Computational Intelligence Based Machine Learning Methods For Rule-Based Reasoning In Computer Vision Applications

T T Dhivyaprabha[1], *Research Scholar* P Subashini[1], *Professor* M Krishnaveni[2], *Assistant Professor*

Department of Computer Science

Avinashilingam Institute for Home Science and Higher Education for Women

Coimbatore, India

ttdhivyaprabha@gmail.com mail.p.subashini@gmail.com krishnaveni.rd@gmail.com

***Abstract*— In robot control, rule discovery for understanding of data is of critical importance. Basically, understanding of data depends upon logical rules, similarity evaluation and graphical methods. The expert system collects training examples separately by exploring an anonymous environment by using machine learning techniques. In dynamic environments, future actions are determined by sequences of perceptions thus encoded as rule base. This paper is focused on demonstrating the extraction and application of logical rules for image understanding, using newly developed Synergistic Fibroblast Optimization (SFO) algorithm with well-known existing artificial learning methods. The SFO algorithm is tested in two modes: Michigan and Pittsburgh approach. Optimal rule discovery is evaluated by describing continuous data and verifying accuracy and error level at optimization phase. In this work, Monk's problem is solved by discovering optimal rules that enhance the generalization and comprehensibility of a robot classification system in classifying the objects from extracted attributes to effectively categorize its domain.**

Keywords— rule discovery; machine learning; Synergistic Fibroblast Optimization (SFO) algorithm; classification problem; robot systems;

I. Introduction

Basically, the idea of artificial intelligence is to replicate the human ways of reasoning in computing. A system can be defined as intelligent, only if it satisfies learning and decision making requirements. Many scientific problems are solved by numerical solutions with high performance computing, where other problems do not have definite algorithms which demand a need of effective algorithms that give solutions through intelligence. Even non-algorithm based problems utilize the field of computational intelligence in areas such as perception, visual perception, control and planning problems in robotics and in many non-linear complex problems. In general, artificial intelligence deals with soft computing that create an interface with reality, whereas intelligence system provides solutions in handling practical computing problems. The knowledge based system (KBS) consists of rule-based reasoning (RBR), case-based reasoning (CBR) and model-based reasoning (MBR), where the combination of KBS can be CBR–RBR, CBR– MBR and RBR–CBR–MBR, and also Intelligent Computing method has the combination of ANN–GA, fuzzy–ANN, fuzzy–GA and fuzzy–ANN–GA. Though there are many methods available for combining soft and hard computing, this paper presents a hybrid method which is effectively carried out by fusing software and hardware computing interconnected with an application. In this research work, a crucial work, based on monk's problem is taken to solve the classification problems, that would be more useful for the field of Human-Computer Interaction (HCI) which has the application of vision and speech analysis. The proposed hybrid model is developed based on a new optimization technique, Synergistic Fibroblast Optimization (SFO), by applying with some well known machine learning methods to solve monk's classification problem. The implemented algorithm obtains optimal logical rules that classify the dataset into predicted class labels. It had been tested on both single mode and iterative mode, where the accuracy of the classification model mainly depends on the quality of knowledge acquired, which can be represented in terms of set of rules. The general description for defining rules is shown in Equation 1, where the rule consists of feature variables (attribute values) and target variable (class).

$$\text{IF} <\text{attribute}_1\ \textit{relational\_operator}\ \text{value}_1\text{logical\_condition}$$
$$\text{attribute}_n\ \textit{relational\_operator}\ \text{value}_n>$$
$$\text{THEN}<\text{Class}> \qquad (1)$$

The implemented SFO discovers certain potential sets of IF-THEN classification rules encoded into real-valued collagens that contain all types of attribute values and corresponding positive and negative classes in dataset. This implication finds optimal solutions that solve error minimisation problem, and the examined results have indicated that SFO outperforms original PSO algorithm [10].

This work is supported by the project titled "Design and Development of Computer Assistive Technology System for Differently Abled Student" (No. SB/EMEQ-152/2013) funded by Science and Engineering Research Board (SERB)-Department of Science & Technology (DST).

TABLE I. DOMAIN OF MONK'S PROBLEM

Id	Attribute	Values
x1	head_shape	round, square, octagon
x2	body_shape	round, square, octagon
x3	is_smiling	yes, no
x4	holding	sword, balloon, flag
x5	jacket_colour	red, yellow, green, blue
x6	has_tie	yes, no

The above Table I with six different attributes analyzes artificial robot domain application. The taxonomy of monk's problem or monk's are interchangeably used in this work, which is categorized into three types, namely monk's problem 1, monk's problem 2 and monk's problem 3 [2][7]. It is considered as a binary classification problem, in which each problem is given by logical condition of a class to classify robot instances into binary class labels (0 and 1). 432 patterns are found in UCI repository, which is available in (https://archive.ics.uci.edu/ml/datasets/MONK's+Problems). Below is the description of three different categories of monk's problem.

A. *Monk's problem 1*

The description of monk's problem 1 is expressed as follows in Equation 2.

IF <(x1 = x2) OR (x5 = red)> THEN Class 1 (2)

For the given attributes information, the above mentioned condition is satisfied, then the corresponding patterns are classified into class 1. Otherwise, it is fit into class 0. From the possible 432 patterns, 124 were selected for the training phase and 432 patterns were chosen for the testing phase.

B. *Monk's problem 2*

Monk's 2 considered as the most complicated monk's problem. The description of monk's 2 is represented as follows in Equation 3.

IF <(x1 = round AND x2 = round) OR (x3 = yes AND x6 = yes)> THEN Class 1 (3)

If exactly two attributes have their first value, it is assigned to class 1, otherwise 0. 169 patterns were used for training the algorithm and all the 432 patterns were selected for testing.

C. *Monk's problem 3*

Monk's 3 is similar to monk's 1 which is depicted as follows in Equation 4.

IF<(x5 = green AND x4 = sword) OR (x5 != blue AND x2 != octagon)> THEN Class 1 (4)

For all the 432 patterns, the above declared expression is satisfied, the pattern set is assigned to class 1, otherwise 0. The training dataset composed of 122 patterns were selected randomly and it contained 5% misclassifications (i.e., noisy data) and the whole 432 patterns were used as test dataset.

The proposed algorithm is tested in two modes: Michigan approach is also known as individual adaptation approach and Pittsburgh approach is a set of rules representing single solution to the problem space [3]. The description of the paper is organized as follows: Section 2 describes Synergistic Fibroblast Optimization (SFO) algorithm. Section 3 deliberates the rule discovery task of SFO. Section 4 deals with the experimentation and discussion based on the results. Section 5 draws the conclusion and scope for the future work.

II. SYNERGISTIC FIBROBLAST OPTIMIZATION (SFO) ALGORITHM

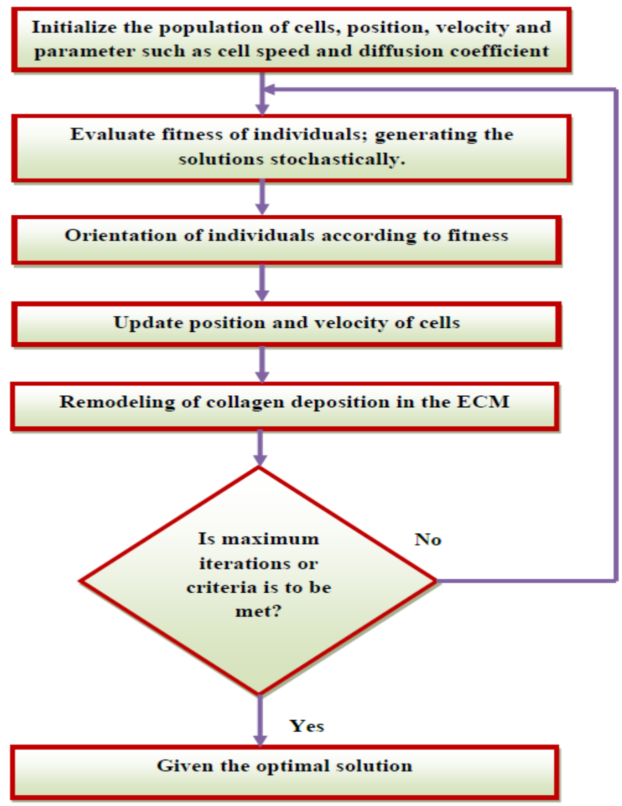

Fig. 1. Life cycle of Synergistic Fibroblast Optimization (SFO) algorithm

Synergistic Fibroblast Optimization (SFO) is a stochastic population based global search algorithm that imitates the collaborative and self adaptive behavior of fibroblast organism in the dermal wound healing process [10]. Each individual in the cell population is composed of three *D*-dimensional vectors, where *D* is the dimensionality of the search space, x_i denotes the position, v_i represents the velocity and ECM designates the matrix representation of collagen protein deposition. For every iteration of the algorithm, cell swarm secretes the collagen, which is randomly chosen from ecm, in the evolutionary space, which is considered as a problem solution. The value of the best result obtained so far is stored in a variable called c$best_{i-1}$ ("previous best") is compared on later iterations with c$best_i$ *("current best").* The cells are further moved to find a better position by updating the x_i. New positions are chosen by adding v_i co-ordinates to x_i, and the algorithm operates by adjusting v_i, which can effectively be seen as a step size. The parameter consists of cell speed (s) and diffusion coefficient (ρ) that act as an external force to maintain swarm diversity in the problem space and slowly converge to the optimal solution. The self organisation and co-operative nature of fibroblast, to heal the wounds, is greatly associated with evolutionary algorithm strategy to discover global optimum in the problem space. Fig. 1. depicts the skeleton of the SFO algorithm. The original process for implementing SFO is given in the algorithm below:

Algorithm: Synergistic Fibroblast Optimization (SFO)
Step 1: Initialize the population of fibroblast cells f_i, i = 1,2,…,n; with randomly generated position (x_i), velocity (v_i) and collagen deposition (ecm) in the n-dimensional problem space. The parameter such as cell speed (s) and diffusion coefficient (ρ)values are defined.
Step 2: Repeat
Evaluate the individual fibroblast using fitness function F (f_i) in n variables for n times.
Step 3: The reorientation of cell can be performed to find optimal (maxima or minima) solution in the evolutionary space.
Step 4: Update the velocity (v^i) and position (x^i) of a cell using the following equations:

$$v_i^{(t+1)} = v_i^{(t)} + (1-\rho)c(f_i^{(t)}, t) + \rho * \frac{f_i(t-\tau)}{\|f_i(t-\tau)\|} \qquad (5)$$

where

t = current time;
τ = time lag;
v^i= velocity of i^{th} cell
ρ = 0.5

$$x_i^{(t+1)} = x_i^{(t)} + s * \frac{v_i^{(t+1)}}{\left\|v_i^{(t+1)}\right\|} \qquad (6)$$

where

μ/min, L = cell length;

Step 5: Remodeling of collagen deposition (c_i) is upgraded in the extracellular matrix (ecm).
Until the predetermined conditions / maximum iterations is met.

Fibroblast has the ability to sense relevant environmental chemical information, and then the cells migrate over the substrate of collagen protein, to replace fibrin present in the wounded region. It is believed that fibroblast has memory based approaches, which use knowledge on the previous search space, to advance the search after a change. SFO movements, to find the optimal solution for solving non-linear complicated problem, are described in the proposed algorithm which is discussed as follows. Step 1 indicates the discrete unit of fibroblast population with randomly generated position and velocity. It has two basic parameters, namely, cell speed and the diffusion co-efficient that need to be fixed. The cell speed is associated with velocity of cell to improve the positive gradient, and the diffusion co-efficient enables fibroblast displacement in the domain space to follow a homogeneous distribution of collagen particles deposited in a co-ordinated way. Step 2 evaluates the fitness of individual cell, using the objective function. Step 3 reveals that the alignment of cell move towards the solution space with best success achieved so far found. Fibroblasts are migrated to a new location in the problem space, which can be achieved by updating the velocity and position of the cell, which is represented in Step 4. The final Step 5 illustrates that the cells are continuously evolved to yield optimum (minima or maxima) which is problem specific, with the synthesis of collagen present in extracellular matrix. In the given spatial co-ordinates, fibroblasts are flown in a divergent way and it slowly converges to the global best solution which helps to avoid cells being trapped in the local optimum (stagnation problem).

III. RULE DISCOVERY WITH SYNERGISTIC FIBROBLAST OPTIMIZATION (SFO)

The proposed method is intended to construct intelligent learning rules for classify the objects from the features extracted in Monks archive to effectively categorize its domain. These generated rules are partitioned into the corresponding class labels which are applied to SFO algorithm for optimal rule selection process. SFO algorithm is implemented to choose fine tuned features that are applied to machine learning techniques such as decision tree, classification based association and feed forward neural network for the effective classification of objects. The following procedure illustrates the consecutive steps involved in the rule discovery task based on SFO optimization technique.

Procedure:
Step 1: *Rules generation* - There are 432 possible rules constructed to define the relationship between attribute values and target labels which satisfy the description of class expressed in monk's 1, monk's 2 and monk's 3 problems.
Step 2: *Rules classification* - Set of generated rules are clustered into two groups, namely, class 1 and class 0. 216 rules are summative into class 1, and 216 rules are aggregated into class 0. Table II demonstrates the model of generation and classification of rules.

TABLE II. SAMPLE OF RULE GENERATION AND RULE CLASSIFICATION

Rule no.	Rules	Class
18	x1=1,x2=1,x3=1,x4=3,x5=1,x6=2	1
53	x1=1,x2=2,x3=1,x4=1,x5=2,x6=2	0
104	x1=1,x2=3,x3=1,x4=1,x5=4,x6=2	0
248	x1=2,x2=3,x3=1x4=1,x5=4,x6=2	0
392	x1=3,x2=3,x3=1,x4=1,x5=4,x6=2	1

Step 3: *Rules selection* - SFO algorithm is implemented to choose optimal rules from the encoded classified rule set.

Step 3.1: Initialize the cell size = 10; swarm size1 = 216 and swarm size2 = 216. These 432 collagens (population) present in an extracellular matrix were assigned with one classification rule.

do

Step 3.2: Each cell evaluate the collagen (rules) as a fitness measure using sphere benchmark function [8]. The mathematical representation of sphere is denoted in Equation 7.

$$f(x) = \sum_{i=1}^{D} x_i^2 \qquad (7)$$

Step 3.3: SFO retrieves optimal rules at each cycle and it is compared with the global optima (best rule) obtained so far.

if ($c_{best-1} < c_{best}$)
Set $c_{best} = c_{best}$;
else
Set $c_{best} = c_{best-1}$;

Step 4: The position (x_c) and velocity (v_c) of the cell are updated at each iteration.

end loop

Step 5: Repeat the steps from 3.2 to 4 until the program had achieved 10000 runs or the predetermined global optima solution is found.

Step 6: Return the optimal classification rules (c_{best}).

The SFO code is repeatedly executed for 10 times, and the fittest rules had selected based on mean of their best outcomes which is depicted in Table III.

Step 7: A set of optimal rules are applied to chosen classification algorithm such as decision tree, classification based association and feed forward neural network for rules formation and representation in the knowledge base.

Step 8: The training instances are assigned to machine learning algorithm as a learning process in the training phase. It enables classification techniques to learn and classify the feature variables into target class variables.

Step 9: The test instances are assigned to predict the unlabeled class instances.

TABLE III. LIST OF OPTIMAL RULES CHOSEN BY SFO

Monk's problem	No. of cycles	Michigan approach	Pittsburgh approach
		Rules	
Monk's Pb 1	10	21,197,390,320 ,335	22,219,386,138,186,248,31 4,36
Monk's Pb 2	10	179,233,363	239,419,405,407
Monk's Pb 3	10	415,337,321	318,302,1,54

IV. EXPERIMENTAL SETTINGS AND OBSERVATIONS

Synergistic Fibroblast Optimization (SFO) algorithm is implemented as a computer program, using java programming language. The fitness landscape analysis of sphere to find global optimum in the evolutionary space is observed [7] in Fig. 6. When the dimensionality of evolutionary space and the number of candidate solutions gets increased for fitness evaluation, SFO algorithm maintains an equal balance between exploration and exploitation state to find global optimum. It signifies that SFO is highly sensitive to the changing environment and the probability of finding best solution is gradually enhanced.

The parameter settings of SFO execution was initialized with the maximum number of iterations = 10000, population size = (216; Class 0 + 216; Class 1) and the cell size = 10.The dataset was divided into 7 segments, namely, D1, D2, D3, D4, D5, D6 and D7. There are totally 60 records found in D1 to D6 sets and D7 set comprises of 72 tuples which were randomly taken from the UCI data archive.

The most common classification techniques are decision trees, rule-based methods, probabilistic methods, SVM methods, instance-based methods and neural networks [1][5][9][12]. Monk's problem is viewed as a discrete binary classification problem. Being a large number of dataset are found in all the three Monk's problem UCI archives, it require machine learning algorithms which have scalable property to efficiently adaptable to huge and diverse kinds of data. Since Monk's dataset have multivariate characteristic, variables associated with each attributes are independent and subjected to modify at regular intervals of time. Moreover, Synergistic Fibroblast Optimization, a bio-inspired computing paradigm needs to be proven that it is compatible with varied machine learning techniques that resolves the classification problem. Therefore, it is tested with a reference set of problems, Monk's dataset. To achieve this, a study on the aforementioned classification techniques have been done and an outcome of this review emphasized that decision tree (DT), classification based association (CBA) algorithm and feed forward neural network (FFNN) could be well suited to solve chosen monk's problem and the following are the inference gained from study on classification algorithms, which reveals that rule based methods, instance based methods, SVM and probabilistic methods could not be a more appropriate approaches for solving Monk's problems dataset.

Rule based methods are similar to decision tree, except that it does not create the distinct hierarchical structure for partitioning the data and it allows data overlapping to improve the robustness of the model. Monk's problems have three different consistent rules; rule based method could not be an appropriate method to solve it.

Instance based methods are also known as lazy learning methods. Because, in this method, the test data are directly used as training instance to create the classification model and it is tailored to particular classifier. Monk's dataset are divided into test and training instances. In this research, a classification system needs to be design, which is trained using training data and evaluate the corresponding model using test data separately. Henceforth, Instance based methods could not be a fitting method to solve this problem.

Support vector machine (SVM) is a well known method for binary classification problem. The features of SVM imply that a pair wise similarity needs to be defined between training instances and test instances in order to create an efficient classification model. The weak associations are existed between training data and test data found in Monk's dataset, SVM method could not be applied to design and develop a classifier model that solve Monk's problem.

Probabilistic methods are the basic classification method. It uses statistical inference to create the classification model and it produces the corresponding output based on posterior probability of test data and priori probability of training data. This method required both training data and test data to find the statistical inference, which is applied as knowledge for designing the classification system. Therefore, probabilistic methods could not be suitable approach to resolve Monk's problem.

Fitness measure was used to evaluate how well the optimal rules selected by SFO improve the accuracy of machine learning algorithm [2]. It was tested in MATLAB and the experimental results were visualized using R-tool.

$$Fitness = \frac{Good\ classification}{Total\ patterns} * 100 \quad (8)$$

where

Good classification is the proportion of patterns which are correctly classified by learning algorithm.

Total patterns are the sum of records found in the database.

Fig. 2. shows the convergence curve for the best collagen obtained by SFO from D1 through D7. Over 100% success rate was achieved at about iteration 6000. The evolution of success rate in Pittsburgh approach shown in Fig. 3. clearly reveals that D1 to D7 dataset had attained faster convergence, but it stays at lower success rate when compared to Michigan approach.

The results presented in Table IV through Table IX evident that SFO is compatible with the varied characteristics of machine learning methods. The intellectual behavior of SFO algorithm enables obtaining optimal rules that improve the performance of classification techniques in terms of accuracy, even though noisy pattern is added to problem 3. It is illustrated that the collaborative and self adaptive behavior of fibroblast enforces collagen particles to move towards the global optimum in the evolutionary space. Moreover, SFO have found the smaller optimum rule set with the minimum number of iterations. This desirable result confirms that SFO has achieved the goal of the proposed work, that is, to discover knowledge which is not only accurate and also comprehensible to the learning process of classification algorithms. It is also observed that Michigan approach outperforms for calculated metrics than Pittsburgh approach. The rule pruning mechanism followed by Pittsburgh approach reduces the number of rules at each cycle which have lead to slightly worse results. This pitfall is done with ease by SFO to improve the performance, generalization, comprehensibility and noise tolerance capacity of machine learning. The learning rate of a novel SFO based binary classifier model is assessed by using standard metrics such as accuracy, sensitivity, specificity and kappa co-efficient [9][12] which is calculated using the confusion matrix denote the disposition of the set of instances for classifiers. To the understanding, the mathematical representation of performance metric is given in Equation 9 and Equation 12.

Accuracy (AC) defined as the proportion of the total number of predictions that are correct. It is determined using the Equation 9.

$$AC = (a+d)/(a+b+c+d) \quad (9)$$

Sensitivity or True Positive rate (TP) distinct as the proportion of positive cases that are correctly identified, which is represented using the Equation 10.

$$TP = d/(c+d) \quad (10)$$

Specificity or True Negative rate (TN) defined as the proportion of negatives cases that are classified correctly as negative. It is calculated using the Equation 11.

$$TN = a/(a+b) \quad (11)$$

Kappa coefficient ($\hat{K}$): is a statistical measure, defined as the qualitative assessment of the classifier model that evaluates the difference between observed accuracy (P_o) and expected accuracy (P_c). It is determined by using the Equation 12.

$$\hat{K} = \frac{(P_o - P_c)}{(1 - P_c)} \quad (12)$$

The proposed model is also evaluated to estimate the error variation through statistical measures that includes root mean square error (RMSE) and mean absolute error (MAE) [6].

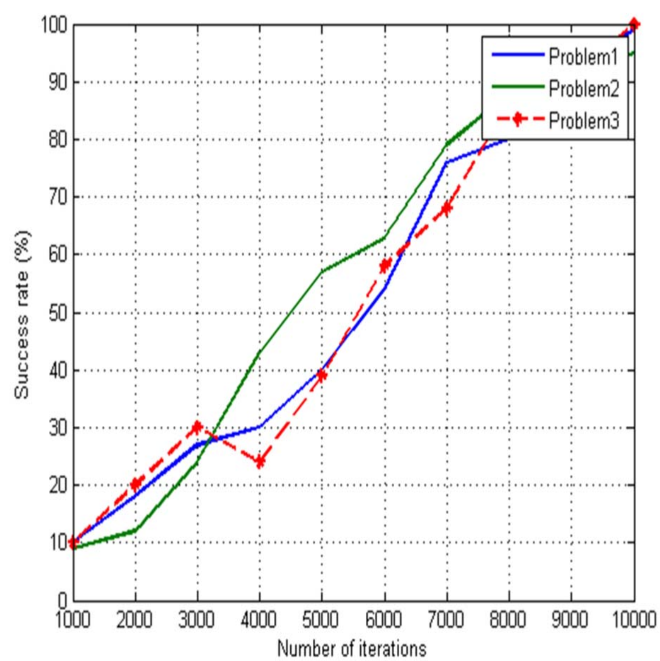

Fig. 2. Best collagen success rate on test set D1-D7 - Michigan approach

TABLE IV. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-1 - MICHIGAN APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*
D1	**100**	0.00	**91.53**	0.49	**100**	0.00
D2	**100**	0.00	**86.41**	0.40	**100**	0.00
D3	**100**	0.00	**95.56**	0.50	**100**	0.00
D4	**100**	0.00	**94.47**	0.40	**100**	0.00
D5	**100**	0.00	**100**	0.00	**100**	0.00
D6	**98.76**	0.50	**93.10**	0.50	**100**	0.00
D7	**100**	0.00	**97.38**	0.57	**100**	0.00

TABLE V. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-2 - MICHIGAN APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*
D1	**98.60**	0.40	**96.23**	0.40	92.60	0.39
D2	**97.20**	0.53	**91.25**	0.50	**96.8**	0.51
D3	**95.59**	0.50	**90.81**	0.47	**100**	0.00
D4	**96.30**	0.52	**98.44**	0.56	**100**	0.00
D5	**93.20**	0.49	**97.55**	0.54	**100**	0.00
D6	**92.70**	0.49	**90.00**	0.47	**100**	0.00
D7	**95.70**	0.51	**92.00**	0.49	**100**	0.00

TABLE VI. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-3 - MICHIGAN APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*
D1	**100**	0.54	**91.80**	0.48	**100**	0.00
D2	**96.45**	0.52	**93.00**	0.48	**100**	0.00
D3	**100**	0.53	**97.40**	0.52	**100**	0.00
D4	**100**	0.53	**97.32**	0.51	**100**	0.00
D5	**100**	0.54	**99.20**	0.54	**100**	0.00
D6	**100**	0.59	**94.80**	0.49	**100**	0.00
D7	**100**	0.56	**95.40**	0.56	**100**	0.00

Added to the discussion, the results presented in Table X through Table XII illustrates that the optimal rules chosen by SFO algorithm reinforce the learning efficiency of chosen machine learning algorithms on both Michigan and Pittsburgh approaches. Specifically, decision tree and feed forward neural network had obtained significant results than classification based association technique. Since monk's problem comprised scattered data, the applied association rule mining algorithm indulged to discover rules based on frequent item set found in database which has lead to suffer performance degradation. Though monk's 2 is considered as a difficult problem, the optimal rules yielded by SFO were compatible with classification algorithms to attain highly qualitative solutions. In the perspective of individual metric analysis, though CBA and DT algorithms slightly give worse results for sensitivity on monk's dataset that contained 67.12% of negative classes, the output obtained for accuracy, specificity and kappa coefficient confirms that SFO based classification techniques had produced promising results. The interesting note revealed during the experimentation is that **t**olerance to noise can be a quite interesting feature of SFO algorithm. Henceforth, the examined results signify that SFO algorithm is more compatible with well-known classification techniques to solve complex problems, even more significantly in noisy data by improving the comprehensibility, generalization and reliability of learning task of machine learning algorithms.

The experimental results portrayed in Table XIII and Table XIV exemplify that the error variance of RMSE and MAE emphasize the proposed work even though RMSE result varies with the variability of the error magnitudes and the total error.

TABLE VII. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-1 - PITTSBURGH APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviatio*
D1	**100**	0.00	46.66	0.48	42.22	0.48
D2	**100**	0.00	**82.22**	0.50	**84.44**	0.52
D3	**100**	0.00	**95.55**	0.50	**100**	0.00
D4	**100**	0.00	**95.55**	0.50	**100**	0.00
D5	**100**	0.00	**88.88**	0.499	**100**	0.00
D6	**100**	0.00	**93.33**	0.50	**95.55**	0.50
D7	**100**	0.00	**88.88**	0.49	**95.55**	0.50

The performance of classification system was examined using ROC (Receiver Operating Characteristic) curve [4][11]. Fig. 4. and Fig. 5. depicts the ROC graph produced for monk's problems on both Michigan and Pittsburgh approaches. An Area of 0.90 to 1.00 represents the perfect classification test and the values found within range of 0.80 to 0.90 signify the good test achieved by classifier models. It is tradeoff between hit rate and false rate of discrete classifier models. Decision tree gets a value of >= 0.98 and Feed forward neural network attains the highest value of 1.00 for monk's problem 1 in Michigan approach and >=0.99 for monk's problem 3 in Michigan and Pittsburgh approaches. The optimal rules obtained by SFO had reinforced the learning process of classification techniques, that enhance the generalization of rules in the knowledge base and the accuracy of classifier models. The empirical observation indicates that decision tree and feed forward neural network had achieved better classification accuracy for monk's 1, monk's 2 and monk's 3 problems rather than classification based association algorithm and it shows that SFO is able to provide a good solution in all the cases in Michigan approach (single mode) than in Pittsburgh approach (iterative mode).The Michigan approach achieves a higher success rate with smaller number of iterations. It is inferred that the evaluation cost for the Pittsburgh approach is high due to two reasons, namely, the larger number of rules needed to represent this problem (high dimensionality) and the requirement of higher number of iterations in order to reach a better success rate.

TABLE VIII. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-2 - PITTSBURGH APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*
D1	**88.88**	0.45	75.55	0.44	40	0.38
D2	**95.55**	0.30	**91.11**	0.28	**95.55**	0.30
D3	**100**	0.00	**100**	0.00	**100**	0.00
D4	**95.55**	0.50	**95.55**	0.50	**100**	0.00
D5	**95.55**	0.50	**95.55**	0.50	**100**	0.00
D6	**93.33**	0.50	**95.55**	0.50	**100**	0.00
D7	**93.33**	0.49	**95.55**	0.50	**100**	0.00

TABLE IX. EXPERIMENTAL RESULTS OF MONK'S PROBLEM-3 - PITTSBURGH APPROACH

Data set	DT		CBA		FFNN	
	Avg succ rate (%)	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*	*Avg succ rate (%)*	*Standard deviation*
D1	**100**	0.00	**82.22**	0.478	**100**	0.00
D2	**99.77**	0.48	**99.77**	0.48	**100**	0.00
D3	**97.77**	0.49	**93.33**	0.49	**100**	0.00
D4	**100**	0.00	**100**	0.00	**100**	0.00
D5	**100**	0.00	**100**	0.00	**100**	0.00
D6	**100**	0.00	**100**	0.00	**100**	0.00
D7	**100**	0.00	**97.77**	0.49	**100**	0.00

TABLE X. PERFORMANCE EVALUATION OF SFO OPTIMIZED CLASSIFIERS FOR MONK'S PROBLEM 1

Metrics	Michigan approach			Pittsburgh approach		
	DT	*CBA*	*FFNN*	*DT*	*CBA*	*FFNN*
Accuracy (%)	99.54	90.27	100	100	83.10	92.59
Sensitivity (%)	99.67	92.28	100	100	84.61	93.93
Specificity (%)	99.20	85.82	100	100	77.65	89.08
Kappa coefficient	0.0113	0.0976	0.0000	0.0000	0.4880	0.1957

TABLE XI. PERFORMANCE EVALUATION OF SFO OPTIMIZED CLASSIFIERS FOR MONK'S PROBLEM 2

Metrics	Michigan approach			Pittsburgh approach		
	DT	*CBA*	*FFNN*	*DT*	*CBA*	*FFNN*
Accuracy (%)	99.79	95.60	100	99.07	92.13	100
Sensitivity (%)	99.69	95.63	100	98.12	91.45	100
Specificity (%)	99.50	95.56	100	99.02	92.93	100
Kappa coefficient	0.0192	0.1602	0.0000	0.0187	0.0889	0.0000

TABLE XII. PERFORMANCE EVALUATION OF SFO OPTIMIZED CLASSIFIERS FOR MONK'S PROBLEM 3

Metrics	Michigan approach			Pittsburgh approach		
	DT	*CBA*	*FFNN*	*DT*	*CBA*	*FFNN*
Accuracy (%)	92.13	89.81	97.22	90.51	89.35	96.53
Sensitivity (%)	85.06	82.43	98.51	80.98	80.24	96.35
Specificity (%)	96.28	94.74	98.15	96.04	94.29	92.95
Kappa coefficient	0.1576	0.2318	0.0778	0.1782	0.1958	0.0882

TABLE XIII. RESULTS OF RMSE

Lear-ning Alg.	Michigan approach			Pittsburgh approach		
	Monk's Pb 1	*Monk's Pb 2*	*Monk's Pb 3*	*Monk's Pb 1*	*Monk's Pb 2*	*Monk's Pb 3*
DT	0.00	0.07	0.0093	0.00	0.09	0.00
CBA	0.07	0.10	0.0787	0.26	0.12	0.06
FFNN	0.00	0.02	0.0000	0.19	0.15	0.00

TABLE IV. RESULTS OF MAE

Lear-ning Alg.	Michigan approach			Pittsburgh approach		
	Monk's Pb 1	*Monk's Pb 2*	*Monk's Pb 3*	*Monk's Pb 1*	*Monk's Pb 2*	*Monk's Pb 3*
DT	0.00	0.07	0.00	0.00	0.0	0.00
CBA	0.07	0.10	0.07	0.26	0.12	0.06
FFNN	0.00	0.02	0.00	0.19	0.15	0.00

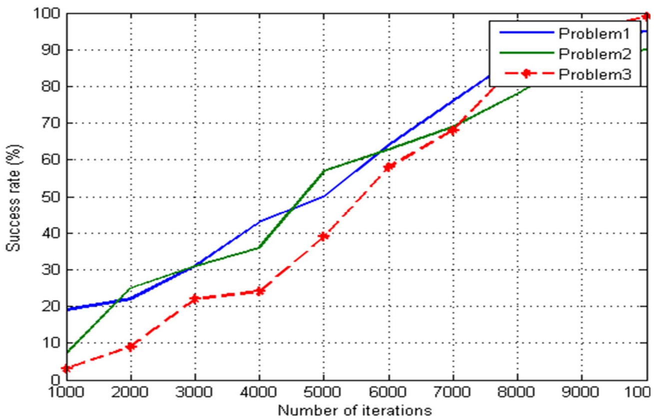

Fig. 3. Best collagen success rate on test set D1-D7 - Pittsburgh approach

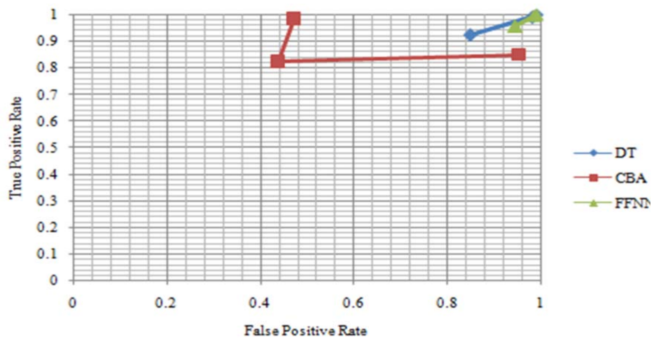

Fig. 4. ROC of monk's problems on Michigan approach

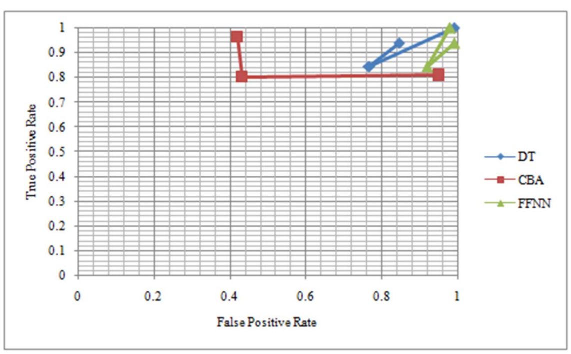

Fig. 5. ROC of monk's problems on Pittsburgh approach

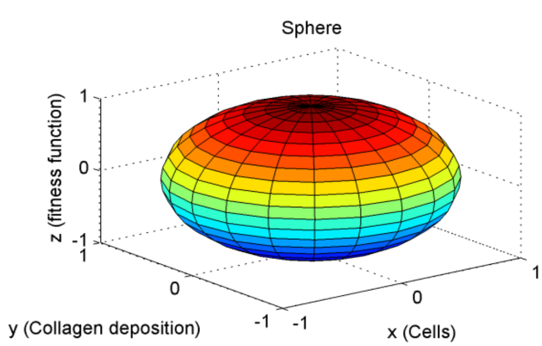

Fig. 6. Sphere Function of SFO Implementation

V. CONCLUSION

Computer Vision is still an open problem even though there are very good algorithms available for controlled environments. These uncertainties are focused by machine learning community with symbolic attributes and simple logical rules. Most available classifiers are uneven and do not resist when the training set changes slightly. This leads to misclassification that plunders the entire system. In real time problems, it is necessary to go for optimal logical rules that satisfy the complex sets. Here, the newly developed SFO algorithm is proposed with well being learning algorithms to find optimum solution that suits complicated classification problems. The investigation and experimentation were carried out with Monk's problem, and from the analysis of various performance metrics, it is confirmed that SFO is compatible with most popular machine learning algorithms to improve the performance of classification system. The work is more focused on computer vision problems and it can be extended to the field of expert systems and robot control systems not only to classify but also to evaluate different cases.

REFERENCES

[1] Alaa Al Deen, Mustafa Nofal, and SuliemanBani-Ahmad, "Classification based on association-rule mining techniques: a general survey and empirical comparative evaluation," Ubiquitous Computing and Communication Journal, vol. 5, pp. 9-17, 2010.

[2] Alejandro Cervantes, Ines galvan, and Pedro Isasi, "Binary particle swarm optimization in classification," ICS AS CR, 2005, pp. 229-241.

[3] Alejandro Cervantes, Ines galvan, and Pedro Isasi, "A comparison between the pittsburgh and michigan approaches for the binary PSO algorithm," IEEE Xplore, 2005, pp. 290-297.

[4] Antonin Slaby,"ROC analysis with Matlab," International Conference on Information Technology Interfaces, 2007, pp. 191-196.

[5] Bangaru Veera Balaji, and Vedula Venkateswara Rao, "Improved classification based association rule mining," International Journal of Advanced Research in Computer and Communication Engineering, vol. 2, pp. 2211-2221, 2013.

[6] T. Chai, and R. R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature," Geoscientific model development, vol. 7, pp. 1247-1250, 2014. DOI= http://dx.doi.org/10.5194/gmd-7-1247-2014.

[7] K. Kaufman, R. S. Michalski, and Pachowicz, "The monk's problems: a performance comparison of different learning algorithms," Thesis report submitted to Carnegie mellon university, 1991, pp. 1-163, 2013.

[8] Momil Jamin, Xiu-She Yang. A literature survey of benchmark functions for global optimization problems. International Journal of Mathematical Modelling and Numerical Optimisation. vol.4, pp. 150-194.

[9] Shamsher Bahadur Patel, Pramod Kumar Yadav, and D .P. Shukla, "Predict the Diagnosis of Heart Disease Patients Using Classification Mining Techniques," IOSR Journal of Agricultureand Veterinary Science (IOSR-JAVS), vol. 4, pp. 61-64, 2013.

[10] P. Subashini, T. T. Dhivyaprabha, and M. Krishnaveni, "Synergistic fibroblast optimization," Proceedings of Joint International Conference – ICAIECES-2016 & ICPCIT-2016, 2016, pp. 1-6.

[11] Tom Fawcett, "An introduction to ROC analysis," Elsevier Pattern Recognition Letters, vol. 27, pp. 861-874, 2005. DOI= http://dx.doi.org/ 10.1016/j.patrec.2005.10.010.

[12] Yusuf Uzun, and Gülay Tezel, "Rule learning with machine learning algorithms and artificial neural networks," Journal of selçuk university natural and applied science, vol.1, pp. 54-64, 2012.