algorithm of selecting class presenter has been applied on selected Attributes subset.

The lampyridae algorithm is applied to each class c_i individually using a set of aptness functions for simulating intensities. The class presenter is extracted from each class to denote this class, in which each class presenter is the most informative Lampyridae in the class. So a number of class labels or swarms are separated, each swarm is flying individually. These swarms contain ranked patient records according to their informative value (intensity) for their class labels.

The main task for this step is to search for or discover patient records (class markers) that hold information about the class. This step contains a set of steps processed as follows: (1) input training patient records and separates each class in a group, (2) assign values for Lampyridae locations, (3) calculate Lampyridae intensity using different aptness functions. After applying steps a number of reruns, the most informative patient record or Lampyridae has been selected as a class presenter for different class labels. The following sub-sections will discuss the sequence of steps in the prototypical construction step.

Input training patient records and separate class labels/kinds of Lampyridae insects
In this step, the prototypical construction step will receive the output of Attribute selection step stated in Section 4.1, as a reduced and refined (Attributes) dataset from the original dataset. The class labels will be separated, where each class is an individual kind of Lampyridae swarm.

Assigning Lampyridae/patient record location
Lampyridae location is one of the parameters that determine the location of Lampyridae in space. In this research, the location of each Lampyridae is denoted through considering each Attribute value in the patient record as a Lampyridae location. The Attribute value in each patient record denotes the effect of this Attribute for recommending this patient record as a candidate class presenter. The location's value of each Lampyridae has changed with each move of a lower intensity Lampyridae to a higher one according to Eq. (3)

3.2.3. Lampyridae/patient record intensity calculation: In this step, each Lampyridae/patient record *(f_i)* is assigned a light intensity value *(L_i)* calculated by an aptness function. Rosenbrock aptness function is used in this research work to denote Lampyridae intensity. Intensity is used to compare among different Lampyridae insects in the same class. The Lampyridae with lower intensity updates its intensity after each movement (to a new location) through a set of reruns. The process from steps 2–3 is a repeated m number of reruns until we reach the best Lampyridae (class presenter). The objective of this step is to ensure picking the most presentable patient records (class markers) for different class labels by comparing intensities for all patient records in the same class individually. The output of this step will be the best Lampyridae/patient record in each class.

The Lampyridae mechanism prototypical construction step is presented in Algorithm 1.

Input: Matrix $S(n,h)$, where S is the dataset after Attribute selection. n is a number of patient records, h is the number of selected Attributes.

Output: Set of created j Lampyridae class markers denoting j class labels.

Prototypical Construction Step

Step 1: Separate each class individually; consider each class c_i as a kind of Lampyridae insects flying in the swarm.
Step 2: Read the training set containing selected Attributes and its class labels for each class.
Step 3: Convert training set into a swarm containing Lampyridae insects $f_1,f_2,f_3,\ldots f_{ntri}$, where ($n_{tri}$) is a number of training patient records in class c_i.
Step 4: Consider each value in patient record vector as a location for Lampyridae.
Step 5: Apply the Lampyridae algorithm for each class separately with different aptness functions to denote intensity for different patient records.
Step 6: Choose the Lampyridae class presenter (best patient record) f_{bestci} for each class that will denote the class c_i using Lampyridae algorithm, where $I=\{1,2,\ldots j\}$.

3.2.4. Lampyridae prototypical usage/prediction step: The prototypical prediction step will focus on the testing dataset. A number of testing patient records n_{te} are considered as unknown Lampyridae insects that fly randomly in the space without any related swarm or class. Consider random space A contains many random Lampyridae insects/testing patient records $A=\{t_1, t_2,t_3,\ldots tn_{te}\}$ flying, where n_{te} is a number of random or unseen Lampyridae insects. The aim of this step is to discover the related class c for each testing patient record t_k. The classification process for unseen Lampyridae insects or testing patient records is developed through three different approaches, which are as follow: classification based on Lampyridae distance, classification based on intensity and classification based on average intensity inside each class (swarm).

3.2.4.1 Lampyridae classification: Lampyridae distance is one of the controlling parameters in the Lampyridae algorithm. It measures how the attraction will be executed between Lampyridae insects. Distance measure plays the role of detecting the nearest class for each testing Lampyridae. In order to measure the relevance between testing Lampyridae insects and swarms (class markers), the distance between Lampyridae insects that required to be classified (testing Lampyridae insects) and class markers will be considered as a similarity measure for allocating unseen Lampyridae insects to their class labels. The distance d_k has been calculated between the location of the testing patient record t_k, where $k=\{1,2,\ldots n_{te}\}$ flying randomly and the location of Lampyridae class markers f_{bestci} which are extracted from different class labels through the previous step. As stated in Section 3 Lampyridae attractiveness is estimated from distances and intensity, the near distance the more attractiveness. After calculating distance D between random Lampyridae insects t_k and Lampyridae class markers f_{bestci} for different class labels, there will be D distances produced, where $D=\{d_1,d_2,\ldots d_j\}$ and j is the number of distances calculated, the number of distances must be equal to the number of class labels. Distances will be compared, the minimum d_{min} distance between t_k and f_{bestci} means the more probability to be attracted to the class c_i that contains the current f_{bestci}. The mechanism is based on the distance calculated between testing patient records in the random space and f_{bestci} of each class. By considering testing patient record t_k flying randomly in space, and 2Lampyridae insects class markers flying with their swarms $C = \{c_1, c_2\}$, for testing patient record t_k there will be 2 distances calculated $D_{calculated} = \{d_{k1}, d_{k2}\}$. Table 1 illustrates the values of calculated distances for testing patient record t_k.

Table 1: Example of calculating a number of similarity distance measures for unseen patient record/Lampyridae

Class Markers	Calculated distances
Lampyridae insects *$class_2$* presenter $f_{best\ 1}$	$d_{k,1}$
Lampyridae insects *$class_2$* presenter $f_{best\ 2}$	$d_{k,2}$

A comparison is carried out for the two distances calculated, to detect the minimum distance between unseen patient record and the two class markers.

Algorithm for prototypical usage/prediction step responsible for classifying testing patient records based on distance.

Input:
- j Lampyridae class markers denoting j class labels
- Testing patient records (denoted by selected Attributes)

Output: Testing patient records/Lampyridae insects t_{nte} allocated for their relative class labels c_i, the accuracy of classification is calculated

Prototypical Usage/Prediction step

Step 1: Consider each testing patient record as an unseen Lampyridae $t_1,t_2,t_3,\ldots t_{nte}$ flying in space A
Step 2: Consider each value in an unseen patient record vector as a location for Lampyridae.
Step 3: Calculate distance using Euclidean distance between each testing Lampyridae and j class markers,

in which *j* different distances are calculated.
Step 4: Find the minimum distance in space between testing patient records and different class markers.
Step 5: a Set class of testing patient records as the class presenter with the minimum distance

ALC is thus modeled for performing the classification task.

4. 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 CVD	Number of patients with no risk of CVD	Number of patients with risk of CVD	Number of patients with no risk of CVD
17	Male 4329 + Female 3911 = 7525 patients	3911	418	2808	388

5. RESULTS AND DISCUSSIONS

Male patients and female patient's 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's 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	3156	339	392	442	87.72	46.37	80.73	33.21
ANN Classifier	3211	393	322	403	88.85	54.97	83.25	42.00
Proposed ALC Classifier	3416	376	255	282	92.37	59.59	87.60	51.07

Table 3: Performance Results – Female Patients

Classifiers	TP	TN	FP	FN	Sensitivity (in %)	Specificity (in %)	Accuracy (in %)	Mathews correlation coefficient (in %)
TSK Fuzzy Classifier	2372	205	321	298	88.84	38.97	80.63	28.32
ANN Classifier	2263	360	303	270	89.34	54.30	82.07	44.48
Proposed ALC Classifier	2471	318	205	202	92.44	60.80	87.27	53.37

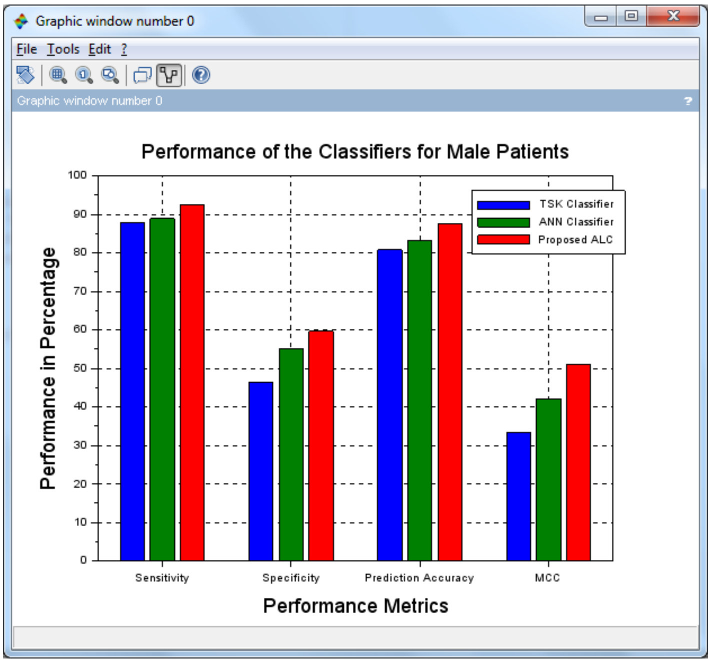

Fig. 1: Performance of the classifiers in male patients

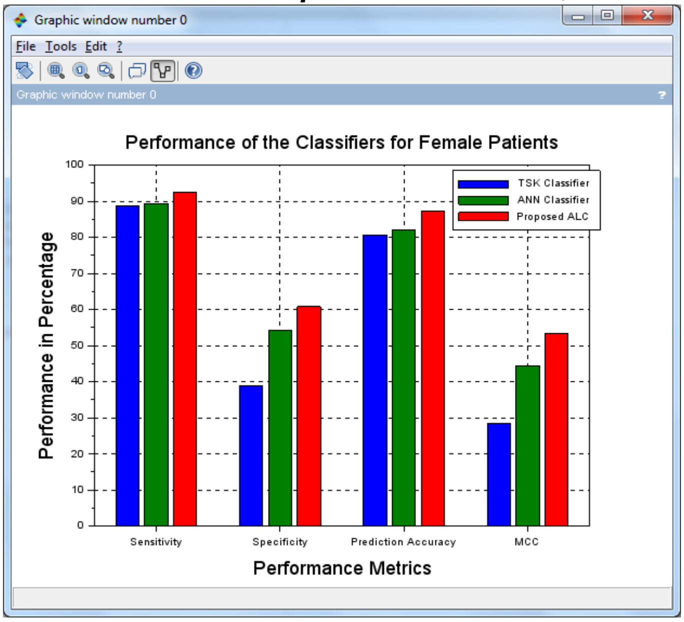

Fig. 2: Performance of the classifiers in female patients

Figure 1 shows the performance analysis in terms of CAHD prediction accuracy for male patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 80.73% and conventional ANN classifier obtains 83.25%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 87.60%. Fig.1. shows the performance analysis in terms of sensitivity for male patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 80.73% and conventional ANN classifier obtains 83.25%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 92.37%. Fig.1. shows the performance analysis in terms of specificity for male patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 80.73% and conventional ANN classifier obtains 83.25%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 59.59%. Fig.1. shows the performance analysis in terms of Mathews correlation coefficient for male patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 33.21% and conventional ANN classifier obtains 42.00%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 51.07%.

Fig.2. shows the performance analysis in terms of CAHD prediction accuracy for female patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 80.63% and conventional ANN classifier obtains 82.07%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 87.27%. Fig.2. shows the performance analysis in terms of sensitivity for female patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 88.84% and conventional ANN classifier obtains 89.34%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 92.44%. Fig.2. shows the performance analysis in terms of specificity for female patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 38.97% and conventional ANN classifier obtains 54.30%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 60.80%. Fig.2. shows the performance analysis in terms of Mathews correlation coefficient for female patients. From the results, it is inferred that conventional TSK fuzzy classifier obtains 28.32% and conventional ANN classifier obtains 44.48%; whereas the proposed ALC classifier outperforms than both TSK classifier and ANN classifier by obtaining 53.37%.

6. CONCLUSION

The usage of soft computing techniques in the medical domain is a 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 ALC 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 87.60% accuracy is obtained for male diabetic patients and 87.27% accuracy is obtained for female diabetic patients. Yet there is more scope for further improving the prediction accuracy and in the near future, some optimization techniques are aimed to be building for attribute selection.

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