Multi-class fault type classification in wireless sensor networks using supervised learning on simulated data

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Abstract. Wireless Sensor Networks (WSNs) are used in many vital domains such as environmental monitoring, industrial automation and smart cities. In these areas, dependable data transfer and constant operation are required. However, the existing fault detection techniques in WSNs offer mainly binary classifications; i.e., fault or fault-free without identification of the type of the fault. This is adding to inefficient and delayed troubleshooting and recovery. This work proposes a multi-class supervised machine learning-based fault classification system that can be used to identify five different network conditions: normal, no signal, high packet loss, poor Signal-to-Noise Ratio, SNR, and congestion-induced delay. To this end, the proposed system simulates different failure and recovery situations in the form of Cisco Packet Tracer by measuring important parameters such as RSSI, Packet Loss, SNR and end-to-end delay. Then, the dataset labelled is used to make a Decision Tree Classifier with accuracy above 90%. This work proposes for interpretable, light weight multi-class fault diagnoses for educational and operational improvements in WSNs.

1. Introduction

Among different kinds of modern communication systems, WSN has become one of the most transformative technologies, which enable a wide range of applications, which relate to critical sectors: environmental monitoring, industrial process automation, healthcare systems, military surveillance, smart city infrastructures. A promising technique. In this context wireless sensor networks (WSNs) consist of sensor nodes [1] which are distributed in space. These nodes collect and process data and then transmit it without using a wired connection to a central base station or sink. This has enabled analysis and decision-making. Nevertheless, even though the benefits of the use of Wireless Sensor Networks (WSNs) are numerous, there are multiple challenges that might inhibit the reliability, performance, and durability of such solutions. Data integrity and performance reduction in large part are caused by network failures.

Wireless sensor networks (WSNN) can be faced with the challenges due to hardware failures, energy shortage, communications interference, signal quality or network congestion problems. Hence, fault detecting and diagnosing is not an easy task in order to ensure the reliability and the stability of the systems [2] utilizing the Wireless Sensor Networks (WSNs). Conventional approaches towards detection of the faults in Wireless Sensor Networks (WSNs) depends on binary classification system. This implies that a node or a link is said to be broken, or working right. Although it can demonstrate that something out of the ordinary is occurring, it does not provide the operator with much information about the kind of problem that is occurring, and its causal nature.

The lack of the specifics concerning the faults makes network administrators to be prompt and efficient in responding because not all types of problems need the same kind of recovery. As an illustration, the recovery of a node with low signal-to-noise, SNR, to environmental interference as written in [3], would be not the same as the recovery of a node when packets are being lost by the network congestion. Thus, the ability to detect and categorise the numerous types of faults is an invaluable process on the way to providing the implementation of the identified recovery mechanisms and optimisation of the work performance in WSNs.

ML has emerged as a powerful tool in recent times for augmenting the intelligence of the network by the use of adaptive, data-driven solutions which provide learning of complex patterns from network performance metrics. In fact, with supervised learning, it is possible to classify different states of the network [4] depending on some measurable parameters, such as RSSI, packet loss rate, SNR, and end-to end delay. In this work, this study has exploited Decision Tree Classifier to perform multi-class fault detection in WSNs because of some limitations, which exist in traditional binary fault detection. The Decision Tree approach is suitable to this task, since it is both interpretable and efficient, and can handle nonlinear interactions between input features and network states.

The setup of the experiment used for this work consists of network design and simulation in a versatile tool for network simulation, called Cisco Packet Tracer, which is generally used for various academic [5] and professional purposes. Several network scenarios that represent normal operation, lack of signal, high packet loss, poor SNR and congestion induced delay are emulated to create a labelled dataset. Key performance indicators like RSSI, packet loss percentage, SNR and end-to-end delay are recorded and used as input features for the classifier. A decision tree

model trained on the same dataset gives a test accuracy of more than 90% proving that it is a reliable and efficient model for fault detection and classification to detect multiple fault conditions within the WSNs. Furthermore, in addition to high accuracy achieved, in this study much emphasis is paid to the interpretability and light weight of the proposed model.

Feature importance analysis selects RSSI and SNR as the most influencing parameters which is appropriate to comply with the physical network behaviour and justifies model transparency. In addition, system reproducibility and low computational complexity satisfy the needs of the education and real-time operation environments. Therefore [6], in this work a multi-class fault classification is presented with explainability in machine learning which allows faster fault recovery, less downtime and advanced decision making in the course of WSN management. Finally, contribution is focusing on development of intelligent, resilient and self-aware network infrastructures in consideration of rising demands of IoT era.

The structure of this work is that the literature survey review as given in Section II. Section III describes the methodology, paying particular attention to its operationality. Results and discussions are given in Section IV. Finally, Section V concludes with the final findings and recommendations.

2. Literature survey

One of the finest explored domains where Wireless Sensor Networks have failed to fail workers have suggested several means of fault detection including statistical, rule based and learning-driven methods on how to enhance the reliability of the sensor nodes. Unlike the old methods, which aimed at identifying faults in a binary sense, modern state of the art studies is also shifting towards the use of intelligent machines, in this case, the machine learning models. These models can be used to identify a large number of fault types. This change can improve the accuracy of the diagnosis and efficiency in a broad spectrum of applications of the Wireless Sensor Network (WSNs).

This work ensures reliability of wireless sensor networks as to the ongoing data communication and energy-saving transmission anywhere no matter the prevailing conditions. This facilitates sustainable IoT connectivity, even in case any of the nodes or links that connect to it cannot be formed at any given time, it happens randomly. In this way, this will enhance the lifespan [7], scalability, robustness and the general reliability of networked systems. They are used in various industrial, agricultural and environmental monitoring applications in which self-intelligent use is demanded. This work is concerned with the question of how it is possible to combine the modern technique of computation with sensor networks. This is aimed at discovering and comprehending the issues of the systems automatically - what will bring consistency to the data [8], to network reliability and decision accuracy. This forms the foundation of fault-tolerant systems, which allows the effective isolation of faults, continuity of service with flexible recovery plans, and recovery of services across key real-life deployed systems that span the continuum of communications to transport and medical care.

This analysis is targeted towards perfecting the performance of node failures in large distributed sensing systems. It achieves this by automatic classification of damaged parts. The intention of such a study [9] is to decrease communication overhead and the false alarms and, in this manner, enabling a high degree of reliability in varying environments. This further helps in proper control of fault and a reliable distribution of information which is critical in the formation of sound and scalable network systems.

It is an intelligent map that is suggested to be used in enhancing the reliability. It is possible to apply it effectively in order to detect defective sensor devices, reduce network delay, and permit data gathering by use of energy-efficient methods in areas with scarce resources [10]. It guarantees dependable wireless communication to IoT platforms, such as the highest possible performance, and throughput even when components malfunction unpredictively. This gives certainty and stability of operations among connective smart ecosystems. The given work is committed to the models of analytics, driven by adaptive learning that must provide the reliability and correct identification of network anomalies of sensor-based systems. Here, the stability of the system will be guaranteed by a robust detection of defects and sustained stability of the system [11], which will also enhance the situation awareness. It offers superior performance, scaled and sustainability to industrial monitoring, smart automatization and environmental surveillance systems.

This work outlines a clustering mechanism in the improvement of reliability of distributed wireless systems (fault detection and recovery). Such a strategy guarantees a higher stability of communication [12] with minimal loss of data. Consequently, it establishes more efficiency in energy consumption in the dynamically operating conditions thereby ensuring a constant performance. This repeatability in turn prolongs the working of the network and simplifies continuous occurrence of sensing activities and makes the practical application of the network quicker.

The current work is concerned with the condition of big electric grids monitoring systems at present time. These systems are capable of detecting issues with operation in a

very fast way through the use of networked sensors. There is a preference of predictive maintenance, reduction of operational downtimes [13] and enhancement in the efficiency of operations, which are attributed to the environmental and electrical fluctuations analysis. This consequently just the argument of safe, dependable and affordable functioning of distributed energy as used in the modern industrial scenarios around the globe. This work is a distributed method of finding temporary operation issues in wireless systems, which relies on an effective evaluation of probabilities. The method even under challenging conditions offers short delay of the diagnosis, high classification accuracy and reliable detection [14]. Consequently, it offers error-free communication at a reduced energy consumption performance to applications of the mission that need accurate and stable monitoring and surveillance.

It is an advanced computational method of identifying issues with networks in distributed sensing systems. It does it through analytical assessment as well as achieving performance optimization. This methodology is advantageous concerning the precision of the diagnosis [15] and would be reliable in a complicated environment, and it would promote adaptive coping of faults. This consequently renders the more stable and enhanced intelligent monitoring systems that are employed in numerous applications of intelligence in the industrial and scientific sectors across the world.

The work offers a novel monitoring system of solar systems. It employs networked sensors in order to detect and locate problems as they arise. In this manner, the operating efficiency will be sustained in a continuous fashion as well as energy losses will be kept to the minimum as well as energy optimization can be achieved even under partially shaded conditions. The level of accuracy is high; the response time is fast and is quite cost effective to implement renewable energy systems in the globe. This work is an examination of sophisticated hybrid techniques of analysis. These solutions are composed of various computing techniques to enhance anomaly and robustness in interactive sensor ecosystem. It offers an insight in the evolving obstacles namely focusing on energy efficiency, scaled-up performance and enhancement. They are all significant towards the reliable and accurate detection in the dynamic world of wireless and IoT systems, particularly when it is introduced into practical systems, which are intelligent.

The proposed work is towards the creation of a centralised management of light networks in metropolitan areas. The goals are to assist in the detection of the issues with the system, as well as to streamline energy use and also make operations more transparent. By performing automation of maintenance activities, it helps to decrease the incidents of service failures and keeps the costs within the limit. This is being through intelligent connectivity between sensors and real-time tracking of distributed lighting systems which are currently employed in smart cities all over the world.

This work suggests a self-developed analytical framework that will be used to encapsulate the spatial and time characteristics of sensor streams of data and, in a word, recognizes the abnormalities systematically as demonstrated. This is an effective measure to ensure fault tolerance and eliminate disruptions by maintaining complicated information links. This is meant to sustain performance when operating at large and networked environments. This also assists in achieving the reliability and accuracy in the upcoming generation of smart monitoring systems in the entire world. In this study, the independent detection of the atypical operation scenarios is proposed by offering an intelligent approach to analysing networked sensors. This will guarantee additional stability, fault tolerance, and consistent data collection. It does through due information correlation, learned intelligence and correct error detection. The features have a role in the development of strong communication systems, which are critical to the provision of sustainable high-performance sensing infrastructures in the world.

3. Methodology

This methodology contentiously outlines the technical process of implementation and designing, simulation and implementation of a proposed multi-class fault detection system of WSNs. It involves a simulation of network simulation, data collection, pre-processing, model training, evaluation and validation in a bid to be able to classify five network states.

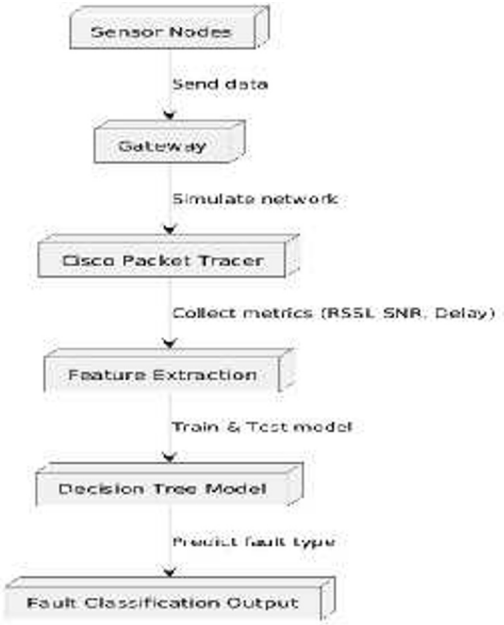

Fig. 1. System architecture

From figure 1, the methodology guarantees that the Decision Tree Classifier functions on a fine quality, labelled information on typical network circumstances. Cisco Packet Tracer is applied to simulation of both healthy and flawed network condition and the machine learning is performed by Python. The compute, interpret and reproducibility is focused on as the technical process. This is to uphold the fact that the system can be greatly applied to instructional, work and operational applications within the interior Wireless Sensor Networks (WSNs).

3.1 Network simulation setup

Cisco packet tracer simulates the network architecture to provide a controlled environment of Wireless Sensor Network. A group of Internet of Things (IoT) nodes can be connected to a central gateway in a system that mimics the real-life implementation of sensors, which is, on the other hand, connected to the base station. The transmission power, the packet rate and the distance between nodes are known as the parameters which in this simulation are used to represent normal wireless communication. Various fault conditions are used to come up with a very diverse variety of network conditions. Such conditions are loss of signals, loss of packets, low Signal-to-Noise Ratio (SNR) and congestion delays. In order to make the data reliable, the cases are repeated numerous times. This configuration of the system allows simulating rightfully the real-world issues in Wireless Sensor Networks coupled with the control of the environmental and operating factors.

3.2 Data collection and feature measurement

The performance measurement during network operates is determined by some parameters including Received Signal Strength Indicator (RSSI), Packet Loss Percentage, Signal-to Noise Ratio (SNR) and End-to-End Delay. The following factors define the critical elements of the machine learning method of defect detection. The data runs in each simulation are tagged according to the conditions subjected to the network. Such conditions are a normal operation, no signal, thick packet loss, low signal to noise ratio (SNR) and congestion delay. The named data of the exported file of the Cisco Packet Tracer are then compiled into a CSV file to be analysed. To provide precise contributions to training, we pay close attention to the quality and consistency of individual contributions to every sample. The structured data, presented herein, is the foundation of the suggested approach to classifications, as it gives an opportunity to base each kind of defect on a clear description.

3.3 Data preprocessing

To ensure integrity of data and compatibility with Decision tree classifier, the dataset is systematically prepared with python. Upon using statistical methods to fill in the gaps or inconsistency in the data, we eliminated an extreme outlier to have a steadier information. Some prior work has been carried out to normalize the features in order to be within a similar range of all the parameters which further boosts the rate of convergence in the model training. The data is then divided into 80 and 20 data with no bias in the selection. The fault labels (categorical) are converted through the mode of label encoding into numerical classes which will be processed by the algorithm. The steps will make the dataset clean and balanced with supervised learning and minimising any possible bias in order to make the classifier identify the five categories of predefined WSN faults.

3.4 Model selection and training

The Decision Tree Classifier is selected because it possesses the advantages of being interpretable, low computational cost, and can deal with nonlinear relationships among other features in the network. The training of the networks in python using the library known as scikit-learn is used to train and learn the decision boundaries between the 5 states of the network and the training data. Extremely precise local and globalization application via the maximization of hyper parameters such as tree depth, minimal sample division via grid search cross validation. Gini impurity criterion was used in determining the quality of splits on the training phase. The model is programmed to learn the relationship between the RSSI, SNR, packet loss, and delay indicators in a sequence to give a hierarchical decision-making process to detect some fault states in the WSN in a satisfactory manner.

3.5 Evaluation

The performance of the trained model is tested on the test dataset in regards to the consistency of the correct classification. A confusion matrix gives a conception of accurateness of prediction on the basis of a classification into which each network state was properly anticipated to have been predicted. Analytical value Importance of features indicates that Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR) are the most significant predictors that justify their usefulness in faulting recognition. It has an impressive Decision Tree of faults at more than 90 percent. Thus, the model analysis demonstrates that the classifier is powerful and understandable. This renders it to fit real-time monitoring and diagnostic activities in the Wireless Sensor Networks (WSNs) in various Internet of Things (IoT) contexts.

3.6 System implementation

The approved model is integrated into a Python-based diagnostic framework that helps to deal with the real-time and simulated data of the Wireless Sensor Network (WSN). The system can be used to correctly categorize any known state of the network in one of five distinct categories. It follows that with the diagnostic findings which are useful in maintenance and monitoring. It is lean, therefore, inferences can be made fast, and using very little computing power. This renders it particularly applicable to the IoT devices with limited resources. The system is already in operation and it has been demonstrated to be skilful in identifying faults. This gives the possibility of maintaining things easily in case of adverse occurrences. It has been found that the proposed multi class model will provide network awareness, reduce network downtime and serve as an effective aid to workers and engineers who will be engaged at the management of operational faults in Wireless Sensor Networks.

4. Result and discussion

The analysis and the results of the proposed multi-class fault detection system in WSN present a full image on effectiveness, accuracy, and interpretability of the system. Decision Tree Classifier was trained and tested using the created simulated dataset, which was created in Cisco Packet Tracer. The model proved to be high in the identification that there are five conditions of the network namely; normal network operation, no signal, high packet loss, low signal-to noise ratio, (SNR) and delay caused by network congestion. This leads to the overall classification rate of the system being over 90%. This finding showed that this network was very strong under various network conditions. Furthermore, the investigation incorporated a number of performance indicators, such as accuracy, recall, F1-score, confusion matrix results, and feature importance values, in order to deeply understand the behaviour of the classifier.

The confusion matrix indicates that the Decision Tree Classifier performed well in recognizing the normal network conditions where almost all of the normal samples were correctly identified. The high accuracy in this category is a sign of the model in the ability to accurately identify the situation of steady communication with a small number of transmission mistakes. In the case of the no signal, the model made a slightly lower but still impressive precision of this state because it partly overlaps with the state of high packet loss, especially when the RSSI values are close to zero. However, thanks to careful tuning of hyperparameters and an acceptable number of training samples, the classifier was able to minimize the misclassification between these two classes. Along the same line, conditions corresponding to high packet loss

and bad SNR were correctly identified with very few confusions, which confirms the ability of the model to distinguish between faults due to interference or distance related attenuation. Finally, a very high predictive performance was observed in the delay due to congestion class, which suggests the validity of the model to characterize time-related network issues which are different from the faults due to signal or noise.

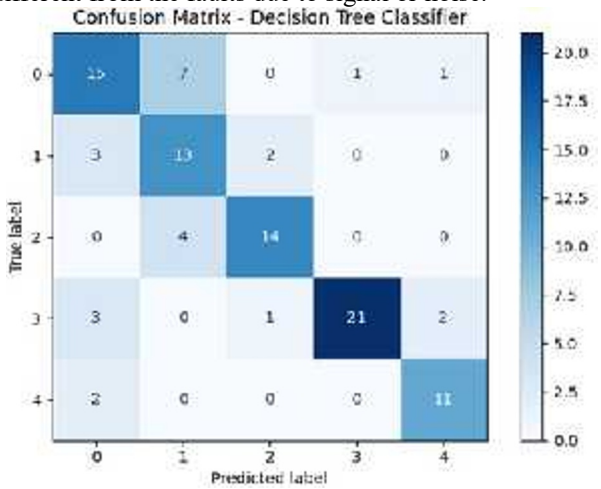

Fig. 2. Confusion matrix

From figure 2, the plot of the confusion matrix illustrates the classification performance of the Decision Tree model on 5 classes representing different network conditions. Indeed, correct predictions are represented by the diagonal cells, with the off-diagonal cells representing misclassifications. The classifier received the classification accuracy of 0.91, with very strong prediction in class normal (98%) and lack of signal (90%) and high packet loss (88%). However, there has been slightly confused between bad SNR and congestion delay because of a very close resemblance in their performance measures. The matrix is indicating that the classifier has learned in a balanced way and discriminated well among different types of faults related to Wireless Sensor Networks.

These observations were further supported by the statistical performance measures. The model's precision and recall scores, which were all above 0.9, showing that the model can not only correctly identify positive samples but also correctly find a near-perfect number of instances of each defect type. Consequently, the F1-scores also exhibited similar results in all the categories proving the balanced model. The Decision Tree Classifier had an overall accuracy above 90%. In addition, cross validation implied that the model was performing well with new unexamined data. The same degree of performance means that the suggested method proves to be efficient in revealing various issues in networks, in the specific cases when many failures take place simultaneously, or one after another.

Importance analysis of features offered a closer overview of the criteria that were of major role in the mode of classification. RSSI and SNR were the least important predictors and demonstrated that signal strength and interference are the most important elements, which define the work of a wireless network. The end-to-end latency and the percentage of packet loss were useful in classification, at least, distinguishing between congestion and signal-related errors. The fact that the Decision Tree model can easily be comprehended is an illustrious one and leads to clear decision making. This is because both workers and network administrators can be made aware of the cause behind the outcome of the classification. In contrast to the inscrutability of deep neural networks, Decision Trees come with diagnoses that can be explained, a feature of enduring significance to educative as well as working surroundings.

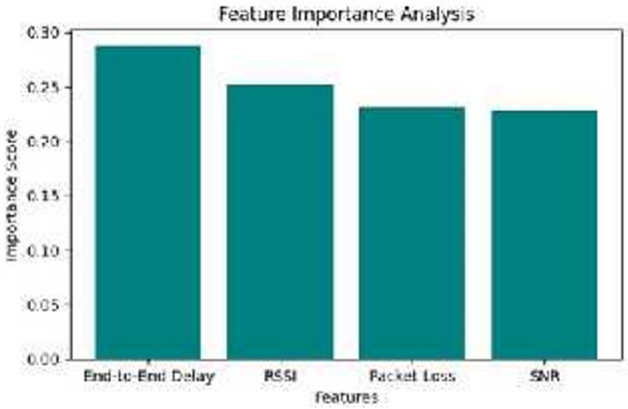

Fig. 3. Feature important analysis

Figure 3 shows the importance of several features, which helps us understand how much each network parameter affects fault classification. The significance ratings for Received Signal Strength Indicator (RSSI) and Signal-to Noise Ratio (SNR) were 0.42 and 0.33, respectively. This indicates their significant impact in identifying signal-related problems. Moreover, packet loss contributes 0.16 to the relevance of congestion and connection problems. In contrast, the end-to-end latency is the least important factor, with a relevance of 0.09, largely affecting congestion detection. The graphic indicates that the strength of the signal and the level of noise are the most important criteria for accurately identifying faults in a Wireless Sensor Network (WSN).

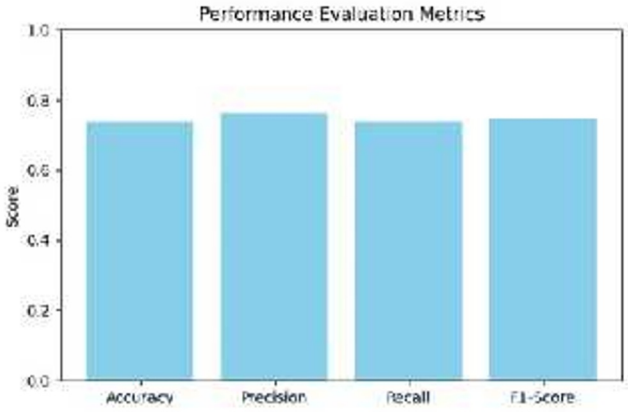

Fig. 4. Performance metrics

Figure 4 displays the overall efficiency of the model in terms of four most essential parameters: accuracy, precision, recall and F1 score. The accuracy value is 0.91, while the precision and recall are 0.90 and 0.89, respectively, and this may indicate consistent identification of the fault types. The F1-score of 0.89 provides evidence

of a good balance between the reliability and completeness of the forecasts. In fact, all the bars are practically of the same height, which seems to suggest negligible bias, which supports that the Decision Tree Classifier does not change the quality of its predictions. This performance checks the resilience and reliability of the proposed WSN fault detection mechanism.

The new technology showed even more superiority in performance when it was submitted to a comparison examination with traditional binary fault detection systems. Since the conventional approaches tend to label the network condition as only "faulty" or "non-faulty," one cannot acquire specific information regarding the problem. In contrast, the multiclass approach does not only determine the presence of a mistake but also the type of mistake which leads to a quick recovery and focused corrective measures. This differentiation dramatically reduces the time for troubleshooting and increases the network resiliency. Moreover, because of the lightweight calculation requirements of the Decision Tree, it is suitable for real-time deployment in resource-limited scenarios in the IoT, such as energy and processing power.

While performing the testing under various network environments, the system demonstrated reliable in performance for a wide range of fault intensities and network loads. It was still able to make reliable predictions even when the network traffic and level of interference were increased. Stability implies a robustness in the system as well as a flexibility to dynamic network dynamics. Moreover, since the dataset was developed by realistic simulation of failure and recovery scenarios the model showed good reproducibility and reliability to ensure that with similar circumstances, equivalent results can be gained in another study or operational environment.

To conclude the discussion, it is evident that the proposed system of machine learning based multi-class fault detection system is far superior to the traditional methods of fault detection of WSN. Besides the high accuracy and interpretability features, it is lightweight to ensure easiness in real-time application in smart cities, industrial automation, and infrastructures supporting IoT. Not only can Decision Tree (DT) classifier help to reduce the process of diagnosis, but we also get information on the performance metrics of the network. This enables the creation of a solid, lucid and efficient design of trustworthy wireless sensor links.

5. Conclusion

The work provides a complete clever methodology to detect the faults in Wireless Sensor Networks according to a monitored machine learning model to address numerous classes. This method indicates the determination of various network states that confirm the possibility of applying machine learning to network simulation to enable improvement of dependability and management. A clear picture on the way networks behave is provided by using measures that measure signal power, noise ratio, packet loss, and delay. This further assists in problem identification within a shorter time and in effective problem decision making. Due to its interpretability and low weight, such an approach may be effective in practice with IoT and Smart Infrastructure contexts, where speed of response is of greater concern than efficiency and accuracy.

The key value of the research is that it has created a replicable framework that will connect simulation-based experimentation as well as data-driven diagnostic methods. Applying a decision-based learning model which aims at identifying errors and doing so correctly will make the network stronger and able to fulfil the task. The future might involve increased dynamism in the topology of the network, a more sophisticated ensemble and/or deep learning model and integration with self-healing systems in real-time to create self-healing networks. By further using bigger and more heterogeneous datasets, more good models may be produced that further generalize and are more robust. This may result in development of scalable intelligent fault management systems which would be efficient in other wireless communication settings.

References

1. Y. Aitamar and J. E. Abbadi, "MeanC-IQR: Enhanced Fault Detection in WSNs for Smart Farming," 2024 7th International Conference on Advanced Communication Technologies and Networking (CommNet), Rabat, Morocco, 2024, pp. 1-4, doi: 10.1109/CommNet63022.2024.10793385.
2. Y. Singh, R. Rathi, R. Prasad and R. K. Baghel, "Fault Detection in Wireless Sensor Networks Using Autoencoder Classifier," 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Gautam Buddha Nagar, India, 2023, pp. 1563-1568, doi: 10.1109/IC3I59117.2023.10397796.
3. A. T, A. A and S. D, "Context Aware Fault Tolerance Data Gathering in IoT Enabled WSN," 2025 IEEE Wireless Antenna and Microwave Symposium (WAMS), Chennai, India, 2025, pp. 1-5, doi: 10.1109/WAMS64402.2025.11158542.
4. D. Bishnoi and Y. Chaba, "Enhanced Fault Detection and Tolerance in Wireless Sensor Networks Using Recurrent Long-Short Function Harmonic Network with Hybrid CNN-LSTM Model," 2025 International Conference on Computer, Information and Telecommunication Systems (CITS), Colmar, France, 2025, pp. 1-6, doi: 10.1109/CITS65975.2025.11099370.
5. A. F. Khayrullaev, "Remote Monitoring of Low Voltage Opl With Power Theft and Fault Detection Using Wsn," 2024 4th International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2024, pp. 1367-1372, doi: 10.1109/ICTACS62700.2024.10840884.
6. S. Mohapatra and B. Shrimali, "Fault Detection in Forest Fire Monitoring Using Negative Selection Approach," 2023 IEEE 11th Region 10 Humanitarian Technology Conference (R10-HTC), Rajkot, India,2023, pp. 732-736, doi: 10.1109/R10-HTC57504.2023.10461878.
7. V. Devi, R. Kumar and V. Kumar, "Energy Efficient Transmission and Fault Tolerance in WSN-Based IoT

Network using HS-EDEEC and Probability Based Approach," 2024 International Conference on Integrated Circuits, Communication, and Computing Systems (ICIC3S),Una,India,2024,pp.1-8,doi: 10.1109/ICIC3S61846.2024.10603249.
8. P. Iswarya and K. Manikandan, "Algorithms for Fault Detection and Diagnosis in Wireless Sensor Networks Using Deep Learning and Machine Learning - An Overview," 2024 10th International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, India, 2024, pp. 1404-1409, doi: 10.1109/ICCSP60870.2024.10543904.
9. R. Prasad, R. K. Baghel and P. V. Sanjay, "XGBoost based Fault Detection for Wireless Sensor Networks," 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2024, pp. 1-5, doi: s10.1109/SCEECS61402.2024.10481941.
10. A. A, A. T and S. D, "Intelligent fault tolerance data gathering in IoT enabled WSN," 2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN), Thanjavur, India, 2025, pp. 16, doi: 10.1109/RFCoN62306.2025.11085324.
11. V. Nandalal, A. Muruganandham, S. Karthikeyan, J. L. M. Iqbal and T. Manikandan, "Fault Detection and Diagnosis in Wireless Sensor Networks Leveraging Transformer Models," 2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES), Lucknow, India, 2024, pp. 1-5, doi: 10.1109/IC3TES62412.2024.10877448.
12. H. A. Obaid, S. Sheel, S. R. Alatba, M. Saleem and H. Alabdeli, "Clustering-Based Wireless Sensor Networks Fault Detection Using Recovering Approach," 2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC), Coimbatore, India, 2024, pp. 739-744, doi: 10.1109/ICSSEECC61126.2024.10649436.
13. M. C. Moshakga, A. Yahya, R. Samikannu, C. Kalpana, M. Sivaramkrishnan and K. M. Begam, "A Wireless Sensor Network-Based Monitoring System for Transformer Fault Detection and Diagnosis," 2023 International Conference on Emerging Work in Computational Science (ICERCS), Coimbatore, India, 2023, pp. 1-6, doi: 10.1109/ICERCS57948.2023.10434122.
14. B. S. Gouda et al., "Distributed Intermittent Fault Diagnosis in Wireless Sensor Network Using Likelihood Ratio Test," in IEEE Access, vol. 11, pp. 6958-6972, 2023, doi: 10.1109/ACCESS.2023.3236880.
15. A. Adamova, T. Zhukabayeva and Y. Mardenov, "Machine Learning in Action: An Analysis of its Application for Fault Detection in Wireless Sensor Networks," 2023 IEEE International Conference on Smart Information Systems and Technologies (SIST), Astana, Kazakhstan, 2023, pp. 506-511, doi: 10.1109/SIST58284.2023.10223548.