Android Malware Classification Using Static Code Analysis and Apriori Algorithm Improved with Particle Swarm Optimization

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***Abstract*— Several machine learning techniques based on supervised learning have been adopted in the classification of malware. However, only supervised learning techniques have proofed insufficient for malware classification task. This paper presents a classification of android malware using candidate detectors generated from an unsupervised association rule of Apriori algorithm improved with particle swarm optimization to train three different supervised classifiers. In this method, features were extracted from Android applications byte-code through static code analysis, selected and were used to train supervised classifiers. Using a number of candidate detectors, the true positive rate of detecting malicious code is maximized, while the false positive rate of wrongful detection is minimized. The results of the experiments show that the proposed combined technique has remarkable benefits over the detection using only supervised or unsupervised learners.**

Keywords*— *Android Malware; Apriori Algorithm; Particle Swarm Optimization, Malware Detection; Benign Program; Static Analysis; Supervised Learning; Unsupervised Learning

I. INTRODUCTION

Data mining method of detecting malware has been very effective in the classification of malware. This field of study can be classified into supervised and unsupervised learning strategies and several techniques [1]. The strategy or technique to be adopted by an expert for the classification task depends on the nature of data and problem to be solved, that is whether the output of the data is categorical or numerical. Learning techniques for supervised data mining includes Rain Forest Neural network, decision tree, Bayesian, Naïve Bayes, Classification-based Multiple Association Rule (CMAR) [24] while unsupervised learning technique is based on clustering algorithm such as k-nearest neighour and some other clustering algorithms. Supervised learning can be basically used for three purposes namely classification, prediction, and estimation depending on the output of data or whether to determine present or future circumstances.

Association rules mining of Apriori algorithm is improved and adopted in this research for feature selection and automatic candidate generation for effective classification. The original Apriori algorithm was proposed by Agrawal R. et al [2] in order to address the problem of mining association rules. The need to improve the efficiency of mining of frequent itemsets (highest occurring items), by reducing the times of scanning the database and reducing the number of candidate item sets, prompted [3] to propose an improved Apriori algorithm based on the classic Apriori algorithm. The basic idea of Apriori algorithm is to generate the frequent itemsets using iterative method in order to generated rules that meet the minimum confidence to form rule sets and outputs [3].

Android malware has been very critical in compromising the security of information on the smartphone, since most facilities available on the conventional operating systems on computer are also present on the android operating system. This has made the security of android phone an important task in order to secure vital information of the user. Machine learning techniques have been widely applied in the classification of malware. The work in [30] used three different features namely: program header, string features, byte sequence features and four classifiers (Naïve Bayes, Rule based classifier, signature based, and Multi-Naïve Bayes classifier) in classifying malware with all other three classifiers outperform signature based method. Another work in [31] combined N-Gram feature with k-nearest neighour classifier for the classification. Researches in [32], [33] have also trained different classifiers using malware features collection and obtained improved performance for different classifier.

The basic ideas in this paper are two namely: one; improving Apriori algorithm using particle swarm optimization as the selection approach for the classification of android malware features, two; classifying android malware features using an improved Apriori algorithm as selection technique to show its effectiveness over original Apriori algorithm and some other selection techniques for malware classification. Apriori algorithm task is basically divided into three namely: candidate generation, candidate counting, and candidate selection. This research adopts particle swarm optimization to improve the generation of candidate detectors (flagbearers) which shall otherwise improve the classification process by maximizing the true positive detection and minimizing the false positive detection. Particle swarm optimization is used initially to generate candidates for later stage while Apriori algorithm is applied for candidate counting and selection in order to have best set of candidate detectors for the supervised training. The research obtained several android applications both good and malicious for the purpose of classification and prediction. The features were extracted from both samples after the thorough analysis of .apk files. Three feature selection approaches were used to select high ranked features from the set of generated features.

The rest of this paper is organized as follows: related works to this research is discussed in section II. Section III discussed the proposed model with its constituent frameworks. In section IV, empirical study, results and conclusion was given to the work. Section V is used to explain the experimental study and discussion. Section VI is used to conclude the work with appropriate recommendations.

II. RELATED WORK

A malware is a computer program that has various kinds of malicious intents [4]. Mobile malwares are those malware designated to operate on the mobile facility for malicious activities. Android operating system being a flexible and open source operating system on the smartphone has been targeted by malware over time. Malware detector is a model or algorithm developed to detect and contain the dastard effects of malicious program [5]. The initial problem of mining association rules was addressed by Agrawal R. et al. [2] Apriori algorithm where the generated frequent itemsets were used to generate rules that meet the minimum confidence to form rule sets and output. The research in [5] used an association rules mining of Apriori algorithm to automatically generate frequent itemsets of program signatures (malware and benign) and extract features from the parsed files for subsequent supervised learning. In another work, Shabtai A. et al. [27] classified games and tools using features extracted from android .apk files of both application.

Due to the challenges of apriori algorithm in generating large quatities of itemsets and time consuming in testing and verifying candidate frequent k-items [3], which have resulted to its inefficiency, different versions of Apriori algorithm have been developed that manifested an improvement in the original algorithm like an improved Apriori algorithm that addressed the inefficiency in Apriori algorithm [3]. This research, in a bid to improve Apriori algorithm for the detection of malicious programs adopts particle swarm optimization in the candidate generation of detector so as to increase the detection process and reduce false alarm rate.

III. THE PROPOSED IMPROVED MODEL AND ITS ASSOCIATED FRAMEWORKS

The effect of improved systems on the application of real world problems remains a huge success and cannot be overemphasized. This proposed improved system is composed of Apriori algorithm and particle swarm optimization combined in a strategic way with negative border as fitness function for selection process and signature extraction. The essence of mining association in malware detection system is to generate best set of features called candidate detectors through unsupervised learning for the supervised training. Association rule could also be used to extract important information from the collected features and to discover useful association rules in the signature. This task can be decomposed into two viz [24]: first, discovering the large itemsets, that is the sets of items that have support s above a predetermine threshold; second, use the large itemsets to generate the signature rules for the features that have confidence above a predetermine threshold.

The Apriori algorithm consists of three basic steps namely; generate phase, count phase, and select phase. The generate phase generates candidate itemsets repeatedly to discover large itemsets (Large-k-itemsets) using $L_k * L_k$ that meet up with minimup support and confidence [24]. The operation is given as in equation 1. $L_k * L_k = \{A \cup B$ where $A, B \in L_k$, and $|A \cap B| = k - 1\}$…. (1), where k = 1 then C_k of k-itemsets were generated using equation 2 as candidate in the next iteration. $|L_k *(|L_k| - 1)/k$ …………………… (2)

Note: $|L_k|$ denotes absolute value of L_k ; C_k is the subset of k-itemsets.

The second phase of the algorithm scan the (k-1)-itemsets to count the support the support for every candidate and select a large k-itemsets L_k for which support s ≥ min threshold. In the select phase, only candidates whose support meets the mininmum threshold are selected for next phase of candidate generation using minima support and minima confidence. The detector generated by [5] proved not to be effective due to the slow generation of candidate detectors by Apriori algorithm. Other researches which include [11], [9], [12] have attempted to provide solution to the association problem of detecting malware using apriori algorithm of association rule mining.

Particle swam optimization (PSO) was developed by Eberhart and Kennedy [34] in 1995 to address the problem of optimization. The problem was model towards the behavior of a group of birds searching for food and follows a particular bird that is nearest to the food. Particle swarm optimization has been applied successfully for the generation of candidate detector in negative selection algorithm for spam detection [7], [14], virus detection [8], feature selection [13], [15], [16], anomaly detection [10], [20], intrusion and misuse detection [17] [18], [19].

A. *Optimization of Apriori Algorithm Candidate generator with Particle Swarm Optimization (AA-PSO)*

The most important task in Apriori algorithm is candidate generation of large k-itemsets with highest frequency and the association of rules. The problem is to generate large k-itemsets that meet the minima support and confidence in a short period of time with efficiency. This paper presents a technique to optimize the generation of large k-itemsets using PSO in order to increase the effectiveness of feature selection, classification and detection model. The particle's velocity and position in an updated standard PSO was given in equations (3) and (4) respectively below:

$$V_{id}(t+1) = wV_{id}(t) + c_1 r_1 (P_{id}best(t) - x_{id}(t) + c_2 r_2 (P_{gd}best(t) - x_{id}(t) \quad (3)$$

$$x_{id}(t+1) = x_{id}(t) + V_{id}(t+1) \quad (4)$$

where i = 1, 2, …, n, n represent the number of particles in the swarm, d = 1, 2, …, D, D is the dimension of solution space. $w \in [0,1]$ is the inertia weight associated to the given particle velocity and position to ensure balance between the local and global search best. Also c_1 and c_2 represent the nonnegative learning factor while r_1 and r_2 uniformly distributed random numbers in the interval [0, 1]. The velocity $V_{id} \in [-V_m, V_m]$, where V_m is a maximum velocity predefine by the users in relation to the objective function. In this paper, we used infrequent items otherwise known as negative border or atypical factor as the fitness function in order to reduce the time and space complexity.

B. Proposed Model Framework

The existing detection algorithm uses Apriori association analysis for its signature extraction which was characterized with shortcomings. This proposed model used Apriori association analysis that has been improved with particle swarm optimization in order to improve the effectiveness and efficiency of the detection and model performance. The particle swarm optimization is used to generate candidates in the early stage with updated velocity and distance as given in equation (3) and (4). After the candidate generation stage, the Apriori algorithm is applied to calculate the supports and eventually generate set of best candidate detectors for supervised learning as shown in figure 1.

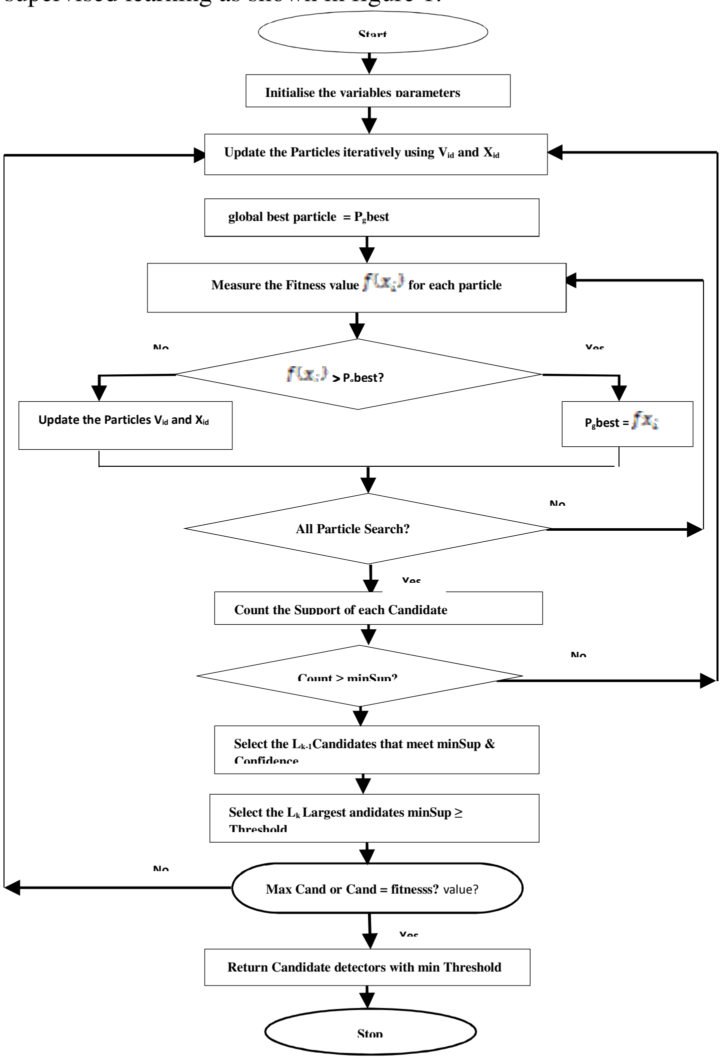


Figure1. Proposed Improved AA-Particle Swarm Optimization candidate generation model

C. Fitness Function

Negative border otherwise called Atypical factor was used in this research as fitness value to calculate fitness function in order to generate set of acceptable and high ranked features that were otherwise use for model training. Negative border is a set of candidate detectors that are infrequent in the data but whose support is counted. These values increase the efficiency in the generation of large candidate detectors. Orthogonalized Gnanadesikan-Kattenring estimator, OGK estimate [28] was adopted in estimating the distance between the instances of the particle population while an efficient outlier mining algorithm [29] was used in getting the atypical instances called outlier.

IV. EMPIRICAL STUDY, RESULTS AND CONCLUSION

This research acquired malware and clean programs from contagiominidump [26] and Googleplay [25] respectively in order to carry out empirical study. Stratified sampling technique was used to create training and test dataset for better representation for Apriori algorithm and Apriori-PSO model. The dataset was partitioned into 70% training and 30% test data. Both training and test set were set of .apk files collected as described above. The training data was used to train the model while the test set was used to test the performance of the model. The entire empirical process was discussed in the following subsection.

A. Dataset Analysis

The steps in the empirical process include data collection, program analysis and disassembling, parsing, features extraction, feature selection, independent test on the dataset, and classification model building.

Set of Android .apk files were collected for both clean and malicious programs. The programs were made up of 1000 malware from contagiominidump and 500 clean programs from official android market googleplay represents 66.7% and 33.3% respectively. In order to analyze the dataset, static analysis in [22], [23] was adopted using combination of tools. After this initial experiment, researchers were able to access the source code of the program and useful features were collected.

File analysis was carried out using stratified sampling technique on the entire programs to balance the number of extracted features from malware and clean programs. After the partitioning of the data, each file is parsed and a vector equivalent to each file was extracted as feature. In order to extract best features from the disassembled parsed files, frequent instruction sequences were search globally in the entire data collection using the combined Apriori and PSO algorithm. The combined model extracted rules from set features for a subsequent supervised learning. The mining was done using a 5% support on the partitions which yields separate rules for malware and clean dataset of 650 rules and 350 rules respectively. The combined rules generated from both malware and clean programs are 335 rules.

These rules were presented to the classifiers for supervised learning on which the model were built to classify programs into malware or benign. In order to select the best rules from the entire set of rules, a signature rule found only in a single class was defined and removed in order not to reduce the detector into signature based. Two percent threshold (2%) was set in order to identify common rules by calculating the distance in the support level of each class. After the removal of signature rule and rule common to both classes, the remaining final rules were 325, which denote the frequent features in the collected programs.

Due to the large number of several features extracted, which might become redundant to the system, unnecessary features were removed leaving us with moderate feature and were selected using new model AA-PSO algorithm and PSO. The final dataset was represented using a vector space model where each program was a vector in N dimensional point with n a number of selected features. A binary variable was defined to represent a malicious application, good application and target variable (malware or benign application).

Statistical test was carried out on the features to examine the existence of relationship or otherwise on the feature and final class value. Those features that were not shown any significant relationship with the target variable were removed from the dataset.

B. Criteria for performance evaluation

The criteria for measuring the performance of the proposed method were based on two basic research questions and were done through the use of statistical quality measures usually used in machine learning.

I). Research Questions

The two research questions on which the proposed model was evaluated are:

a) Can we improve the detection rate by train the supervised learners with unsupervised learners rather than using only supervised learners for classification?

b) Is the detection rate of model depends on the quality and quantity of extracted features, feature extraction and selection techniques?

II). *Statistical Test:*

The statistical tests used to evaluate the performance of Apriori association rules and Apriori-PSO in the detection of malware include Accuracy (ACC), Correlation Coefficient, True positive rate (which measure sensitivity), False positive rate (specificity measure) and Average mean value.

a) The Accuracy measure

In order to measure the accuracy, we formulate a confusion matrix table represented by figure upon which the accuracy definition was based.

	True	False
	Accept (P)	Reject (N)
True (T)	TP	TN
False (F)	FP	FN

Figure 2. Truth table for Application classification

We defined **TP** (True positive) as the malware that was actually classified as malware i.e. **TPR** is the proportion of positive instances classified correctly.

TN: Benign program that was classified as Benign i.e. **TNR** is the proportion of negative instances classified correctly.

FP: Non-malware that was classified as malware i.e. **FPR** is the proportion of negative instances classified wrongly as positive (malware).

FN: Malware that was classified as Benign i.e. **FNR** is the proportion of positive instances wrongly classified as negative (non-malware)

Therefore:

$$TPR = \frac{TP}{TP+FN} \tag{5}$$

$$TNR = \frac{TN}{TN+FP} \tag{6}$$

$$FPR = \frac{FP}{FP+TN} \tag{7}$$

$$FNR = \frac{TN}{TN+FN} \tag{8}$$

The accuracy actually measures the proportion of correctly classified instances (features)

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Correlation Coefficient (CC) measures the quality of two or more classification techniques in machine learning.

$$CC = \frac{(TP)(TN)-(FP)(FN)}{(TP+FN)\,(TP+FP)(TN+FN)} \tag{10}$$

V. EXPERIMENTAL SETTINGS AND IMPLEMENTATION

The basis of our experiment was based on research questions defined in section five upon which statistical tests were carried out. First, we aim to compare the effectiveness of combination of supervised with unsupervised learners with using individual classifier for detection. Second is to examine whether the detection rate of model depends on the quality of extracted features, feature extraction and selection techniques. To this end, features were extracted and selected using PSO and Apriori-PSO extraction and selection techniques, three classifiers adopted for classification are CMAR (classification-based Multiple Association Rule), NN (Neural Network), and Bayes classifiers (BC).

Since the accuracy (ACC), false positive rate (FPR), and true positive rate depend on the quality of features and classifier and measure the effectiveness of classifiers, the results display in table 1 and figure 3 (a and b) obtained as a result of combination of three classifiers with selectors AA, PSO, and AA-PSO over a number of iterations as given below:

a) AA with the three classifiers (NN, CMAR, BC)
b) PSO with the three classifiers (NN, CMAR, BC)
c) AA-PSO with the three classifiers (NN, CMAR, BC)

TABLE 1. COMBINATION OF CLASSIFIERS WITH FEATURE SELECTORS WITH THREE DIFFERENT ITERATIONS

Classifiers/Selector	**Iterations**			**Mean FPR**				**Mean Acc**
	100	200	400					
	FPR				ACC			
AA-CMAR	0.446	0.219	0.099	0.255	0.55	0.776	0.893	0.740
AA- NN	0.321	0.159	0.072	0.188	0.676	0.838	0.923	0.812
AA-BC	0.163	0.076	0.039	0.092	0.795	0.898	0.945	0.881
PSO-CMAR	0.382	0.189	0.094	0.222	0.614	0.807	0.890	0.775
PSO-NN	0.222	0.113	0.057	0.131	0.786	0.893	0.947	0.875
PSO-BC	0.097	0.046	0.022	0.055	0.857	0.929	0.964	0.917
AA-PSO-CMAR	0.320	0.159	0.079	0.186	0.676	0.838	0.919	0.811
AA-PSO-NN	0.216	0.117	0.061	0.132	0.845	0.921	0.960	0.909
AA-PSO-BC	0.030	0.015	0.007	0.017	0.952	0.976	0.988	0.972

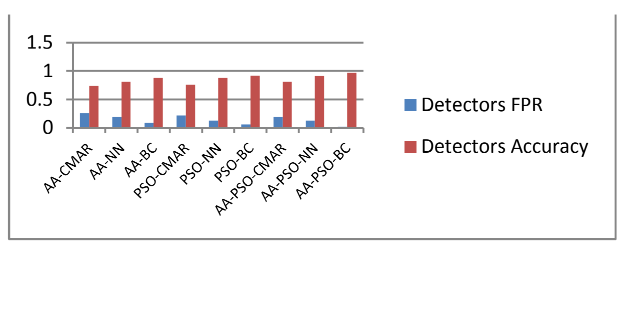


Figure 3a

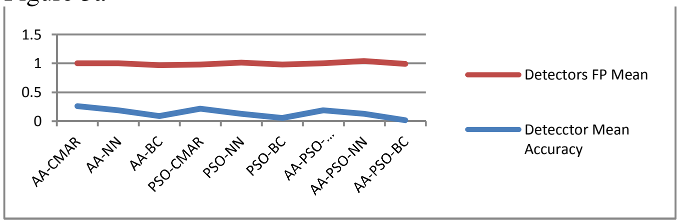


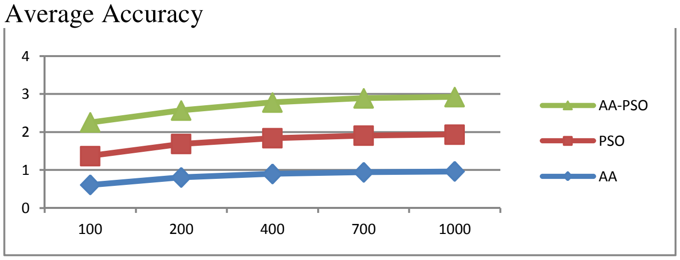
Figure 3b

Figure 3a and 3b shows FPR and Accuracy of combination of Detectors AA, PSO, AA-PSO and classifiers NN, CMAR, BC

TABLE 2. FPR, TPR, CC, AND ACCURACY FOR EACH COMBINATION OF HIGHEST RANKED FEATURES AND FEATURE SELECTORS.

Metrics	Feature Quantity	Selection Methods		
		Apriori (AA)	PSO	AA-PSO
FPR				
	100	0.3636	0.1765	0.0790
	200	0.1600	0.0790	0.0375
	400	0.0828	0.0375	0.0183
	700	0.0443	0.0210	0.0104
	1000	**0.0302**	**0.0146**	**0.0072**
TPR				
	100	0.5882	0.7200	0.8478
	200	0.7742	0.8478	0.9205
	400	0.8814	0.8526	0.9593
	700	0.9293	0.9216	0.9765
	1000	**0.9504**	**0.9540**	**0.9835**
Accuracy				
	100	0.6071	0.7619	0.8810
	200	0.8036	0.8810	0.8830
	400	0.8975	0.9405	0.9410
	700	0.9419	0.9660	0.9828
	1000	**0.9598**	**0.9762**	**0.9881**
CC				
	100	0.2395	0.5314	0.7630
	200	0.6106	0.7629	0.8811
	400	0.7274	0.8811	0.9405
	700	0.8243	0.9320	0.9660
	1000	**0.8761**	**0.9524**	**0.9762**

Average Accuracy



Number of selector features

Figure 4: showing the accuracy of Feature selectors with varying number of features.

VI. Experimental Results and Discussion

In order to compare the effectiveness of an improved AA-PSO, Mean Accuracy and False positive rate of the obtained results were computed to examine the distribution of the populations of the experimented algorithms. It was discovered, at the end of 1000 iteration with threshold values of between 0.1 and 1 that the combination of Apriori and Particle swarm optimization (AA-PSO) performance is better than that of AA and PSO. Mean Accuracy, Error rate, and Mean Absolute Error value were also calculated to determine best combination of classifiers and selectors.

Table 3 presents the distribution of AA, PSO, and AA-PSO and shows that there is correlation between means of the three algorithms. Table 3 also shows that the accuracy of AA-PSO is 93.5% compare to that of AA and PSO which stand at 84.2% and 90.5% respectively at 0.2 threshold. The true positive rate and false positive rate of an improved model AA-PSO are 93.8% and 3.1% compare with that of AA and PSO which were 82.5%, 13.6% and 85.9%, 6.6% respectively.

Table 4 is used to present the results of the combination of classifiers with selectors. The table shows the best mean accuracy of 97.2% for new model AA-PSO with Bayes classifier over PSO-BC and AA-PSO-NN with 91.7% and 90.9% which follow respectively

TABLE 3. AVERAGE VALUES OF MODEL RESULTS FOR AA, PSO, AND AA-PSO.

Model	ACC	CC	FPR	TPR	TP	FP	TN	FN
AA	0.8420	0.6556	0.1362	0.8247	0.8792	0.1139	0.7679	0.1993
PSO	0.9051	0.8120	0.0657	0.8592	0.9431	0.0569	0.8671	0.1329
AA-PSO	0.9352	0.9053	0.0305	0.9375	0.9715	0.0285	0.9336	0.0664

TABLE 4. MEAN ACCURACY, ERROR RATE, MEAN ABSOLUTE ERROR, AND MEAN SQUARE ERROR OF THREE ITERATIONS, 100, 200, AND 400.

Model	Mean Acc	Error	MAE
AA-CMAR	0.740	0.260	0.260
AA-NN	0.812	0.188	0.188
AA-BC	0.881	0.119	0.119
PSO-CMAR	0.775	0.225	0.225
PSO-NN	0.875	0.125	0.125
PSO-BC	0.917	0.083	0.083
AA-PSO-CMAR	0.811	0.189	0.189
AA-PSO-NN	0.909	0.092	0.092
AA-PSO-BC	0.972	0.028	0.028

VII. Conclusion

The improvement of the Apriori algorithm for the extraction and selection of candidate detector for the training of classifiers was explored in this research. The Apriori algorithm was improved using particle swarm optimization to increase the effectiveness in the generation of candidate detectors for supervised learning. The Atypical variable which represents the instance that does not relate nor has similarity with other instances in the data are used as values to derive fitness function.

In order to test an improved algorithm, features were extracted from Android application .apk files. The features were used for the classification process of Android applications into malware or benign application. The results of the experimentation, using 1500 malicious and good application from contagiomobile and google play show that an improved model AA-PSO with Bayesian classifier has the best accuracy of 95.7%. The results of FPR and TPR from the experiment also justify the performance of the models through correlation coefficient.

This research combines the supervised and unsupervised learning strategies in order to ensure maximum result in the classification efficiency. The research shows that the static features of a mobile application can be used together with machine learning classifiers through the combination of supervised and unsupervised strategies to classify malicious and good applications. The improved AA-PSO was used as unsupervised strategy to generate candidates that were used to train three different supervised classifiers namely Neural Network, Classification-based Multiple Association Rule (CMAR) and Bayesian classifier (BC). The results supervised classifiers show that the combination of AA-PSO with Bayes

Classifier outperforms other two combinations while Neural Network combination with selectors is better than AA combination as shown by their mean accuracies and error rates in table 4.

FUTURE RESEARCH

The authors intend to implement this result on an Android smartphone and other platform in order to examine the real life efficiency of the improved system.

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