Inductive and Explorative Analysis in M Learning Systems Using Fish School Optimization

Chandrasekar V.[1*] and Mahalakshmi M.[2]
1. Department of CSE, Vimal Jyothi Engineering College, Kannur, Kerala, INDIA
2. Department of CSE, University of Gondar, ETHIOPIA
*vchandruskce@gmail.com

Abstract
In the current study, we discuss the history of mobile learning (m-learning) of benefits, drawbacks as well as problems present in it. M-learning is a novel domain of research which has is rising as a tool for the educational system. M-learning may be utilized for enhancing the learning experiences of students as well as the lecturers. Subgroup Discovery (SD) is adequate to discover the dependencies, that is, finding relationships between dependent as well as various independent parameters, for inductive as well as explorative data analysing jobs. Classifications Based on Association (CBA) that has its basis in a priori algorithms to find association rules. The procedure of Particle Swarm Optimization (PSOA) in discovering optimum values adopts the behaviour of animals in nature. PSOA comprises of a swarm of particles wherein all particles denote candidate solutions. Fish School Search (FSS) signifies a new technique of swarm intelligence to search for the global optimal value, and it owes its inspiration to the schooling activity of fishes in nature. FSS is proven to be efficient in functions optimizations, parameters estimations, combinatorial optimizations, as well as least square support vector machines, as well as geo-technical engineering issues. The outcomes are attained with improved performance.

Keywords: Mobile Learning (M-Learning), Subgroup Discovery (SD), Classification Based on Associations (CBA), Particle Swarm Optimization (PSOA), Fish School Search (FSS).

Introduction

Education is a procedure through which an individual's body, mind, as well as character are built as well as strengthened. It also allows for the individual's holistic development of personality via knowledge acquisition. The knowledge obtained by a learner is dependent on the learning environment as well. In m-learning environments, several mobile devices may be utilized, for instance, mobile phone, personal digital assistants (PDAs), notebooks, tablets, personal computers and so on. For effectively integrating m-learning within a wireless classroom setting, it is necessary for every student in the classroom to possess their own computational devices which have their own wireless transmission capabilities for conducting learning jobs.

M-learning decreases complex working as well as the redundant works taken up by lecturers. It permits teachers to view readily accessible material, transferring, or broadcasting them to the learners. The learners will also be able to see the lessons via videos. To watch the videos, they perform online tests as well as see their grades. Engaging learners in learning activity, involves the exploration, organization of online courses-related resources, answer the questions/assignment utilizing their mobile devices. The m learning is the technique of e-learning that has its basis in the usage of mobile devices, at any point, in any place. It integrates data services as well as mobile services. The teaching as well as learning procedure may be executed at any place, any time, in all devices in in a cost-effective manner.

The benefits of m-learning systems include: usage of cheap technology, improved opportunity to obtain skills at an easy page, privacy when utilizing shared facilities, and so on. The drawbacks, however, also include: increased possibility of cheating, unfair advantage for tech-savvy students, absence of practical, hands-on lessons such as chemistry or physics experiments, lack of socializing among the students leading to a feeling of isolation and so on.

Moodle refers to an open source Learning Management Systems (LMS), that is grounded in a strong pedagogical principle, that was primarily built within an academic context. After registration, anybody can access Moodle, which provides several functions that range from courses management, repositories for courses materials, to monitoring of student activity. The main benefit of the platform is that it is self-contained, wherein the previously mentioned functions are incorporated into one platform, therein leading to the creation of a virtual classroom. Mobile Learning Engine (MLE)-Moodle is a plugin for Moodle that includes an m-learning option to this platform.

Data mining focuses on the discovery of knowledge from datasets and has been described as the nontrivial procedure to identify validated, new, possibly useful, as well as comprehensible pattern in data. The methods may be split into descriptive as well as predictive induction. The latter performs extraction of knowledge with the intention of predicting class value of unknown samples while the former focuses on discovering knowledge from data in the format of patterns [1]. SD refers to a method of the former kind which performs extraction of useful relationships amongst various parameters in terms of a special characteristic called the target parameter. SD is vastly useful in real world applications, including detections of heart diseases and brain ischemia, analysis of financial as well as commercial information, census data mining and so on.

A metaheuristic is described as a repetitive generation procedure that performs guiding of subordinate heuristics through combination of intelligent distinct concepts to explore as well as exploit search space; learning schemes are utilized for structuring data for finding effectively closet-to-optimum solutions. Metaheuristic protocols are approximate methods that may be utilized for solving complicated issues. Popular metaheuristic protocols include Genetic Algorithm (GA), Simulated Annealing (SA), as well as Tabu Search (TS). GA emulates the evolutionary procedue in nature, while TS utilizes the memory structure in living creatures, and SA mimics the annealing procedure of crystalline solids. This work proposes the M Learning systems using fish school optimization and discuss SD mining. Section 2 reviews literature related to the proposed method. Section 3 details the methodology employed, while Section 4 presents a discussion of the outputs of the experimental evaluations conducted in proposed work. Section 5 is the conclusion to the paper.

Related Works

Al-Khalifa and An[2] gave a mobile snap shot response system that utilizes cameras incorporated with cell phones as well as Quick Response (QR) codes for leveraging students interactions in classrooms. Possible objectives of systems are to increase the connectivity between instructors as well as the students through providing students the chance to evaluate the lectures contents as well as post inquiries to instructors after classes. Mobile snap shot response system has been built, executed as well as tested; evaluations of users have proven the systems' ease of usage.

Luna et al[3] suggested a novel grammar-guided genetic programming protocol for SD. The protocol known as Comprehensible Grammar-Based Algorithm for SD (CGBA-SD), merges the needs of finding understandable rules with the capacity of mining expressive as well as flexible solutions because of the usage of context-free grammar. Luna et al., [4] suggested an evolutionary protocol to mine rare-class association rules to gather learner use data from Moodle systems. The investigators analysed the usage of various variables of the protocol as well as how they define the rule features, as well as offers some illustrations of them to display their interpretability, as well as utility in e-learning environment.

Bastos Filho et al[5] analysed the effect of FSS operators on the performance of the protocol in 6 benchmarks. The investigators evaluated the effect of all swimming operators in a separate manner. The investigators also discovered that the volitive method was operator which permits almost all exploration capabilities in the searching procedure. The assessments performed prove that, on average, optimal outcomes are got solely when FSS operators are activated. This implies that every operator is comparatively relevant as well as complementary. Furthermore, the investigators contrasted the FSS output with certain PSOA variants, and proced that FSS performed better than PSOA in certain cases.

de Lima Neto and de Lacerda[6] studied how weight based FSS impacts the automated splitting of school to solve multi-modal benchmark issues. The primary adjustment to generic FSS for producing the weight-based FSS (wFSS), is the inclusion of a relation amongst fishes only depending on factual, pre-existing indication of individual successes. The execution led to a light protocol as well as a technique which yields more adequate potential solutions for optimization issues. Hu et al., [7] built several AI optimization protocols like GA, Ant Colony Optimization (ACO), PSOA, Etc. Artificial Fish School Algorithm (AFSA) is a novel optimizing technique.

Boulkabeit et al[8] suggested a recently proposed bio-inspired optimizing protocol. FSS is employed to the Finite Element Model (FEM) update issue. The output of the protocol is contrasted with 2 other meta-heuristic protocols, GA as well as PSOA. It is noted that averagely, FSS as well as PSOA provide more precise outputs than GA. A small adjustment to the FSS is suggested. The adjustment increases the performance of FSS on FEM update issue that had a restricted search space.

Yi and Yang[9] suggested a hybridized Artificial Fish School Optimization Algorithm (HAFSOA), heuristic data was utilized to construct imrpoved initial individuals; its searching capacity of global optimum solution was enhanced through combining altered fish school optimizations as well as DE. Additionally, through the taking of various visual distances for 3 behaviours, prey, cluster, as well as follow, convergence speeds of the suggested HAFSOA was sped up. Several QAP experiment outputs reveal that the suggested HAFSOA solves Quadratic Assignment Problem (QAP) better.

Methodology

Mobile devices are becoming more and more powerful, connected, as well as capable of providing improved user experiences as well as novel services on the basis of locations as well as contexts of users that presents novel opportunities for learning. SD protocols may be both predictive, discovering rules in the provided historical information, as well as a characteristic of interest; as well as descriptive, finding useful patterns in the information. In the current section, SD-LMS, CBA, SD mining, Apriori-SD, SD-PSO as well as SD-FSS techniques are detailed.

Subgroup Discovery in Learning Management Systems (LMS): SD tasks primarily rely on the 4 characteristics given below: target parameter, sub-group description language, quality function, as well as search scheme. The target parameter can be binary, nominal or even numerical. Description language defines the individual from the generic population that belongs to the sub-group. Sub-group description languages may be single-relation or even multi-relation. In the event of single-relation propositional languages, it may be specified thus: Assume Ω_A is the set of very attribute with a related domain $dom(\mathrm{a})$ of values. V_A is specified as the (universal) set of feature values in the format $(a=v), a \in \Omega_A, v \in dom(a)$.

SD $sd=\{e_i\}$ is specified by the conjunction of a series of selection expressions. The selectors $e_i=(a_i,V_i)$ refer to selections on domains of features, $a_i \in \Omega_A,\ V_i \subseteq dom(a_i).\ \Omega_{sd}$ represents the set of every potential sub-group description [10].

Quality function $q:\Omega_{sd} \times V_A \rightarrow R$ assesses a sub-group description $sd \in \Omega_{sd}$ provided a target parameter $t \in V_A$. Exceptional quality functions for binary target parameters is provided by (1):

$$qBT=\frac{p-p0}{\sqrt{p0.(1-p0)}}\sqrt{n}\sqrt{\frac{N}{N-n}} \tag{1}$$

Wherein p signifies the relative frequency of the target parameter in the sub-group; p0 signifies the relative frequency of the target parameter in the overall population; N signifies size of the overall population, while n represents size of the sub-group. Then, quality functions may be utilized for measuring the features of the sub-groups as per the analytic questions.

Classification Based on Associations (CBA): The main operation of CBA- Rule Generator (CBA-RG) [11] is the finding of every rule item which supports above minsup. Rule items are of the format as in formula (2):

$$<condset,\ y> \tag{2}$$

Wherein condset signifies a set of items, y Î Y represents a class label. The support count of condset (known as condsupCount) signifies the quantity of cases in D which comprise the condset. Support count of rule item (known as rulesupCount) signifies the quantity of cases in D which comprise the condset as well as are labelled with class y. All rule items essentially represent rules in formula (3):

$$condset \rightarrow y \tag{3}$$

wherein support is (rulesupCount / |D|) *100%, wherein |D| signifies size of the data set, as well as wherein confidence is (rulesupCount / condsupCount)*100%. Rule items which fulfil minsup are known as frequent rule items, whereas the remaining are known as infrequency rule items. For instance, the below are ruleitems in (4):

$$<\{(A,\ 1),\ (B,\ 1)\},\ (class,\ 1)> \tag{4}$$

Wherein A as well as B refer to features. If support count of condset {(A, 1), (B, 1)} is 3, support count of rule item is 2, as well as the overall quantity of cases in D is 10, then support of rule item is 20%, while confidence is 66.7%. If minsup is 10%, then rule item fulfils the minsup condition, it is frequent.

APRIORI-SD: The primary alteration of APRIORI-C protocol, ensuring it adequate for SD, involves the execution of a sample weighting strategy in rules postprocessing, an altered rule quality function involving sample weights into the weighted relative accuracy heuristics, a probabilistic classification strategy, as well as the usage of ROC space to improve the assessment of found rules [12].

The pseudocode of APRIORI-SD protocol so that the input argument of the protocol is: Examples, Classes, minSup, minConf as well as k samples are the set of training samples; classes refer t the values of the class feature, variable k defines the threshold for covered sample elimination in rules postprocessing guaranteeing the convergence of protocol, as well as variables minSup as well as minConf represent the APRIORI minimum support as well as confidence variables, restraining rule search. Default value of variables in APRIORI-SD refer to min-Sup ¼ 0.03, minConf ¼ 0.8 as well as k ¼ 5.

APRIORI-SD creates the initial set of rules through function APRIORI-C. The function utilizes APRIORI-C protocol – with no features sub-set choosing in data preprocessing as well as with no rules postprocessing – to discover every rule with class feature at right-hand side, fulfilling minSup as well as minConf restrictions. Rules set is arranged as per the weighted relative accuracy quality functions from best to worst. Best rule is chosen, covered samples are re-weighted, while the process iterates the steps till a terminating condition is fulfilled. Every sample has been covered more than k number of times, else no rules are left in the rules set.

Subgroup Mining: Fundamental sub-group mining protocol is documented sufficiently as well as summed up here. Various sub-group patterns (for instance, for continuous or discrete target parameters), searching schemes, as well as quality functions. Searches are ordered as iterated generic to specific, generating as well as testing process. In all iterations, a set of parent sub-groups is extended in every possible way, the resultant specialized sub-groups are assessed, while sub-groups are chosen which are utilized as parent sub-groups for the subsequent cycle, till a pre-set iteration depth is attained, or no more important sub-group is discovered. There is a normal partial ordering of sub-group description [13].

The statistical significances of sub-groups is computed through quality functions. As a generic quality function, SubgroupMiner utilizes conventional binomial tests for verifying if the target shares are considerably distinct in sub-groups like in (5):

$$\frac{p-p_0}{\sqrt{p_0(1-p_0)}}\sqrt{n}\sqrt{\frac{N}{N-n}} \tag{5}$$

The z-score quality function on the basis of comparison of target group shares in sub-group (p) with share in complementary sub-set balances 4 conditions: sizes of sub-group (n), difference of target share (p-p0), as well as level of target share in overall population (p0). The quality function is symmetrical with regard to the complementary sub-group. It is the same as the χ2-test of dependence between sub-group S as well as target group T, as well as the co-relation coefficient for (binary) sub-group as well as target group parameters. For continuous target parameters as well as the deviating mean patterns, quality functions are like, utilizing mean as well as variance rather than share p as well as binary case variance p0 (1-p0).

Particle Swarm Optimization (PSOA): PSOA has been utilized by several applications for solving various issues. PSOA is inspired by animal societal behaviour, specifically those who function as a swarm, with no particular leader. This is found in fishes as well as birds who form schools and flocks, respectively. Generally, a swarm that do not have a leader discover food randomly , follow a member of the group which are nearest the food source. The swarm achieves best criterion concurrently via communications amongst members who are already at an improved location. Animals that have improved conditions inform it to their flock while the rest will go towards that location concurrently. This happens iteratively till optimal condition or food source is found [14].

Exploring refers to the capacity of the searching protocol for exploring various regions in the search space for locating an adequate optimal value. Exploiting refer to the capacity of the searching protocol for concentrating the searching process near a promising region for refining the potential solution. With these two abilities, particles in the swarm move throughout the hyper space as well as have 2 crucial reasoning capacities: the memories of their best positions - local best (lb) as well as information of global or neighborhood's best - global best (gb).

The location of the particles are affected by velocities. Assume $x_i(\mathrm{t})$ represents the location of particles in search space at time step t; unless mentioned differently, t represents discrete time step. Positions of the particles are altered through addition of velocities $v_i(\mathrm{t})$ to current position in equations (6 & 7):

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{6}$$

$$v_i(t) = v_i(t-1) + c_1 r_1(localbest(t) - x_i(t-1) + c_2 r_2(globalbest(t) - x_i(t-1)) \tag{7}$$

Fish School Search (FSS): FSS is a new method to search in higher dimensional spaces that owes its inspiration to the behaviour of fishes. As with other intelligent methods that have their basis on populations of living organisms, FSS is advantageous because of the group behaviour which improves mutual survival. In a broad way, FSS comprises operators which may be grouped in the groups given below: 1) higher dimensional search capacity, 2) automated choosing between exploring as well as exploiting, 3) self-adapting guidance toward expected solution[15].

Feeding operator: To discover higher quantity of food, fish move independently, and increasing or decreasing in weight, based on their success in finding food sources. Fish weights variant is proportional to normalized differences between evaluation of fitness functions of earlier as well as current fish positions with respect to food concentrations of the spot. Evaluation of food concentrations takes into consideration every problem dimension, as in (8):

$$W_i(t+1) = W_i(t) + \frac{f[x_i(t+1)] - f[x_i(t)]}{\max\{|\, f[x_i(t+1)] - f[x_i(t)]|\}} \tag{8}$$

Wherein $W_i(t)$ signifies weights of fishes *i*, $\vec{x}_i(t)$ signifies positions of fishes *I* while $f[\vec{x}_i(t)]$ assesses the fitness functions (that is, quantity of food) in $\vec{x}_i(t)$.

Extra points were incorporated for ensuring convergence towards richer regions of the space happens in a more rapid manner. These include:

- Fish weights variations are assessed once in each FSS iteration;
- An extra variable, called weight scale (W_{scale}) was formulated for limiting the weights of fish. Fish weights varies between "1" & W_{scale}.
- Every fish is born with weight as $\frac{W_{scale}}{2}$.

Swimming operator: Swim pattern of fishes are the output of combining 3 distinct movements. The three classes are 1) individual, 2) collective-instinct, as well as 3) colletive-volition.

Individual movement: Individual movements happen for all fishes at every cycle of the FSS protocol. Swimming direction is arbitrarily selected. Given the candidate destination point is in the boundaries, fishes assess if the food density is improved in comparison to current position. For including greater arbitrariness in search procedure, individual steps are multiplied by arbitrary numbers created by uniform distribution within [0, 1].

Collective-instinctive movement: Once every fish has moved independently, weighted averages of these movements on the basis of the instant successes of every fish in the school is calculated. This implies that fishes which have more success in independent movement affect the resultant direction of movements more than the rest. When the final direction is calculated, all fishes are relocated. The movement has its basis in the fitness evaluation improvement attained, as given in (9).

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \frac{\sum_{i=1}^{N} \Delta \vec{x}_{ind\ i}\{f[x_i(t+1)] - f[x_i(t)]\}}{\sum_{i=1}^{N}\{f[x_i(t+1)] - f[x_i(t)]\}} \quad (9)$$

Wherein $\Delta \vec{x}_{ind\ i}$ signifies the displacement of the fish i because of the individual movements in FSS iteration.

Collective-volitive movements: After the first two movement is carried out, an extra position alteration is required for all fishes in the school: this is the collective volitive movement. This was formulated as an final success evaluation on the basis of the incremental weight variations of fishes overall. Otherwise put, the final movement has its basis in the total performance of the school.

The fish-school barycenter is got through consideration of every fish position as well as weight, as given by (10).

$$Bari(t) = \frac{\sum_{i=1}^{N} \vec{x}_i(t) W_i(t)}{\sum_{i=1}^{N} \vec{x}_i(t)} \quad (10)$$

For the current movement, a variable known as volitive step ($step_{vol}$) is also specified. A novel position like in (11) is evaluated, if the total weight of school rises in the FSS iteration; if the total weight reduces, it uses (12).

$$\vec{x}_i(t+1) = \vec{x}_i(t) - step_{vol}.rand.[\vec{x}_i(t) - Bari(t)] \quad (11)$$

$$\vec{x}_i(t+1) = \vec{x}_i(t) + step_{vol}.rand.[\vec{x}_i(t) - Bari(t)] \quad (12)$$

Wherein rand signifies an arbitrary number that is uniformly created within [0, 1]. It reduced linear stepvol along the cycles as well.

Breeding operator: This may be understood as a powerful indicator of good conditions. Sizes of new fishes k is the average of size of parents i as well as j, as given by (13). Initial positions of the novel fishes will be the midpoint of its parents, as given by(14). Practically, this represents the expected refinement of the searching procedure in the case of success, that is, the idea of exploiting.

$$\vec{W}_k(t+1) = \frac{\vec{W}_i(t) + \vec{W}_j(t)}{2} \quad (13)$$

$$\vec{x}_k(t+1) = \frac{\vec{x}_i(t) + \vec{x}_j(t)}{2} \quad (14)$$

To retain the quantity of fish in the school as a constant, when novel fish are generated, smallest fishes are discarded.

FSS cycle and Terminating Conditions: FSS protocol begins through arbitrary generation of fish school, as per the variables which control fish size as well as initial position. With regard to dynamics, central notion of FSS is that every nature-inspired operator functions independent of the three classes considered. Searching procedure is enclosed within loops, wherein invocation of the earlier operator occurs till a minimum of a terminating criterion is fulfilled. For now, terminating condition considered for FSS are given below, limit of cycles, time limit, maximal school radius, minimal school weight, maximal fishes quantity, as well as maximum breeding count.

Results and Discussion

In this section, the CBA CfMin 0.5, Apriori-SD CfMin 0.5, Subgroup Miner, SDPSO CfMin 0.5, SDFSO CfMin 0.5, CBA CfMin 0.9, Apriori-SD CfMin 0.9, SDPSO CfMin 0.9, SDFSO CfMin 0.9 techniques are evaluated. The table 1 shows the summary of results such as number of rules, coverage, significance and accuracy.

From the table 1, it can be observed that the SDFSO CfMin 0.5 has lower number of rules by 187.27% for CBA CfMin 0.5, by 35.29% for Apriori-SD CfMin 0.5, by 44.44% for subgroup miner and by 13.33% for SDPSO CfMin 0.5. The SDFSO CfMin 0.9 has lower number of rules by 188.67% for CBA CfMin 0.9, by 15.38% for Apriori-SD CfMin 0.9, by 58.82% for subgroup miner and by 15.38% for SDPSO CfMin 0.9.

From the table 1, it can be observed that the SDFSO CfMin 0.5 has lower coverage by 127.3% for CBA CfMin 0.5, by 154.61% for Apriori-SD CfMin 0.5, by 114.06% for subgroup miner and by 18.14% for SDPSO CfMin 0.5. The SDFSO CfMin 0.9 has lower number of rules by 9.15% for CBA CfMin 0.9, by 69.89% for Apriori-SD CfMin 0.9, by 102.87% for subgroup miner and by 19.67% for SDPSO CfMin 0.9.

From the table 1, it can be observed that the SDFSO CfMin 0.5 has higher significance by 30.34% for CBA CfMin 0.5, by 45.41% for Apriori-SD CfMin 0.5, by 11.58% for subgroup miner and by 52.66% for SDPSO CfMin 0.5.

Table 1
Summary of Results

Techniques	Quantity of rules	Coverage	Significance	Accuracy
CBA CfMin 0.5	213	0.3926	28.32	0.6243
CBA CfMin 0.9	206	0.112	36.42	0.6844
Apriori-SD CfMin 0.5	10	0.6814	24.22	0.6214
Apriori-SD CfMin 0.9	7	0.212	35.88	0.6624
Subgroup Miner	11	0.3187	34.24	0.6345
SDPSO CfMin 0.5	8	0.1046	22.42	0.7245
SDPSO CfMin 0.9	7	0.1245	32.33	0.7688
SDFSO CfMin 0.5	7	0.0872	38.45	0.8045
SDFSO CfMin 0.9	6	0.1022	40.67	0.8466

The SDFSO CfMin 0.9 has lower number of rules by 11.02% for CBA CfMin 0.9, by 12.51% for Apriori-SD CfMin 0.9, by 17.16% for subgroup miner and by 22.84% for SDPSO CfMin 0.9.

From the table 1, it can be observed that the SDFSO CfMin 0.5 has higher accuracy by 25.22% for CBA CfMin 0.5, by 25.68% for Apriori-SD CfMin 0.5, by 23.62% for subgroup miner and by 10.46% for SDPSO CfMin 0.5. The SDFSO CfMin 0.9 has lower number of rules by 21.18% for CBA CfMin 0.9, by 24.41% for Apriori-SD CfMin 0.9, by 28.64% for subgroup miner and by 9.63% for SDPSO CfMin 0.9.

From the table 1, it can be observed that the SDPSO CfMin 0.9 has lower number of rule by 15.38% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher coverage by 15.83% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher significance by 5.61% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher accuracy by 5.09% for SDPSO CfMin 0.5.

Conclusion

M-Learning is a domain which includes the usage of mobile computing as well as wireless technologies for enabling the learning which can happen at any place as well as at any time. The execution schemes of M-learning are extremely significant for all nations because of the benefits which go along with it, for instance, easy access to education as well as improved interactions between the instructor as well as the learner. But, several problems are also present with implementing M-learning, particularly with regard to developing countries. SD refers to a data mining method which finds useful relations between various parameters with regard to a property of interest.

In this work, proposed LMS, CBA, AP-SD, Subgroup Miner, PSO and FSO. Results show that the SDPSO CfMin 0.9 has lower number of rule by 15.38% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher coverage by 15.83% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher significance by 5.61% for SDPSO CfMin 0.5. The SDPSO CfMin 0.9 has higher accuracy by 5.09% for SDPSO CfMin 0.5.

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