Indonesian Journal of Electrical Engineering and Computer Science
Vol. 33, No. 1, January 2024, pp. 261~268
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i1.pp261-268

Optimizing ant colony system algorithm with rule-based data classification for smart aquaculture

Mohd Mizan Munif[1], Husna Jamal Abdul Nasir[1], Muhammad Imran Ahmad[1,2]
[1]Faculty of Electronic Engineering and Technology, Universiti Malaysia Perlis (UniMAP), Kuala Perlis, Malaysia
[2]Institute of Sustainable Agrotechnology (INSAT), Universiti Malaysia Perlis (UniMAP), Kuala Perlis, Malaysia

Article Info

Article history:

Received Sep 5, 2023
Revised Oct 11, 2023
Accepted Nov 7, 2023

Keywords:

Ant colony system
Classification rules
Data classification
Smart aquaculture
Water quality

ABSTRACT

Aquaculture is one of many industries where the use of artificial intelligence (AI) techniques has increased dramatically in recent years. Internet of things (IoT), AI, and big data are just a few of the technologies being used in smart aquaculture to increase productivity, efficiency, and system sustainability of aquaculture systems. Data classification, which involves finding patterns and relationships in huge datasets, is one of the most important tasks in smart aquaculture. The ant colony system (ACS) has been used to solve a number of optimization issues, including data classification. To provide a more practical and successful solution, this study proposes an improved ACS algorithm for rule-based data classification in smart aquaculture. The proposed algorithm combines the advantages of ACS and rule-based classification to optimize the number of rules and accuracy. The experimental results showed that the proposed algorithm outperformed the traditional AntMiner algorithm in terms of the number of rules and accuracy. The improved pheromone update technique could potentially increase data classification accuracy and convergence in smart aquaculture systems.

Corresponding Author:

Husna Jamal Abdul Nasir
Faculty of Electronic Engineering and Technology, Universiti Malaysia Perlis (UniMAP)
Perlis, Malaysia
Email: husnajamal@unimap.edu.my

1. INTRODUCTION

Smart aquaculture is intelligent aquaculture management that uses smart devices in an appropriately prepared environment to monitor environmental parameters in real time and make decisions based on the data collected. Internet of things (IoT), big data, artificial intelligence (AI), fifth generation (5G), cloud computing, and robotics can automate and remotely manage smart aquaculture [1], [2]. The combination of these technologies can control machinery, facilities, and other devices to operate entire systems for successful production with minimal human intervention. Smart aquaculture collects data from sensors, sends it to a database in real time, and turns it into meaningful information. This information can be further analyzed and classified accordingly to enable data driven decision making. Some smart aquaculture systems can also be controlled remotely and require less human labour. Thus, smart aquaculture aims to develop the aquaculture industry in an environmentally and economically sustainable manner [3].

Traditional aquaculture involves seed selection, water preparation, feeding, and care [4], [5]. Aquaculture workers struggle with water quality management because water samples must be taken regularly. It is tedious to clean ponds and tanks, and unexpected changes in water quality can lead to many adverse effects as they can occur outside of the regular cleaning schedule. Another challenge is that there are instances whereby diagnoses and treatments cannot be performed while the pond-dwelling fish are still alive. These factors ultimately affect productivity and quality. Smart aquaculture solves the classic problems of aquaculture with innovative production methods, by incorporating advanced technologies such as real-time monitoring, automation, data analysis, and many more [6], [7].

Intelligent water quality monitoring in smart aquaculture uses temperature, hydrogen potential, and dissolved oxygen to determine water quality suitable for aquatic animal breeding, rearing, and harvesting [8], [9]. Systematic data classification is essential for managing huge amounts of real-time data with different properties in each sequence. Data classification is classified as a nondeterministic polynomials (NP) complete problem that is algorithmically intractable. NP complete problems provide flexible predictions and evaluations in polynomial-time. One of the best ways to solve the NP complete problem is to use metaheuristic algorithms that go through all conceivable optimization options to find the best solution [10].

Ant colony optimization (ACO) which is one of the metaheuristic algorithms has successfully improved classification performance in terms of accuracy, model size and execution time [11]–[13]. ACO is inspired by the foraging behaviour of real ants to find the shortest path from nest to food source. Ants use chemical substance called pheromone to communicate with each other [14], [15]. Pheromone is dispersed by the ants along the traversed path and can attract other ants to use the same path. Pheromone is volatile and dissipate gradually where the path with low pheromone value is longer than the path with high pheromone value. Therefore, it needs to be dispersed continuously by the other ants to mark the optimal path for the next ants to follow [16]. There are many ACO variants such as ant system (AS), ant colony system (ACS), elite ant system, rank based ant system, and max-min ant system (MMAS) that have been applied to solve the NP complete problems [17].

In data classification, ACO can be used for rule development to accurately classify dataset instances. Each regulation is symbolized by a pheromone-trailing ant [18]. Ants prefer rules with a higher pheromone concentration. The algorithm starts with random rules where each rule contains a collection of requirements outlining the properties and values an instance must have to be assigned to a class. The ants are scattered across characteristics. Each ant then selects a feature based on the pheromone concentration and a heuristic function that evaluates the importance of the the feature to the classification problem. A fitness function analyses the correctness of each rule’s classification model using the existing set of rules [19]. The ants alter their pheromone trail based on feature grade. The characteristics’ efficacy determines the strength of the pheromone trail. By encouraging the ants to choose the same traits in subsequent iterations, the method converges on a subset of attributes. Weak characteristics with low pheromone concentration may be removed from the subset to prevent the algorithm from converging to a poor solution. After selecting the best features, a classification model can be created [20].

A-HACO which integrates the artificial bee colony (ABC) strategy into the ACO algorithm, was introduced by [21] to optimize the classification process. ACO is applied to evaluate the quality of rules, dynamically adjusting the number of ants after a classification rule is created along with the quality of the rule evaluation function. The higher the quality of the rule evaluation functions, the more ants are produced compared to the lower quality functions. After the classification rule is created, ABC is applied to determine the range of continuous attribute values. Even though A-HACO has achieved an outstanding accuracy value when compared with the other algorithms, the other performance metrics must also be considered during the classification process.

ACS-AntMiner was proposed by [20] which combines ant miner classification algorithm and the ACS algorithm to improve the selection of an appropriate number of terms to be included in the classification rule. The importance rate (IR) is introduced by ACS-AntMiner as a pre-pruning criterion that depends on the probability (pheromone and heuristic) amount. Based on the proposed IR, only the important terms are added to each rule to prevent noisy data. The ACS algorithm is responsible for controlling the IR parameter through the learning process of the Ant-Miner algorithm. The experimental results showed that ACS-AntMiner outperformed ant-miner, TACO-Miner, and CAnt-Miner algorithms in terms of accuracy and number of terms. However, the performance of ACS-AntMiner was not compared with other variants of the ACS algorithm.

ACO-based multi-label feature selection technique called Ant-TD which uses a heuristic learning approach was proposed by [22] to improve the search process. The proposed approach integrates heuristic learning with the ACO algorithm by using temporal differences to learn a heuristic function from experience. The state transition rule based on probabilistic and greedy rules produces the transition function for the feature selection search space. At the same time, a learned heuristic function is formed by the state value function that is updated by the temporal differences together with the global pheromone update. The experimental results showed that Ant-TD performed better than the other algorithms in terms of accuracy, average precision, and execution time. However, Ant-TD did not consider the local pheromone update which may lead to the local optima problem.

The self-training using associative classification using ant colony optimization (ST-AC-ACO) algorithm was proposed by [23] to improve the self-training classification accuracy. ST-AC-ACO consists of three main components namely the self-training mechanism of semi-supervised learning, associative classification principles, and the ACO-based rule construction process. ACO is employed in this algorithm to label and classify the unlabeled data. Heuristic function and pheromone value are the components used in selecting the subsequent term to be added to the rule. The experimental results showed that ST-AC-ACO performed better than other algorithms in terms of accuracy. However, ST-AC-ACO was not compared with the other ACO variants.

Based on the previous research works discussed above, it can be concluded that ACO approaches are effective in enhancing the data classification process. In this paper, an ACS based algorithm for data classification called ACS-E is proposed to optimize the classification process in smart aquaculture. The main focus of the proposed classification algorithm is to improve the pheromone update techniques in optimizing the accuracy and number of classification rule. The utilization of dynamic pheromone update and pheromone decay in the local and global pheromone updates is an enhancement over previous Ant-Miner algorithms. In the first phase, a control parameter is employed to prevent the possibility of excessive buildup on a single parameter and to maintain a minimum amount of overfitting of noisy data. During the global pheromone update phase, the update rule uses a decay rate that gradually decreases the pheromone values over a period of time. The performance of the proposed algorithm was compared with the traditional AntMiner algorithm in terms of accuracy and number of rules. Section 2 discusses the details about the proposed algorithm while experimental results are presented in section 3. Finally, concluding remarks are highlighted in section 4.

2. METHOD

The enhanced ant colony system (ACS-E) algorithm is proposed to improve the accuracy of the data classification process in smart aquaculture. Figure 1 shows the proposed ACS-E framework which consists of three phases namely rule construction, pheromone update, and performance evaluation. The training dataset is added to a list of discovered rules to construct the rule. Then, the instances covered by the construction rules are removed from the training dataset. This procedure is repeated until the number of uncovered instances is greater than the maximum number of uncovered instances.

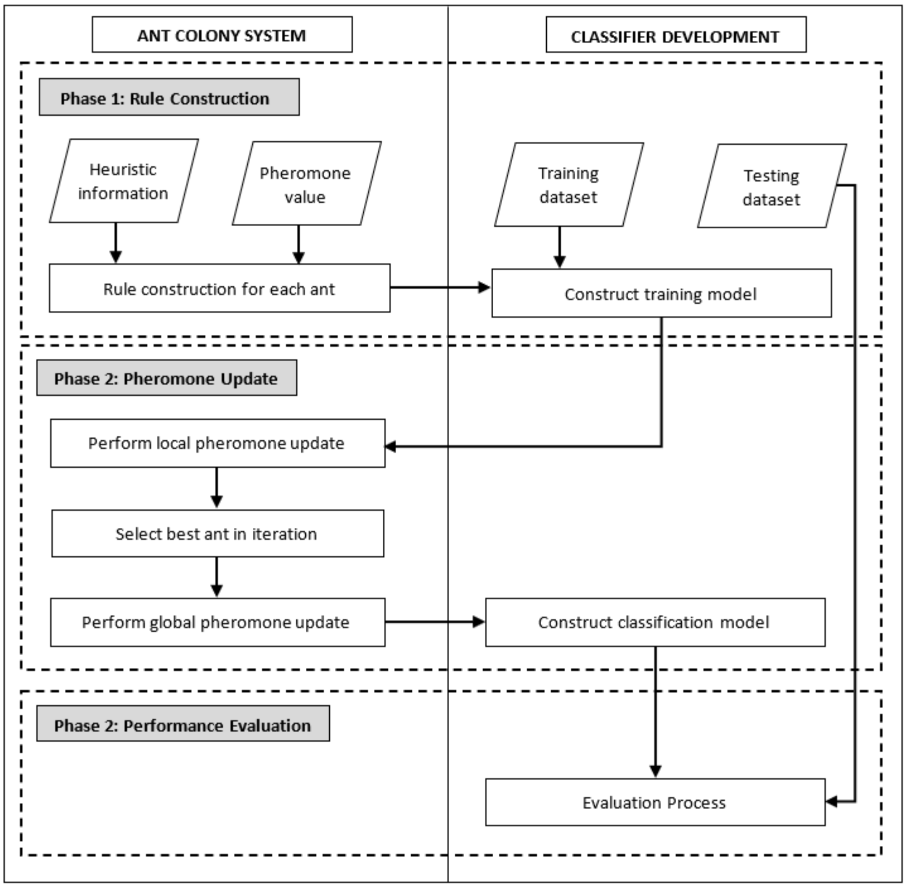

Figure 1. ACS-E framework

During the rule construction phase, each ant begins by selecting terms to be added in the rule. The pheromone value and the heuristic information are two key elements considered in selecting the terms. It is calculated by using the probabilistic decision rule (1) where $[\tau_{ij(t)}]$ is the amount of pheromone concentration for each term in iteration t and $[\eta_{ij}]$ is the heuristic information for each term. The number of the attribute in the dataset is represented by a while the number of difference values for each attribute is represented by bi. The value of xi is set to 0 if the attribute has already been visited by the ant, and 1 otherwise. The ant adds one term at a time to enhance the classification accuracy. The process of adding terms will be terminated when all attributes have been visited.

$$Probability = \frac{[\tau_{ij(t)}]\,[\eta_{ij}]}{\sum_{i=1}^{a} xi.\sum_{j=1}^{bi}[\tau_{ij(t)}]\,[\eta_{ij}]} \tag{1}$$

In the pheromone update phase, the irrelevant terms are removed to trim the rule constructed by each ant. The proposed algorithm determines the prediction class of the pruning rules by assigning the majority class of the instances covered by the rule. This process is repeated to optimize the quality of the rule. ACS-E collects feedback to improve the quality of the discovered rule by using the local pheromone update (2) where f is the evaporation rate value that controls the accumulation on certain parameter to prevent the limitless buildup.

$$\tau_{n(t+1)} = (1-f).\tau_{n(t)} + f.\mathrm{S(t)} \tag{2}$$

$S(t)$ is the quality of the discovered rule defined by (3) where N_T is the the total number of instances that are not covered by the rule and do not belong to the projected class and P_T is the total number of instances the rule applies and belong to the anticipated class. N_F is the total number of cases the discovered rule applies and whose class from the predicted class. P_F is the total number of instances with a class that is predicted by the rule but are not covered by the found rule.

$$S(t) = \frac{[N_T][P_T]}{(P_T+N_F)(N_T+P_F)} \tag{3}$$

This process is repeated until all the ants have discovered all the rules. Furthermore, the best rules among all discovered rules in the iteration are inserted into the list of discovered rules. ACS-E collects global feedback from the best rule in the iteration by using the global pheromone update (4) where f is the quality decay parameter and $\mathrm{S}(\mathrm{t}_{best})$ is the quality of the best discovered rule. After all steps are completed, a new iteration starts with the same flow.

$$\tau_{n(\mathrm{t}_{best})} = (1-f).\tau_{n(\mathrm{t}_{best})} + f.\mathrm{S}(\mathrm{t}_{best}) \tag{4}$$

3. RESULTS AND DISCUSSION

The performance of the ACS-E algorithm was evaluated using 10-fold cross validation [24], [25]. ACS-E divides the dataset into ten (10) equally sized subsets where 80% are used for the training process and 20% are used for the testing process. To ensure that all subsets are utilized, this procedure is run ten (10) times with different subsets for training and testing. Then, the performance of all folds is averaged and the standard deviations are calculated. Two performance metrics are used to evaluate the performance of ACS-E which are classification accuracy and number of rules. The classification accuracy is based on the correctly classified instances in the test data. In each round, the classifier performs the training and tests the performance of training subsets consisting of a certain number of instances. Meanwhile, the number of rules is determined by the size of the discovered rule list.

The water quality of smart aquaculture datasets such as Realfish [26], [27], Kiribati [28], sensor data [29], and Sentinel [30] are used to compare the performance of the proposed ACS-E algorithm with the other algorithms. These benchmark datasets are secondary data that are selected based on the literature. These datasets are gathered from a variety of dataset sources, including public datasets and Google dataset. The sensor data dataset consists of three fundamental water quality parameters which are temperature, pH, and water turbidity. Two sets of Arduino-based digital sensors were utilized to collect data at two distinct water depths from a fishpond on the ground of Khan Jahan Ali Hall, Khulna University. As for the Sentinel dataset, the water quality data includes dissolved oxygen, salinity, pH, turbidity, temperature, and water condition. The collection of Sentinel data was performed at two marine sites at the Tasmanian sea in Australia. For the Realfish dataset, the collection method was developed by applying an IoT framework for real-time monitoring of the aquatic environment with an Arduino and sensors. Five ponds were analyzed using three sensors for pH, temperature, and turbidity. The Kiribati dataset is a complete collection of water quality monitoring data organized by the Commonwealth Marine Economies Programme that carried out around Tarawa, Kiribati. The key parameters measured were nutrients, chlorophyll, total suspended solids, E. coli, intestinal Enterococci, vibrio, and ESBL-producing bacteria. However, because the data collected were extensive, the temperature, pH, dissolved oxygen, turbidity, and salinity were also recorded and are shown in the dataset.

Several ant-mining classifiers such as ACS-AntMiner and Ant-Miner are used to determine the performance of the proposed ACS-E algorithm in terms of classification accuracy and the number of rules. The parameter specifications listed in Table 1 were adopted and adapted from [20] to ensure that all ant-mining classifiers use the same parameter values and provide a fair evaluation of the experimental results. These parameters are selected because they were used by [20] and were proven to be effective in validating the classification accuracy and the rule term numbers.

Table 1. Experimental parameters

Description	Value
Number of Ants	10
Minimum number of cases that each rule must cover	5
Maximum of uncovered cases by the discovered rule	10
Number of iterations	100
Evaporation rate	0.3
Alpha	1

Figure 2 shows the average classification accuracy of all algorithms where a higher accuracy value indicates that the classification algorithm is more accurate. As shown in the figure, the proposed ACS-E algorithm achieved higher accuracy as compared to the others in all datasets. The integration of global and local pheromone updates along with the inclusion of pheromone decay distinguishes the ACS-E algorithm from other comparable algorithms, and as a powerful solution for smart aquaculture data classification. Its adaptability to dynamic environments combined with its ability to control the balance between exploitation and exploration positions ACS-E as a promising approach in this field.

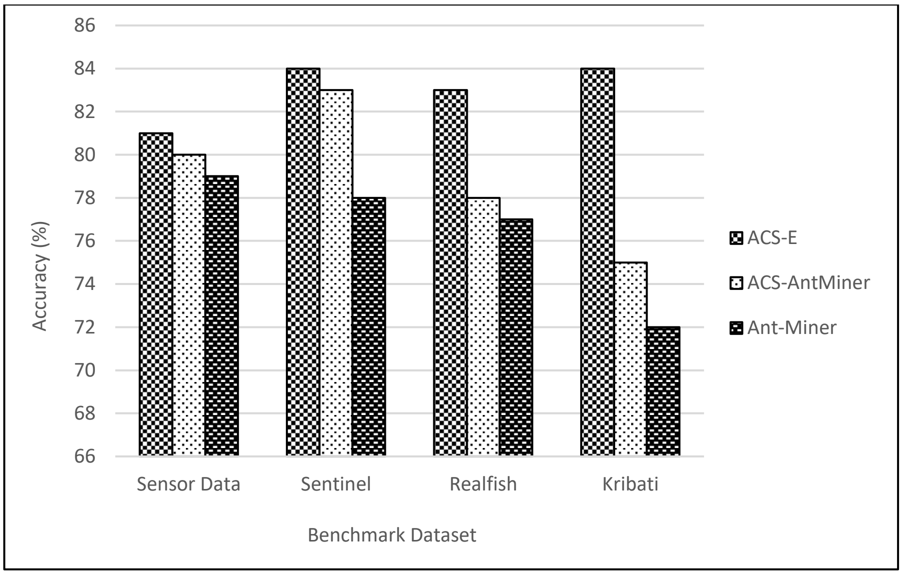

Figure 2. Average classification accuracy of all ant-based classification algorithm

A statistical test was performed to calculate the standard deviation of the average classification accuracy as presented in Table 2. As shown in the table, ACS-E attained the best standard deviation result in 3 out of 4 datasets. These results show that ACS-E is consistent and stable during the experiments as compared to ACS-AntMiner which has the second-best accuracy and standard deviation.

Table 2. Statistical test for the average accuracy value

Dataset	Algorithm	Average accuracy	Standard deviation
Sensor data	ACS-E	81%	2.77
	ACS-AntMiner	80%	6.67
	Ant-Miner	79%	3.48
Sentinel	ACS-E	84%	3.40
	ACS-AntMiner	83%	5.17
	Ant-Miner	78%	3.27
Realfish	ACS-E	83%	4.73
	ACS-AntMiner	78%	2.91
	Ant-Miner	77%	3.35
Kiribati	ACS-E	84%	4.00
	ACS-AntMiner	75%	4.53
	Ant-Miner	72%	4.42

Table 3 shows the number of rules discovered by all algorithms in a 10-fold cross-validation process. The results show that ACS-E performs better in 2 out of 4 datasets which are realfish and sensor data. The combination of global pheromone update and local pheromone update in ACS-E promotes exploitation of the best solution and exploration of the potential new solution. Despite the promising results with non-real-time datasets, the ACS-E should be further validated with real-time datasets which requires data collection from the actual aquaculture environment. Due to implementation costs, the use of real-time datasets is not feasible in this study.

Table 3. Number of discovered rules

	Sensor data	Sentinel	Realfish	Kiribati
ACS-E	6.1	6.3	6.1	6.2
ACS-AntMiner	6.2	6.3	6.3	6.1
Ant-Miner	6.2	6.2	6.1	6.3

4. CONCLUSION

In summary, this study proposes ACS-E which is an improved ant-based algorithm for optimizing the data classification in smart aquaculture. The experimental results have shown that ACS-E outperforms the existing ant-based algorithms which are ACS-AntMiner and Ant-Miner, in terms of average classification accuracy and the number of rules discovered. However, instead of using real time dataset, these experiments were conducted using an existing dataset from the internet. To implement the ACS-E algorithm in a real-time aquaculture environment, several steps must be performed. For example, the data collection process involves the deployment of specialized sensors such as temperature probes, dissolved oxygen meters, and pH sensors to continuously monitor crucial parameters in the aquaculture environment. These sensors provide real-time data on water quality, enabling the ACS-E system to make data driven decisions. However, challenges may arise, such as sensor calibration, maintenance, and the need for data synchronization across multiple sensors. In terms of hardware requirements, a robust sensor network with reliable communication devices and data storage capabilities is essential. For example, wireless sensor nodes equipped with low-power communication protocols, such as Zigbee or LoRa, can be deployed throughout the aquaculture facility to gather data from various locations. The collected data is then processed using computing resources, such as powerful microcontrollers or cloud-based systems, depending on the scale of the operation. Scalability is another important consideration as expansion requires the ACS-E system to handle increasing data volumes and computational demands. For instance, in a large-scale farm with hundreds of sensor nodes spread across multiple ponds, efficient data aggregation techniques and distributed processing algorithms become crucial to maintain real-time performance and minimize communication overhead. By incorporating these practical aspects, this study aims to provide insight into the real-world applicability of the ACS-E system in aquaculture environments. Understanding the challenges associated with data collection, hardware requirements, and scalability will help researchers and practitioners effectively implement the ACS-E system, leveraging its potential for optimizing aquaculture operations and improving decision making processes. While the findings in the experiments are promising, there are also several areas of improvement for future research works. The proposed ACS-E algorithm could be hybridized with the other potential algorithms to improve the classification process and could also be used for other machine learning tasks beyond classification, such as clustering or regression. Moreover, the proposed ACS-E algorithm could be applied to various classification problems across many domains such as natural language processing, medical diagnosis, image classification, and object recognition. Overall, the study contributes to the growing field of ACO algorithms and their applications in machine learning and data mining. The results have ultimately demonstrated the potential of ACS-E as an effective tool for predictive modeling and decision making in aquaculture and other domains, and have shown several promising directions for future research.

ACKNOWLEDGEMENTS

The authors acknowledge the financial support provided by the Ministry of Higher Education through the Fundamental Research Grant Scheme (FRGS) under a grant number of FRGS/1/2021/ICT02/UNIMAP/02/5.

REFERENCES

[1] C. Wang, Z. Li, T. Wang, X. Xu, X. Zhang, and D. Li, "Intelligent fish farm-the future of aquaculture," *Aquaculture International*, vol. 29, no. 6, pp. 2681–2711, Dec. 2021, doi: 10.1007/s10499-021-00773-8.

[2] C. Yu, Z. Hu, B. Han, Y. Dai, Y. Zhao, and Y. Deng, "An intelligent measurement scheme for basic characters of fish in smart aquaculture," *Computers and Electronics in Agriculture*, vol. 204, p. 107506, Jan. 2023, doi: 10.1016/j.compag.2022.107506.

[3] D. Sharma and R. Kumar, *Smart aquaculture: Integration of sensors, biosensors, and artificial intelligence*. Springer, 2021, doi: 10.1007/978-3-030-66165-6_21.

[4] T. T. E. Vo, H. Ko, J. H. Huh, and Y. Kim, "Overview of smart aquaculture system: focusing on applications of machine learning and computer vision," *Electronics (Switzerland)*, vol. 10, no. 22, p. 2882, Nov. 2021, doi: 10.3390/electronics10222882.

[5] F. Maulana, H. Fakhrurroja, and M. Lubis, "Smart dashboard design and water sensor integration architecture by applying internet of things (IoT) technology using data analysis and prediction methods," in *Proceedings - International Conference Advancement in Data Science, E-Learning and Information Systems, ICADEIS 2022*, Nov. 2022, pp. 1–7, doi: 10.1109/ICADEIS56544.2022.10037490.

[6] T. Imai, K. Arai, and T. Kobayashi, "Smart aquaculture system: a remote feeding system with smartphones," in *2019 IEEE 23rd International Symposium on Consumer Technologies, ISCT 2019*, Jun. 2019, pp. 93–96, doi: 10.1109/ISCE.2019.8901026.

[7] C. V. Mahamuni and C. S. Goud, "Unveiling the internet of things (IoT) applications in aquaculture: a survey and prototype design with ThingSpeak analytics," *Journal of Ubiquitous Computing and Communication Technologies*, vol. 5, no. 2, pp. 152–174, Jun. 2023, doi: 10.36548/jucct.2023.2.004.

[8] K. B. R. Teja, M. Monika, C. Chandravathi, and P. Kodali, "Smart monitoring system for pond management and automation in aquaculture," in *Proceedings of the 2020 IEEE International Conference on Communication and Signal Processing, ICCSP 2020*, Jul. 2020, pp. 204–208, doi: 10.1109/ICCSP48568.2020.9182187.

[9] J. Gladju, B. S. Kamalam, and A. Kanagaraj, "Applications of data mining and machine learning framework in aquaculture and fisheries: a review," *Smart Agricultural Technology*, vol. 2, p. 100061, Dec. 2022, doi: 10.1016/j.atech.2022.100061.

[10] S. Bukhari, K. R. Ku-Mahamud, and H. Morino, "Load balancing using dynamic ant colony system based fault tolerance in grid computing," *International Journal of Communication Networks and Information Security*, vol. 11, no. 2, pp. 297–303, Apr. 2019, doi: 10.17762/ijcnis.v11i2.3861.

[11] H. N. K. Al-Behadili, K. R. Ku-Mahamud, and R. Sagban, "Hybrid ant colony optimization and iterated local search for rules-based classification," *Journal of Theoretical and Applied Information Technology*, vol. 98, no. 4, pp. 657–671, 2020.

[12] M. Paniri, M. B. Dowlatshahi, and H. Nezamabadi-pour, "MLACO: a multi-label feature selection algorithm based on ant colony optimization," *Knowledge-Based Systems*, vol. 192, p. 105285, Mar. 2020, doi: 10.1016/j.knosys.2019.105285.

[13] F. Karimi, M. B. Dowlatshahi, and A. Hashemi, "SemiACO: a semi-supervised feature selection based on ant colony optimization," *Expert Systems with Applications*, vol. 214, p. 119130, Mar. 2023, doi: 10.1016/j.eswa.2022.119130.

[14] M. Dorigo and T. Stützle, *Ant colony optimization: overview and recent advances*. Boston, MA: Springer, 2010, doi: 10.1007/978-1-4419-1665-5_8.

[15] M. Faisal and F. Albogamy, "Ant colony optimization algorithm enhancement for better performance," in *2023 IEEE World AI IoT Congress, AIIoT 2023*, Jun. 2023, pp. 701–710, doi: 10.1109/AIIoT58121.2023.10174442.

[16] H. J. Abdul Nasir, K. R. Ku-Mahamud, and E. Kamioka, "Parameter adaptation for ant colony system in wireless sensor network," *Journal of Information and Communication Technology*, vol. 18, 2019, doi: 10.32890/jict2019.18.2.8286.

[17] R. Bhavya and L. Elango, "Ant-inspired metaheuristic algorithms for combinatorial optimization problems in water resources management," *Water (Switzerland)*, vol. 15, no. 9, p. 1712, Apr. 2023, doi: 10.3390/w15091712.

[18] I. Bida and S. Aouat, "Swarm intelligence-based decision trees induction for classification - a brief analysis," in *2020 2nd International Workshop on Human-Centric Smart Environments for Health and Well-Being, IHSH 2020*, Feb. 2021, pp. 165–170, doi: 10.1109/IHSH51661.2021.9378746.

[19] S. Prajapati, H. Das, and M. K. Gourisaria, "Feature selection using ant colony optimization for microarray data classification," in *2023 6th International Conference on Information Systems and Computer Networks, ISCON 2023*, Mar. 2023, pp. 1–6, doi: 10.1109/ISCON57294.2023.10112054.

[20] H. N. K. Al-Behadili, R. Sagban, and K. R. Ku-Mahamud, "Adaptive parameter control strategy for ant-miner classification algorithm," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, vol. 8, no. 1, Mar. 2020, doi: 10.52549/ijeei.v8i1.1423.

[21] A. Ma, X. Zhang, C. Zhang, and B. Zhang, "An adaptive hybrid ant colony optimization algorithm for the classification problem," *Information Technology and Control*, vol. 48, no. 4, pp. 590–601, Dec. 2019, doi: 10.5755/j01.itc.48.4.22330.

[22] M. Paniri, M. B. Dowlatshahi, and H. Nezamabadi-pour, "Ant-TD: ant colony optimization plus temporal difference reinforcement learning for multi-label feature selection," *Swarm and Evolutionary Computation*, vol. 64, p. 100892, Jul. 2021, doi: 10.1016/j.swevo.2021.100892.

[23] H. H. Awan and W. Shahzad, "Semi-supervised associative classification using ant colony optimization algorithm," *PeerJ Computer Science*, vol. 7, pp. 1–46, Sep. 2021, doi: 10.7717/peerj-cs.676.

[24] H. Shahraki and S. H. Zahiri, "Ant colony optimization and decision function estimation," *Intelligent Decision Technologies*, vol. 11, no. 1, pp. 71–78, Apr. 2017, doi: 10.3233/IDT-160278.

[25] Anuradha, A. Singh, and G. Gupta, "ANT-FDCSM: a novel fuzzy rule miner derived from ant colony meta-heuristic for diagnosis of diabetic patients," *Journal of Intelligent and Fuzzy Systems*, vol. 36, no. 1, pp. 747–760, Feb. 2019, doi: 10.3233/JIFS-172240.

[26] M. M. Islam, "Real-time pond water dataset for fish farming," *kaggle*. https://www.kaggle.com/datasets/monirmukul/realtime-pond-water-dataset-for-fish-farming (accessed Aug. 01, 2023).

[27] M. M. Islam, M. A. Kashem, and J. Uddin, "Fish survival prediction in an aquatic environment using random forest model," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 3, pp. 614–622, Sep. 2021, doi: 10.11591/ijai.v10.i3.pp614-622.

[28] C. A. Graves, A. Powell, M. Stone, F. Redfern, T. Biko, and M. Devlin, "Kiribati water quality monitoring data - March 2019," *data.cefas*. https://data.cefas.co.uk/view/20538 (accessed Aug. 01, 2023).

[29] A.-A. Nahid, A. I. Arafat, T. Akter, M. F. Ahammed, and M. Y. Ali, "KU-MWQ: a dataset for monitoring water quality using digital sensors," *data.mendeley*, 2020. https://data.mendeley.com/datasets/34rczh25kc/4 (accessed Aug. 01, 2023).

[30] The Commonwealth Scientific and Industrial Research Organisation, "Sentinel sensors and water quality," *data.csiro*. https://data.csiro.au/collection/csiro:44682 (accessed Aug. 01, 2023).

BIOGRAPHIES OF AUTHORS

Mohd Mizan Munif He holds a Bachelor Degree of Computer Science in Data Communication and Networking from Universiti Teknologi Mara, Malaysia in 2022. He is currently a master student in Computer Engineering at Universiti Malaysia Perlis, Malaysia. His research work is about a data classification and swarm intelligence. He can be contacted at email: mohdmizan@studentmail.unimap.edu.my.

Husna Jamal Abdul Nasir She is a Senior Lecturer at the Faculty of Electronic Engineering and Technology, Universiti Malaysia Perlis, Malaysia. She holds Bachelor of Science in Information Technology (Networking) and Master of Science in Information Technology from Universiti Utara Malaysia in 2009 and 2011 respectively. She also earned her Ph.D. in Computer Science from Universiti Utara Malaysia in 2020, specializing in ant colony optimization and wireless sensor network. Her research areas include swarm intelligence, network routing, distributed computing, and data classification. She can be contacted at email: husnajamal@unimap.edu.my.

Assoc. Prof. Dr. Muhammad Imran Ahmad He is a Associate Professor and Director for the Institute of Sustainable Agrotechnology, Universiti Malaysia Perlis (UniMAP), Malaysia. He received B.Eng. in Electrical and Electronic Engineering from Universiti Teknologi Malaysia (UTM), M.Sc. degree in Electronic System Engineering from USM and Ph.D. degree in Computer Engineering from Newcastle University, United Kingdom. His research areas include biometric, signal and image processing, nonlinear signal analysis and the application of IoT in smart farming. He can be contacted at email: m.imran@unimap.edu.my.