

Analysis of fault diagnosis in wireless sensor networks using Artificial Intelligence techniques

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Abstract: Wireless Sensor Networks, also known as WSNs, have emerged as an indispensable element in a wide range of contemporary applications, such as healthcare, environmental monitoring, industrial automation, and smart city infrastructures. Nevertheless, network performance, dependability, and data integrity can be negatively impacted by node failures, communication mistakes, packet loss, and sensor malfunctions. By combining deep learning and machine learning approaches, this study offers an AI-based framework for WSN fault diagnosis, which improves problem identification and categorisation. A number of network defects can be efficiently identified using the suggested methodology, which includes data pretreatment, feature extraction, model creation, and comparative performance evaluation. The results show that by efficiently learning complicated patterns from sensor data, AI-based systems deliver problem diagnosis that is more accurate, adaptive, and dependable than traditional methods. Furthermore, feature engineering and data preprocessing significantly improve classification performance and reduce misclassification rates. The proposed framework supports real-time fault monitoring, predictive maintenance, and intelligent decision-making, thereby enhancing network reliability, operational efficiency, and system resilience. The study demonstrates that AI-driven fault diagnosis offers a scalable and efficient solution for developing robust and dependable Wireless Sensor Networks in dynamic and resource-constrained environments.

Keywords: Wireless Sensor Networks; Artificial Intelligence; Fault Diagnosis; Machine Learning; Deep Learning; Fault Detection; Long Short-Term Memory

1. INTRODUCTION

In recent years, WSNs have become an essential tool for a wide range of real-world applications, including healthcare, smart agriculture, industrial automation, environmental monitoring, smart cities, and military surveillance. The many sensor nodes that make up a WSN work together to gather data, process it, and send it on to a main base station. Despite their extensive use, WSNs are prone to a number of problems, such as malfunctioning nodes, broken connections, lost packets, running out of power, faulty sensors, and software or hardware mistakes. When these problems occur, the network's performance, data dependability, energy consumption, and general stability and efficiency can all take a hit.

Conventional approaches to fault identification mostly include statistical analysis, threshold-based monitoring, and rule-based procedures. While these methods work well for simple fault detection, they frequently fail to spot complicated, dynamic, and time-dependent fault patterns in WSNs on a wide scale. In addition, traditional approaches sometimes fail to adjust to evolving network conditions, leading to slowed fault detection, higher false alarm rates, and less accurate diagnostics. Intelligent fault diagnostic methods that can provide accurate, adaptable, and real-time fault detection are in high demand due to the rising complexity of contemporary sensor networks.

Due to the ability to automatically analyse massive amounts of sensor data, recent developments in AI, especially ML and DL, have revolutionised fault diagnosis in WSNs. AI-powered models have the remarkable ability to understand intricate spatial and temporal relationships, correctly identify various sorts of faults, and anticipate impending problems in the network before they impact its performance. Classification performance has been well-exhibited by machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN). On the other hand, deep learning models like CNN, RNN, and LSTM networks are more adept at representing sequential sensor data and capturing long-term temporal dependencies. These methods boost operational efficiency and network dependability by making fault detection more accurate, decreasing false alarms, and facilitating predictive maintenance.

Using a combination of DL and ML, this research suggests a paradigm for AI-based defect diagnostics in Wireless Sensor Networks. To facilitate real-time network monitoring and enhance diagnostic accuracy, the suggested method makes use of data preprocessing, feature engineering, and intelligent classification models. To find out how well both conventional and AI-based methods work, we compare and contrast their precision, computing efficiency, scalability, and capacity to pinpoint where problems are. This study's results aid in the creation of Wireless Sensor Networks that are dependable, scalable, and energy-efficient, and also shed light on how artificial intelligence can be used for intelligent problem diagnostics.

2. RESEARCH OBJECTIVES

1. To identify and classify the different types of faults occurring in Wireless Sensor Networks (WSNs), and evaluate their impact on network performance, data reliability, and system stability.

2. To analyze and compare existing artificial intelligence (AI) techniques used in fault detection and diagnosis in WSNs, focusing on their accuracy, scalability, and real-time applicability.
3. To develop and implement AI-based models for effective fault detection and diagnosis in WSNs, with an emphasis on enhancing system resilience, data integrity, and predictive maintenance capabilities.
4. To perform a comparative analysis between traditional fault diagnosis methods and AI-based approaches in WSNs, highlighting improvements in fault detection accuracy, fault localization speed, energy efficiency, and overall network robustness.

3. RESEARCH METHODOLOGY

This research presents a framework for Wireless Sensor Networks (WSNs) fault diagnosis that uses AI to enhance network reliability and the accuracy of fault detection through the integration of DL and ML protocols. Gathering data, cleaning it up, extracting features, building a model, testing it, and comparing results are the six main steps of the methodology. Using sophisticated predictive models, the workflow was developed to discover and classify common WSN issues, such as node failure, packet loss, communication errors, energy depletion, and sensor defects.

To begin, models were developed and tested on a simulated WSN dataset that included both healthy and unhealthy network states. Preprocessing methods were utilised to enhance the quality of the data, as raw sensor data frequently includes noise, missing values, and inconsistencies. These methods included data cleaning, normalisation, and management of missing values. Packet delivery ratio, throughput, signal strength, communication delay, and node energy consumption were among the network properties that were subsequently extracted through feature engineering. These elements improved the models' capacity to differentiate between typical and abnormal settings and gave meaningful depictions of network behaviour.

Machine learning algorithms Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbours (KNN) were trained on the processed dataset. Three deep learning models, namely CNN, RNN, and LSTM, were also trained on the dataset. The baseline classification performance was established using machine learning models, and defect diagnosis was

improved by capturing complicated spatial and temporal correlations in sensor data using deep learning models. In order to improve the model's performance and decrease overfitting, optimisation and hyperparameter tuning were utilised.

We used confusion matrix analysis to measure classification reliability and conventional metrics for classification, including accuracy, precision, recall, and F1-score, to measure the model's performance. To conclude, the effectiveness of the proposed LSTM-based framework for intelligent fault diagnosis in WSNs was evaluated by comparing it to existing methodologies. Wireless sensor networks can benefit from the methodology's methodical framework for building scalable, real-time AI-based fault diagnosis systems that are accurate, efficient, and able to increase network reliability.

4. RESULTS AND DISCUSSION

The proposed AI-based architecture for WSN defect diagnostics was tested using a variety of ML and DL models, including SVM, Random Forest, KNN, CNN, RNN, and LSTM. Node failure, packet loss, communication errors, energy depletion, and sensor failures were some of the simulated WSN faults used to evaluate performance. Accuracy, precision, recall, F1-score, and confusion matrices were also employed. Classification accuracy was greatly enhanced by data cleansing, feature extraction, and model fine-tuning. Due to its resilience and capacity to manage nonlinear data, Random Forest outperformed the other machine learning models; SVM came in second, while KNN performed rather poorly on big datasets. Deep learning models demonstrated superior fault detection capabilities, with LSTM producing the highest accuracy by effectively capturing long-term temporal dependencies in sensor data. CNN performed well in spatial feature extraction, whereas RNN effectively modeled sequential patterns.

The results confirm that AI-based methods outperform conventional fault detection techniques by providing higher detection accuracy, better adaptability, and improved reliability. Although deep learning models require greater computational resources, their superior performance makes them suitable for large-scale and dynamic WSN applications. The study also suggests that hybrid AI approaches combining ML and DL can provide an optimal balance between accuracy, computational efficiency, & real-time fault diagnosis.

Performance Analysis

Performance analysis showed that all AI models successfully detected and classified various WSN faults. Random Forest was the best-performing machine learning algorithm because of its robustness and high classification accuracy, while SVM performed well for binary classification. KNN showed lower performance due to its sensitivity to noise and higher computational cost. Among deep learning models, CNN effectively extracted spatial features, RNN captured sequential dependencies, and LSTM achieved the highest performance by learning long-term temporal patterns in sensor data. Overall, deep learning models outperformed traditional ML methods in complex fault scenarios. The findings demonstrate that AI-based fault diagnosis significantly improves network reliability, fault detection accuracy, and operational efficiency. Furthermore, effective data preprocessing, feature engineering, and model optimization were found to be essential for achieving high-performance and scalable fault diagnosis in Wireless Sensor Networks.

Machine Learning Models

There are significant disparities in the classification performance, resilience, and suitability for real-time network monitoring when comparing machine learning models for defect diagnosis in Wireless Sensor Networks (WSNs). The accuracy, precision, recall, and F1-score were used to evaluate three popular machine learning algorithms: SVM, RF, and KNN. Random Forest outperformed all of the other models in terms of overall performance, with scores of 94.9% for F1-score, 95.6% for accuracy, and 95.1% for precision. The ensemble learning method it employs improves prediction accuracy, reduces overfitting, and efficiently deals with nonlinear and noisy sensor data by combining numerous decision trees. These characteristics make Random Forest highly suitable for detecting faults such as node failures, packet loss, and communication disruptions in dynamic WSN environments.

Table 1 Performance of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	91.2	90.5	89.8	90.1

Random Forest	95.6	95.1	94.8	94.9
KNN	88.3	87.6	86.9	87.2

Additionally, the SVM proved to be quite capable in classification, with scores of 90.1% for F1-score, 89.8% for recall, 90.5% for precision, and 91.2% for accuracy. By determining the best decision limits, SVM efficiently distinguishes between healthy and unhealthy network circumstances. Its adaptability is limited in large-scale, dynamic sensor networks, nevertheless, because its performance drops marginally when dealing with extremely complicated and nonlinear information. With an F1-score of 87.2%, an accuracy of 88.3%, a precision of 87.6%, and recall of 86.9%, K-Nearest Neighbours (KNN) performed the worst of the three models. When it comes to prediction, KNN is computationally expensive and extremely vulnerable to noise and irrelevant characteristics, but it's easy to apply and produces good classification results for smaller datasets. Due to these restrictions, it is not as useful for diagnosing faults in WSNs in real time. These results were subsequently validated by confusion matrix analysis. Random Forest produced the highest number of correctly classified instances with the fewest false positives and false negatives, indicating superior predictive reliability. SVM also showed balanced classification performance, whereas KNN exhibited relatively higher misclassification rates.

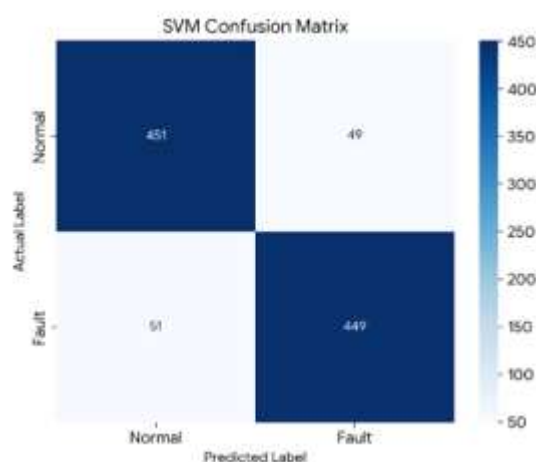


Figure 1: SVM Confusion Matrix

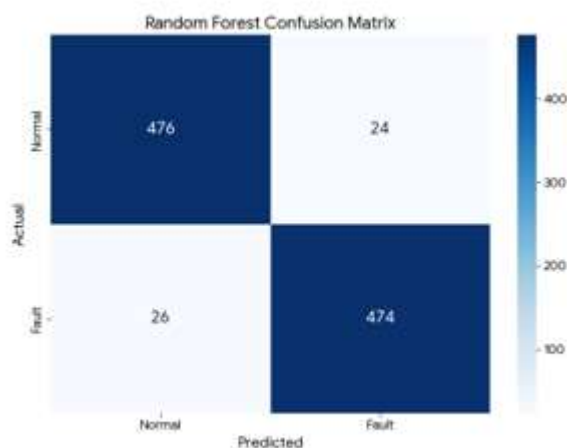


Figure 2: Random Forest Confusion Matrix

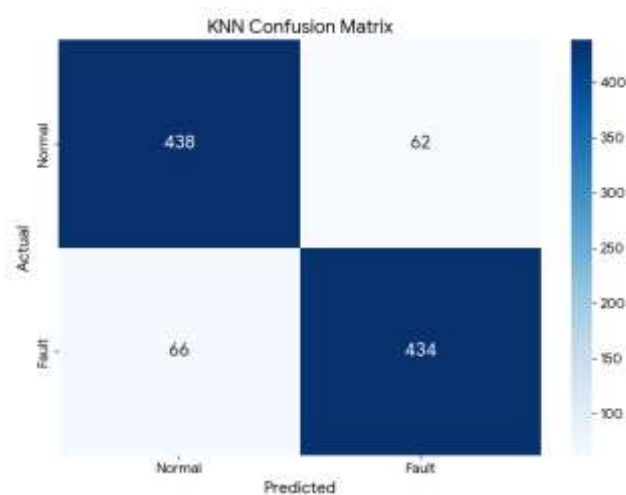


Figure 3: KNN Confusion Matrix

Overall, the comparative analysis demonstrates that RF is the most effective machine learning model for fault diagnosis in Wireless Sensor Networks, offering the highest classification accuracy, robustness, and generalization capability. When it comes to intelligent defect identification in complicated and ever-changing WSN environments, ensemble-based approaches like Random Forest are superior than SVM's dependable performance on structured datasets and KNN's basic baseline approach. These results highlight the significance of picking the right machine learning methods to boost fault management system efficiency, decrease downtime, and increase network dependability.

Deep Learning Model Performance Analysis

In order to determine how well deep learning models operate for WSN fault diagnostics, their performance was tested. We examined three popular architectures, CNN, RNN, and LSTM, using traditional assessment measures like F1-score, recall, accuracy, and precision. The results show that DL models outperform traditional ML methods in classification tasks, especially when dealing with time-dependent and sequential sensor data.

Table 2 Performance of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	96.8	96.2	95.9	96.0
RNN	94.5	93.9	93.5	93.7
LSTM	97.9	97.4	97.1	97.2

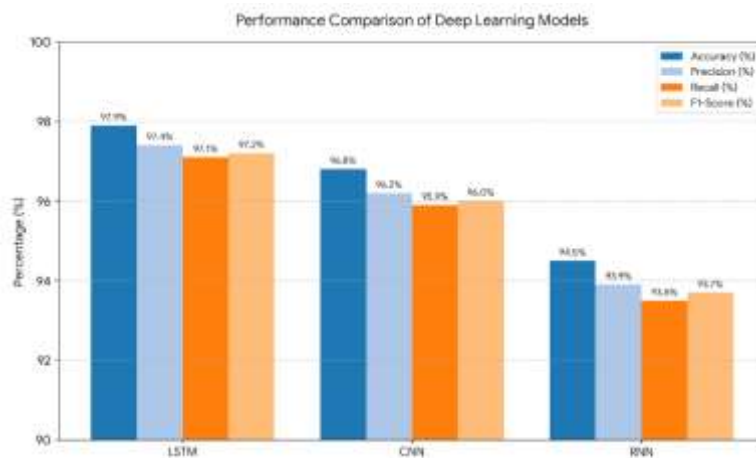


Figure 4: Performance of Deep Learning Models

Overall, LSTM performed the best of the models that were tested, with a 97.9% accuracy rate, 97.4% precision, 97.1% recall, and 97.2% F1-score. The memory cell architecture successfully records complicated failure patterns and long-term temporal relationships in sensor data, which is the reason for its better performance. Because of this feature, LSTM can reliably differentiate between healthy and unhealthy network circumstances, making it an excellent choice for intelligent network monitoring and real-time problem prediction. The CNN model

also demonstrated excellent classification capability, achieving 96.8% accuracy, 96.2% precision, 95.9% recall, and a 96.0% F1-score. CNN effectively extracts spatial features from sensor readings and identifies localized anomalies, making it a reliable model for fault detection in WSNs. Although originally designed for image processing, its feature extraction capability proved beneficial for identifying complex patterns in sensor datasets. The RNN model recorded an accuracy of 94.5%, precision of 93.9%, recall of 93.5%, and an F1-score of 93.7%. While RNN successfully captured sequential relationships in the data, its performance was slightly lower than CNN and LSTM due to limitations in retaining long-term dependencies, which affected its ability to recognize complex fault patterns over extended time sequences.

Confusion matrix analysis further validated the performance of all three models. LSTM produced the highest number of correctly classified fault and non-fault instances while maintaining the fewest false positives & false negatives, confirming its robustness and reliability. CNN also achieved high classification accuracy with minimal misclassification, whereas RNN showed comparatively higher error rates but remained effective for sequential fault detection.

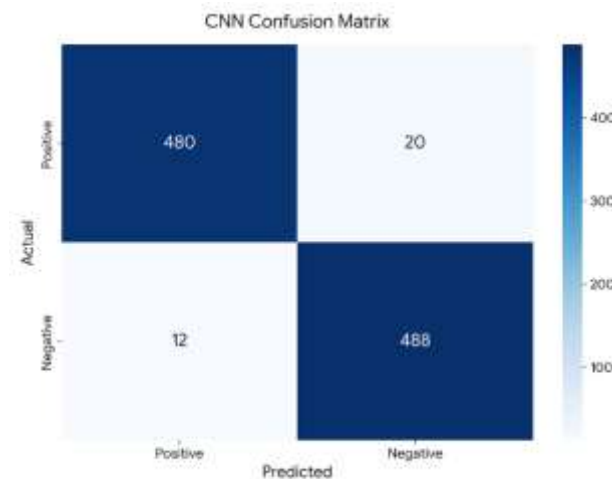


Figure 5: CNN Confusion Matrix

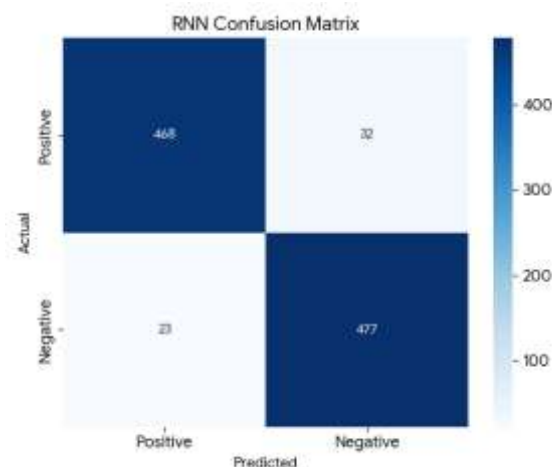


Figure 6: RNN Confusion Matrix

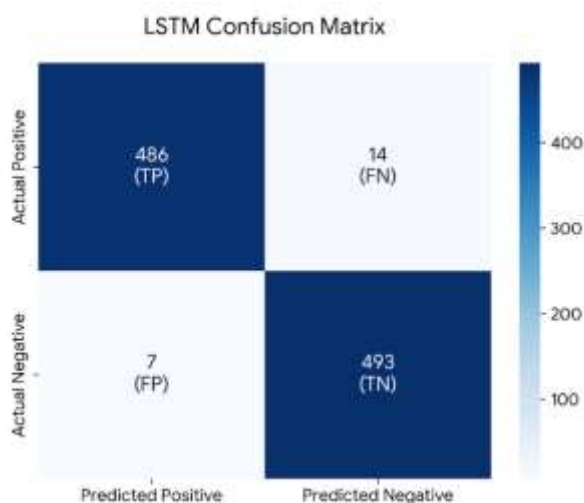


Figure 7: LSTM Confusion Matrix

In conclusion, the results show that defect diagnosis in Wireless Sensor Networks is much more accurate and dependable when using deep learning models. Intelligent and large-scale WSN applications benefit greatly from these models' capacity to learn complicated spatial and temporal variables, despite the fact that they demand more computer resources and training times than conventional machine learning techniques. Among the evaluated models, LSTM emerged as the most effective approach, offering the best balance of predictive accuracy, robustness, and fault detection capability for real-time wireless sensor network monitoring.

5. COMPARATIVE ANALYSIS

The efficacy of various Wireless Sensor Network (WSN) defect diagnosis algorithms was assessed by a comparative analysis. Using classification accuracy as the main assessment criterion, the study compared the new LSTM-based framework to the existing LSTM and XGBoost models. By efficiently learning complicated temporal patterns and enhancing classification reliability, the findings show that the suggested model offers better defect detection capability. By processing sequential sensor data and identifying time-dependent fault patterns, the traditional LSTM model attained an accuracy of 81.7%. However, its performance was limited in dynamic and noisy WSN environments, reducing its ability to generalize across diverse fault scenarios. In contrast, the XGBoost model achieved a significantly higher accuracy of 95.0% due to its ensemble learning mechanism, which effectively handles nonlinear data, reduces overfitting, and improves classification stability. Despite its strong predictive capability, XGBoost does not efficiently capture long-term temporal dependencies that are essential for analyzing continuous sensor data streams. The proposed LSTM-based model outperformed both existing approaches by achieving an accuracy of 97.9%. The improved performance is attributed to enhanced data preprocessing, optimized model architecture, effective feature representation, and better learning of temporal dependencies. These improvements enabled the model to reduce false classifications, improve fault detection accuracy, and provide more consistent predictions under varying network conditions.

Table 3: Performance Comparison of Existing and Proposed WSN Fault Detection Models

Models	Accuracy %S	References
LSTM	81.7	[140]
XGBoost	95	[141]
Proposed model LSTM	97.9	-----

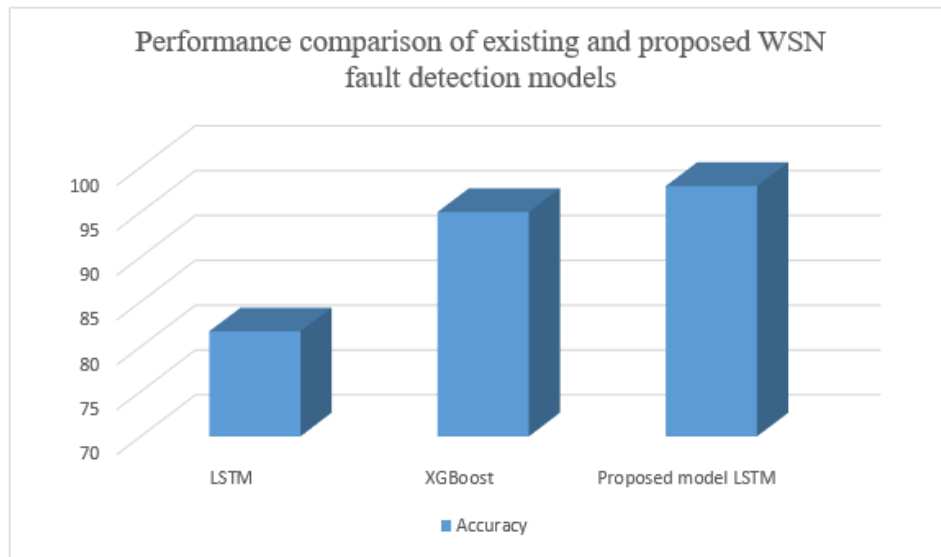


Figure 8: Performance Comparison of Existing and Proposed WSN Fault Detection Models

When compared to standalone LSTM and XGBoost models, the suggested LSTM framework provides a more stable and extensible answer to the problem of WSN failure diagnosis. It is ideal for intelligent network monitoring and real-time defect identification because to its increased accuracy and resilience. The results also show that WSN defect diagnostic systems can be much more efficient, reliable, and perform better overall when using optimised training methodologies in conjunction with cutting-edge deep learning methods.

6. CONCLUSION

This study demonstrates that Artificial Intelligence (AI) provides an effective and reliable solution for fault diagnosis in WSNs. By integrating ML and DL techniques, the proposed framework successfully detects and classifies various network faults, improving diagnostic accuracy, network reliability, and operational efficiency. The incorporation of data preprocessing and feature engineering further enhances model performance by reducing noise, improving feature representation, and minimizing misclassification. When compared to more traditional techniques of fault diagnosis, AI-based systems excel in areas such as scalability, real-time fault identification, and adaptability. Deep learning models show superior capability in learning complex spatial and temporal patterns, while machine learning algorithms offer computational efficiency for resource-constrained environments. Overall, the proposed

framework supports intelligent network monitoring, predictive maintenance, and timely fault identification, thereby reducing network downtime and maintenance costs. The results show that AI-driven fault detection is a strong and scalable method for creating smart Wireless Sensor Networks that can handle the load of contemporary real-time applications.

7. FUTURE SCOPE

Artificial intelligence models for resource-constrained WSN can be developed with a focus on lightweight and energy-efficient algorithms in future research. Make better decisions and diagnose problems in real time with the help of Explainable AI (XAI), the IoT, and Edge Computing. Network dependability, scalability, and robustness can be further improved by investigating hybrid deep learning models and proving the suggested framework on large-scale real-world deployments.

References

1. P. Moriano, S. C. Hespeler, M. Li, and M. Mahbub, "Adaptive anomaly detection for identifying attacks in cyber-physical systems: A systematic literature review," *Artif. Intell. Rev.*, vol. 58, no. 9, 2025, doi: 10.1007/s10462-025-11292-w.
2. Y. Al-Dunainawi, B. R. Al-Kaseem, and H. S. Al-Raweshidy, "Optimized Artificial Intelligence Model for DDoS Detection in SDN Environment," *IEEE Access*, vol. 11, no. October, pp. 106733–106748, 2023, doi: 10.1109/ACCESS.2023.3319214.
3. S. Zaman *et al.*, "Security Threats and Artificial Intelligence Based Countermeasures for Internet of Things Networks: A Comprehensive Survey," *IEEE Access*, vol. 9, pp. 94668–94690, 2021, doi: 10.1109/ACCESS.2021.3089681.
4. P. K. Myakala, C. Bura, and A. K. Jonnalagadda, "Artificial Immune Systems: A Bio-Inspired Paradigm for Computational Intelligence," *J. Artif. Intell. Big Data*, vol. 5, no. 1, pp. 1–13, 2025, doi: 10.31586/jaibd.2025.1233.
5. V. K. Kapu and G. R. Karri, "Efficient Detection and Mitigation of Rushing Attacks in VANETs Using RAID: A Novel Intrusion Detection System," *J. Comput. Sci.*, vol. 19, no. 9, pp. 1143–1159, 2023, doi: 10.3844/jcssp.2023.1143.1159.
6. O. Ebong, A. Edet, A. Uwah, and N. Udoetor, "Comprehensive Impact Assessment of Intrusion Detection and Mitigation Strategies Using Support Vector Machine

- Classification,” *Res. J. Pure Sci. Technol. E*, vol. 7, no. 2, pp. 50–69, 2024, doi: 10.56201/rjpst.v7.no2.2024.pg50.69.
7. H. Liu *et al.*, “Stacked Intelligent Metasurfaces for Wireless Sensing and Communication: Applications and Challenges,” pp. 1–8, 2024, doi: 10.1109/MWC.001.2500002.
 8. J. Zhang, K. Zhang, Y. An, H. Luo, and S. Yin, “An Integrated Multitasking Intelligent Bearing Fault Diagnosis Scheme Based on Representation Learning Under Imbalanced Sample Condition,” *IEEE Trans. Neural Networks Learn. Syst.*, vol. 35, no. 5, pp. 6231–6242, 2024, doi: 10.1109/TNNLS.2022.3232147.
 9. C. Wang, N. Tang, Q. Zhang, L. Gao, H. Yin, and H. Peng, “Expert Experience and Data-Driven Based Hybrid Fault Diagnosis for High-Speed Wire Rod Finishing Mills,” *C. - Comput. Model. Eng. Sci.*, vol. 138, no. 2, pp. 1827–1847, 2024, doi: 10.32604/cmes.2023.030970.
 10. L. Rajaoarisoa, N. K. M’Sirdi, M. Sayed-Mouchaweh, and L. Clavier, “Decentralized fault-tolerant controller based on cooperative smart-wireless sensors in large-scale buildings,” *J. Netw. Comput. Appl.*, vol. 214, pp. 1–12, 2023, doi: 10.1016/j.jnca.2023.103605.
 11. Y. Zhang, Y. Chen, J. Wang, and Z. Pan, “Unsupervised Deep Anomaly Detection for Multi-Sensor Time-Series Signals,” *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 2, pp. 2118–2132, 2023, doi: 10.1109/TKDE.2021.3102110.
 12. F. Zijie, M. A. Al-Shareeda, M. A. Saare, S. Manickam, and S. Karuppayah, “Wireless sensor networks in the internet of things: review, techniques, challenges, and future directions,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 31, no. 2, pp. 1190–1200, 2023, doi: 10.11591/ijeecs.v31.i2.pp1190-1200.