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RECEPTACLE - ARTIFICIAL BEE COLONY (R–ABC) CLASSIFIER FOR CLASSIFICATION OF GESTATIONAL DIABETES

S. Kavipriya and T. Deepa
Department of Computer Science, Sri Ramakrishna College of Arts and Science for Women, Coimbatore, Tamil Nadu, India
E-Mail: kavipriya.vignesh@gmail.com

ABSTRACT

Limiting the feature subset size and expanding the classification accuracy for performing the prediction of heart disease among gestational diabetes patients in the dataset is one among the thrust research area in the field of healthcare informatics and its related application domains. In this research work a receptacle artificial bee colony (R-ABC) classifier is employed for performing the aimed task. Certain enhancements are made with the conventional ABC algorithm in terms of using negligible free vitality, swarming separation task conspire, two - point crossover operation and two - way mutation operation are performed. Quick non-commanded arranging are arbitrarily decided for every present solution in the utilized honey bee stage. Between the present solution and its neighbourhood solution and specifically the proposed solution generator is connected to shape another solution set. With the help of edge esteem the classification is performed. Performance metrics such as sensitivity, specificity, true positive rate, false positive rate, precision, accuracy and time taken for feature selection are taken into account. The results are demonstrated with better performance.

Keywords: feature selection, data mining, gestational diabetes, accuracy, time taken, risk prediction.

1. INTRODUCTION

Data mining in wellbeing informatics is a computational procedure for mining realities from accessible clinical databases. Data mining is comprehensively delegated prescient data mining and elucidating data mining. Characterization and prediction falls under the classification of prescient data mining. Risk prediction of gestational ailments is one among the push examine region in the field of clinical decision emotionally supportive network. Learning based clinical decision emotionally supportive network for the most part comprises of three segments in particular information base, surmising motor and instrument to convey. Non-information based CDSS makes utilization of machine learning calculations to be specific help vector machine, importance vector machine, simulated neural system and extraordinary learning machine. These machine learning calculations face PCs to procure from authentic practices or potentially discover designs in accessible clinical data. The non-learning based CDSS neglects the prerequisite for scripting rules and for capable information. By and by, these non-information construct CDSS situated in light of machine adapting potentially won't explain the foundations for their decisions and henceforth known as "secret elements", for the reason that no expressive actualities about the working will be recognized by human examination.

All the clinical experts don't make utilization of such non-learning specifically for analyze because of the unwavering quality and responsibility reasons. Then again, they are utilized for plan and advancement of post-demonstrative frameworks, for ominous examples for clinicians to domain on it. As of late, assorted data mining techniques have been utilized for decision bolster for coronary illness risk prediction. Certain techniques are depicted in early which incorporates decision tree, neural system, and affiliation run mining, (R Alizadehsani *et al*., 2013, J Nahar *et al*., 2013, I.Kurt *et al.*, 2008, M.G. Tsipouras *et al*., 2008). Decision tree is anything but difficult to actualize and decipher and it gives a tree-based grouping to building up a prescient model as per free factors (M.J. Berry and G. Linoff., 1997). Decision tree is by all accounts one the exact calculations among data mining devices.

2. LITERATURE REVIEW

B. Dennis and S. Muthukrishnan, 2014 proposed Adaptive technique based Genetic Fuzzy System with the target of optimizing rules and membership functions for medical data classification process. To establish the efficiency of the proposed classifier the presentation of the anticipated genetic-fuzzy classifier was evaluated with quantitative, qualitative and comparative analysis. Hybrid Prediction Model (HPM) proposed by B.M. Patil *et al.*, 2010 used Simple K-means clustering algorithm aimed at validating chosen class label of given and subsequently applying the classification algorithm to the result set. C4.5 algorithm was used to build the final classifier model by using the k-fold cross-validation method. J. Jabez Christopher *et al.*, 2015 used a meta-heuristic approach called Wind-driven Swarm Optimization (WSO). The individuality stands in the inspiration of biology that underlies the algorithm. It utilizes a new metric called Jval, to analyze and evaluate the rule-based classifier efficiency. Rules were extracted from decision trees. WSO was used to obtain different permutations and combinations of rules whereby the optimal rule set that satisfies the requirement of the developer was used for predicting the test data.

J. Mattila *et al*., 2012 presented a novel generic clinical decision support system, which models a patient's disease state statistically from heterogeneous multistage data, where the goal was to aid in diagnostic work by analyzing all available patient data and highlighting the relevant information to the clinician. Jamal Salahaldeen Majeed Alneamy and Rahma Abdulwahid Hameed

Alnaish, 2014 intended to use the hybrid teaching learning based optimization (TLBO) algorithm and fuzzy wavelet neural network (FWNN) for heart disease diagnosis. The TLBO algorithm was applied to enhance performance of the FWNN. The hybrid TLBO algorithm with FWNN was used to classify the Cleveland heart disease dataset obtained from the University of California at Irvine (UCI) machine learning repository. Kalpana M and Kumar AS,2012 expressed the prominent features of the fuzzy expert system by applying the algorithm Fuzzy Assessment Methodology using K ratio, that was to diagnosis the diabetes Fuzzy Assessment Methodology using k ratio was developed. Fuzzy Expert System consists of following elements such as Fuzzification interface, Fuzzy Assessment Methodology using K ratio and De-fuzzification interface.

Kamadi V.S.R.P. Varma *et al.*, 2014 proposed a method to minimize the calculation of Gini indices by identifying false split points and used the Gaussian fuzzy function because the clinical data sets were not crisp, where the efficiency of the decision tree depends on many factors such as number of nodes and the length of the tree, pruning of decision tree plays a key role. Kindie Biredagn Nahato *et al*., 2016 proposed a classifier that combines the relative merits of fuzzy sets and extreme learning machine (FELM) for clinical datasets. The three major subsystems in the FELM framework were pre-processing subsystem, fuzzification subsystem and classification subsystem. Missing value imputation and outlier elimination were handled by the pre-processing subsystem.

Manjeevan Seera *et al.*, 2014 proposed Hybrid Intelligent System which consists of Fuzzy based Min–Max neural network, the Classification and Regression Tree, and the Random Forest model and its efficacy as a decision support tool for medical data classification was examined. Genetic Programming based method proposed by Muhammad Waqar Aslam *et al*., 2016 has been used for diabetes classification, which was also used to generate new features by making combinations of the existing diabetes features, without prior knowledge of the probability distribution. Medical Diagnosis System proposed by Vijaya K *et al.*, 2010 predicted the severity of the cardiovascular diseases, where system was built by combining the relative advantages of fuzzy logic, neural network and genetic algorithm. The input variables that were non-discrete were fuzzified and fed as input to train the neural network.

3. RECEPTACLE - ARTIFICIAL BEE COLONY (R–ABC) CLASSIFIER

Emphasizing the choice can be considered as a multi-objective issue through two primary incompatible objectives which were (a) restricting the element subset size (b) increasing the accuracy of classification. In spite of the accomplishment of Artificial Bee Colony (ABC) in various fields, there exist no multi-objective ABC based approaches. To cover this issue and increasing the accuracy of classification, ABC based multi-objective component determination approaches with its two executions are proposed in this paper.

The standard ABC algorithm proposed for single objective issues can't be utilized for solving the issues of multi-objective. So some alterations are required on likelihood computation, planning of solution refreshment and planning of solution development to the issues in multi-objective. Forced by the idea and thoughts of non-dominated sorting GA II (NSGAII) [T.Hamdani et al.,2007] and non-dominated sorting synchronous ABC (NSSABC) [B.Akay, 2013], we developed and simulated both the binary and ceaseless forms of the multi-objective ABC approach, named Receptacle–ABC (R-ABC).

3.1 Calculation of probabilities for onlookers

For non multi-objective issue, likelihood is basically appointed to sustenance, where it is not advisable for multi-objective issues since they have excess of one objective. In this similar way, plotting of likelihood task can be accompanied as:

$$P_i = \frac{New\ fitness_i}{\sum_{i=1}^{SN} Newfitness_i}$$

Where $Newfitness_i$ depends on Gibbs distribution (L.D. Landau and E.M. Lifshitz., 1980, X. Zou *et al.*, 2004) and rank estimation by Pareto. In Gibbs distribution plan, structure in thermo-dynamical balance at a given temperature, reduces the energy utilization. Since the key objectives of multi-objective problem closely resemble the guideline of finding the base free energy state in a thermodynamic framework, in R-ABC a fitness task strategy proposed in (X. Zou *et al*., 2004) is utilized to process the fitness.

$$New\ fitness_i = \frac{1}{\mathrm{R(i)} - \mathrm{T} * \mathrm{S(i)} - \mathrm{d(i)}}$$

where $R(i)$ is the Pareto rank estimation of the individual i, $T > 0$ is a predefined consistent respect indicated as temperature, $d(i)$ is the swarming separation controlled by the swarming separation task conspire [K.Deb *et al.*, 2002], and

$$\mathrm{S(i)} = -P_T\ \mathrm{(i)log_{pr}(i)}$$

where

$$P_T(i) = (1/Z)\ exp\ (-R(i)/T)$$

and

$$Z = \sum_{1}^{SN} exp\left(\frac{-R(i)}{T}\right)$$

where $P_T(i)$ is the Gibbs distribution, Z is the segment capacity and SN is the populace estimate.

This fitness task conspire unites to the Pareto-ideal solutions with a different variety of solutions

available in view of the rule of thermodynamics (X. Zou *et al*., 2008).

3.2 Procedure for individual update

To update or refresh the individuals, avaricious determination is connected between the current and recently produced individual through transformation and hybrid. Be that as it may, the individuals don't generally overwhelm alternate individual in multi-objective situation. Hence, a quick non-commanded arranging plan rather than avaricious determination is connected to choose better individual with bring down cost to be held in the populace. The motivation behind this plan is to sort individual as indicated by the level of non-mastery. Every solution is contrasted with different solutions with decide if it is ruled. Solutions that are not commanded by some other solution shape the primary non-overwhelmed Pareto front. To discover the solutions, it is showed up in the main front are incidentally marked down and a similar method is rehashed. For every solution p, two elements need to be figured, which are the quantity of solutions ruling solution p (introduced as n_p) and the quantity of solutions commanded by solution p (introduced as S_p). In the non-overwhelmed arrangement, great solutions are dictated by positioning the determination technique, and a specialty strategy is connected to keep sub-populaces of good focus. The quick non-ruled arrangement for set P is given in Algorithm 1 [K.Deb *et al.,* 2002].

```
start
    foreach p ϵ P do
        foreach q ϵ P do
            if p dominates q then
                S_p = S_p + {q}
            else
                n_p = n_p + 1
            end
        end
        if n_p = 0 then
            F_1 = F_1 ∪ {p}
        end
    end
    i = 1;
    while F_i ≠ o do
        H = 0;
        foreachp ϵ F_i do
            foreachq ϵ F_i do
                n_q = n_q − 1;
                if n_q = 0then
                    H =∪ {q};
                end
            end
        end
        i = i + 1;
        F_i = H;
    end
end
```

Algorithm 1: Pseudo code of quick non-commanded arranging.

3.3 Procedure of produce new individual

Because of the huge dimensionality and the mind boggling cooperation's among highlights, a few changes in the algorithm are necessarily required to defeat the scourge of dimensionality and to build the classification precision together. To look through the solution space in depth and to keep up decent variety in the populace, in-depth search is required. To accomplish this, every solution of the populace ought to be assessed in alternate points of view. R-ABC utilizes distinctive portrayals which are binary and persistent space, individually, so they utilize diverse approaches to create new solutions. In R-ABC, for every solution x_i neighbourhood solution x_k chosen by means of arbitrary determination in the phase of utilized honey bee or through probabilistic choice in the phase of onlooker honey bee. Following determination process (that is the selection process), the 2-point crossover and 2-way mutation are consecutively connected to produce new child-bee.

3.3.1 Two-point crossover

Two positions are arbitrarily decided on binary guardians x_i *and* x_k. Everything between the places of x_i is replicated to x_k to create the main posterity. At that point, everything between the places of x_k is replicated to x_i, to create the last one. By this way, two child-bees are produced.

3.3.2 Two-way mutation

Another mutation plot is connected in this investigation. In initial stage, a number inside the scope of 0 and 1 is consistently created. In the event, created number is more prominent than 0.5, a situation with esteem 1 is picked and its position is set to 0. Something else, a situation with esteem 0 is picked and its position is set to 1. Along these lines, decent variety is fulfilled in solution age and two child-bees are produced. In the same way new child-bees are created for each parent bee.

In view of the general structure and the above mentioned scheme, one can see that the proposed algorithm provided solution is arbitrarily fit for every current solution in the phase of employed honey bee. Between the present solution and its neighbourhood solution, the proposed solution generator is connected to shape another solution set S; along these lines, four child-bees are produced for every solution. It's necessary to note that the connected algorithm NSG is utilized. After the employed honey bee stage is finished, the solutions in the association set of X and S are positioned utilizing non-commanded arranging, and SN number of solutions are chosen to refresh the populace set X through rank and swarming separation. At that point, the spectator honey bee eliminate is conveyed. In the spectator honey bee stage, a neighbour is haphazardly picked utilizing thermodynamic standards, and afterward hereditarily propelled NSG generators are connected to create new solutions as in utilized honey bee stage. From that point onward, the populace set X is refreshed by choosing the SN most elevated positioned solutions from the association set of X and S.

3.4. Portrayal and fitness function

Every solution speaks to the actuation code (chosen or not-chosen) of the corresponding highlight. While launch codes change in the range in the vicinity of 0 and 1, they appear through discrete esteems 0 and 1. On the off chance that the launch code of a position is more prominent than a client determined limit esteem, its relating highlight is chosen; else, it isn't chosen. In this examination, the edge esteem is characterized as 0.5 as in [B. Xue *et al* 2013 & 2014].

4. ABOUT THE DATASET

The performance of the proposed R-ABC is experimented in PIMA Indian diabetes dataset [Kindie Biredagn Nahato *et al.*, 2016] that has been obtained from National Institute of Diabetes and Digestive and Kidney Diseases. The chosen dataset is multivariate in nature and it contains 768 instances with 9 attributes including the class label. 268 instances are identified as the patients with gestational diabetes. The attribute contains mixture of integer and real numbers. The attribute information is shown in Table-1.

Table-1. Attribute Information of PIMA Dataset.

S. No.	Feature	Description	Domain	Zero entry
1	Preg	Number of times pregnant	0-5	111
2	Glu	Plasma glucose concentration a 2 h in an oral glucose tolerance test	0-199	5
3	Bp	Diastolic blood pressure (mm Hg)	0-122	35
4	Skin	Triceps skin fold thickness (mm)	0-99	227
5	Insulin	2-h serum insulin (mu U/ml)	0-846	374
6	BMI	Body mass index (kg/mtsq)	0-67	11
7	DPF	Diabetes pedigree function	0.078-2.42	-
8	Age	Age (years)	21-81	-
9	Class	Class label	0 or 1	NIL

5. PERFORMANCE METRICS

Experiments were conducted on the selected clinical datasets using SCILAB 6.0.0. The performance metrics namely, accuracy, sensitivity, specificity, True Positive Rate (TPR), False Positive Rate (FPR) and precision were used for evaluating the proposed work. The metrics are computed by considering True Positives (TP), False Negatives (FN), True Negatives (TN) and False Positives (FP). True Positives (TP) refer to those instances that are truly identified as a diseased patient by the classifier. If the patient is not correctly classified, it becomes False Negatives (FN). Healthy instances correctly identified by the classifier becomes True Negatives (TN), if not it becomes False Positives (FP).

Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
True Positive Rate (TPR)	$\frac{TP}{TP+FN}$
False Positive Rate (FPR)	$\frac{FP}{TN+FP}$
Precision	$\frac{TP}{TP+FP}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$

6. RESULTS AND DISCUSSIONS

The overall performance analysis of the FELM and the proposed CFS based SVM (CFS-SVM) in terms of TP, TN, FP, FN, sensitivity and specificity is presented in Table-2. Also the performance analysis in terms of TPR, FPR, precision and Accuracy is portrayed in Table-3.

Table-2. Performance Analysis of TP, TN, FP, FN, Sensitivity and Specificity.

Metrics →	TP		TN		FP		FN		Sensitivity		Specificity	
Algm / Rate	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)
80-20	199	216	49	37	10	6	10	9	95.22	96.00	83.05	86.05
70-30	186	214	53	35	20	9	9	10	95.38	95.54	72.60	79.55
60-40	178	202	52	41	21	12	17	13	91.28	93.95	71.23	77.36
50-50	177	200	44	41	22	13	25	14	87.62	93.46	66.67	75.93

Table-3. Performance Analysis of TPR, FPR, Precision, Measure and Accuracy.

Metrics →	TPR		FPR		Precision		Accuracy	
Algm / Rate	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)	FELM	Proposed (R-ABC)
80-20	95.22	96.00	16.95	13.95	95.22	97.30	92.54	94.40
70-30	95.38	95.54	27.40	20.45	90.29	95.96	89.18	92.91
60-40	91.28	93.95	28.77	22.64	89.45	94.39	85.82	90.67
50-50	87.62	93.46	33.33	24.07	88.94	93.90	82.46	89.93

As far as inferences from the results are concerned, the accuracy of the proposed R–ABC is improved and the time taken for feature selection is reduced. It is to be noted that the existing and proposed classifiers are allowed to train first and tested next.

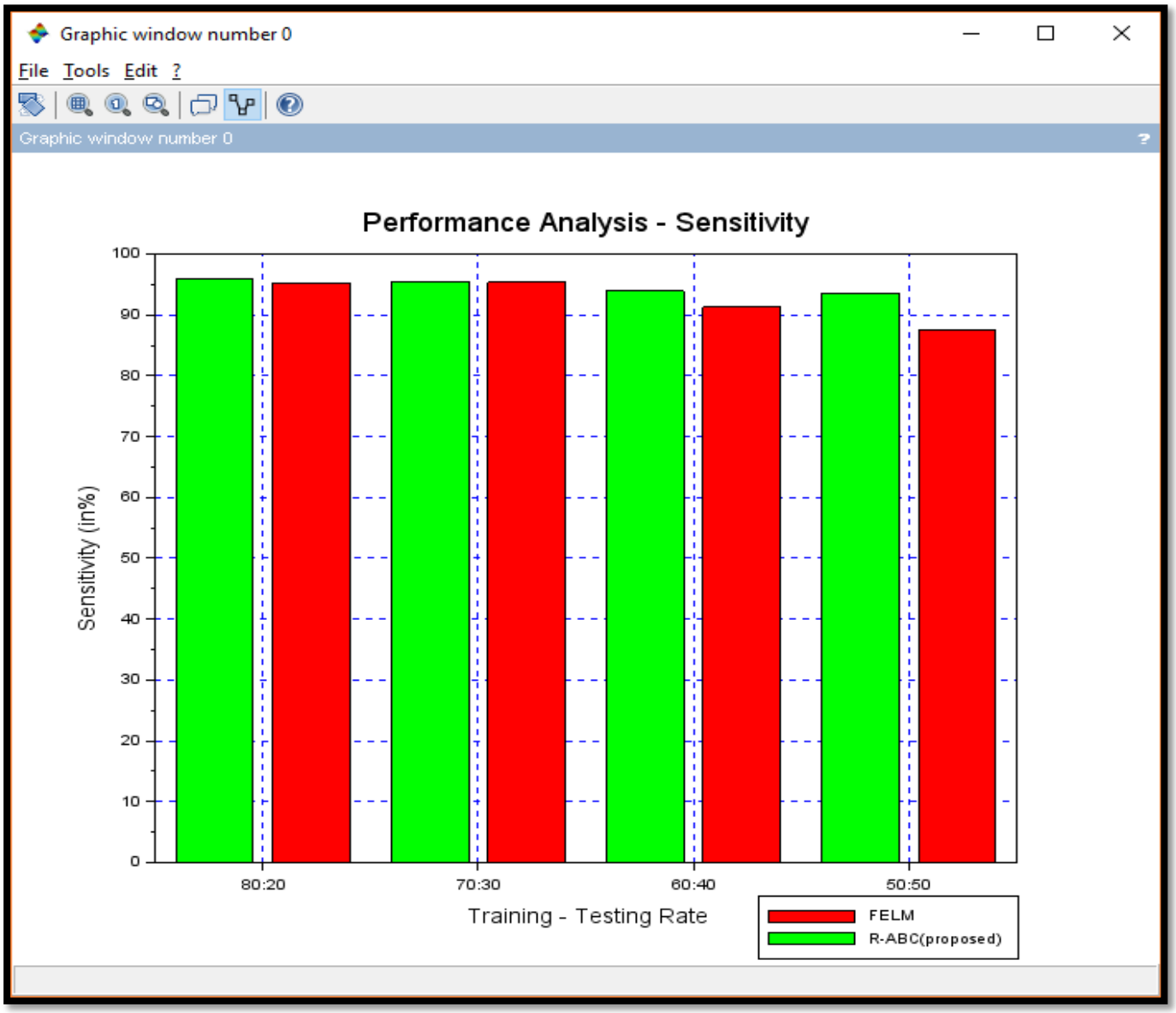

Figure-1. Performance comparison of sensitivity for FELM Vs R–ABC with varying training and testing rate.

Sensitivity is the measure of proportion of actual positives which are correctly identified as positives by the classifier. From the Figure-1 it is clearly evident that the proposed classifier performs better in identifying the positives than the FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al*., 2016). The result values of Figure-1 are predicted in Table-2.

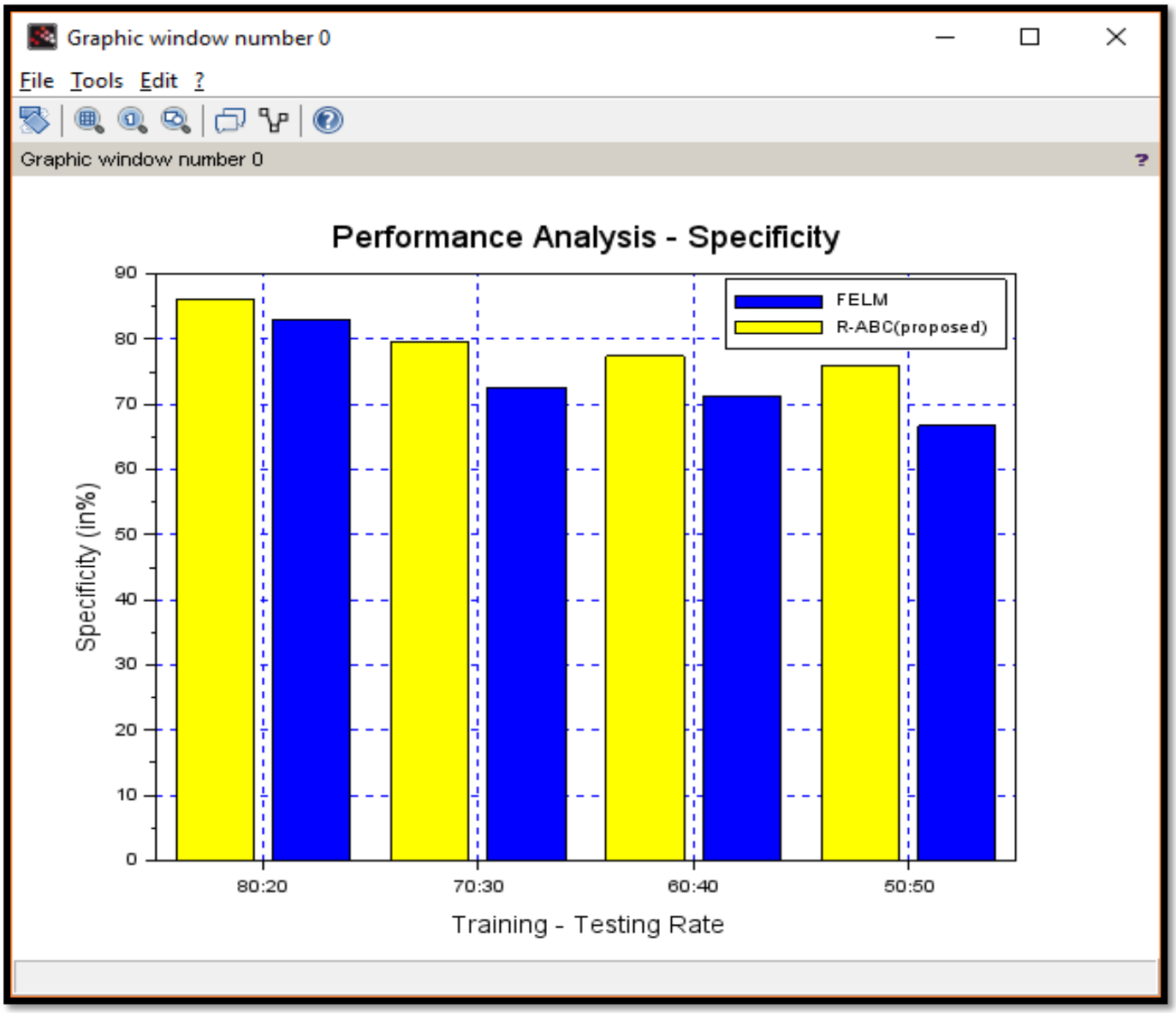

Figure-2. Performance comparison of specificity for FELM Vs R–ABC with varying training and testing rate.

Specificity is the measure of classifier's ability to identify negative results. From the Figure-2 it can be observed that the proposed mechanism does not work better in terms of specificity than the FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.,* 2016). This is due to the degree of relevance mismatch. The result values of Figure-2 are predicted in Table-2.

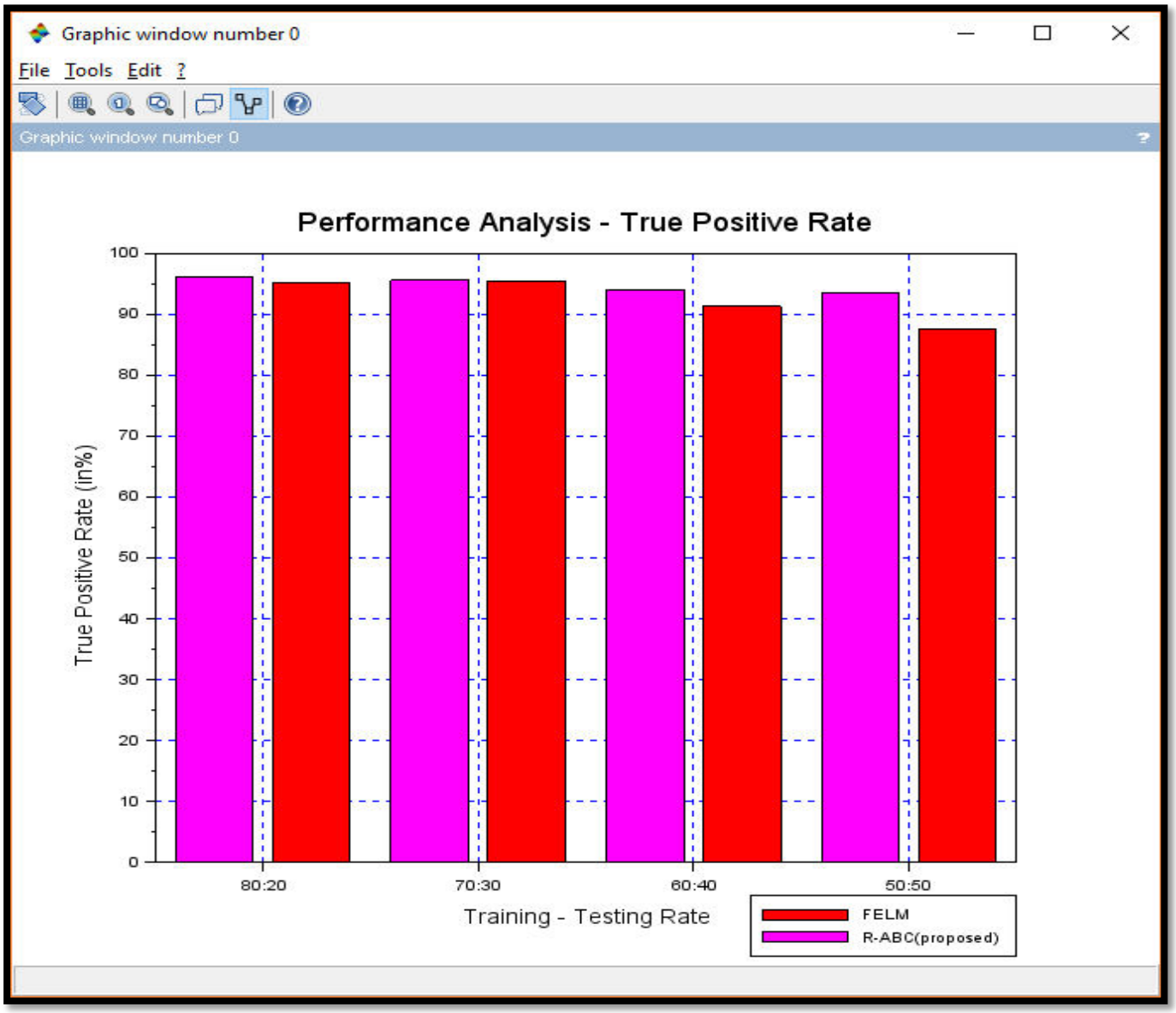

Figure-3. Performance comparison of true positive rate for FELM Vs R–ABC with varying training and testing rate.

True Positive Rate (TPR) refers to the positives that were correctly labelled by the classifier. From the Figure-3, it is evident that the proposed R–ABC produces better TPR than the FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.*, 2016). The result values of Figure-3 are predicted in Table-3.

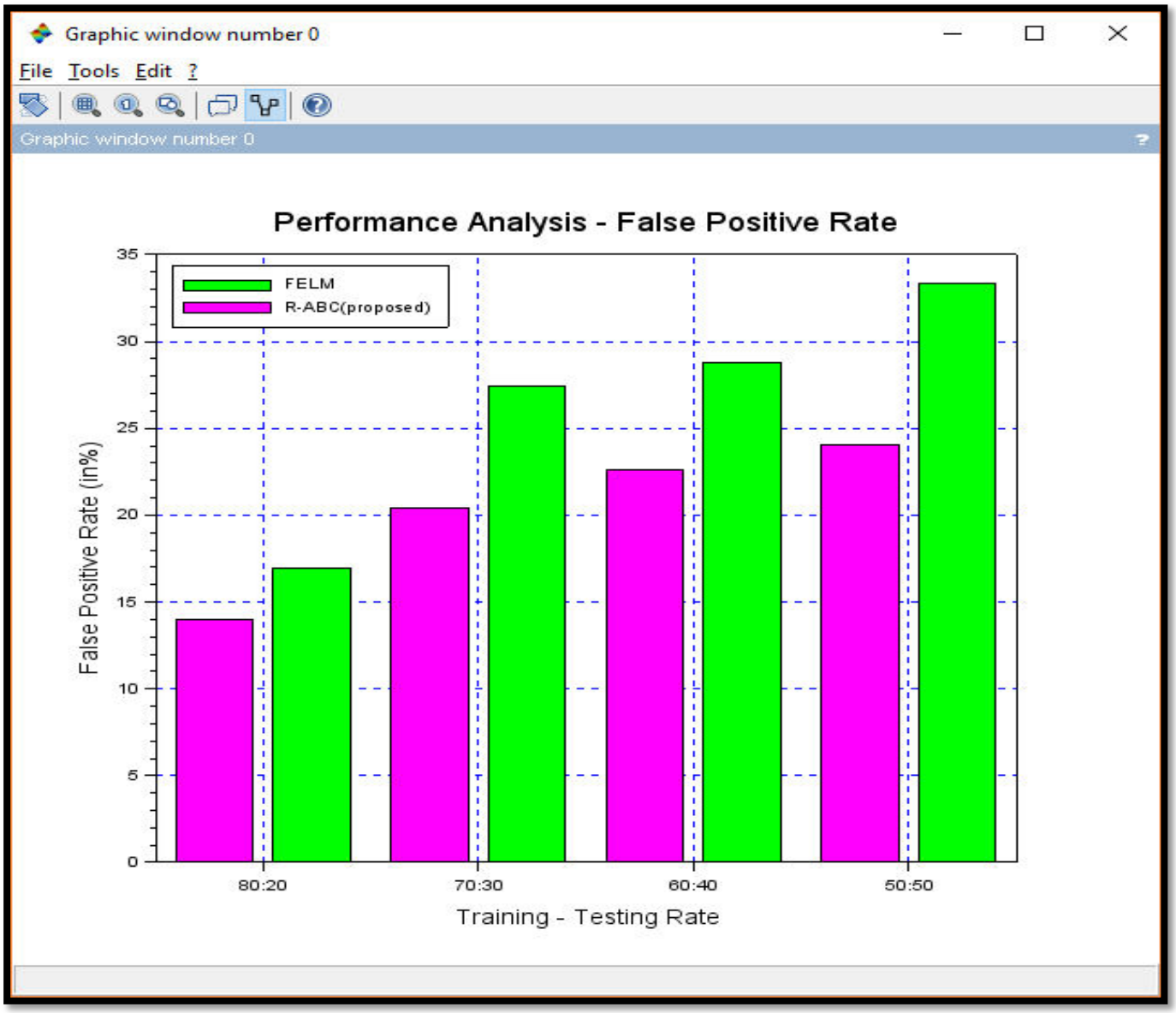

Figure-4. Performance analysis comparison of false positive rate for FELM Vs R–ABC with varying training and testing rate

False Positive Rate (FPR) refers to the negatives that were incorrectly labelled as positive. From the Figure-4, it is clear that R–ABC attains the certain degree of relevance mismatch and results in producing a little bit of increase in the false positive rate in certain Training and Testing Rate when comparing with FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.*, 2016). The result values of Figure-4 are predicted in Table-3.

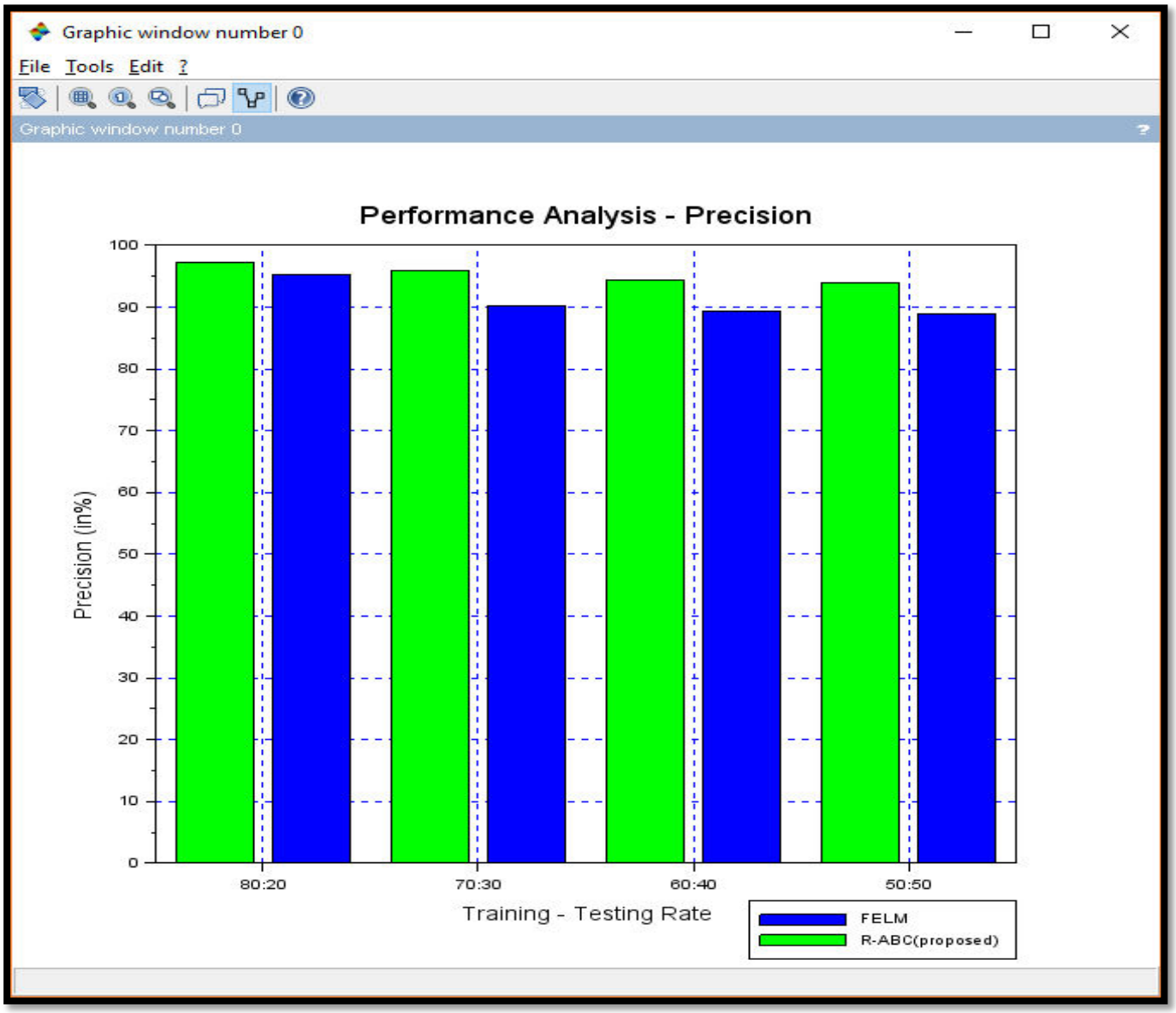

Figure-5. Performance analysis comparison of precision for FELM Vs R–ABC with varying training and testing rate.

Precision is the measure of accurately predicted positive values to the total predicted positive values. From Figure-5 it is clear that, R-ABC predicts the accurate positives than the FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.*, 2016). The result values of Figure-5 are predicted in Table-3.

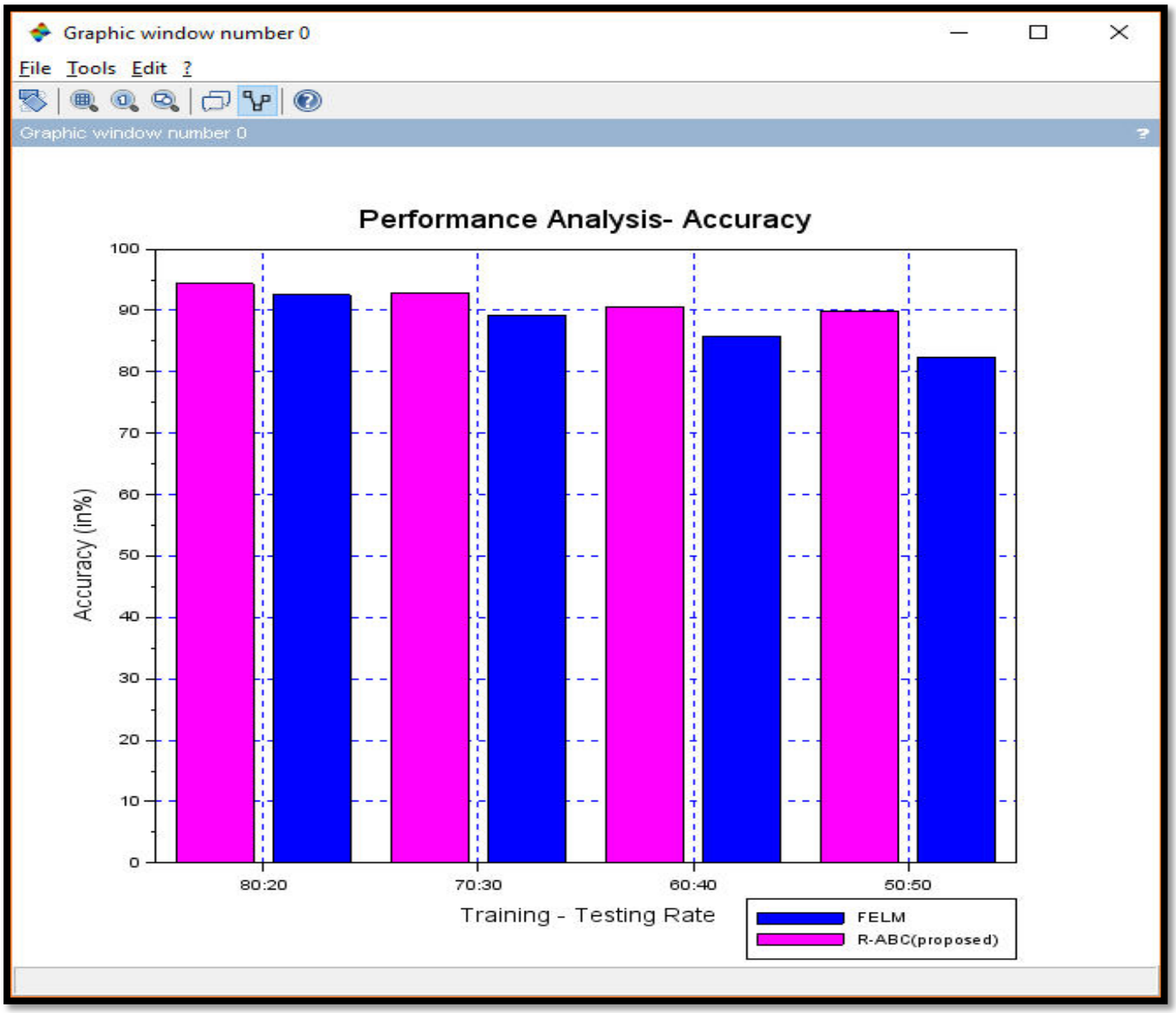

Figure-6. Performance analysis comparison of Accuracy for FELM Vs R-ABC with varying training and testing rate.

Accuracy is the measure of ratio of correctly predicted observation to the total observations. The accuracy result is portrayed in Figure-6 and it illustrates that the proposed R–ABC harvests better accuracy than FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.*, 2016). The result values of Figure-6 are predicted in Table-3.

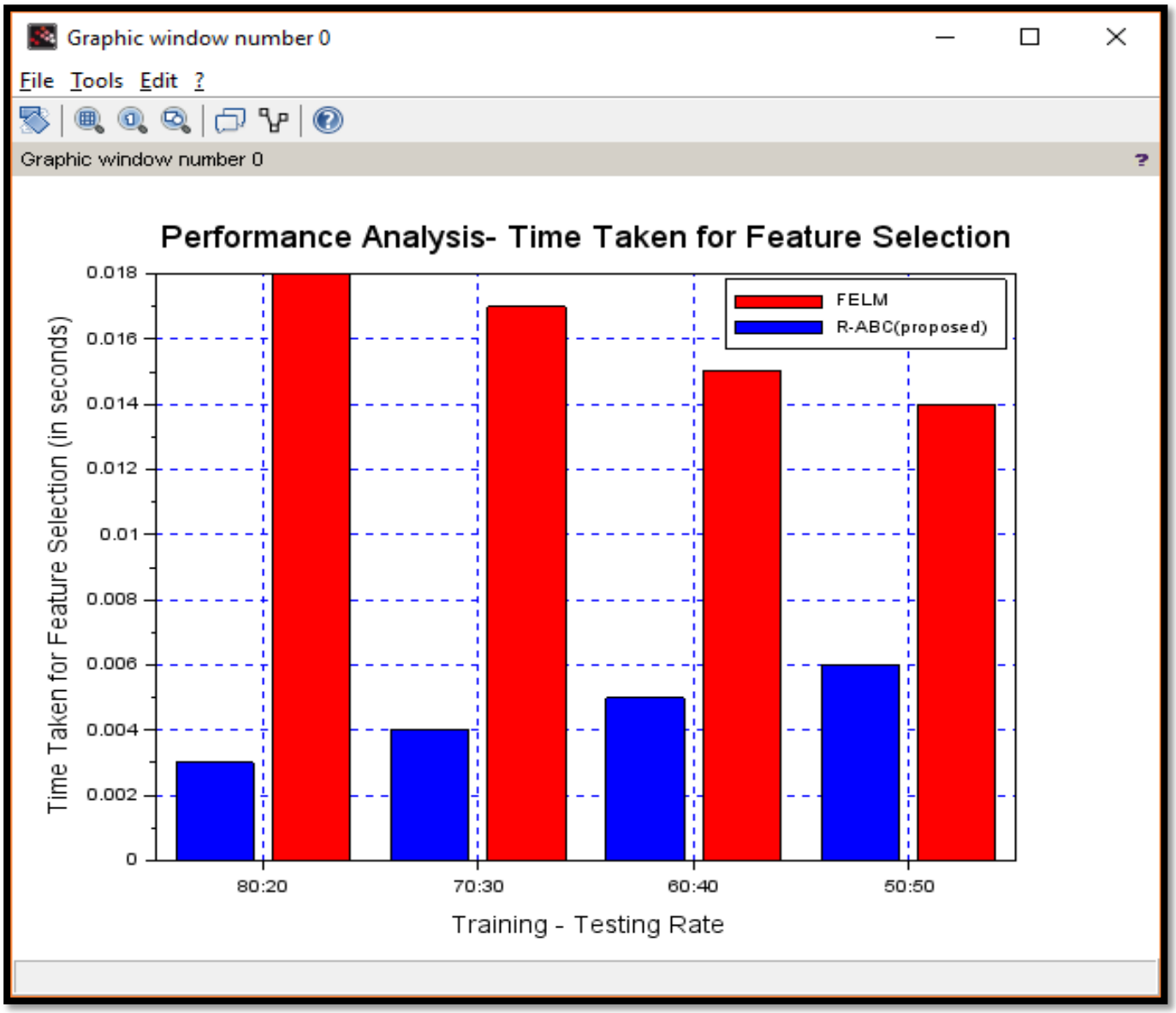

Figure-7. Performance analysis comparison of elapsed time for PCA-SVM Vs R–ABC with varying training and testing rate.

Time taken is the measure of finding how much period the algorithm takes for feature selection. Figure-7 shows that R–ABC took less time for feature selection than the FELM (Fuzzy-sets and Extreme Learning Machine) (Kindie Biredagn Nahato *et al.*, 2016).

7. CONCLUSIONS

In this phase of research, in order to reduce the complexity of feature selection and classification, a receptacle artificial bee colony (R-ABC) classifier is proposed. Unlike conventional ABC, many modifications are done by making use of negligible free vitality, swarming separation task conspire, two - point crossover operation and two - way mutation operation are performed. Quick non-commanded arranging arbitrarily is decided for every present solution in the utilized honey bee stage. Between the present solution and its neighbourhood solution and specifically the proposed solution generator is connected to shape another solution set. With the help of edge esteem the classification is performed. Performance metrics such as sensitivity, specificity, true positive rate, false positive rate, precision, accuracy and time taken for feature selection are taken into account. The simulation results are presented that attained better performance in terms of the chosen performance metrics.

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