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USING DECISION TREE-BASED OPTIMIZATION ALGORITHM TO DESIGN AN INTELLIGENT E-LEARNING PLATFORM EVALUATION METHOD FOR IRAQI MINISTRY OF HIGHER EDUCATION (MOHE)

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ABSTRACT E-learning has a great influence in the modern universities, especially in higher education institution. Today there are a number of local and international e-learning platforms available on-line to provide scientific content, quizzes, and exams, most of them are not concerning student's behavior in these platforms or the goodness of the system performance, therefor an optimization algorithm have been proposed to create an intelligent e-learning platform to upgrade the available ones, to shed the lights on each student's behavior, and to automatically evaluate the performance of the proposed LMS learning environment, in order to create an optimal education platform for Iraqi post graduate studies, a decision tree classification algorithm have been used along with particle swarm optimization algorithm (PSO) in order to create a hybrid algorithm to enhance the decision tree especially (C4.5). A customized dataset consist of (demographic data, student's score, and student's behavior) used to train the classifier, and then other classification algorithms have been used to make a comparison with the proposed algorithm. Our proposed algorithm shows promising results among other classification techniques.

KEYWORDS : E-learning, LMS, Iraqi post graduate studies, decision tree, and particle swarm optimization.

INTRODUCTION

Modern technologies is the language of our education reality today, therefore e-learning platform takes the credit of being the most interested education method among schools, institutions, and universities. Higher education studies have been the focus of many scientific institution in Iraq to keep pace with the advanced technologies and to upgrade the Iraqi education reality, e-learning on the other side has been recently used in the Iraqi universities as a blended learning method along with traditional learning, In this research we use the most widely used classification algorithm along with most interested optimization algorithm to present an intelligent algorithm to measure the effectiveness and efficiency of the proposed scientific platform. Decision tree algorithm has been used to create a classification technique to classify the goodness of the proposed platform. Decision tree is a machine learning tool used widely for classification and prediction problems, the most important advantage of decision tree is that it facilitates a complex problem by breaking it down into more simpler form, hence providing an easy interpret solutions by classify the given problem into an IF-THEN rule. Because decision tree performs a greedy search in its nature and it is a top-down algorithm, there is a possibility to be trapped into a local optimal path and never reaches a global optimal one which is the desired one (C.-H. Jun et al., 2013). Therefore an optimization algorithm has been used to overcome this possibility, these algorithm is called Particle Swarm Optimization (PSO) algorithm. PSO algorithm is used for its marvelous search ability. It is used in various fields to overcome a search problem (K.-H. Chen et al., 2014). It is a population-based artificial intelligence which mimics the social behavior of flocks of birds. The flocks try to find an optimal solution in the given search space, each particle in the swarm has its own velocity and position each particle position has the possibility to be a global optimal solution (K.-H. Chen et al., 2014). Many studies have been taken place to classify a dataset using an optimized classification algorithms based on swarm intelligence techniques, the following studies summarize these techniques, (C.-H.Jan et al., 2013) proposed an adaptive particle swarm algorithm to enhance the splitting threshold of a decision tree algorithm the results shows that the proposed method has great impact for enhancing the accuracy of decision tree prediction. (K.-H. Chen, et al., 2014) their research suggested a novel study to optimized a decision tree classifier by utilizing PSO algorithm for cancer classification by using 11 gene expression of cancer and compare the proposed algorithm with other dataset, their results shoes that the optimized decision tree has a promising results of the classification accuracy. (M. Liu, 2015) proposed a swarm optimization algorithm as a strong method to measure a student's course engagement of long-short term activates in a cloud-based platform. (K. Govindarajan et al., 2015) analyzed the performance of the students using clustering mechanism applied by their proposed parallel PSO algorithm (PPSO) to perform a quality measurement of the proposed clustering method. (A. A. Yahya,2017)) used PSO algorithm as a classifier, this paper studies how efficient can PSO algorithm be if it is used in the educational data mining section based on Rocchio algorithm (RA). (S. M. H. Hasheminejad and M. Sarvmili, 2018) proposed a research to predict the student's final score by using PSO algorithm and compare the results with other classification algorithms to find that their proposed algorithm, S3PSO has a great advantage in classification accuracy of the proposed Moodle dataset. Section two includes our practical work to design and implement the proposed e-learning platform, section three explains the algorithms that used to build the model, section four is about applying the proposed model, section five discusses the results, and section six contains the conclusion and the suggested future work.

2. Practical work

Practical work consists of two steps:

First step is to design and implement an electronic e-learning platform for selective courses that targeted Iraqi higher education studies. The proposed e-learning platform allows postgraduate students, especially computer science majors, to choose the courses they wish to study optionally. After the student chooses the course, there are several stages to pass the chosen course. The course is divided into three sections (easy, medium and difficult), and each section to have quizzes and tests to determine the progress of the student and the level of difficulty or ease of course, after that we developed an algorithm to determine the success rate of the students. There are also several measures to predict the behavior of the student inside the platform. The electronic platform contains several pages, such as an electronic library containing several scientific materials and a chat room that allows students to ask a questions and communicate, and there are additional courses such as the English language course, At the end of the course for the student who will pass all stages of the given there are a certification upon the completion of the course, and according to the student's behavior we will be calculated the efficiency and effectiveness of the proposed e-learning platform as following diagram shows first step of practical work:

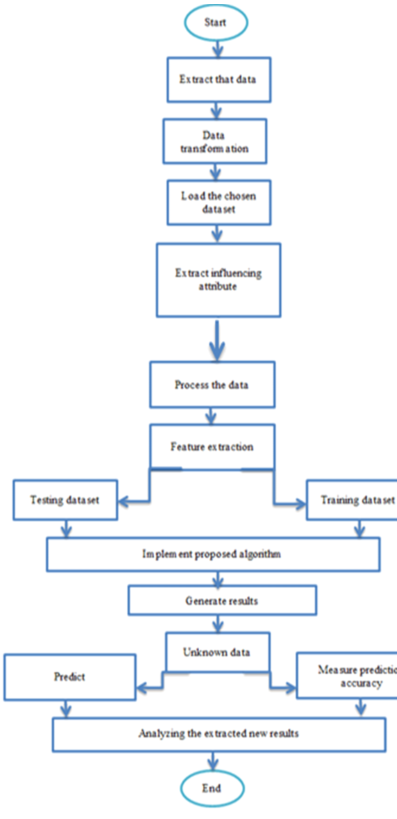


Figure1. Practical work-First step

Second step:

Is about determined the optimization algorithms as well as customizing the training dataset to train the proposed classifier.

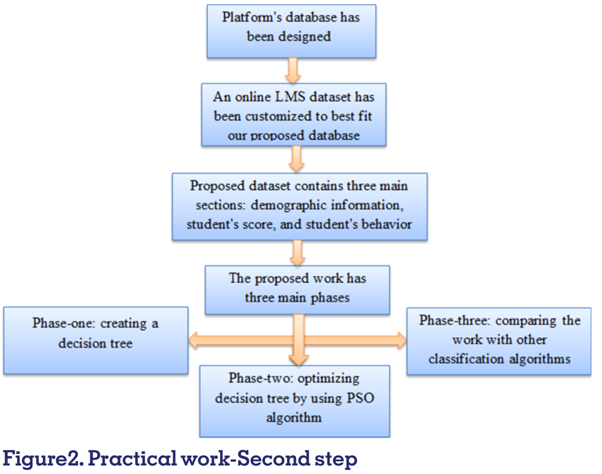


Figure2. Practical work-Second step

3. Intelligent system-evaluation Algorithm (ISEA)

In the era of technology and digital progress we are currently experiencing the existence of electronic platforms is available to a large extent, especially in the field of e-learning because of the importance of education in general, but e-learning platforms are currently available almost all provide scientific materials electronically with some general characteristics of e-learning link to traditional education, but These platforms do not follow the students' learning behavior in the electronic platform and do not evaluate the system performance. In this sense, we have to raise this proposed e-learning platform to an intelligent learning platform based on the principle of artificial intelligence that monitors the learning behavior of each student. Based on these data, the system evaluates itself in general and produce's a the results to five major evaluation dataset and shows the results to the supervisors of the platform to make the necessary decision to modify the platform or to follow the behavior of students inside the platform, the proposed algorithm includes two main phases, first phase is constructing a decision tree algorithm especially C4.5 for its great knowledge representation capabilities, C4.5 has been posted in the first ten algorithms in data mining (C. Turato et al., 2012). Second phase is about optimizing C4.5 algorithm by utilizing swarm intelligence especially PSO algorithm.

3.1 Phase-one: Decision Tree algorithm

Decision tree is a form of machine learning and it is widely used for classification and prediction techniques successfully in many fields such as patient diagnoses, customer's evaluation, and networks detection (C.-H. Jun et al., 2013).. The decision tree algorithm is quite familiar for its robustness and knowledge proficiency with a learning time complexity of O (n log 2n) (A.C. Tan et al., 2003). It is a common analytical classifier produced by Ross Quinlan in 1993. Primarily, C4.5 is an expansion of Quinlan's earlier ID3 algorithm. C4.5 can be applied to create a decision tree for classification. The learning algorithm utilizes a divide-and conquers approach. C4.5 classifier managing both mix of numeric and categorical characteristics dataset, classifying continuous attributes, creating decision trees, deriving rules, and can even classify data for which characteristics are missing (J.R. Quinlan, 1993). In order to construct a decision tree we need to do the following steps:

1-Data Collection:

Determine the dataset that will be used as a training data to train the classifier on pre-defined labels in order to make a prediction/classification of unknown patterns.

2-Data Pre-processing:

The collected training dataset have to be cleansed in order to remove any noisy data that can affect the correctness of the classification, and then the collected dataset have been modified to be suitable to the proposed e-learning platform.

3-Transforming Classification Rules:

Decision tree classifier making supervised learning classification based on IF-THEN rules, in order to follow up classification new rules needed to be constructed to train the classifier. Training dataset with the attribute and the type of each column as well as the classification rules based on the student's score and learning behavior information. Table (1) illustrates the proposed LMS student's scoring and learning behavior attributes that will be used as inputs to produce e-system evaluation classifier C4.5 input is student's demographic info. Plus student's score C4.5 output is system performance assessment/evaluation according to a pervious learning dataset and c4.5 inputs.

Table1. LMS parameters

Num.	Attribute	Type
1.	Pre-Test-score	Number (0-100)
2.	Quiz-1-score	Number (0-100)
3.	Quiz-2-score	Number (0-100)
4.	Quiz-3score	Number (0-100)
5.	Final-score	Number (0-100)

6.	Number-of-passed-levels	Number (0-4)
7.	Pass-Fail	Binary (0-1)
8	Certification	Binary (0-1)
9.	S2-Open-library	Binary (0-1)
10.	T2-Take-e-course	Binary (0-1)
11.	U2-Enter-chat	Binary (0-1)
12.	V2-Number-of-material-downloaded	Number (0-10)
13.	Assessment	Number (0-110)
14.	System-performance	Polynomial

4-Loading the Training Dataset:
The dataset fields that will be entering the evaluation process to assess the overall system evaluation will be determined. Then decide the column that will be used as a label to classify the entire performance of the platform, after assigning the values for each column.

3-Data Classification:
Using decision tree classifier, especially C4.5 classification algorithm (1) as the following:

Start
Input: Training dataset
Output: Classification rules, Labeled data
Step1: Import Dataset, from a local data repository.
Step2: Visualized the data, for every attribute a, locate the normalized information gain ratio of splitting on the pre-determined labeled attribute.
Step3: Let the labeled attribute has the highest normalized information gain.
Step4: Calculate the statistics.
Step5: Find a decision rule that breaks on the labeled attribute.
Step6: Repeat on the subset achieved by splitting on the labeled attribute, and append those nodes as children of the node.
Step7: Create a decision tree.

End

Algorithm1. C4.5

3.2 Phase-two: Particle Swarm Optimization (PSO) algorithm: This phase has two sub phases:

First sub-phase: is preparing the particle swarm optimization (PSO) algorithm and chooses its inputs and outputs. It is an evolving optimizing algorithm acquired of a biological action of birds. It is named as Particle Swarm Optimizer. By each particle, there are two uses describing a particle's location and speed. Moreover, each particle has a knowledge element that mixes two kinds of data: cognitive data (particle's own experience) and social data (entire swarm's experience). While the cognitive information describes the best solution a particle has ever produced in its records, social information is the best place the swarm has ever produced. Collectively, the cognitive and social information is utilized to determine the speed of particles and then their next positions. Typically, PSO begins with an arbitrary initialization of particles' velocities and positions. Next, the particles flow from one position to another to obtain an optimal solution.is par Because we don't want the classifier to be trapped in a non-optimal solution space, we calculate the fitness that is suitable for all particles in the search space (J. Kennedy and R. C. Eberhart, 1995). The reason of using PSO optimization algorithm along with decision tree algorithm is because as we mentioned before decision performs a top-down greedy search method which tries to find a local optimal solution at each step with the purpose of finding a global optimal one. And because of that a decision tree may be trapped in a local optimal solution space. Figure (3) illustrates the local optimal solution space starting at M, a greedy algorithm will find the local maximum at "m", oblivious to the global maximum at "A". In machine learning there is a value called a cost function which is a value that needed to be minimized according to a given dataset, sometimes an algorithm can be trapped in one of a local optimum values that makes the value of cost function high which is something we don't want it to happen.

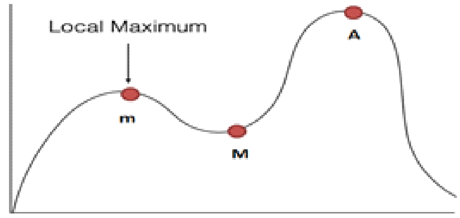
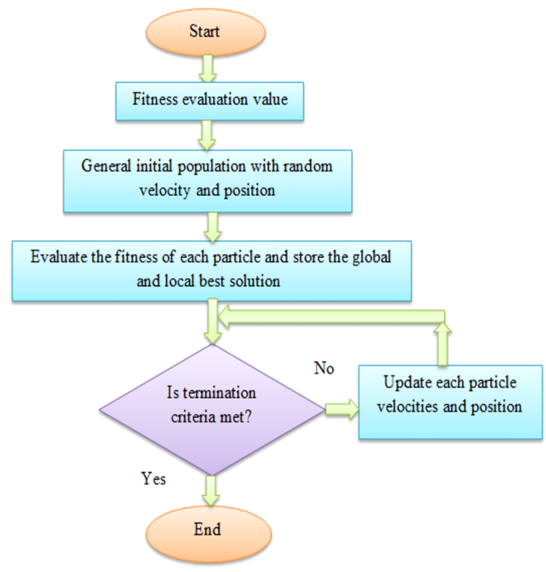


Figure3. Local optimal solution

So when a decision tree search for a splitting criteria, it takes only one attribute at a time, this procedure may produces a hazard of trapping the search in a local optimal solution area, wears the splitting criteria has to be simultaneously searched to avoid such problem. Simultaneously search means that the algorithm must take every possible criteria at the same time which will eventually leads to producing a large computational time, to bypass this procedure a two phase hybrid algorithm is proposed, first phase is construction a decision tree and second phase is optimizing the constructed decision tree. This algorithm is used for its great search capabilities, each particle (P) is considered a point into a search space (N-dimensional space), which is in the e-learning platform case it is the dataset repository, every particle is subject for following its fitness utilizing a suggested fitness function that assesses the performance of the particle in every repetition. Every particle is connected with a similar velocity (V), which supports the particle flow from one location (X) to the optimal location, the ability to memorize a previous position. The PSO confluence of the PSO depends on the individual location (P-best) of the particle and the global optimal position (G-best) of the entire group. The flowchart of the PSO algorithm shown in the following flowchart:



Flowchart-1.Particle swarm optimization

As mentioned before the particles are moving in a search space of N-dimensional to find an optimal solution, the progress of the particles is guided by the position vector of all particles and a velocity (speed) vector. In an N-dimension exploration place, the position and velocity are expressed as the following: The *ith* particle position represented as$xi=[xi^1,xi^2,\ldots,xi^n]$. and the particle velocity vector represented as $vi=[vi^1,vi^2,\ldots,vi^n]$. Each particle returns a path in a search space which is related to the best solution (fitness) that has been recorded by one particle, this value is called "P-best" which is the local best solution denoted as: $PBi=[pbi\wedge 1, pbi\wedge 2,\ldots pbi\wedge n]$. In addition to this value, a global best value will be selected to be the best solution that will be denoted as "G-best" denoted as: $GBi=[gbi^1, gbi^2,\ldots,gbi^n]$, which is the best value that has been reached by the neighbored particle so far. At the end the algorithm will find a global optimal solution for a given function, the position of a particle can represent a candidate solution, the particles initialize the search space randomly, where xi^d: i= 1,2,3,....,m (m is the number of particles) and d=1,2,3...,n (n is the dimensions of the data). Then the particles will update their position and velocity according to Equation (1) And (2) as the following:

$$v_{id}^{new} = w \times v_{id}^{old} + c1r1\,(pb_{id}^{old} - x_{id}^{old}) + c2r2\left(gb_{d}^{old} - x_{id}^{old}\right) \qquad (1)$$

Where: $d = 1,2,3,\ldots,D$, and $x_{id}^{new} = x_{id}^{old} + v_{id}^{new}$, $d = 1,2,3,\ldots D;\ i = 1,2,3,\ldots,N$ (2)

Where (W) is the internal weight, it specifies the contribution of a previous velocity to a current one. (C) is a scaling coefficient which is a constant positive value; it specifies the ability of social learning. (R) is a random number that adds randomness to the movements of the particles, (V-max) and (V-min) are the values of the velocities; (N) is the size of the entire swarm. The given Algorithm shows general particle swarm optimization algorithm (2).

```
Start
Input: Initialization weight, and velocity, swarm size,
number of particles, acceleration coefficient, random
value.
Output:  Global optimal solution
Step1: While the termination condition is not met
For each particle:
a. Estimate the fitness of the current particle
b. Examine it to its local best position P-best value;
update it if there's a value best than the current one.
c. Compare it to a global G-best value; update it if
there's a value best than the current one.
d. Compute a new velocity V
Step2: Move the particle to its new position X
Step3: Update
End for
End
```

Algorithm2. PSO

Second sub-phase: optimizing the proposed decision tree to make a hybrid system-evaluation algorithm to evaluate the performance of the platform. This phase includes optimizing the decision tree through creating a decision tree as mentioned before by using C4.5 that has split a criterion that chooses the best attribute to make it the root node, this criterion is the Information gain ratio. The Information gain (S, A) of a point A corresponding to set of patterns S, is described as Eq. (3)

$$\text{Information Gain }(S,A) = \text{Entropy}(S) - \sum \text{value}(A)\frac{|Sv|}{|S|}\,\text{Entropy}(Sv) \qquad (3)$$

Where value (A) is the inclination of every probable utility for attribute (A), and (Sv) is the subset of S for which A has value v. Remark the first phase in the equalization for Gain is only the entropy of the initial set S and the next set is supposed to value of the entropy after S is partitioned utilizing feature A. The predicted entropy represented by the second term is the rank sum of the entropies of each subset Sv, measured by the fraction of samples |Sv|/|S| that belong to (Sv). Gain (S, A) is, consequently, the assumed decrease in entropy generated by recognizing the value of feature A.

The Entropy is given by Eq. (4):

$$\text{Entropy}(S) = \sum_{i=1}^{c} -\text{pi}\log 2\ \text{pi} \qquad (4)$$

4. Proposed Approach

This research provides an integrated approach that combines a C4.5 classifier with a PSO algorithm for the attributes selection that reduces the time complexity for more efficient and effective decision tree classification for a given LMS dataset attributes.

4.1 Solution Representations:

In this proposed method a particle represents a potential solution in the N-dimension space, the particles represent a binary array with length n, where n is the total number of attributes of the LMS dataset. The value of 1 bit presents a selected attribute, whereas, a value of bit 0 represents an unselected attribute. For instance, the particle 011010 with six attributes selected and creates a binary expression the data indicated that the second, third, and fifth attributes are selected only. Table (2) gives an example of the particles over attributes: The proposed dataset of the LMS consist of two types of information.

First type: is demographic data that includes:

Table2. Spreading particles over dataset attributes

Name	Abbreviation	Type	Description
Student ID	SID	Input attribute	Student's profile number
First name	FNM	Input attribute	Student's first name
Last name	LNM	Input attribute	Student's last name
Gender	GRD	Input attribute	Student's gender male/female
Mobile	MOL	Input attribute	Student's mobile number
E-mail	EMI	Input attribute	Student's or faculty e-mail
Password	PAS	Input attribute	Student's encrypted password
University	UNI	Input attribute	Student's university that uses this LMS
Country	COU	Input attribute	Student's country

Second type: is the student's scoring system inside the platform, Table (3)

gives an example of the student's scores with particles over attributes.

Table3. Student's scores with particles over attributes

Name	Abbreviation	Type	Description
Pre-test	PRT	Input attribute	Pre-test score of 100/100
Level 1 quiz	L1Q	Input attribute	Level 1 quiz score
Level 2 mid-test	LMT	Input attribute	Level two middle test

Level 2 final-test	LFT	Input attribute	Level three final test
Final score	FSC	Input attribute	Final score of the fourth above scores
Pass-fail	PAF	Input attribute	Either pass or fail the course
Certification	CER	Input attribute	Either took certification or not
Open-library	OPL	Input attribute	Open platform library page
Take-e-course	TEC	Input attribute	Take the English extra course
Enter chat	ENC	Input attribute	Either enter chat or not
Number of materials downloaded	NUB	Input attribute	Number of books downloaded from library page
Number of levels	NPL	Input attribute	Number of passed levels
System performance	SYP	Input attribute	System self-evaluation

The following example in table (4) shows the attributes of one iteration, control attributes (CA) will be the attributes of value 1 bit, parameter attributes (PA) will be the attributes of value 0 bit. Result attribute: is either 0 or 1. The table illustrates an entire iteration.

Table4. Illustrates one iteration

Abbreviation	Value	Attributes
SID	0	PA
FNM	0	PA
LNM	0	PA
GRD	1	CA
MOL	0	PA
EMI	0	PA
PAS	0	PA
UNI	1	CA
COU	1	CA
PRT	1	CA
LIQ	0	PA
LMT	0	PA
LFT	1	CA
FCS	0	PA
PAF	1	CA
CER	1	CA
OPL	1	CA
TEC	1	CA
ENC	1	CA
NUB	0	PA
NPL	1	CA
SYP	1	CA

Table (5) shows the result of 1 iteration as the following:

Table5. Results of one iteration

Results:	
1st. iteration	00010001110010111111011

Then we update the dimension d of particle i according to Eq. (5) and Z refer to spreading of the random variable:

$$x_{id}^{new} = 1 \; if \; \Omega\left(vi_{id}^{new}\right) > Z(1{,}0) \quad (5)$$

$$x_{id}^{new} = 0 \; otherwise \quad (6)$$

Where $\Omega(a) = \frac{1}{1} + e^{-a}$ (7)

$a \rightarrow -\infty$ $\Omega(a) \rightarrow 0$ (8)

$a \rightarrow +\infty$ $\Omega(a) \rightarrow 1$ (9)

When a specific mathematical model is lacking, a sigmoid function is often used.

4.2 Initialization of population

The population of the particles in the search space is initialed in the search space of dimension-n, starting the PSO algorithm with a relatively good initial value can lead to a better solution and it can also reduce the convergence time. A probability of 1/2 initial values were assigned to the binary values (0, 1), (if Z(0,1)>0.5) $X_{id}^{new} = 1, else\ X_{id}^{new} = 0$ For the importance of observing the learning behaviors of each student registered in the platform, we assign 5 attributes with a special weight, in order to specify the actual system performance and the most important attribute represents the heavier weights among all given weights. Table (6) shows the process of giving these attributes the weights depends on the following proposed rules:

Table6. Shows the proposed weight

Parameter	Parameter role	Proposed values	
Internal weight (w)	Controlling the impact of the velocity history over a new velocity	Pass-Fail	40
		Certification	30
		Open-library	20
		Take-English-course	15
		Enter-chat	5

The assessment attribute will calculate theses weights according to a proposed formula and it will produce a natural number between 0 and 110 and according to these results the system-performance attribute will be evaluated, the least system-performance value is bad and the greatest one is excellent. In order to create a training dataset an arbitrary spreading of these weights needed to take place, so that a 1000 rows will be produced to calculate the student's scores, student's learning behavior's, and overall system performance.

4.3 Fitness function

Fitness function is the most important part in our proposed C4.5-PSO algorithm; this function calculates the best particle in the population (the goodness). Fitness function assists in recognizing a particular assemblage of characteristics. We apply the C4.5 decision tree to create a pattern of the selected column subset and later assess the learned model. Meanwhile, a PSO creates a selective feature subset, we operate the C4.5 algorithm. As a result, we produce a classifier in the structure of a decision tree which is estimated. We provide this method ten-times cross-validation, what validation does is break the dataset in 10 subsets (trains and builds a model on 9 data subsets) and measure the performance over the 10th data subset, Then it iterates, it selects the 9th different ones and selects another separate test-data subset, then builds the model and measures the performance, and then finally it begins to average that. A function of accuracy will be evaluated according to this formula: Final Accuracy= average (Iteration1, Iteration2, etc.) in order to give an average performance of the model This Operator performs a cross validation to estimate the statistical performance of a learning model. Table (7) gives the following iterations:

Table7. Shows the tenth proposed iterations

1 Iteration	2 Iteration	3 Iteration	4 Iteration	5 Iteration	6 Iteration	7 Iteration	8 Iteration	9 Iteration	10 Iteration

In our purposed method, we applied the C4.5 error estimation rate) as the fitness function of PSO. Accuracy is a generally adopted metric for estimating the achievement of classifiers for years. Accuracy is estimated by Eq.

4.4 The suggested approach:

Utilizing the PSO algorithm simultaneously with C4.5 classifier to mark a class label to estimate the performance of the proposed intelligent e-learning platform. The parameters we applied for PSO are declared as follows: the number of particles in the group was arranged to the number of LMS dataset attributes. C1 and c2 both began at 2, whereas the lower and higher velocities initiated at -5 and 5, sequentially. The inertia weight (w) rated at 0.2. The method was reproduced till either the fitness of the assigned particle

obtained 1.0 or the number of the iterations was performed by the default value of T, which was 1000. Here, the PSO parameter configuration held by a study on different similar examination studies concerning the utilization of PSO, we directed many experiments to test such parameter framework which gives the best goal rate.

Algorithm3. The Proposed Hybrid algorithm

Start
Input: Number of particles, swarm size, $C1, C2, R1, R2, W, Vmax, Vmin$
Output: Global optimal solution
Step1: Initialize population.
Since termination criteria is not met yet, spread the particles (p),
Step2: Evaluate fitness value (the particles evaluated by (C4.5)).
If fitness value of xi is greater than PBi , then PBi = xi
If fitness value of xi is greater than GBi , then GBi = xi
For d = 1; d < no. of the lables; d + +
$v_{id}^{new} = w \times v_{id}^{old} + c1r1\,(pb_{id}^{old} - x_{id}^{old}) + c2r2\,(gb_{d}^{old} - x_{id}^{old})$
If $(v_{id}^{old} > Vmax)$ then $V_{id}^{new} = Vmax$
If $(v_{id}^{old} < Vmax)$ then $V_{id}^{new} = Vmin$
If $(sigmond(v_{id}^{new}) > Z\,(0, 1)$, then $x_{id}^{new} = 1$, else $x_{id}^{new} = 0$
Step3: Next d, i
End for
End

5. EXPERIENCES AND RESULTS:

This section will illustrate in details the result of implementation and evaluation of the proposed method, The proposed model is designed and implemented on the PC that has processor Intel® Core(TM) i5-3230M CPU @ 2.60GHz, and the operating system is Windows 8 (64 bits) and RAM is 4GB. The programming language used is the PHP, HTML5/CSS, and Script language. The Local Web Server used for hosting the proposed platform is the Apache Server; table (8) shows the array of performance attributes:

Table8. Shows number of samples

No.	Label	#of samples
1.	Excellent	370
2.	Very good	401
3.	Good	75
4.	Medium	56
5.	Bad	98
		Total: 1000

5.2 Proposed decision tree discovery rules: The following rules are given to extract knowledge from the proposed optimized decision tree algorithm

Table9. Decision tree rules

Attribute	Rules

Pre-Test-score	IF ((pre-test=0, then print "1"
	IF ((pre-test>=10, pre-test<=50, then print "2")
	IF ((pre-test>=60, pre-test<=70, then print "3")
	IF ((pre-test>=80, pre-test<=100, then print "4")
	Else, print "0"))))

Q2-Pass-Fail	IF((final-score>50),then print 1, else print 0)
R2-Certification	IF((final-score>=50),then print 1, else print 0)
S2-Open-library	S2 Is a character for numbering IF((the student open library, then print 1, else print 0)
T2-Take-english-course	T2 Is a character for numbering IF((the student take English course, then print 1, else print 0)
U2-Enter-chat	U2 Is a character for numbering IF((the student enter, then print 1, else print 0)

Assessment	SUM(Q2,R2,S2,T2,U2)

System-performance	IF ((System performance<=110, System-performance>90), then print "Excellent"
	IF ((System-performance<=90, System-performance>70), then print "Very Good"
	IF ((System-performance<=70, System-performance>40), then print "Medium"
	IF ((System-performance<=40, System-performance>0), then print "Good"
	Else, print "Bad"))))

5.3 Classification accuracy

In this section classification accuracy will be compared with other machine learning (supervisor learning) classification tools which are, WEKA data mining software was used to compare our proposed method with other machine learning classification algorithms on the same customized LMS dataset, the output results illustrates in the following table (10):

Table10. Comparison with other classification

Model X	Correctly classified instances	Incorrectly classified instance	Kappa statistics	Mean absolute error
Logistic Regression	44.4444 %	55.5556 %	0	0.3752
Naive Bayes	55.1667 %	44.8333 %	0.3988	0.2151
Random Forest	60.8333 %	39.1667 %	0.4499	0.2325
Lazy K-Star	21.1676 %	78.8232 %	0	0.357
J48 (C4.5)	66.3333 %	33.6667 %	0.5609	0.1782
C4.5- PSO	99%	0%	1	0

our proposed algorithm has the maximum accuracy among all the classifiers yet a minimum runtime among them which is the objective of our research to enhanced a decision tree result by using PSO algorithm to prevent the classifier to be trapped in a local optimal solution and to spend more time in making a classification process of a given data values. Figures (4) illustrate the accuracy for the given classifiers:

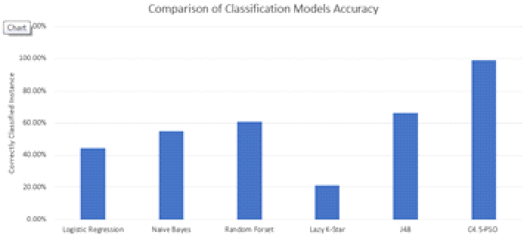


Figure4. Classification accuracy

6. CONCLUSION

E-learning platform presented in this research offers an intelligent system capable of self-evaluation, through the learning behavior of the students and their scores. The purpose of creating an intelligent e-learning environment is to distinguish the performance of the entire platform through the use of artificial intelligence algorithm we create a hybrid algorithm using a decision tree (C4.5) algorithm along with particle swarm optimization (PSO) algorithm to improve the quality of Iraqi e-learning platform for higher education studies, most of the available e-learning platforms doesn't assess the performance of the system intelligently, such as assessing the performance of the platform, ease of the educational content or evaluating the student's behavior in dealing with the platform and their learning abilities. The accuracy of the model to make a supervised machine learning classification method able to classify an unknown patterns based on pre-defined labeled patterns taking in account other data values, the data was collected and determine in advance in order to train the classifier then the patterns of the classified label was then evaluated. Then a comparison with other classification techniques have been taken place, the results show that the proposed algorithm has 99% accuracy which is a promising result. Besides these results there need be a development for a future work that can take place to improve education reality, the suggestion is to include more a bigger dataset, with additional attributes for instance (prediction student's performance from a previous dataset, detect student's cheating, and predict the success or the failure of students before the end of the course) by using other classification methods for example (artificial neural networks ANN).

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