An Integrated Grasshopper Optimization Algorithm with Artificial Neural Network for Trusted Nodes Classification Problem

https://doi.org/10.3991/ijoe.v19i04.37579

Baydaa Mohammad Mushgil[1(✉)], Ola Marwan Assim[2], Muayad Khalil Murtadha[3], Hanaa M. Mushgil[4]
[1]Information and Communication Engineering Department, Al-Khwarizmi College of Engineering, University of Baghdad, Baghdad, Iraq
[2]College of Engineering, Computer Department, Mosul University, Mosul, Iraq
[3]Computer Center, University of Baghdad, Al-Jaderiya, Baghdad, Iraq
[4]Computer Department, College of Science, AlNahrain University, Jadriya, Baghdad, Iraq
baydaait@kecbu.uobaghdad.edu.iq

Abstract—Wireless Body Area Network (WBAN) is a tool that improves real-time patient health observation in hospitals, asylums, especially at home. WBAN has grown popularity in recent years due to its critical role and vast range of medical applications. Due to the sensitive nature of the patient information being transmitted through the WBAN network, security is of paramount importance. To guarantee the safe movement of data between sensor nodes and various WBAN networks, a high level of security is required in a WBAN network. This research introduces a novel technique named Integrated Grasshopper Optimization Algorithm with Artificial Neural Network (IGO-ANN) for distinguishing between trusted nodes in WBAN networks by means of a classification approach, hence strengthening the safety of such networks. Feature extraction process is done by using Linear Regression-Based Principal Component Analysis (LR-PCA). The test results demonstrated that the proposed IGO-ANN method attains the greatest performance in terms of accuracy, end to end delay and packet delivery ratio regarding trusted WBAN nodes classification than certain existing methods.

Keywords—Wireless Body Area Network (WBAN), security, trusted nodes, Grasshopper Optimization Algorithm (GOA), Artificial Neural Network (ANN)

1 Introduction

All parts of the globe may be linked together via sensor nodes, and sensors play a crucial role in today's communications technology. Wireless sensor networks are a form of wireless communication (WSN). As a subset of WSN, Wireless Body Area Networking (WBAN) is designed to function in localized areas rather than over vast areas. WBAN is now being used in the medical field for real-time patient monitoring. WBAN is a type of network created specifically for the human body and its needs, such as the ability to detect, monitor, control, and transmit various vital signs such as temperature, humidity, etc. There are a lot of network nodes in a WBAN, and they all do different things [1, 2]. Due to the several fields of engineering that have made strides in recent years, conventional medical methods can be bolstered by cutting-edge technology solutions. "Very Large-Scale Integration (VLSI)" improvements have made it feasible to integrate sensors and MEMS on devices no bigger than a few millimeters. The development of low-power short-range communication technologies has enabled wireless connection of sensors and devices easy, leading to the advent of WSN, which is acknowledged as the future basis of WBAN. The processing burden on these WSNs has been reduced because of developments in networking and algorithms, which have made large amounts of computing power and data analysis inexpensively accessible [3–5]. While it is ideal for network nodes to have complete confidence in all other network nodes, this is not always the case due to the risk of adversaries posing as trusted nodes to steal information. The term "trust management" is used to describe the process of deciding how much faith to place in a given node. For data to be processed and sent correctly, every node in the network must be able to identify every other node and respond appropriately if any of the nodes are compromised [6–8]. The individuals and the healthcare providers have a vested interest in the WBAN's efficacy. Time just adds to the difficulties encountered by developing technology. As can be seen below, WBAN faces a wide range of difficulties. There are a total of six categories that may be used to describe these difficulties: energy, mobility, security and communications, networking, quality of service, and collaboration. While other concerns must be addressed, security is paramount. Inexpensive sources of power and data analysis have relieved these WSNs of some of their processing responsibilities. Contributions of this work is,

- 50 sensor nodes were gathered and analyzed from the WBAN's trustworthy nodes for the research.
- Linear Regression-Based Principal Component Analysis is used for the feature extraction procedure (LR-PCA).
- Integrated Grasshopper Optimization Algorithm with Artificial Neural Network (IGO-ANN) for classifying trustworthy nodes in WBAN networks to increase their safety.

The rest of the paper is organized as follows: A related work is included in Part II. The suggested technique is presented in Part III. Part IV contains the analysis of the experiment results. The conclusion is given in Part V.

2 Related work

This paper reviews several research papers and technical reports authored by diverse writers. In [9], they described a new PBFT method that eliminates the problems of high communication cost, inefficient consensus, and random leader node selection that plague the original PBFT algorithm used by the consortium blockchain. Experimental results demonstrate that the enhanced PBFT algorithm enhances consensus efficiency by decreasing communication times in comparison to classic PBFT, thereby solving the issue of rising nodes and traffic volume. Reference [10] is the core WBAN system's underlying idea and basis with applications. The patient's convenience or distance again from receiving equipment must be considered when designing a system to transport patient data in the monitored room and outdoors without change or loss. Reference [11, 12] purpose was to compare and contrast two primary types of communication waves used in WBAN applications those with long-range and those with short-range—to determine the optimal conditions for employing each. To address the issue of path loss in WBAN, a protocol is suggested in the study [13]. Three sets of scenarios implemented in the OMNET++ framework serve this function. The suggested solution's results were compared with the RSS route loss factor across three different delay and data rate criteria. Improving the efficiency of the WBAN network is the primary focus of the study [14]. This demonstrates IKS's potential to deliver robust network performance in the WBAN setting. To create a reliable monitoring system, it is crucial to provide optimal network performance in a wireless body area network. This is especially true for devices involved in the transmission of life-critical signals, such as sensors. Reference [15] discussed the benefits and uses of big data analytics, as well as the issues and complications that may arise during their implementation in large-scale WBAN. Connectivity and technological advancement have made it simpler to collect data on a vital topic, which can then be used for research and the creation of practical solutions to common problems. Reference [16–18] described energy-saving solutions at the physical, media access control (MAC), and network layers. At last, a few research topics are suggested that address the needs of the application. Due to the difficulties of recharging or replacing nodes, the issue of energy consumption is receiving increasing attention. Reference [19, 20] suggested a unique structural method to deal with route loss in WBAN and elaborates on the costs associated with it. To get parameters, crucial data about the human body is measured and applied to three different case situations inside the new framework scheme. Simulations of both external and internal conversations are practiced. Experiments of on-body communication have revealed that route loss increases with both transmission distance and frequency. Reference [21, 22] offered HTTRP, a novel routing protocol for WBANs that introduces a new route selection mechanism. The simulation findings reveal that our HTTRP protocol outperforms the TARA protocol, which is a representation of TARP, in terms of network "longevity, charge balancing, temperature rise, and throughput". To deal with the issue of sensors being too hot and having uneven energy usage. Reference [23, 24] provided an effective routing protocol for monitoring cattle health and behavior while conserving energy, this research proposes a metaheuristic technique for identifying ideal clusters in WBANs. The comparative findings demonstrate that the suggested method is successful in implementing energy-efficient protocols of WBAN for remote monitoring applications. Reference [25] presents a "Fuzzy Control (FC)"-based "Energy-Aware Routing Protocol (EARP)" by first constructing a FC model of residual node energy as well as network quality, then utilizing fuzzy rules, flexible reasoning, then defuzzifier to pick the ideal forwarder node. Simulations show that EARP beats current protocols in network longevity and data transfer efficiency.

3 Proposed work

Individual nodes located in a person's clothing, on the body, or even beneath the skin are linked together in a WBAN. The nodes in the network are often connected by a wireless communication channel, and the network itself typically. Covers the user's whole body. The transceiver, battery, CPU, and sensor are its four main parts. The sensor nodes of a WBAN enable wireless monitoring at any time, in any place. Figure 1 depicts the architecture of the suggested methodology.

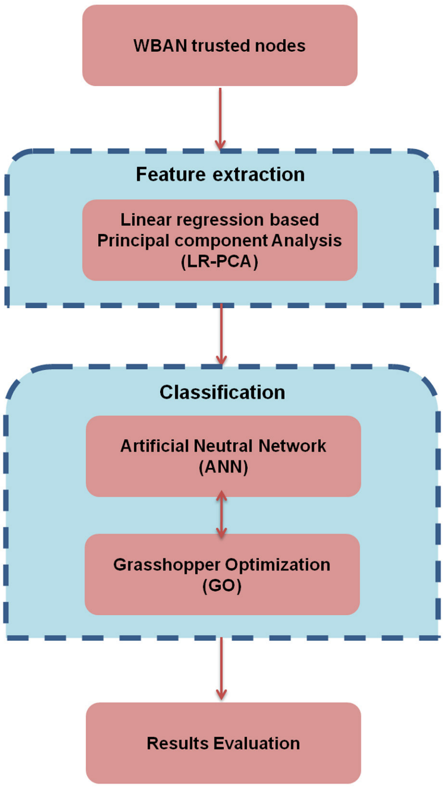

Fig. 1. Architecture of suggested methodology

3.1 WBAN trusted nodes

In this research, we analyzed a network of 52 sensor nodes, each transmitting data at a rate of 514 bytes per second. Each sensor node transfers data in packets of 514 bytes in size, with a transmission delay of 101 milliseconds (ms) between data cycles in two consecutive sequences. Batteries power each sensor node so that data may be sent and received reliably at all times. Sensor node batteries have an initial energy capacity of 1000 J each.

3.2 Feature extraction using Linear Regression based Principal Component Analysis [LR-PCA]

The present value of a tracked attribute may be predicted using linear regression, a basic statistical technique. It uses spatial correlation to forecast the present value $(\hat{y}_{kl})$ of one attribute by adding measured values of other characteristics in a linear fashion. As a model for the anticipated attribute value, we get (1):

$$\hat{y}_{kl} = b_0 + b_1 y_{k1} + b_2 y_{k2} + \cdots \tag{1}$$

The repressors coefficients, denoted by b_i are weights. These factors are calculated by dividing the covariance of B_I and B_J characteristics by the variance of B_J throughout this training phase in (2):

$$b_i = \frac{Cov(B_I, B_J)}{Var(B_I)} = \frac{\sum_i (y_{iK} - \bar{B}_I)(y_{il} - \bar{B}_l)}{\sum_i (y_{il} - \bar{B}_l)} \tag{2}$$

The model is then used to make predictions about the value of each attribute $(\hat{y}_{kl})$ at each occurrence, based on the training data. The next step is to determine whether or not the observed value $(\hat{y}_{kl})$ deviates significantly from the expected value $(\hat{y}_{kl})$ and so qualifies as deviations from normal. After the data has been smoothed, principal component analysis (PCA), a strong tool of the data analysis approach, may be used to probe the curve's hidden characteristics. In multivariate data analysis, principal component analysis was frequently employed to reduce a complex problem to a smaller group of variables that jointly accounted for the largest amount of variability. These factors are substantially less numerous, but their association is much higher. The mathematical solution to this problem resembled finding the Eigen value, with the extra variables serving as the problem's primary functional components. Data on many different variables were available at a large number of discrete points in time for the function under study. The work, therefore, faced the dimensionality problem if time was assumed to be the independent variable in the context of the functional analysis. With this in mind, the functional PCA method may be employed to accomplish the same end—a reduction in the number of dimensions of the original issue. Similar functional similarities to those found in EV charging were suppressed by the application of PCA, a dimensionality reduction method for data, in the modeling of traffic flow patterns. The deal is closed with this. The approach was fairly similar to what was done in the multivariate case. The dependent $x_i(s)(s \in T)$ was compared to the independent variables X_{ij} in (3),

$$f_i = \int \beta(s) x_i(s) = \int \beta x_i \tag{3}$$

Where, $\beta(s)$ = Weight value.

3.3 Classification using Integrated Grasshopper Optimization Algorithm with Artificial Neural Network [IGO-ANN]

This research aims to classify the trusted nodes in WBAN using a hybrid model comprised of ANN and IGO:

1. Analysis of the critical success elements influencing the total project cost in WBAN.
2. Develop a model based on influencing factors to improve the accuracy of local predictions. Grasshoppers are produced in large numbers at the outset. The first 19 dimensions of Grasshopper, shown to be in binary format and responsible for feature selection, are indeed 20 in total. Each dimension's absence of value indicates that it is disregarded in ANN calculations. Alternatively, if there is just one number, then implies that the appropriate factor is included in the ANN computations. In addition, the number of neurons in the ANN's hidden layer is defined by the grasshopper's 20th dimension. In a nutshell, every grasshopper exhibits its own unique ANN architecture, with its own set of fixed active components. Other studies have also validated the rapid and satisfying performance of the aforementioned method. For better network generalization, k-fold cross-validation is often utilized. Information is partitioned into k almost equal-sized folds for analysis. In the first step, (k1) folds are chosen to be utilized in the network's development, while the final fold is employed for evaluation and validation. Within the second stage, we'll pick an extra (k−1) fold to train on, before using that one to validate and test the network is trained. This procedure will be repeated until all folds have been utilized in the training, validation, and testing processes. When training a network with fixed architecture, the initial weights and biases are chosen at random, thus the process is repeated 20 times before saving the final, best network. The effectiveness of an ANN with a given framework and set of parameters is determined by the mean performance of the top networks at each stage.

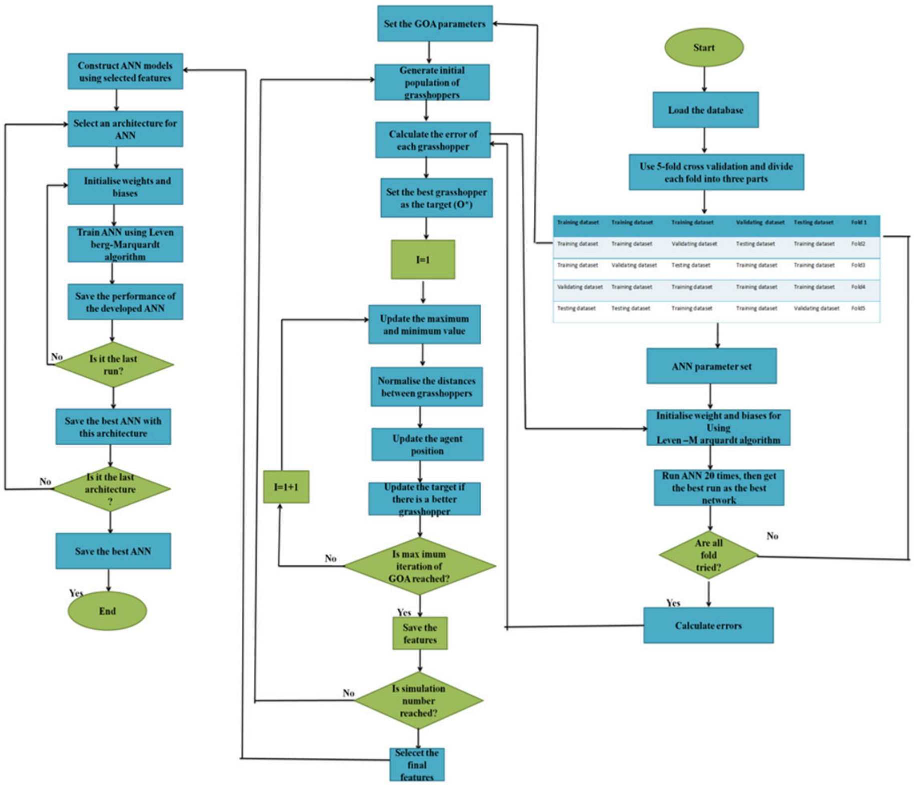

Fig. 2. Flowchart of the IGO-ANN model

The IGOA-ANN model flowchart is shown in Figure 2. It's important to remember that the performance of the constructed models may be assessed using statistical metrics like the "root-mean-squared-error (RMSE), mean-absolute-error (MAE), mean-absolute-percentage-error (MAPE), Pearson correlation coefficient (R) and OBJ".

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|T_i - O_i| \tag{5}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{T_i - O_i}{T_i}\right| \times 100 \tag{6}$$

$$R = \frac{\left(n\sum_{i=1}^{n}T_iO_i - \sum_{i=1}^{n}T_I\sum_{i=1}^{n}O_i\right)^2}{\left(n\sum_{i=1}^{n}T_i^2 - \left(\sum_{i=1}^{n}T_i^2\right)\right)\left(n\sum_{i=1}^{n}O_i^2 - \left(\sum_{i=1}^{n}O_i\right)^2\right)} \tag{7}$$

$$\begin{aligned} OBJ = & \left(\frac{n_{Training} - n_{Validating} - n_{Testing}}{n_{Training} + n_{Validating} + n_{Testing}} \right) \frac{RMSE_{Training} + MAE_{Training}}{R_{Training} + 1} \\ & + \frac{2n_{Validating}}{n_{Training} + n_{Validating} + n_{Testing}} \times \frac{RMSE_{Training} + MAE_{Training}}{R_{Validating} + 1} \\ & + \frac{2n_{Testing}}{n_{Training} + n_{Validating} + n_{Testing}} \times \frac{RMSE_{Training} + MAE_{Testing}}{R_{Testing} + 1} \end{aligned} \tag{8}$$

When solving the following equations, where n is the total number of data points, T_i and O_i are the expected and observed values for the ith data point, and n Training, n Validating, and n Testing are the total number of data points n in the training dataset, the validation dataset, and the test dataset, respectively. The RMSE, MAE, and R-value are all added together to get the OBJ value. A higher R-value and lower RMSE, MAE, and OBJ values indicate a more precise model. Finally, the IGO algorithm parameters are set, a seed population of grasshoppers is formed, and the k-fold cross-validation method is used to evaluate each grasshopper's mistake. The winner is determined by whose grasshopper makes the fewest errors. Each cycle of IGOA involves updating the grasshopper's position and selecting the best grasshopper based on the new information. To produce the final grasshopper, which stands in for the trusted nodes' active components, they must be run until it reaches its maximum number of iterations. Since the number of grasshoppers used in the simulation is completely random, the program is run 100 times. After all, simulations have been completed; the final factors are chosen based on the frequency with which each active factor occurred throughout all scenarios. Then, the acquired final factors are used to train and verify ANN models of various architectures. Due to the inherently unpredictable nature of ANN initial weights and biases, we run each design 20 times.

4 Results and disscusion

4.1 Results

In this research, we proposed the IGOA-ANN for trusted nodes. Network Simulator-2 (NS-2) measures the suggested method's effectiveness. The suggested method is compared to the existing methods such as deep neural network [DNN], support vector machine [SVM], and long short-term memory [LSTM]. Simulation results show the suggested methodology improves the state-of-the-art in every relevant statistic. Accuracy, end-to-end delay, and packet delivery ratio measure system efficiency. One technique to assess the precision of a method is to use a statistic that considers how well each part of the method functions individually. If all concerns are equally important, that's a good sign. To calculate this (9), we take the entire number of concepts and divide it by the total number of confirmed assertions.

$$\text{Accuracy} = \frac{T_{\text{positive}} + T_{\text{Negative}}}{T_{\text{positive}} + T_{\text{Negative}} + F_{\text{positive}} + F_{\text{Negative}}} \tag{9}$$

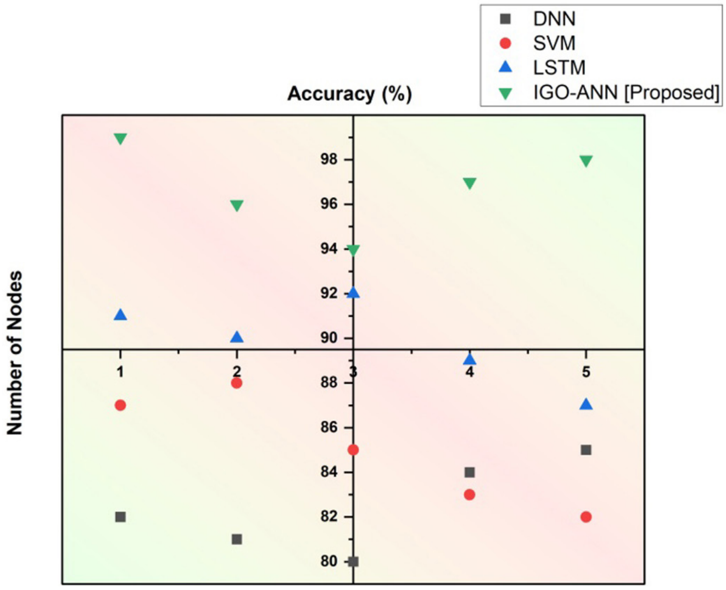

Fig. 3. Comparison of accuracy

Figure 3 displays the accuracy of the suggested and existing methods. The proposed work has the greatest accuracy than that of the existing approaches throughout this examination. We evaluate the suggested work of IGO-ANN in comparison to existing techniques like DNN, SVM, and LSTM. By dividing the total packets transmitted from the source node by the total packets received at the master controller node, we can get the Packet Delivery Rate. The PDR may be calculated with the help of the following (10).

$$\text{PDR} = \frac{\sum_{j=1}^{n} P^{j}_{\text{Success\_Delivered}}}{\sum_{j=1}^{n} P^{j}_{\text{Send}}} * 100 \tag{10}$$

$P_{\text{Success-Delivered}}$ indicates how many packets arrived at the sensor nodes successfully, whereas P_{Send} indicates how many were sent from the first sensor node.

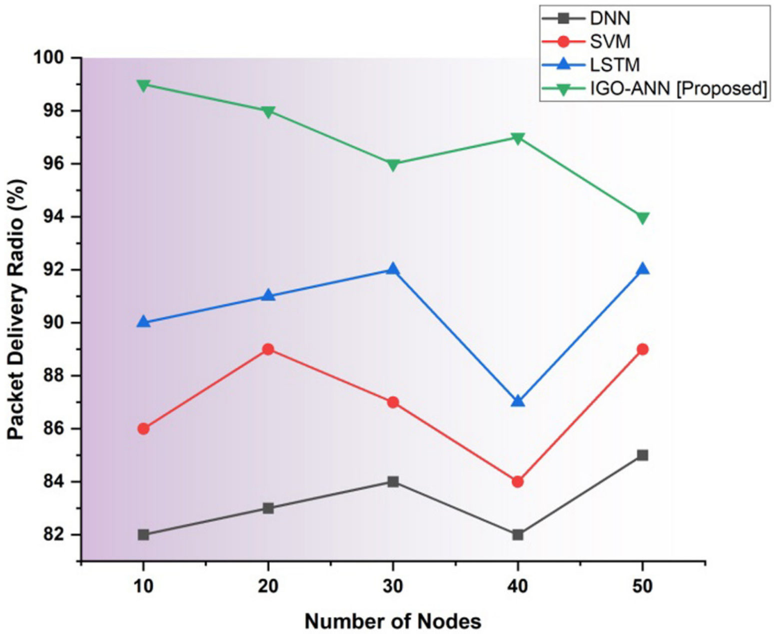

Fig. 4. Comparison of packet delivery ratio

Figure 4 shows the comparison of the PDR. The suggested method of IGO-ANN has a greater PDR than the existing methods like DNN, SVM, and LSTM.

End to End [E2E] delay. The E2E delay is the time it requires for packets to make it from the sensor node it originated from to the data center in which it will be processed. Time-consuming variables including transmission, queuing, processing, and propagation are taken into account. E2E delay may alternatively be thought of as the time it takes to send a packet and the time it takes to receive that packet. The E2E delay is calculated using (11).

$$E2E_{Delay} = \frac{\sum_{j=1}^{n}\left(Received_j^{Time} - Send_j^{Time}\right)}{n} \tag{11}$$

Given that n is the number of packets transferred, we may assume that each packet takes $Received^{Time}$ seconds to travel from the source node to the sink node, and $Send^{Time}$ seconds to go from the sink node to the source node.

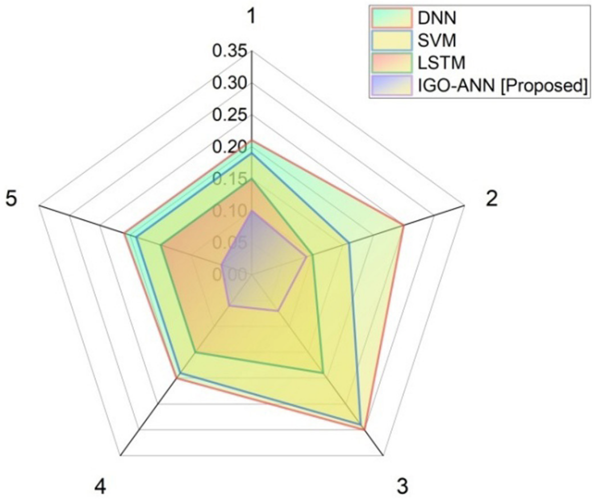

Fig. 5. Comparison of the end to end delay

Figure 5 depicts the comparison of E2E delay. When compared to the existing techniques like DNN, SVM, and LSTM the proposed IGO-ANN has a minimum E2E delay.

4.2 Discussion

The data indicate that how proposed methodology is an improvement over the current system, which has several general flaws. The following are some of the drawbacks of current methods. DNN order to outperform alternative methods needs access to a huge amount of data. Due to the complexity of the data models, it is excessively expensive to train. Large data sets are difficult for SVM to process. Data with noise (overlapping target classes) makes SVM ineffective. When the parameters of individual data points exceed those of the training data samples, SVM performs poorly. The dropout technique is difficult to implement on LSTMs, making over fitting a common problem. Dropout is a regularization technique for training a network in which input, as well as repeated connections to LSTM units, are stochastically removed from activation as well as value updates. According to our findings, the proposed method is superior to the existing technique since it fixes shortcomings in the methods now in service.

5 Conclusion

In this research, we proposed the IGO-ANN for the trusted nodes classification problem. 50 sensor nodes were gathered and analyzed from the WBAN's trustworthy nodes for the research. Linear Regression-Based Principal Component Analysis (LR-PCA) is used for the feature extraction procedure. Results from the experiments showed that the suggested IGO-ANN technique achieves the best performance in terms of accuracy, end-to-end delay, as well as packet delivery ratio in classifying trusted WBAN nodes. The proposed approach outperforms the existing techniques. Due to technological limitations, the suggested approach cannot be employed with massive datasets because of its simplified structure. The value of this study can be enhanced by more data analysis in the future. Future research will evaluate additional node attributes, such as supplies, to enhance the trust nodes technique. The uncertainty component of the trust value can be mined for an algorithm that can assess if a node is faulty.

6 References

[1] K. Kalaiselvi, L. Vanitha, K. Deepa Thilak, T. Rajesh Kumar, S. Saranya, and K. Kumaresan, "Performance Analysis of Malicious and Link Failure Detection System Using Deep Learning Methodology," *Wireless Personal Communications*, pp. 1–16, 2021. https://doi.org/10.1007/s11277-021-08790-9

[2] O. H. Yahya, and I. A. Aljazaery, "Reducing the Data Rate in Internet of Things Applications by Using Wireless Sensor Network," *International Journal of Online and Biomedical Engineering*, vol. 16, no. 3, pp. 107–116, 2020. https://doi.org/10.3991/ijoe.v16i03.13021

[3] O. Haddad and M. A. Khalighi, "Enabling Communication Technologies for Medical Wireless Body-Area Networks," in *2019 Global LiFi Congress (GLC)*, *IEEE*, pp. 1–5, 2019. https://doi.org/10.1109/GLC.2019.8864122

[4] H. T. ALRikabi, and H. T. Hazim, "Secure Chaos of 5G Wireless Communication System Based on IOT Applications," *International Journal of Online & Biomedical Engineering*, vol. 18, no. 12, 2022. https://doi.org/10.3991/ijoe.v18i12.33817

[5] H. T. Salim, A. H. M. Alaidi, A. S. Abdalrada, and F. T. Abed, "Analysis the Efficient Energy Prediction for 5G Wireless Communication Technologies," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 14, no. 08, pp. 23–37, 2019. https://doi.org/10.3991/ijet.v14i08.10485

[6] A. Algarni, "A Survey and Classification of Security and Privacy Research in Smart Health-Care Systems," *IEEE Access,* vol. 7, pp. 101879–101894, 2019. https://doi.org/10.1109/ACCESS.2019.2930962

[7] H. T. Hazim, and H. Alrikabi, "Enhanced Data Security of Communication System Using Combined Encryption and Steganography," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 16, pp. 144–157, 2021. https://doi.org/10.3991/ijim.v15i16.24557

[8] Jaafar Q. Kadhim, and I. A. Aljazaery, "Enhancement of Online Education in Engineering College Based on Mobile Wireless Communication Networks and IOT," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 18, no. 02, 2023. https://doi.org/10.3991/ijet.v18i01.35987

[9] X. Zheng, W. Feng, M. Huang, and S. Feng, "Optimization of PBFT Algorithm Based on Improved C4. 5," *Mathematical Problems in Engineering*, vol. 2021, 2021. https://doi.org/10.1155/2021/5542078

[10] I. Al_Barazanchi, H. R. Abdulshaheed, and M. S. B. Sidek, "Innovative Technologies of Wireless Sensor Network: The Applications of WBAN System and Environment," *Sustainable Engineering and Innovation, ISSN 2712–0562*, vol. 1, no. 2, pp. 98–105, 2019. https://doi.org/10.37868/sei.v1i2.69

[11] I. Al Barazanchi, H. R. Abdulshaheed, and A. Shibghatullah, "The Communication Technologies in WBAN," *Int. J. Adv. Sci. Technol*, vol. 28, no. 8, pp. 543–549, 2019.

[12] N. Alseelawi, and H. T. Hazim, "A Novel Method of Multimodal Medical Image Fusion Based on Hybrid Approach of NSCT and DTCWT," *International Journal of Online & Biomedical Engineering*, vol. 18, no. 3, 2022. https://doi.org/10.3991/ijoe.v18i03.28011

[13] I. Al_Barazanchi, A. S. Shibghatullah, and S. R. Selamat, "A New Routing Protocols for Reducing Path Loss in Wireless Body Area Network (WBAN)," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 9, no. 1–2, pp. 93–97, 2017.

[14] I. Albaeazanchi, H. R. Abdulshaheed, S. A. Shawkat, and S. R. B. Selamat, "Identification Key Scheme to Enhance Network Performance in Wireless Body Area Network," *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 7, no. 2, pp. 895–906, 2019. https://doi.org/10.21533/pen.v7i2.606

[15] H. R. Abdulshaheed, H. H. Abbas, E. Q. Ahmed, and I. Al-Barazanchi, "Big Data Analytics for Large Scale Wireless Body Area Networks; Challenges, and Applications," in *International Conference of Reliable Information and Communication Technology*, 2022: Springer, pp. 423–434. https://doi.org/10.1007/978-3-030-98741-1_35

[16] Y. Niu, S. I. Kadhem, I. A. Al Sayed, Z. A. Jaaz, H. M. Gheni, and I. Al Barazanchi, "Energy-Saving Analysis of Wireless Body Area Network Based on Structural Analysis," In *2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) IEEE*, pp. 1–6, 2022. https://doi.org/10.1109/HORA55278.2022.9799972

[17] I. A. Aljazaery, and A. H. M. Alaidi, "Encryption of Color Image Based on DNA Strand and Exponential Factor," *International Journal of Online & Biomedical Engineering*, vol. 18, no. 3, 2022. https://doi.org/10.3991/ijoe.v18i03.28021

[18] A. H. Alaidi, and K. Nasser, "The Application of Wireless Communication in IOT for Saving Electrical Energy," *International Journal of Interactive Mobile Technologies*, vol. 14, no. 01, pp. 152–160, 2020. https://doi.org/10.3991/ijim.v14i01.11538

[19] I. Al_Barazanchi *et al.*, "Proposed a New Framework Scheme for the Path Loss in Wireless Body Area Network," *Iraqi Journal for Computer Science and Mathematics*, vol. 3, no. 1, pp. 11–21, 2022. https://doi.org/10.52866/ijcsm.2022.01.01.002

[20] A. H. M. Alaidi, R. M. Al_airaji, H. T. Alrikabi, I. A. Aljazaery, and S. H. Abbood, "Dark Web Illegal Activities Crawling and Classifying Using Data Mining Techniques," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 10, 2022. https://doi.org/10.3991/ijim.v16i10.30209

[21] S. Bouldjadj, and Z. Aliouat, "High Throughput and Thermal Aware Routing Protocol (HTTRP) for Wireless Body Area Networks," *Ingénierie des Systèmes d'Information*, vol. 25, no. 1, 2020. https://doi.org/10.18280/isi.250106

[22] I. Al_Barazanchi *et al.*, "Research Methodology Design for WBAN Smart System Connection to Control Covide19 Patients Remotely," *Journal of Telecommunication Control and Intelligent System*, vol. 1, no. 3, 2021.

[23] F. Saleem *et al.*, "Ant Lion Optimizer Based Clustering Algorithm for Wireless Body Area Networks in Livestock Industry," *IEEE Access*, vol. 9, pp. 114495–114513, 2021. https://doi.org/10.1109/ACCESS.2021.3104643

[24] S. H. Abbood, M. Rahim, and A. Hadi, "DR-LL Gan: Diabetic Retinopathy Lesions Synthesis Using Generative Adversarial Network," *International Journal of Online and Biomedical Engineering*, vol. 18, no. 3, 2022. https://doi.org/10.3991/ijoe.v18i03.28005

[25] X. Wang, G. Zheng, H. Ma, W. Bai, H. Wu, and B. Ji, "Fuzzy Control-Based Energy-Aware Routing Protocol for Wireless Body Area Networks," *Journal of Sensors*, vol. 2021, 2021. https://doi.org/10.1155/2021/8830153

7 Authors

Baydaa Mohammad Mushgil received her BSc from University of Mosul in 2005 in computer engineering. Worked at University of Baghdad as an engineer at Alkawarizmi College of Engineering 2008–2013. Received her MSc. In computer and embedded systems from Universiti Putra Malaysia. she is working at University of Baghdad as an assistant lecturer at Alkawarizmi College of Engineering since 2018 Her main areas of research interest are signal processing, Information Security and IoT.

Ola Marwan Assim received her BSc from the University of Mosul in 2009 in computer engineering. Received her MSc. In computer science and technology from Andhra University in India in 2013. Worked at almamoon University as an assistant lecturer (2014–2015) and at Kirkuk University (2016–2017). She is working at the University of Mosul as an assistant lecturer at the College of Engineering since 2017 till now. Her main areas of research interest are Networks, Internet of Things (IoT), control, signal processing, and Deep learning. She can be contacted by Email: ola.marwan@uomosul.edu.iq.

Muayad Khalil Murtadha received B.Sc. and M.Sc. in Electronics and Communication Engineering from University of Baghdad in 1997 and 2000, respectively. He received PhD degree in Communication and Network Engineering from UPM University in 2017, Malaysia. He was involved in many national projects to design and deploy local and wide area communication networks, taking leadership of several activities. Currently, he is assistant professor at University of Baghdad. His current research interests include mobile communications, wireless networks, 5G, and mobility management in heterogeneous. He has many published paper in peer reviewed journals. Email: muayad.khalil@cc.uobaghdad.edu.iq

Hanaa M. Mushgil received her Master degree in 2014 in computer sciences, now she is a lecturer assistant at Al-Nahrain University, she has around 15 years teaching in different fields of computer sciences, her research interest areas are: information systems, artificial intelligence and others. She can be contacted by Email: hanaa.mohammed@nahrainuniv.edu.iq

Article submitted 2022-12-12. Resubmitted 2023-01-20. Final acceptance 2023-01-23. Final version published as submitted by the authors.