Secure and reliable wireless advertising system using intellectual characteristic selection algorithm for smart cities

Yousra Abdul Alsahib S. Aldeen, Haider Mohammed Abdulhadi
College of Science for Women, Department of Computer Science, University of Baghdad, Iraq

Article Info

Article history:

Received Dec 6, 2019
Revised Mar 25, 2020
Accepted Apr 11, 2020

Keywords:

Internet of things
Intrusion detection system
Mobile ad-hoc networks
Multiple fusion sensors
Wireless advertising

ABSTRACT

Smart cities wireless advertising (smart mobile-AD) filed is one of the well-known area of research where smart devices using mobile ad hoc networks (MANET) platform for advertisement and marketing purposes. Wireless advertising through multiple fusion internet of things (IoT) sensors is one of the important field where the sensors combines multiple sensors information and accomplish the control of self-governing intelligent machines for smart cities advertising framework. With many advantages, this field has suffered with data security. In order to tackle security threats, intrusion detection system (IDS) is adopted. However, the existing IDS system are not able to fulfill the security requirements. This paper proposes an intellectual characteristic selection algorithm (ICSA) integrated with normalized intelligent genetic algorithm-based min-max feature selection (NIGA-MFS). The proposed solution designs for wireless advertising system for business/advertising data security and other transactions using independent reconfigurable architecture. This approach supports the wireless advertising portals to manage the data delivery by using 4G standard. The proposed reconfigurable architecture is validated by using applications specific to microcontrollers with multiple fusion IoT sensors.

Corresponding Author:

Yousra Abdul Alsahib S. Aldeen,
College of Science for Women,
Department of Computer Science,
University of Baghdad, Iraq.
Email: yousraalkaalesi@gmail.com

1. INTRODUCTION

Intrusion detection system (IDS) is playing a significant role for data security of wireless advertising data in mobile ad-hoc networks (MANET) platform. IDS systems are used to detect the known and unknown attacks [1-3]. The attacks detection on wireless advertising in mobile ad hoc networks is a difficult task than fixed wired networks, because of the nodes mobility and dynamic topologies [4, 5]. In these networks, the networks are more complex where maintenance and other complexities exist [6, 7]. Moreover, few more additional challenges are also present in the detection of attacks including lack of monitoring facilities for the mobile nodes in the network. Therefore, there is need to design more suitable approach to handle these networks characteristics and need to analyze the security attacks datasets to develop an efficient IDS. Recently, the attacks detection of intruders effectively on wireless advertising in MANET is processed using featuring approaches [8]. Classification methods are used to categorized the nodes into normal and abnormal which are based on certain conditions. Many soft computing techniques are introduced in the past with effective datasets [9]. Additionally, the existing classification techniques are not able to classify the datasets successfully to detect the intruders with all kinds of attacks. In [10], a feature selection technique is introduced for improving the classification accuracy [11].

In this context, this paper proposes a trust based routing protocol for find the suitable and secure routes in the network. Specifically, an Intellectual characteristic selection algorithm (ICSA) integrated with normalized intelligent genetic algorithm based min-max feature selection (NIGA-MFS) designs for effective pre-processing of intrusion detection dataset in wireless advertising frame work of smart cities. The rest of the paper is organized as follows: section 2 presents the related work in the domain. Section 3 illustrates the proposed approach, its process, design and algorithm. Section 4 discusses the simulation results and discussion. Paper concludes in last section with future direction.

2. RELATED WORK

This section discusses the existing approaches to deal the security attacks in wireless advertising MANET.

2.1. Feature selection techniques

Feature selection techniques are introduced by many researchers who are working in the areas of medical data mining, image processing and intrusion detection. In all these applications, feature selection is used to select the optimal number of features from the datasets consisting of more number of features. In the past, several research works have accomplished by various researchers. Among them, in [12] authors proposed the first incremental based algorithm for feature selection which is used to find the relevant features which are suitable to solve the problem with optimal number of features. In their work, the number of features and patterns are huge in their dataset.

Therefore, the proposed and effective method for feature selection can help in dimensionality reduction. They also designed an incremental probabilistic algorithm as an alternative approach to the exhaustive and heuristic methods. In [13], authors proposed an incremental feature selection algorithm (IFSA) which is dynamic in nature for taking decisions over the different functionalities. This algorithm is capable to avoid the re-computation process instead of retraining the subset from scratch. In [14], authors developed a new evolutionary-incremental framework for feature selection. This framework is applied on an ordinary evolutionary algorithm called genetic algorithm. This framework introduced some generic modifications on ordinary evaluation algorithms which are compatible with the variable length of solutions. Moreover, this framework is deployed for performing classification operation with two new operators namely addition and deletion operators which change the length of solutions randomly.

In [15], authors proposed a new unsupervised feature selection method for effective decision making over the dataset. In [16], authors proposed a new model for feature selection based on combination of incremental mixed variable ant colony optimization (IACOMV) and support vector machine (SVM) for solving the model selection problems effectively. In [17], authors proposed a machine learning algorithm version of the binary bat algorithm (BBA) for performing effective classification. However, all discussed approaches are not suitable for feature selection in intrusion detection applications [18]. Moreover, the existing feature selection algorithms are more complex and hence they consume lot of time for convergence. Therefore, a new feature selection algorithms needed to address the existing approaches limitations and best solution for selecting optimal number of features.

3. INTELLECTUAL CHARACTERISTIC SELECTION ALGORITHM (ICSA)

Due to random deployment of static sensor nodes and environmental factors, existence of many issues and loop holes in wireless sensor networks (WSN) is inevitable in smart cities. These limitations result in reducing the data transmission performance in terms of data reliability, data transfer in wireless advertising and in energy consumption in wireless advertising frameworks. Consequently, the fulfill the all network requirements is an important factor for prolonging the network lifetime on wireless advertising in MANET platform. The proposed framework shows in Figure 1.

The network lifetime of the internet of things (IoT) sensor nodes can be improved by deploying the additional mobile sensors and static sensor deployment. Finding the number of additional IoT sensors in the networks leads to optimization problem. Intellectual characteristic selection algorithm (ICSA) presents to obtain the best/optimal coverage with high reliability of data transfer of network area by IoT sensor nodes. The required numbers of static sensors are deployed randomly in the monitoring area. After deployment of the sink nodes, nodes send a hello message to all other sensor nodes in the network, as a reply the nodes send their location and node_id to sink node. By using these information, sink nodes apply the binary detection model to detect the holes in the coverage of monitoring region during information transmission on wireless advertising platform. After obtaining the coverage map, the sink calculates the optimal number of additional sensor required and deploys those mobile sensors randomly. Each mobile sensor is modeled as a charged particle in electromagnetism algorithm and the ICSA algorithm calculates the total force applied on the mobile sensor by neighbor's IoT sensors and fitness (Ai) values.

$$Ai = [W1 * Info\ Gain\ ratio\ (IGR)\ (Ai) + W2 * IGR\ (Mutation\ (Ai)) + W3 * IGR\ (Crossover\ (Ai, Aj)\ ]/[W1 + W2 + W3]; \quad (1)$$

$$Ai >= Th\ AND\ Aj >= Th \quad (2)$$

$$SS = SS\ U\ (Ai)\ U\ (Aj); \quad (3)$$

$$Ai >= Th\ AND\ Aj < Th \quad (4)$$

$$SS = SS\ U\ (Ai); \quad (5)$$

$$Ai < Th\ AND\ Aj >= Th \quad (6)$$

$$SS = SS\ U\ (Aj); \quad (7)$$

From the (1-4) denote the fitness function to check the Info gain ratio (IGR) and features are selected (SS) based on the threshold (Th) AND fitness (Aj) function as presents in the Algorithm 1. The total force determines the direction of the mobile node; move the mobile node accordingly; if the mobile node is not in optimum position, then apply genetic operators on the location of the sensor and apply AVFA algorithm. This will continue till all the mobile sensors are moved to optimal location.

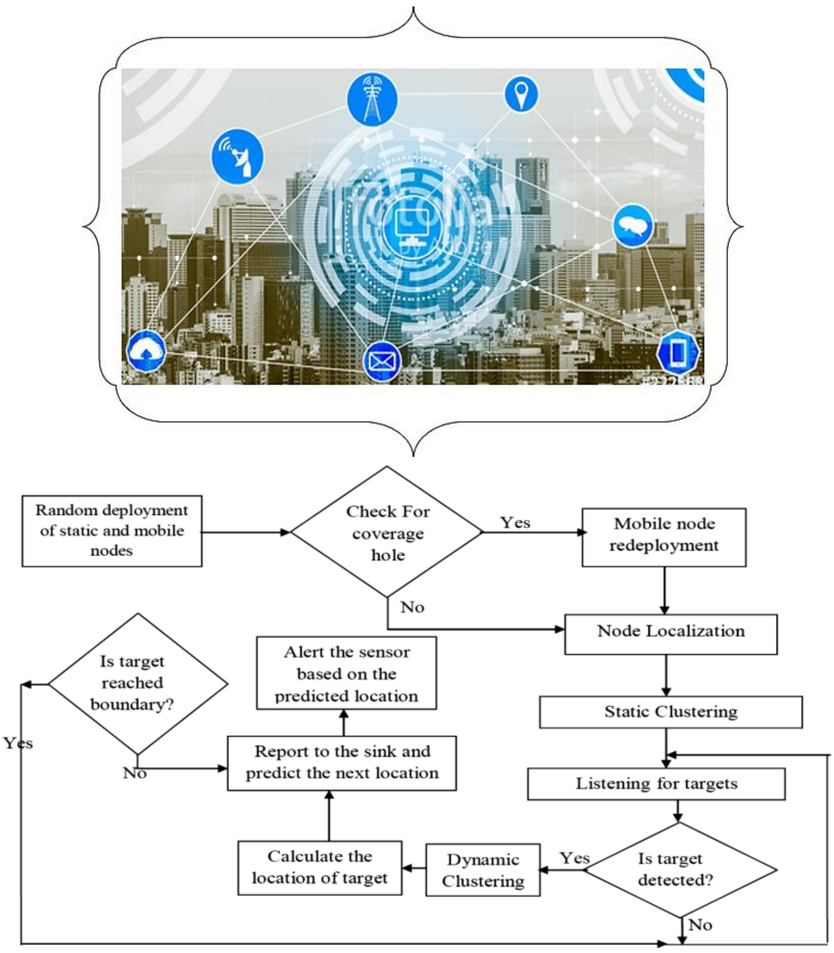

Figure 1. Overall operation of the proposed framework for wireless advertising

In this work, ICSA is proposed with the combination of GA and IAASA. Here, IAASA selects the initial subsets and then applies the crossover fitness selection (CFS) formulation for finalizing the exact features which are useful for identifying the four types of attacks. Finally, the hidden semi-Markov model (HSMM) [19] and SVM [20] are used for classification for selected features. These classification tasks are carried out using the existing classifier to test the performance of the proposed feature selection algorithms. The IAASA uses the IGR which is computed using the (8-10).

$$Info(D) = -\sum_{j=1}^{m}\left[\frac{freq(C_j, D)}{|D|}\right] log_2 \left[\frac{freq(C_j, D)}{|D|}\right] \quad (8)$$

$$Info\ (F) = -\sum_{i=1}^{n}\left[\frac{|F_i|}{|F|}\right] \times info\ (F_i) \quad (9)$$

$$IGR(A_i) = \left[\frac{Info(D) - Info(F)}{Info(D) + Info(F)}\right] \times Info(F_i) \quad (10)$$

Here, D is the dataset, Ci is the fragments made from the dataset, F is the feature set with Fi as the feature and IGR indicates the information gain ratio (IGR). The word info indicates the information gain values. Now, the steps of the proposed Algorithm 1 are as follows:

Intelligent agent based incremental feature selection algorithm	
Step 1:	The intelligent agents divide the dataset D into n subsets of equal size and named as C1, C2,…Cn.
Step 2:	Agent computes the IGR value for every attribute (A_i) of the dataset using (4) to obtain the value of IGR(A_i) and is expressed as: $IGR(A_i) = \left[\frac{Info(D) - Info(F)}{Info(D) + Info(F)}\right] \times Info(F_i)$
Step 3:	The agent selects a feature from dataset which has maximum IGR.
Step 4:	Now the agent divides the sub datasets C_i into two subsets based on their distance between the neighbour nodes.
Step 5:	Make the first part of each subset as parents in the genetic algorithm.
Step 6:	Compute the fitness values using the formula Fitness (A_i) = [W1 * IGR (A_i) + W2 * IGR (Mutation (A_i)) + W3 * IGR (Crossover (A_i, A_j)] / [W1+W2+W3]; Fitness (A_j) = [W1 * IGR (A_j) + W2 * IGR (Mutation (A_j)) + W3 * IGR (Crossover (A_i, A_j)] / [W1+W2+W3];
Step 7:	*If* Fitness (A_i) >= Threshold AND Fitness (A_j) >= Threshold then Selected feature set SS = SS U (A_i) U (A_j);
Step 8:	*If* Fitness (A_i) >= Threshold AND Fitness (A_j) < Threshold then Selected feature set SS = SS U (A_i);
Step 9:	*If* Fitness (A_i) < Threshold AND Fitness (A_j) >= Threshold then Selected feature set SS = SS U (A_j);
Step 10:	*If* A_i is included in SS then select the next attribute from the first subset and call it as A_i
Step 11:	*If* A_j is included in SS then select the next attribute from the second subset and call it as A_j
Step 12:	Repeat this process until all attributes are tested with the rules used in this procedure.
Step 13:	Return SS
Step 14:	*If* No attributes are selected then change the Threshold with Threshold = Threshold * 0.9 and go to step 6.

Further in order to improve the reliability and classification accuracy NIGA-MFS algorithm is used for wireless advertising in smart cities. In this work, all the dataset is converted into a standard format which uses the numerical values between 0 and 1 so that it is easy to compare during the classification process. For this purpose, the minimum and maximum values are considered as the boundaries for each attribute and the attribute length is computed using the difference between the maximum and the minimum values. The normalized value is computed using the formula given in (11).

$$Normalized\ Value\ (I) = \frac{Given\ Value\ (I)}{(Max\ Value - Min\ Value)} \quad (11)$$

where, I indicate the Ith data record, given value is the present value, normalized value is the computed value which lies between 0 and 1, max value is the maximum value of the values for the particular attribute and Min value is the Minimum value of the values for the particular attribute. The input data are normalized on each record by dividing the max-min value by the maximum value and hence all the data are converted into uniform format with a range of values from 0 to 1. This pre-processing helps the decision making process to carry out easier comparisons. For this purpose, a new feature selection algorithm called GA based Min-Max feature selection algorithm is proposed. The steps of the NIGA-MFS Algorithm 2 are as follows:

Normalized intelligent GA based min-max feature selection (NIGA-MFS) algorithm

```
Input:     All features (Fi, i=1 to n), Number of generations K, Population size PS,
           Crossover probability (CPi), Mutation probability (MPi).
Output:    Set of selected features SFi, i = 1 to m.
NIGA-MFS ( )
Begin
Step 1:    Initialize the population from the dataset as Fi, i=1 to n; n =41, Maximum
           number of generations = 1000;
Step 2:    Convert the features into feature numbers n binary form to represent them using
           1s and 0s.
Step 3:    Form two parents by selecting two attributes at random
Step 4:    Remove them from Fi and name them PA1 and PA2.
Step 5:    Initialize SFi = { } and Generation count = 1;
Step 6:    Initialize the weights with W1=0.6, W2=0.4, CPi =0.5 and MPi=0.5.
Step 7:    For each chromosome Fi present in the selected attributes population
           {
           i.  Apply uniform crossover with a probability CPi and mutation operation with
               probability MPi.
           ii. Find the normalized Min-Max value using the formula
               Min-Max Value (I) = Given Value (I) / (Max Value – Min Value)
           iii.       Evaluate Fitness (i)= [ W1 * RoundOf (Min-Max Value(i)) +
               W2 * TruncateOf (Min-Max Value(i)+0.5)] / (W1 + W2)
           iv. If fitness value of Fi > Threshold Then
               FSi = FSi U Fi
Else
      Read next attribute
Step 8:    If Generation_Count < 1000 Then
           Go to Step 7
Step 9:    Return FSi.
```

The results of the feature selection algorithm and the classification algorithms with full features and selected features are selected using the proposed feature selection algorithm for reliable data transfer which is discussed in the results and discussion section.

4. RESULTS AND DISCUSSION

The efficiency of the ICSA is integrated with NIGA-MFS for optimal feature selection for reliable data transfer in wireless advertising for smart cities in MANET platform with IoT sensors is analyzed in this section. The proposed method successfully detects the sensible region which examines the optimized cluster centers for reliable data transmission and members that leads to create the effective transmission path from source to destination in smart city environment. Then the performance of the proposed system is analyzing by using the following metrics.

a) Coverage fraction
   Coverage fraction is metric to analyze, how the neighbor nodes are successfully examining while analyzing the sensible nodes in wireless sensor networks of smart cities.
b) Energy consumption
   Energy consumption is one the important metric that is used to measure how much power is consumed while transmitting the information from source to destination without making any information loss.
c) Accuracy
   The last metrics is accuracy in which the cluster formation efficiency is examined. Accuracy is analyzed in terms of using number of nodes along with number of clusters.

By using the above efficiency metrics, excellence of the system is evaluated with the help of simulation setup, which is discussed as follows.

The excellence of proposed technique performance is analyzed using simulation setup that is compared with traditional methods. During the implementation process, the proposed system uses the following simulation parameter that is listed in the Table 1.

Table 1. Simulation parameter

Simulation Parameter	Parameter Value
Simulator	NS2 (v.2.29)
Transmission Range	500*500 square meters
Bandwidth	4 Mbps
Interface Queue Length	45
Packet size	512 bytes
Traffic type	CBR
Packet rate	20 packets/sec
Topology size	700 * 700m^2
Number of nodes	20,30,…50
Number of trials	30
Simulation Time	800 sec
Maximum Speed	40 m/s
Counter Threshold (C)	6
RAD Tmax	0.02 seconds

After simulation network simulator (NS2) setup, the next step is implementation of ICSA- NIGA-MFS and the graphical representations are created for examining the system efficiency. Along with the simulation setup, the efficiency of the system is analyzed in terms of different performance metrics such as coverage fraction, accuracy of cluster and energy consumption metrics. Depending on the various discussions cluster head and centroid node is selected using the ICSA integrated NIGA-MFS with effective manner. Then the efficiency of cluster is examined in terms of precision, recall and accuracy metrics, which is explained as follows.

a) Recall

Recall is also called as the true positive rate which helps to determine how exact the cluster head is chosen from the collection of nodes. The recall value is calculated as follows,

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False Negative}} \tag{12}$$

In (12), recall value is estimated, if the system ensures high true positive rate then the method successfully selects the exact cluster with effective manner.

b) False negative rate (FNR)

False negative rate is also called as miss rate that measures how much fraction of the elements classified as negative is false. The FNR value is estimated as follows:

$$\text{False Negative Rate} = \frac{\text{False Negative}}{\text{True Positive} + \text{False Negative}} \tag{13}$$

In (13), false negative rate is estimated, if the system ensures low negative rate then the method successfully selects the exact cluster with effective manner.

c) Precision

Precision is also called as Positive Prediction Value (PPV), it shows how much fraction of the elements truly positive is classified as positive. Higher PPV means better classification. The Precision value is estimated as follows,

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Postive} + \text{False Positive}} \tag{14}$$

Based on the (14) precision, recall values, accuracy is estimated as follows.

d) Accuracy (ACC)

Accuracy shows how much fraction of the total elements classified correctly. Higher ACC means better classification. It is calculated as follows in (15).

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{(\text{True positive} + \text{True negative} + \text{False positive} + \text{False Negative})} \tag{15}$$

Based on the above accuracy metric, the obtained clustering accuracy value is shown in Table 2.

Table 2. Performance analysis of clustering accuracy

	IACOMV	SVM	BBA	ICSA-NIGA-MFS
Accuracy	0.75	0.84	0.83	0.97
precision	0.74	0.85	0.76	0.98
Recall	0.83	0.54	0.66	0.89
False Negative Rate	0.91	0.6	0.71	0.55

Based on Table 2, ICSA-NIGA-MFS (accuracy-0.97%, precision-0.98% and recall-0.55%) is more reliable in data transfer when compared to other methods such as IACOMV (accuracy-0.75%, precision-0.74% and recall-0.83%) SVM (accuracy-0.84%, precision-0.85% and recall-0.54%), BBA (accuracy-0.83%, precision-0.76% and recall-0.66%) and ICSA-NIGA-MFS (accuracy-0.97%, precision-0.98% and recall-0.55%). Based on Table 2, it is clearly showing that the ICSA integrated NIGA-MFS ensures the high accuracy while detecting exact cluster head, and eliminating the false nodes while transferring data in wireless advertising for smart cities when compared to the other methods. Even though introduce method effectively form the region and clusters with high accuracy, the network must consume minimum energy that leads to improve overall network lifetime while transmitting data from source to destination in wireless advertising for smart cities. The low utilization of energy leads to improve the overall transmission rate which also eliminates several difficulties. So, ICSA integrated NIGA-MFS algorithm in cluster head to collect the data from base station from the member nodes by multi-hop manner, which saves the energy consumption of cluster head and participants in WSN of smart cities. In IACOMV and EMHR protocols, energy burden is due to the long-haul communication links between header and the cluster members. However, the energy dissipation is directly relative to the exponent of data transmission distance. The energy consumption of the ICSA integrated NIGA-MFS algorithm is less than that of IACOMV, SVM and BBA [21]. Less energy consumption means longer lifetime of network and then the graphical representation of residual energy is shown in Figure 2. Table 2 shows the energy consumption where energy measurement is based on joules.

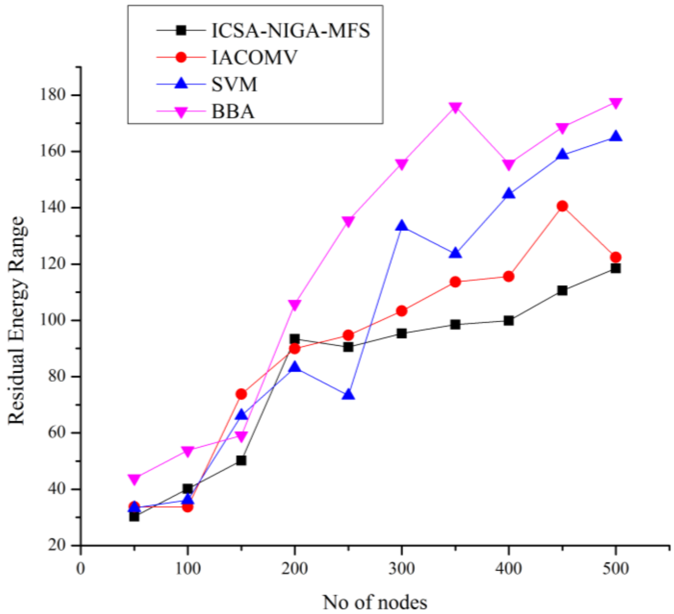

Figure 2. Performance analysis based on energy

As shows in Figure 2 is the proposed ICSA integrated NIGA-MFS obtained a high energy saving which leads to improve overall network [22] lifetime. Depending on the above simulation result, the ICSA integrated NIGA-MFS algorithm transmits the data from one node to another node by consumed minimum power that used to maintain the network lifetime when compared to other methods for wireless advertising in smart city environment. In addition to this, effective utilization of nodes, network routing [23] and power reduces the other failures in network with effective manner.

The above Figure 3 shows that the comparison of coverage fraction for the various models are recognized sensitive region from the defined coverage area with reasonable simulation runs in defined area [24]. The obtained coverage fraction is better for ICSA integrated NIGA-MFS when compared to the existing sensing IACOMV, SVM and BBA. This successful examination of sensing region helps to analyze the number of nodes in region with effective manner that used to form the cluster with different number of rounds and nodes in sensor network for smart city framework [25].

As shown Figure 4, depending on the number of cluster nodes efficiency, the successful formations of cluster enhance the data transmission process by maximizing the network lifetime in wireless advertising framework for smart city platform. The formed cluster leads to reduces the high-energy consumption while transmitting the data from source to destination node in smart city platform which helps to improve the efficiency of the network.

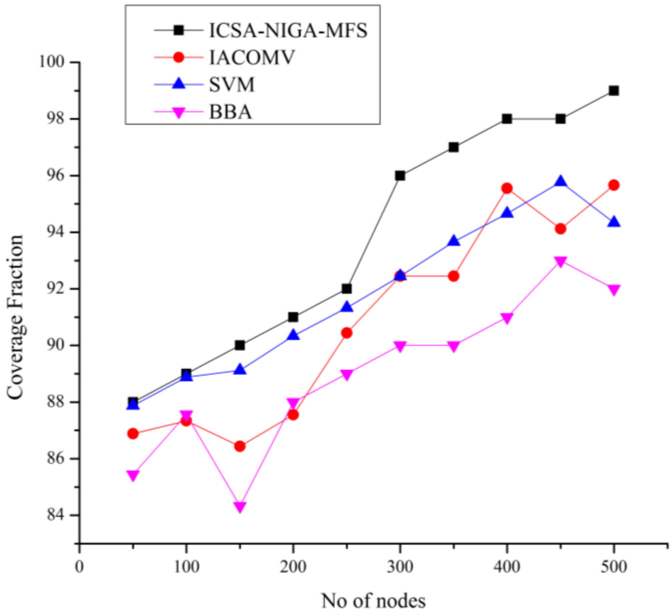

Figure 3. Performance analysis based on coverage fraction

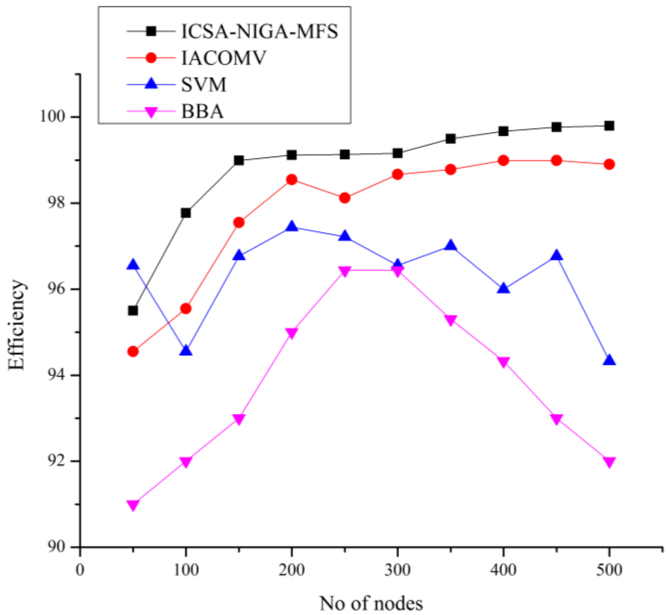

Figure 4. Performance analysis based on efficiency

Figure 5 depicts the comparison of average time taken between ICSA integrated NIGA-MFS compared to the existing sensing IACOMV, SVM and BBA models. It is visible that ICSA integrated NIGA-MFS outperforms in comparison with the other three algorithms. ICSA integrated NIGA-MFS ahead with minimum computational time and the minimum computational time is due to the membership function evaluation.

As shown in the Figure 6, however, ICSA integrated NIGA-MFS has lesser time for data transmission between the IoT sensor nodes in smart city platform, which grows exponentially as the size of the IoT nodes and links increases in smart city platform. ICSA integrated NIGA-MFS achieves the optimal solution in a maximized network lifetime for the node generation with less optimum time than IACOMV, SVM and BBA models. Thus the proposed solution shows the optimal set of features which are selected by the proposed intelligent incremental feature selection algorithm.

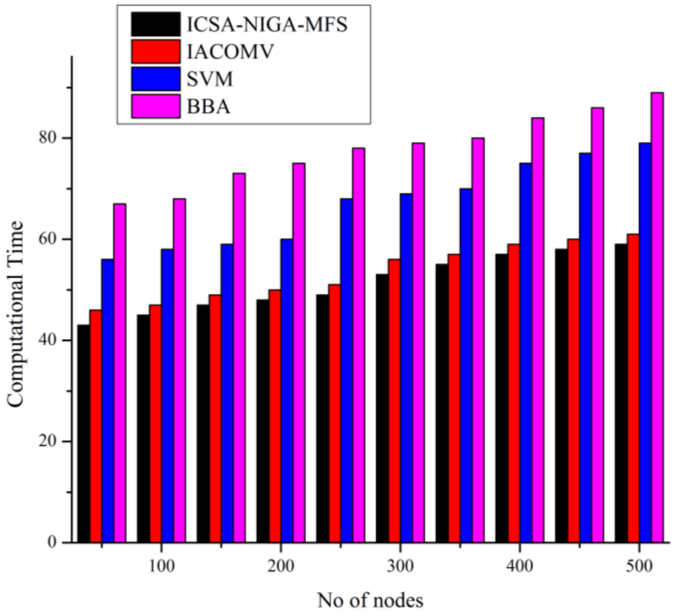

Figure 5. Average computational time analysis

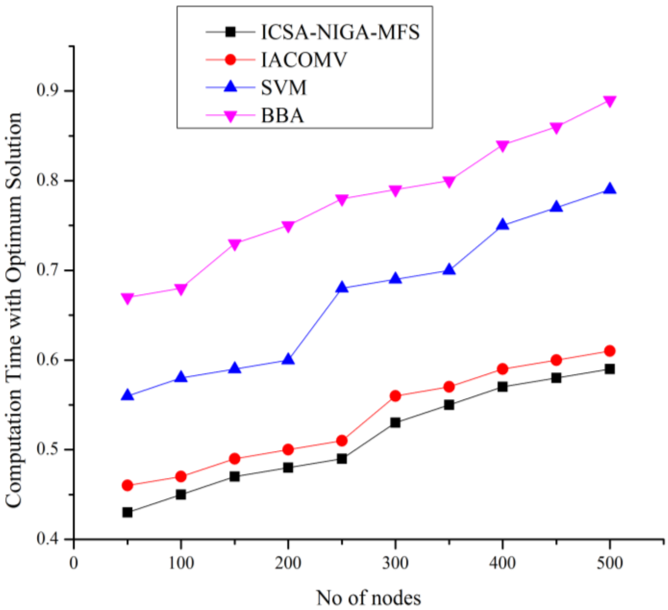

Figure 6. Average computational time with optimum solution

5. CONCLUSION

In this paper, ICSA integrated NIGA-MFS algorithm is proposed for wireless advertising system. The proposed feature selection algorithms along with classifiers is used and itis observed that both the feature selection algorithms increased the classification accuracy. Moreover, ICSA integrated NIGA-MFS algorithm provided better results than the feature selection using the ICSA due to the use of normalization with genetic algorithms. Both the algorithms reduced the classification time in comparison with IACOMV, SVM and BBA models. Hence, the ICSA-NIGA-MFS achieves better performance in terms of classification accuracy and classification time by the use of the proposed pre-processing techniques which is most suitable for wireless advertising in smart city environment for reliable data transmission. In future, the proposed algorithm will apply on other domain like, smart grids, edge computing, industrial IoT and underwater sensor networks.

ACKNOWLEDGEMENTS

This work was supported by University of Baghdad.

REFERENCES

[1] A. Gupta, R. K. Jha, P. Gandotra, and S. Jain, "Bandwidth spoofing and intrusion detection system for multistage 5G wireless communication network," *IEEE Transactions on Vehicular Technology,* vol. 67, no. 1, pp. 618-632, 2017.
[2] M. S. Aliero, I. Ghani, K. N. Qureshi, and M. F. A. Rohani, "An algorithm for detecting SQL injection vulnerability using black-box testing," *Journal of Ambient Intelligence Humanized Computing,* vol. 11, no. 1, pp. 249-266, 2020.
[3] K. N. Qureshi, F. Bashir, and A. H. Abdullah, "Provision of Security in Vehicular Ad hoc Networks through An Intelligent Secure Routing Scheme," *2017 International Conference on Frontiers of Information Technology (FIT)*, pp. 200-205, 2017.
[4] E. Benkhelifa, T. Welsh, and W. Hamouda, "A critical review of practices and challenges in intrusion detection systems for IoT: Toward universal and resilient systems," *IEEE Communications Surveys Tutorials,* vol. 20, no. 4, pp. 3496-3509, 2018.
[5] A. Sharif, J. P. Li, and M. A. Saleem, "Internet of things enabled vehicular and ad hoc networks for smart city traffic monitoring and controlling: a review," *International Journal of Advanced Networking Applications,* vol. 10, no. 3, pp. 3833-3842, 2018.
[6] A. Mehmood, A. Khanan, M. M. Umar, S. Abdullah, K. A. Z. Ariffin, and H. Song, "Secure knowledge and cluster-based intrusion detection mechanism for smart wireless sensor networks," *IEEE Access,* vol. 6, pp. 5688-5694, 2017.
[7] K. Qureshi, A. H. Abdullah, O. Kaiwartya, F. Ullah, and S. I. A. Altameem, "Weighted link quality and forward progress coupled with modified RTS/CTS for beaconless packet forwarding protocol (B-PFP)," *Telecommunication Systems,* 2016.
[8] K. N. Qureshi, M. M. Idrees, J. Lloret, and I. Bosch, "Self-Assessment Based Clustering Data Dissemination for Sparse and Dense Traffic Conditions for Internet of Vehicles," *IEEE Access,* vol. 8, pp. 10363-10372, 2020.
[9] Q. Yaseen, F. Albalas, Y. Jararwah, and M. Al- Ayyoub, "Leveraging fog computing and software defined systems for selective forwarding attacks detection in mobile wireless sensor networks," *Transactions on Emerging Telecommunications Technologies,* vol. 29, no. 4, 2018.
[10] P. M. Shakeel, S. Baskar, V. S. Dhulipala, S. Mishra, and M. M. Jaber, "Maintaining security and privacy in health care system using learning based deep-Q-networks," *Journal of Medical Systems,* vol. 42, no. 10, 2018.
[11] H. Alanazi, A. Abdullah, K. Qureshi, and A. Ismail, "Accurate and dynamic predictive model for better prediction in medicine and healthcare," *Irish Journal of Medical Science,* vol. 187, no. 2, pp. 501-513, 2018.
[12] A. Brandão, H. São Mamede, and R. Gonçalves, "A smart city's model secured by blockchain," *International Conference on Software Process Improvement*, Springer, pp. 249-260, 2018.
[13] M. Dorigo and T. Stützle, "Ant colony optimization: overview and recent advances," Handbook of Metaheuristics: Springer, pp. 311-351, 2019.
[14] V. O. Costa and C. R. Rodrigues, "Hierarchical ant colony for simultaneous classifier selection and hyperparameter optimization," *2018 IEEE congress on evolutionary computation (CEC)*, pp. 1-8, 2018.
[15] M. M. Mafarja and S. Mirjalili, "Hybrid binary ant lion optimizer with rough set and approximate entropy reducts for feature selection," *Soft Computing,* vol. 23, no. 15, pp. 6249-6265, 2019.
[16] T. M. Mohamed and H. M. Moftah, "Simultaneous ranking and selection of keystroke dynamics features through a novel multi-objective binary bat algorithm," *Future Computing Informatics Journal*, vol. 3, no. 1, pp. 29-40, 2018.
[17] D. Guha, P. K. Roy, and S. Banerjee, "Binary Bat Algorithm Applied to Solve MISO-Type PID-SSSC-Based Load Frequency Control Problem," *Iranian Journal of Science Technology, Transactions of Electrical Engineering,* vol. 43, no. 2, pp. 323-342, 2019.
[18] A. Tharwat and A. E. Hassanien, "Optimizing Support Vector Machine Parameters Using Bat Optimization Algorithm," Machine Learning Paradigms: Theory and Application: Springer, pp. 351-374, 2019.

[19] T. Islam, M. E. Islam, and M. R. Ruhin, "An analysis of foraging and echolocation behavior of swarm intelligence algorithms in optimization: ACO, BCO and BA," *International Journal of Intelligence Science,* vol. 8, no. 01, pp. 1-27, 2018.
[20] S. Mirjalili, "Evolutionary algorithms and neural networks," Studies in Computational Intelligence, 2019.
[21] R. Hamidouche, Z. Aliouat, and A. M. Gueroui, "Genetic algorithm for improving the lifetime and QoS of wireless sensor networks," *Wireless Personal Communications,* vol. 101, no. 4, pp. 2313-2348, 2018.
[22] S. S. L. Preeth, R. Dhanalakshmi, R. Kumar, and P. M. Shakeel, "An adaptive fuzzy rule based energy efficient clustering and immune-inspired routing protocol for WSN-assisted IoT system," *Journal of Ambient Intelligence Humanized Computing,* pp. 1-13, 2018.
[23] T. Kaur and R. Kumar, "Mitigation of Blackhole Attacks and Wormhole Attacks in Wireless Sensor Networks Using AODV Protocol," *2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE),* pp. 288-292, 2018.
[24] M. Banerjee, J. Lee, and K. K. R. Choo, "A blockchain future for internet of things security: a position paper," *Digital Communications Networks,* vol. 4, no. 3, pp. 149-160, 2018.
[25] M. Torres Ruiz, M. D. Lytras, and H. Mathkour, "Innovative services and applications of wireless sensor networks: Research challenges and opportunities," SAGE Publications Sage UK: London, England, 2018.

BIOGRAPHIES OF AUTHORS

Dr. Yousra Abdul Alsahib S. Aldeen. Head of Assurance and Performance Assessment Unit-College of Science for Women-University of Baghdad. Ph.D. in Computer Network. Research Interests: Cloud Privacy, IOT, Computer Network, Smart City, Cloud of Things, etc. 1994 she has got BSc in Computer Science (Al-Mustansiriyah University). 2006 She has got MSc in Computer Network (Iraqi Commission for computers and informatics). 2017 PhD at Faculty of Computing, University Technology Malaysia, UTM, 81310 UTM Skudai, Johor, Malaysia.

Haider Mohammed Abdulhadi. Head of Avi-cenna E-Learning Unit - College of Science for Women-University of Baghdad. .1999 he has got B.Sc. in electrical engineering (Al Mustansiriyah University). 2009 he has got M.Sc. in Electronic Systems (Kharkov Polytechnic Institute - Ukraine).