International Journal of System Design and Computing (IJSDC)
Volume 3, Issue 1, January – June (2025)

RESEARCH ARTICLE

REAL-TIME, ENERGY-EFFICIENT IIOT FAULT DETECTION USING BOARD-IIOT FRAMEWORK

Ghazanfar Ali Safdar[1, *] and Xiaochun Cheng[2]

[1]Senior Lecturer, Department of Computer Networking, University of Bedfordshire, United Kingdom, LU2 8DL & England.

[2]Senior Lecturer, Department of Computer Science, Swanesa University, Bay Campus, Fabian Way, Swansea, SA1 8EN, Wales, UK.

*Corresponding e-mail: ghazanfar.safdar@beds.ac.uk

Abstract – The Industrial Internet of Things (IIoT) is an essential factor behind the digital transformation of conventional industries by enabling the connection of sensors, instruments, and other industrial devices to the Internet for efficient data gathering and analysis. This connectivity facilitates greater financial gains, enhanced productivity, and improved operational performance. However, it poses some challenges, such as network latency, sensor sample latency, and dependability. To tackle these issues, a novel Belgua Optimized deep leARning framework for fault detection in IIoT (BOARD-IIoT) has been proposed in this paper for real time monitoring and fault prediction. The proposed BOARD-IIoT method utilizing the Sparse Principal Component Analysis (SPCA) for feature extraction which efficiently capturing the most relevant features from complex data. Beluga Whale Optimization (BWO) to select the most significant features that enhance the classification accuracy. The proposed system employs the Heterogeneous Neural Network (HNN) for classification. The efficacy of the suggested technique has been evaluated using specific metrics including F1score (F1S), accuracy, precision (PR) and recall (RC). The accuracy of the BOARD-IIoT approach in the machine failure dataset is 0.8%, 1.2% and 0.4% higher than existing AE-AnoWGAN, GA-Att-LSTM and DyEdgeGAT techniques respectively.

Keywords *– Industrial Internet of Things, Sparse Principal Component Analysis, Beluga Whale Optimization, Heterogeneous Neural Network.*

1. INTRODUCTION

IIoT technology lowers the costs of human resources for businesses while significantly increasing and optimizing the production and operational efficiency of industrial equipment [1]. However, IIoT technology also makes production equipment more complicated. Consequently, the likelihood of equipment failure is increased by the volume of sensor data generated. Furthermore, during actual industrial production, the rigorous operating conditions of industrial equipment as well as the external environment have an impact [2,3].

IIoT and DL have proved essential to contemporary industry [4]. With the use of these technologies, numerous industrial systems have been successfully monitored. Edge devices and other new frontiers have been opened by IIoT with DL. However, this development also raises new issues including secure IoT platforms and specialized hardware systems. In the meantime, IIoT-enabled industrial motors are also being watched to prevent operations from stopping due to component deterioration [5,6].

Vibration analysis is typically used to discover flaws in industrial settings, identifying motor problems at their earliest stages [7]. The right sensor must be chosen based on factors including weight, power consumption, cost, tolerance, size reliability, and range in order to perform vibration analysis effectively. Nevertheless, these methods have inherent drawbacks, such as system complexity and noise sensitivity in an actual setting. Machine learning and deep learning are two recent advances in AI, have created new avenues for industrial diagnosis and prognosis in order to get over these drawbacks of model-based techniques [8-10].

These techniques are also known as data-driven methods since they have the ability to directly evaluate the raw data [11]. These techniques are widely used to create efficient approaches that can analyze vast amounts of data in IIoT contexts. Other possible reasons for missing data include malfunctioning sensors that occasionally provide readings, packet loss during wireless communication, or malicious attackers interfering with the communication medium while it is being sensed, processed, stored, or sent. In addition, methods need to be lightweight in order to meet the demands of real-time IoT applications [12,13]. Here is a summary of this work's primary contributions:

- The key goal of this work is to provide an efficient method for Fault detection in IIOT to automatically find problems in machines early to prevent damage, reduce costs, and improve safety.

- To improve data quality, the gathered data from sensors are first pre-processed using data mining and data logging.
- The BOARD-IIoT technique leverages feature extraction by using SPCA to capture features efficiently and raise the classification model's accuracy.
- Next feature selection, here Beluga Whale Optimization is used to get the best features for classification.
- The selected features are then used to train the Heterogeneous Neural Network for classification, allowing it to correctly classify data into two classes such as Fault and Non-Fault.
- The effectiveness of the suggested technique is evaluated utilizing parameters like accuracy, recall (RC), f1-score, precision.

The rest of the work is ordered as follows. The literature review is covered in Part II. The created Fault detection in IIOT is described detail in Part III. The results and observations from the experiment are shown in Part IV. The recommendations and conclusion are in Part V.

2. LITERATURE REVIEW

In 2021, Dzaferagic, M., et al [14] suggested generative adversarial networks (GANs) to assist with the modules for classification defect detection and produce missing sensor measurements. The findings demonstrate that even when sensor measurements necessary for the monitoring system's correct operation are consistently missing, the impact on problem identification and classification is lessened by the GAN imputed data.

In 2021, Chetot, L., et al [15] suggested a channel estimation and sensor identification technique based on approximate message forwarding that takes into account the association between each sensor's activity probability and the physical factors observed by the access point. For an expected activity probability of 0.35, simulation results show that the proposed technique enhance the normalized MSE of the channel estimation by up to 5dB.

In 2021, Tran, M.Q., et al [16] suggested a IoT architecture that uses ML models to prevent cyberattacks and provide safe and dependable online induction motor status monitoring. With an exceptional accuracy of 99.03%, the recently proposed IoT architecture with Random Forest algorithm effectively detects motor problems caused by vibration in IIoT environments.

In 2024, Rigas, S., et al [17] suggested a novel DL-based architecture that uses time-series data from sensors mounted on shipboard machinery to focus on the PdM defect detection problem in maritime operations. The ultimate score was over 75%, with 119 out of 149 files showing more than adequate overall performance.

In 2024, Dong, J., et al [18] suggested a genetic algorithm, attention mechanism, and edge-cloud collaboration (GA-Att-LSTM) method-based enhanced long short-term memory (LSTM) method to detect IIoT facility anomalies. Five conventional machine learning techniques were outperformed by the results, which show an F1-score of 84.2%, precision of 89.8%, accuracy of 99.6% and recall of 77.6%.

In 2024, Zhao, M. and Fink, O., [19] suggested a novel method for early-stage fault detection in IIoT environments called DyEdgeGAT (Dynamic Edge via Graph Attention). The findings demonstrate that DyEdgeGAT performs robustly under novel operating settings and significantly surpasses other baseline methods for identifying faults, particularly in the early stages when the severity is modest.

In 2024, Liu, R., et al [20] suggested a novel autoencoder Wasserstein generative adversarial network (AE-AnoWGAN), an integrated unsupervised learning technique that does not require labeled data to detect aberrant bearings and perform anomaly localization. Because of this, the approach has a high efficiency in detecting anomalies, which makes it appropriate for real-time monitoring applications.

3. PROPOSED METHODOLOGY

In this portion, a BOARD-IIoT a method has been developed to enhance the accuracy of fault detection. Initially the datas are gathered from sensor nodes that can collaboratively monitor and transmit information to Gateway that connects all the sensors to processing unit for secure data transmission. Gathered data undergoes into pre-processing stages such as Data logging and Data mining to enhance the data quality. After pre-processing the essential features are extracted using SPCA. For feature selection, Beluga Whale Optimization is used select best features. Finaly the selected features are fed into Heterogeneous Neural Network which classifies into two classes such as Fault or Non-Fault. In Figure 1, the BOARD-IIoT approach's overall workflow is displayed.

3.1. Data collection

Sensors are incorporated inside the induction machines to continuously gather data, which means gathering real-time information from sensors on machines to monitor their condition and performance. The data like temperature, vibration, pressure, sound, gas levels, current, etc. are collected to detect abnormal behaviour and helps to monitor machine health. The collected data are sent to central system called gateway that connects all the sensors to processing unit for secure data transmission.

3.2. Data Pre-processing

This process removes duplicates, fills missing values that may cause incorrect or misleading analyses. Pre-Processing stage enhances the quality of data for accurate classification.

3.2.1. Data mining

The practice of drawing practical patterns and models from a large dataset is known as data mining. In a decision-making activity, these models and patterns are useful. The quality of the data is essentially what drives data mining.

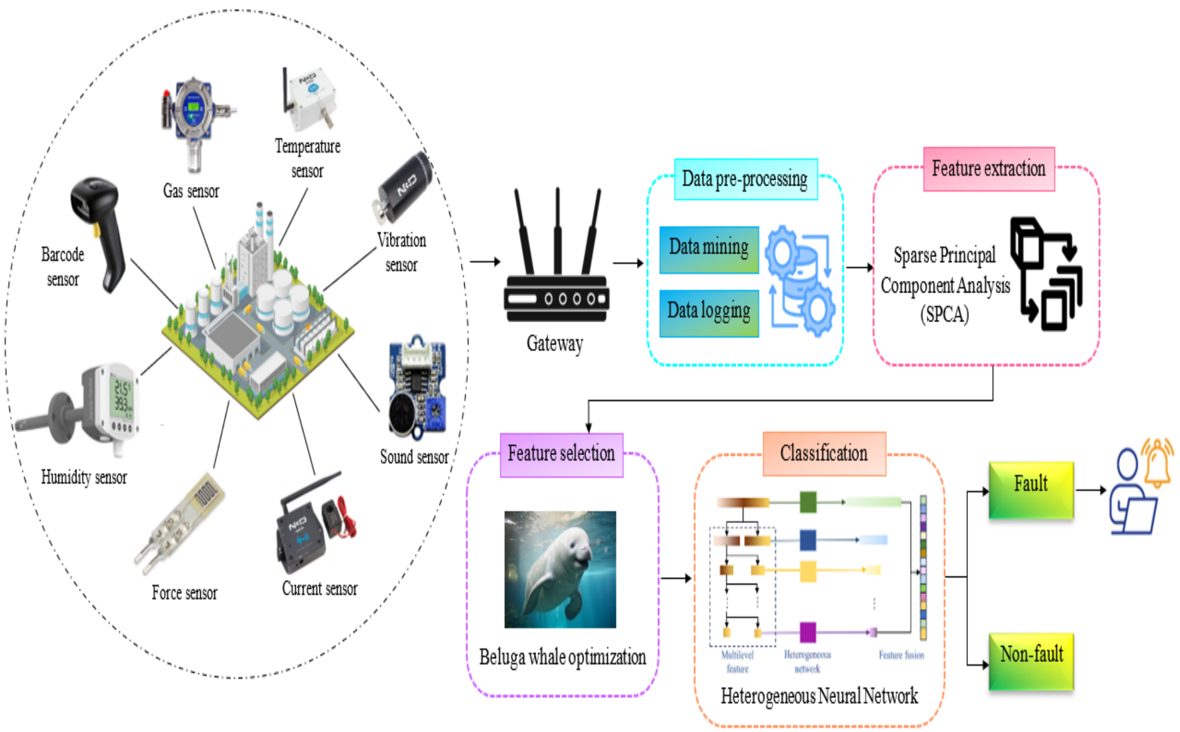

Figure 1. Proposed BOARD-IIoT methodology

3.2.2. Data logging

Data logging refers to the process of recording and storing information about the data during the pre-processing stage to ensure transparency, monitoring and perform debugging during data preparation.

3.3. Feature extraction using SPCA

This work uses the SPCE to extract the relevant information from the unprocessed data. The BOARD-IIoT technique leverages feature extraction by using SPCA to capture features efficiently and raise the classification model's accuracy.

$$v = \underset{v}{argmax}\ v^T \sum v \quad \text{s.t.} \ ||v||_2 = 1,\ ||u||_0 \leq M, \tag{1}$$

3.4. Feature selection via Beluga Whale Optimization

Feature selection has become a crucial data preprocessing method that has attracted a lot of attention in the last few decades. This technique chooses the best subset of characteristics from the original dataset, increasing classification accuracy while decreasing data size. Feature selection is carried out by Beluga Whale optimization, which draws inspiration from the hunting, swimming and falling behaviors of beluga whales.

3.4.1. Exploration Phase

The way beluga whales swim in pairs is replicated in the BWO exploration phase. As stated below, they move at random in a mirrored or synchronized fashion:

$$\begin{cases} Z_{i,j}^{S+1} = Z_{i,q_1}^{S} + \left(Z_{r,q1}^{S} - Z_{i,q_j}^{S}\right)(1+r_1)\sin(2\pi r_2),\ j = even \\ Z_{i,j}^{S+1} = Z_{i,q_j}^{S} + \left(Z_{r,q1}^{S} - Z_{i,q_j}^{S}\right)(1+r_1)\cos(2\pi r_2),\ j = odd \end{cases} \tag{2}$$

where Z is the current iteration, $Z_{i,j}^{S+1}$ is the new position for the i^{th} beluga whale, qj (j = 1, 2, …, d) is a random number selected from d-dimension, Z_{i,q_j}^{S} is the position of the i-th beluga whale on qj dimension, ,$Z_{r,q1}^{S}$ *and* Z_{i,q_j}^{S} are the current positions for i-th and r-th beluga whale (r is a randomly selected beluga whale) r1,r2 are random number between (0, 1), sin(2πr2) and cos(2πr2) toward the surface are the mirrored beluga whales' mean fins.

3.4.2 Exploitation Phase

The BWO exploitation phase imitates beluga whale predation behavior. In order to jointly forage and travel in accordance with the locations of neighboring beluga whales, it interact to one another then exchange information about their whereabouts, which can be depicted as follows:

$$Z_i^{S+1} = r_3 Z_{best}^{S} - r_4 Z_i^S + D_1 \cdot M_n \cdot (Z_r^S - Z_i^S) \tag{3}$$

where Z_i^{S+1} is the updated position of the ith beluga whale, and Z_r^S *and* Z_i^S are the present locations of the i^{th}beluga whale and the randomly select whale. The Z^S best is the optimal position for the current iteration S, r3 and r4 are random numbers between (0,1), and D1 is a measure of flight intensity that is based on the random jump intensity coefficient.

3.5. classification using Heterogeneous Neural Network

The HNN approach was created to accurately classify tasks. The idea of training stability provides the robustness and dependability of the outcomes when evaluating the HNN's effectiveness. HNN for classification, which enables it to reliably divide data into two groups, such Fault and Non-Fault.

4. RESULT AND DISCUSSION

In this section, the suggested BOARD-IIoT approach is implemented in a Python simulator. The performance of the suggested approach was assessed using several key efficacy metrics including accuracy, precision, F1-score and recall.

4.1. Dataset Description

The suggested BOARD-IIoT model is assessed for IIoT fault detection (Huang and Guo, 2019) using a machine failure dataset made publically available by BigML. This dataset is divided into seven date variables, fifteen numeric variables, and four text variables. It has 28, features, and 8,784 items.

4.2. Evaluation Metric

This section describes the metrics used to assess the proposed methodology. The efficacy of the suggested approach has been assessed metrics using namely F1-Score, Recall, Precision, and Accuracy.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (4)$$

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{FP+Tp}} \quad (5)$$

$$\mathrm{F1-score} = \frac{2*(\mathrm{PR}*\mathrm{Recall})}{(\mathrm{PR+Recall})} \quad (6)$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{(\mathrm{TP+FN})} \quad (7)$$

4.3 Performance Analysis

The proposed BOARD-IIoT technology has been compared with existing IoT fault detection methods, such as AE-AnoWGAN, GA-Att-LSTM, and DyEdgeGAT.

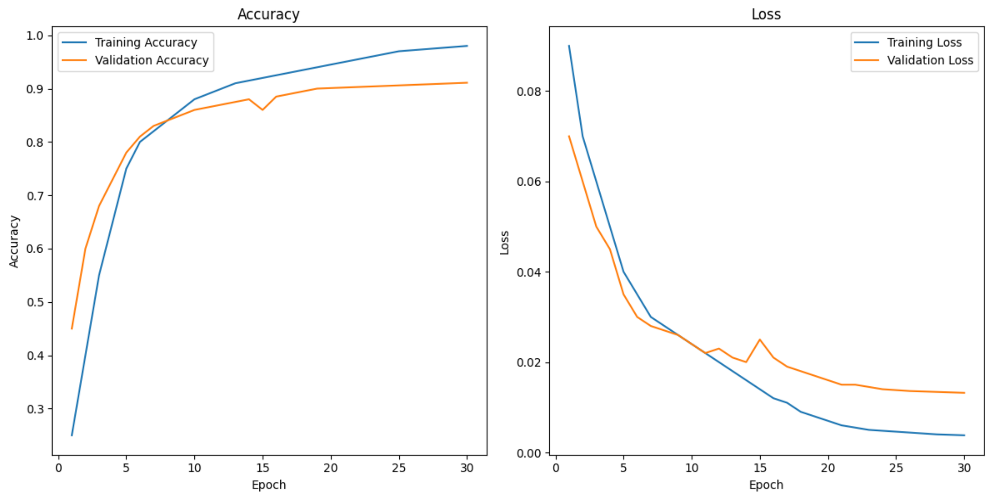

Figure 2. Accuracy and Loss curve for BOARD-IIoT method

The proposed BOARD-IIoT approach has achieved an overall accuracy of 98.63% on the dataset. Figure 2 demonstrates the accuracy and loss charts of the suggested fault detection techniques show how the validation and testing were categorized. These plots illustrate the technique's efficiency, highlighting its effectiveness in identifying faults. The moderate loss numbers also show that learning was successful and that overfitting was kept to a minimum throughout the training period.

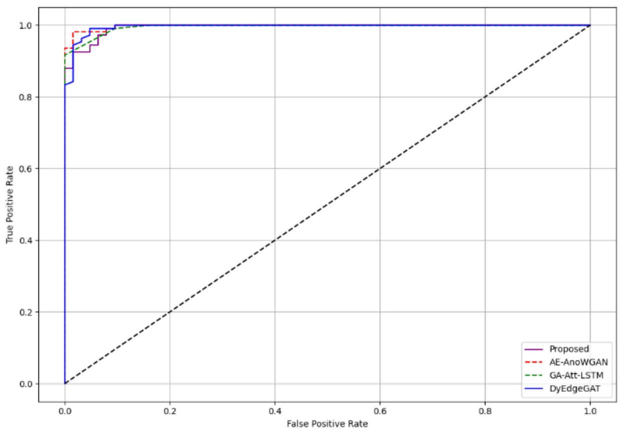

Figure 3. Roc curve for BOARD-IIoT method

The ROC curve for fault detection outcomes using the machine failure dataset is shown in Figure 3. In comparison to the machine failure dataset, BOARD-IIoT technique produced a comparatively high AUC of 96.9 for normal cases and 97.4 for high cases.

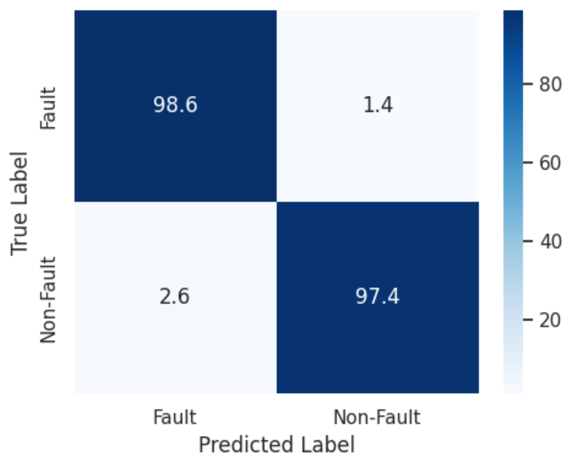

Figure 4. Confusion Matrix

For classification tasks, Figure 4 shows confusion matrices with performance predicted labels on Fault and

Non-Fault 98.6% of labels are identified, with 1.4% being classified as normal and 1.20% as somewhat elevated. The classifier performs well across all datasets, especially when it comes to Fault detection.

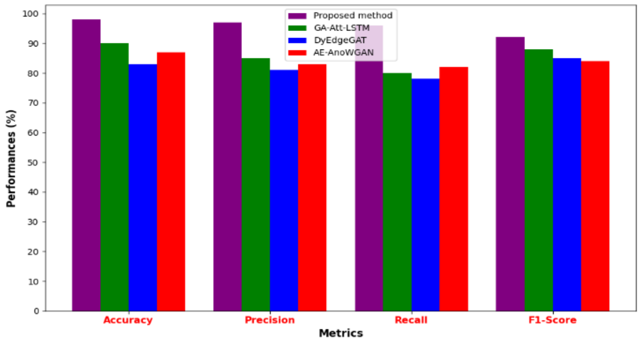

Figure 5. Performance Analysis

The performance study of categorization classes using the machine failure dataset is shown in Figure 5. For the machine failure dataset, the recommended method's F1-Score, accuracy, recall, precision, and F1-score are 98.63%, 98.14 and 97.42%, respectively.

5. CONCLUSION

This research suggests a new BOARD-IIoT method for efficiently detecting fault in IIoT. The SPCA method is utilized for feature extraction in order to efficiently capture features. For feature selection, Beluga Whale Optimization is employed to enhance the classification model's accuracy. By feeding these selected features into the Heterogeneous Neural Network, the network is able to classify data reliably into two classes: Fault or Non-Fault. In addition to increasing Fault detection, this method successfully diagnoses and identify several fault kinds in real-time operating situations. The proposed approach is evaluated using f1score, recall, accuracy, and precision. For the machine failure dataset, the proposed method's F1-Score, accuracy, recall and precision are 97.42%, 98.14 and 98.63%, respectively. The accuracy of BOARD-IIoT methodology is 1.2%, and 0.4% higher in the machine failure dataset than the current AE-AnoWGAN, GA-Att-LSTM and DyEdgeGAT methods. The proposed framework needs to use many effective deep learning algorithms in the future to further enhance the effectiveness of diagnosis and detection. Furthermore, many industrial IoT applications and scenarios can be researched in order to create further DT-based automated diagnosis systems.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

Not applicable.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

[1] Y.Y.O. Al Belushi, P.J. Dennis, S. Deepa, V. Arulkumar, D. Kanchana, and R. YP, "A Robust Development of an Efficient Industrial Monitoring and Fault Identification Model using Internet of Things," In *2024 IEEE International Conference on Big Data & Machine Learning (ICBDML)*, pp. 27-32, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] A. Khanna, R. Sharma, A. Dhingra, and N. Dhaliwal, "Preventive breakdown and fault detection of machine using industrial IOT in maintenance and automation," *Materials Today: Proceedings*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] S.F. Chevtchenko, E.D.S. Rocha, M.C.M. Dos Santos, R.L. Mota, D.M. Vieira, E.C. De Andrade, and D.R.B. De Araújo, "Anomaly detection in industrial machinery using IoT devices and machine learning: A systematic mapping," *IEEE Access*, vol. 11, pp.128288-128305, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] N. Trapani, and L. Longo, "Fault detection and diagnosis methods for sensors systems: a scientific literature review," *IFAC-Papers on Line*, vol. 56, no. 2, pp. 1253-1263, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] F. Li, J. Lin, and H. Han, "FSL: federated sequential learning-based cyberattack detection for Industrial Internet of Things," *Industrial Artificial Intelligence*, vol. 1, no. 1, pp. 4, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] G.A. Sampedro, M.A.P. Putra, J.M. Lee, and D.S. Kim, "Industrial internet of things-based fault mitigation for smart additive manufacturing using multi-flow BiLSTM," *IEEE Access*, vol. 11, pp. 99130-99142, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] E.H. Abualsauod, "Machine learning based fault detection approach to enhance quality control in smart manufacturing," *Production Planning & Control*, pp. 1-9, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] P. Zhou, C. Li, C. Chen, D. Wu, and M. Fei, "P 3 AD: Privacy-Preserved Payload Anomaly Detection for Industrial Internet of Things," *IEEE Transactions on Network and Service Management*, vol. 20, no. 4, pp. 5103-5114, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] J. Huang, and H. Hu, "Hybrid beluga whale optimization algorithm with multi-strategy for functions and engineering optimization problems," *Journal of Big Data*, vol. 11, no. 1, pp. 3, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] A.G. Hussien, R.A. Khurma, A. Alzaqebah, M. Amin, and F.A. Hashim, "Novel memetic of beluga whale optimization with self-adaptive exploration–exploitation balance for global optimization and engineering problems," *Soft Computing*, vol. 27, no. 19, pp. 13951-13989, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] C. Peng, Z. Li, M. Wang, and M. Ma, "Dynamics in a memristor-coupled heterogeneous neuron network under electromagnetic radiation," *Nonlinear Dynamics*, vol. 111, no. 17, pp. 16527-16543, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Y. Xie, Z. Yao, and J. Ma, "Formation of local heterogeneity under energy collection in neural networks," *Science China Technological Sciences*, vol. 66, no. 2, pp. 439-455, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] C.S. Ranganathan, R. Sampathrajan, M. Venkatesh, N. Mishra, E.N. Ganesh, and S. Murugan, "Fault Detection in Building Infrastructure Using IoT Sensors and Bayesian Network,"

In *2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI)*, pp. 437-442, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[14] M. Dzaferagic, N. Marchetti, and I. Macaluso, "Fault detection and classification in Industrial IoT in case of missing sensor data," *IEEE Internet of Things Journal*, vol. 9, no. 11, pp. 8892-8900, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[15] L. Chetot, M. Egan, and J.M. Gorce, "Joint identification and channel estimation for fault detection in industrial IoT with correlated sensors," *IEEE Access*, vol. 9, pp.116692-116701, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[16] M.Q. Tran, M. Elsisi, K. Mahmoud, M.K. Liu, M. Lehtonen, and M.M. Darwish, Experimental setup for online fault diagnosis of induction machines via promising IoT and machine learning: Towards industry 4.0 empowerment," *IEEE access*, vol. 9, pp.115429-115441, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[17] S. Rigas, P. Tzouveli, and S. Kollias, "An End-to-End Deep Learning Framework for Fault Detection in Marine Machinery," *Sensors*, vol. 24, no. 16, p.5310, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[18] J. Dong, Z. Li, Y. Zheng, J. Luo, M. Zhang, and X. Yang, Real-time fault detection for IIoT facilities using GA-Att-LSTM based on edge-cloud collaboration," *Frontiers in Neurorobotics*, vol. 18, pp. 1499703, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[19] M. Zhao, and O. Fink, Dyedgegat: Dynamic edge via graph attention for early fault detection in iiot systems," *IEEE Internet of Things Journal*, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[20] R. Liu, D. Xiao, D. Lin, and W. Zhang, Intelligent bearing anomaly detection for industrial Internet of Things based on auto-encoder Wasserstein generative adversarial network," *IEEE Internet of Things Journal*, vol. 11, no. 13, pp. 22869-22879, 2024. [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

Ghazanfar Ali Safdar received a BSc (Hons) in Electrical Engineering from University of Engineering and Technology, Pakistan in 1997. He subsequently received M.Eng in Computer Science and Telecommunications from University of Technology, Grenoble, France in 2001. He was awarded a PhD from Queen's University Belfast, UK in 2005 for his work in the area of power-saving MAC protocols for the IEEE 802.11 family of wireless LANs. He then worked from 2005-2008 with the same university as a Research Fellow involved in the security and authentication protocols for wireless networks. Ghazanfar Ali is currently working as a lecturer in Computer Networking at University of Bedfordshire. He has also worked as R & D engineer with Carrier Telephone Industries (SIEMENS), Pakistan and Schlumberger, France. Dr Ghazanfar Ali Safdar, has been selected to be an associate editor for IET Networks, the journal of the prestigious Institution of Engineering & Technology.

Xiaochun Cheng is a Senior Lecturer in the Department of Computer Science at Swansea University, United Kingdom. Based at the Bay Campus, Fabian Way, Swansea, he contributes to teaching, research, and academic development within the field of computer science. Dr. Cheng's expertise spans across advanced computing methods, emerging technologies, and applied research aimed at solving real-world challenges. At Swansea University, he actively engages in mentoring students, conducting innovative research, and collaborating with academic and industry partners to advance knowledge in the discipline.

Arrived: 20.05.2025
Accepted: 22.06.2025