Detecting sensor faults in wireless sensor networks for precision agriculture using long short-term memory

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ABSTRACT

The reliable acquisition of soil data from wireless sensor networks (WSNs) deployed in farmlands is critical for optimizing precision agriculture (PA) practices. However, sensor faults can significantly degrade data quality, hindering PA techniques. Our work proposes a novel long short-term memory (LSTM) network-based method for fault detection in WSNs for PA applications. Unlike traditional methods, our approach utilizes a lightweight, transfer learning-based LSTM architecture specifically designed to address the challenge of limited labeled training data availability in agricultural settings. The model effectively captures temporal dependencies within sensor data sequences, enabling accurate predictions of normal sensor behavior and identification of anomalies indicative of faults. Experimental validation confirms the effectiveness of our method in diverse real-world WSN deployments, ensuring data integrity and enhancing network reliability. This study paves the way for improved decision-making and optimized PA practices.

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1. INTRODUCTION

Precision agriculture, a data-driven farming approach, revolutionizes crop production by optimizing resource utilization and maximizing yields. This paradigm shift not only boosts agricultural efficiency but also mitigates the escalating global food crisis. By meticulously monitoring environmental factors and crop conditions, precision agriculture empowers farmers to make informed decisions [1], [2], ultimately reducing production costs and minimizing environmental impact [3]. Central to this transformation is the integration of wireless sensor networks (WSNs) [4], which provide real-time data on crucial parameters like soil moisture, temperature, and acidity.

WSN has emerged as a critical technology in modern agriculture, enabling precision agriculture by providing real-time data on environmental conditions [3]. However, the deployment of WSNs in harsh agricultural environments often leads to sensor failures, compromising data integrity and impacting the accuracy of agricultural decisions [5], [6]. Existing fault detection techniques for WSNs have limitations, particularly in handling complex data patterns and dynamic environmental conditions. Traditional methods often rely on statistical analysis or rule-based approaches, which may not be sufficient to detect subtle anomalies [7]. To address these challenges, machine learning techniques, especially deep learning, offer promising solutions [8]. This paper proposes a novel fault detection approach using long short-term memory (LSTM) networks [9] to accurately identify faulty sensor nodes in WSNs, as well as aims to improve the reliability and accuracy of WSN-based agricultural systems by leveraging the ability of LSTMs to capture temporal dependencies in sensor data.

The rest of this work is organized as follows: Section 2 provides a critical analysis of existing fault detection approaches in WSNs, highlighting their strengths, weaknesses, and applicability to the proposed methodology. Section 3 details the proposed fault detection approach, including the techniques, algorithms, and system architecture employed. Section 4 focuses on the performance and effectiveness of the proposed approach. It is evaluated and discussed in detail, supported by results and comparative analysis. In the last section, the paper is summarized, key findings are reiterated, and potential avenues for future research are explored.

2. BRIEF review

In this section, we review various approaches to handling fault measurement in WSNs, highlighting their advantages and disadvantages. A distributed fault detection approach enables sensor nodes within a network to make local decisions autonomously, sharing information to collectively manage faults and enhance network resilience, scalability, energy efficiency, and adaptability. For instance, a fault detection mechanism based on support vector regression (SVR) and neighbor coordination [10] leverages redundant meteorological data to predict sensor behavior and generate residual sequences for fault identification. This method enhances fault detection accuracy and reduces false alarms, especially in sparse WSNs with high failure rates. However, it introduces computational complexity and potential scalability issues in large-scale networks. Similarly, Yuan *et al.* [11] present a distributed Bayesian algorithm (DBA) that integrates Bayesian networks and border node adjustments to improve accuracy in dense networks with high fault rates. This approach demonstrates superior performance compared to traditional distributed fault detection methods but may face challenges in large-scale implementations.

Trend correlation and self-starting mechanisms offer another approach. In [12], a strategy is proposed that analyzes data trends against neighborhood median values to effectively identify faulty sensor nodes. This method shows promising results in detection accuracy and false alarm rates, with low computational complexity and reduced communication overhead. However, its performance under dynamic network conditions and complex fault patterns requires further investigation. Support vector machine (SVM) based classification techniques [13] utilize kernel functions to handle complex, nonlinear data, achieving high detection rates. Validation using real-world datasets has shown superior performance compared to existing methods, with potential extensions toward predictive fault detection.

Comparative studies provide additional insights. In [14], fault detection techniques such as convex hull, naïve Bayes, and convolutional neural networks (CNNs) were evaluated. CNNs demonstrated superior performance in fault detection, but further research is needed to optimize charging strategies for multiple mobile charging units using reinforcement learning techniques. Neural network-based approaches [15] integrate gradient descent and evolutionary algorithms to detect, diagnose, and isolate faulty nodes. These methods, while showing improved performance metrics, face challenges in computational complexity and optimization for resource-constrained WSN environments.

Unsupervised machine learning techniques have also been explored. A network anomaly detection system (NADS) [16] employs a data-driven distance metric and Laplacian Eigenmap to map network connections into a feature space where anomalies are more distinguishable. This approach improves accuracy in detecting normal and false positive connections while maintaining comparable attack and false negative rates, though it introduces computational complexity and challenges in handling dynamic network environments. Additionally, fault detection and isolation (FDI) methods for surveillance sensor networks, such as in [17] emphasize the importance of network redundancy for effective FDI and intrusion detection. However, these methods reveal limitations in handling high fault rates and simultaneous intrusions.

Lastly, other notable methods include a metric-correlation-based distributed fault detection (MCDFD) approach [18], which analyzes correlations between sensor node system metrics and employs a modified CUSUM algorithm to detect potential failures. This method's strengths include low communication overhead and robust performance under challenging conditions, but its reliance on system metric correlations may limit applicability in complex fault patterns. Similarly, a fault detection approach utilizing non-negative matrix factorization (NMF) for feature extraction [19] demonstrates promising results in detecting anomalies in soil moisture sensor readings, highlighting NMF's potential for fault detection in WSNs.

In light of the above investigations, we propose LSTM-based fault detection methods due to their ability to capture temporal dependencies within sensor data. These methods provide accurate predictions of normal sensor behavior and effectively identify anomalies. This approach offers significant benefits for energy consumption and real-time decision-making in WSNs, ensuring the integrity of critical data and enhancing the reliability of precision agriculture practices.

3. SYSTEM MODELLING

Precision agriculture technology involves optimizing agricultural inputs like water, fertilizers, and pesticides based on real-time data to enhance crop yield and quality. WSNs play a pivotal role in this context by providing continuous monitoring of environmental conditions such as soil moisture and temperature [3], [20]. This data-driven approach enables farmers to make informed decisions regarding irrigation, fertilization, and harvesting, thereby improving resource efficiency and reducing waste [21], [22]. However, the reliability of these decisions is contingent upon the accuracy of sensor data, necessitating robust fault detection mechanisms to identify and mitigate erroneous readings.

3.1. WSN architecture

The proposed WSN system comprises four sensor nodes strategically deployed across a farmland area. Two nodes are dedicated to monitoring soil temperature, while the remaining two measure soil moisture. These sensor nodes are responsible for data acquisition and initial processing before transmitting it wirelessly to a central sink node, Figure 1 shows the model of WSN architecture.

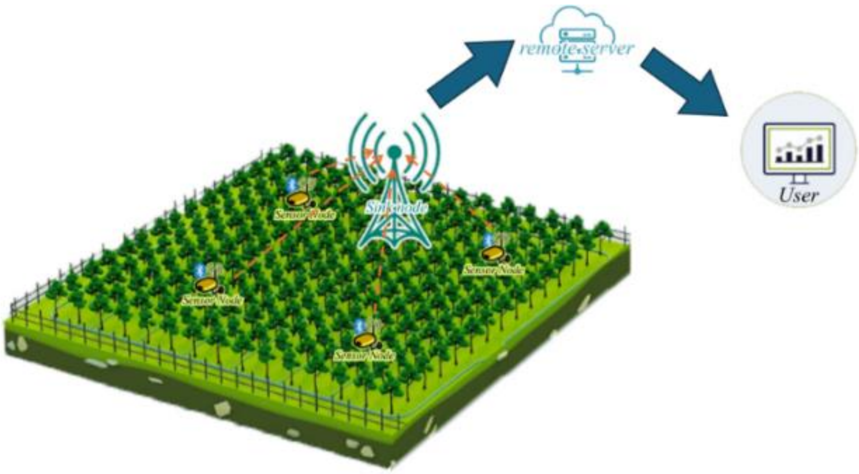


Figure 1. The model of WSN architecture

The sink node serves as the data aggregation point, collecting sensor readings from all nodes. It performs data preprocessing, including filtering, normalization, and potential feature extraction, to prepare the data for further analysis. Once processed, the data is transmitted to a remote server and forwarded to the user interface for visualization, decision-making, and potential storage [23]. This hierarchical architecture allows for distributed data collection, centralized processing, and remote access to the collected information.

3.2. Proposed method: fault detection based on LSTM

LSTM networks as shown in Figure 2, a specialized type of RNN, excels at modeling sequential data by capturing intricate temporal dependencies. This capability makes them highly suitable for a wide range of applications (*e.g.*, time series analysis) [9], [24]. LSTM networks excel in capturing intricate temporal dependencies within sequential data. This capability is particularly advantageous for fault detection in WSNs, where identifying anomalies often requires understanding the dynamic behavior of sensor readings over time. LSTM-based approaches can accurately predict normal sensor behavior and flag deviations indicative of potential faults by effectively modeling these temporal patterns. This proactive approach to fault detection enables timely interventions, enhancing the overall reliability and efficiency of WSNs.

Compared to traditional fault detection methods that rely on static thresholds or statistical models, LSTM networks offer superior performance in handling complex and non-linear sensor data patterns. Furthermore, our LSTM-based model is designed to optimize resource utilization in resource-constrained WSN environments, ensuring efficient processing without compromising detection accuracy. This makes it particularly well-suited for the unpredictable and dynamic environments typical of precision agriculture, where maintaining the integrity of critical data and conserving energy is paramount. To facilitate understanding of the notation used throughout this paper, Table 1 provides a summary of the key symbols and their corresponding definitions.

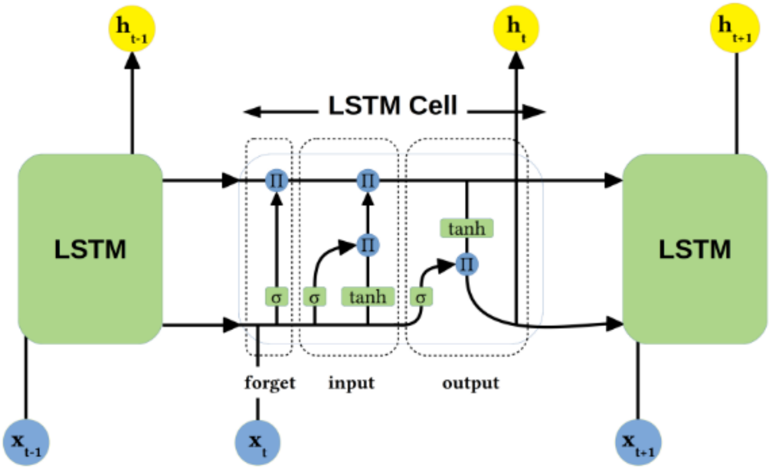


Figure 2. Basic LSTM architecture [25]

Table 1. Notation

Notation	Description
x_t	is the input at time step t
σ	sigmoid function
W_f	weight for the forget gate
W_i	weight for input gate
W_C	weight for cell state
W_o	weight for output gate
b_f	bias for the forget gate
b_i	Bias for input gate
b_C	Bias for cell state
b_o	bias for output gate

LSTM networks are designed to capture long-term dependencies in sequential data by using a set of gates to control the flow of information, Figure 2 shows the basic LSTM architecture [25]. Here are the key components and equations. For a given time t, the components of the LSTM states can be expressed as:
Forget gate:

$$f_t = \sigma\left(W_f\,[h_{t-1}, x_t] + b_f\right) \quad (1)$$

Input gate:

$$i_t = \sigma(W_i\,[h_{t-1}, x_t] + b_i) \quad (2)$$

Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot \breve{C}_t \quad (3)$$

where:

$$\check{C}_t = tanh(W_c\,[h_{t-1}, x_t] + b_c) \quad (4)$$

Output gate:

$$o_t = \sigma(W_o\,[h_{t-1}, x_t] + b_o) \quad (5)$$

Hidden state update:

$$h_t = o_t \odot tanh(\breve{C}_t) \quad (6)$$

LSTM networks employ σ sigmoid activation functions to regulate the flow of information through input, forget, and output gates, producing values between 0 and 1. These gates modulate the cell state, which acts as the network's memory component. The intricate interplay of these elements is learned through a specialized form of backpropagation known as backpropagation through time (BPTT) [26]. BPTT iteratively adjusts the network's parameters to minimize the prediction error, enabling the LSTM to effectively capture and utilize temporal dependencies within the data [27].

3.3. LSTM paradigm

Gather time-series data from sensors, including soil temperature, and soil moisture. After that, the data is normalized to a range suitable for neural networks. Furthermore, create sequences of a fixed length from the normalized data. In our paper, a sequence length of 100 means using 100-time steps to predict the next value. For a sequence length of *N*:

$$\pi_i = [y_i, y_{i+1}, \dots \dots \dots, y_{i+N-1}]$$

Where y are the normalized sensor readings.

The next step is computing the components of such cell at each time step t. After that, we move to anomaly detection. For anomaly detection, we compare the prediction errors with a dynamically calculated threshold. The system flags any sensor readings with errors exceeding this threshold as anomalies.

The prediction error is the absolute difference between the real reading and the predicted reading. At time step t:

$$error^{(t)} = \left| real^{(t)} - predicted^{(t)} \right| \quad (7)$$

The dynamic threshold θ is defined based on the mean μ and standard deviation δ:

$$\theta = \mu \pm k \cdot \delta \quad (8)$$

where:

$$\mu = \frac{1}{n}\sum_{t=1}^{n} error^{(t)} \quad (9)$$

and:

$$\delta = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(error^{(t)} - \mu)^2} \quad (10)$$

For each sensor reading at step time *t*, if the prediction error exceeds the threshold, flag the reading as an anomaly.

$$\text{anomaly}^{(t)} = \begin{cases} 0 & if \;\; \delta^{(-)} < error^{(t)} < \delta^{(+)} \\ 1 & otherwise \end{cases}$$

4. SIMULATION RESULTS AND DISCUSSION

In this section, we present a comprehensive analysis of the proposed fault detection system's performance based on experimental results and comparative evaluations. The effectiveness of the LSTM model in accurately predicting normal sensor behavior and identifying anomalies is discussed. Furthermore, the impact of various system parameters and potential limitations are explored.

4.1. Data collection and preprocessing

In our research, a WSN comprising four sensor nodes was deployed across a $12 \times 12\ m$ farmland area. Two sensor nodes were dedicated to monitoring soil temperature, while the remaining two measured soil moisture levels Figure 3. Collected data was transmitted wirelessly via Bluetooth to a central sink node at one-minute intervals over a simulation period of 1500 minutes. The simulations were conducted to evaluate the proposed system's performance using MATLAB R2020a software. The hardware platform employed consisted of an Intel(R) Core (TM) i7-8550U processor, an Intel(R) UHD 620 graphics card, 8 GB of RAM, and 256 GB of ROM.

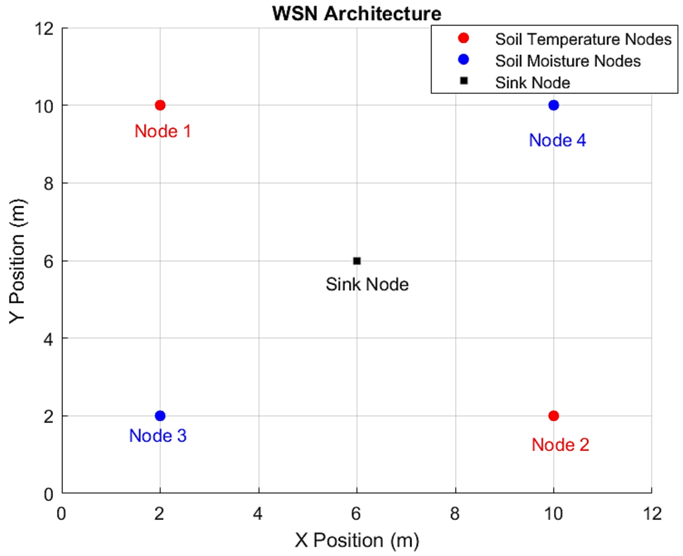


Figure 3. WSN layout

To establish a comprehensive dataset for fault detection, sensor readings were collected from the deployed WSN at 5-minute intervals over 1,500 minutes. The acquired data underwent a preprocessing phase to ensure data quality and suitability for subsequent analysis; Table 2 shows the simulation parameters. A robust framework for fault detection in WSNs was established, and the LSTM model was meticulously crafted to predict normal sensor behavior. Following dataset preprocessing and partitioning into training, validation, and testing subsets, the LSTM architecture (with its recurrent design and memory cells) was trained using BPTT. This iterative process optimized model parameters by minimizing prediction errors. The model generated predictions for validation and testing datasets by employing sequence lengths of 25 and 500 points, a dropout rate of 0.2, and 50 LSTM units. These configurations were strategically chosen to serve as benchmarks, offering insights into the nuances of short-term dependencies captured by the 25-point sequences and the comprehensive understanding of extended temporal patterns enabled by the 500-point sequences. The dropout rate of 0.2 fostered model generalization and countering overfitting, while the 50 LSTM units facilitated effective learning from the sequential nature of sensor data. This approach aims to significantly enhance fault detection in WSNs by robustly modeling sensor behavior across diverse timescales, paving the way for future optimizations and advancements in sensor network reliability.

Table 2. Simulation parameters

Parameter	Values
Area	12 m^2
Number of nodes	4 sensor nodes + 1 sink node
Sensor types	2 for soil temperature, 2 for soil moisture
Simulation time	1500 minutes
Data transmission interval	5 minutes
Communication	Bluetooth
Bandwidth	100 Kbps
Packet size	50 bytes
Queue size	100 packets

Figure 4 illustrating the comparative analysis between real sensor readings and predictions generated by the LSTM model trained on non-faulty data. Figure 4 (a) and Figure 4 (b) contrast the real readings and model predictions during normal operating conditions of the soil temperature sensor, while Figure 4(c) and Figure 4(d) compare the predicted and actual reading results under normal operating conditions of the soil moisture sensor. This visual depiction offers a comprehensive insight into the model's efficacy in capturing intricate patterns and dynamics inherent in the sensor data. The alignment between predicted and actual sensor readings underscores the model's capability to simulate normal sensor behavior accurately, validating its training process and configuration choices. Such findings affirm the LSTM model's potential as a robust tool for fault detection in WSNs, promising enhanced reliability and performance in real-world applications.

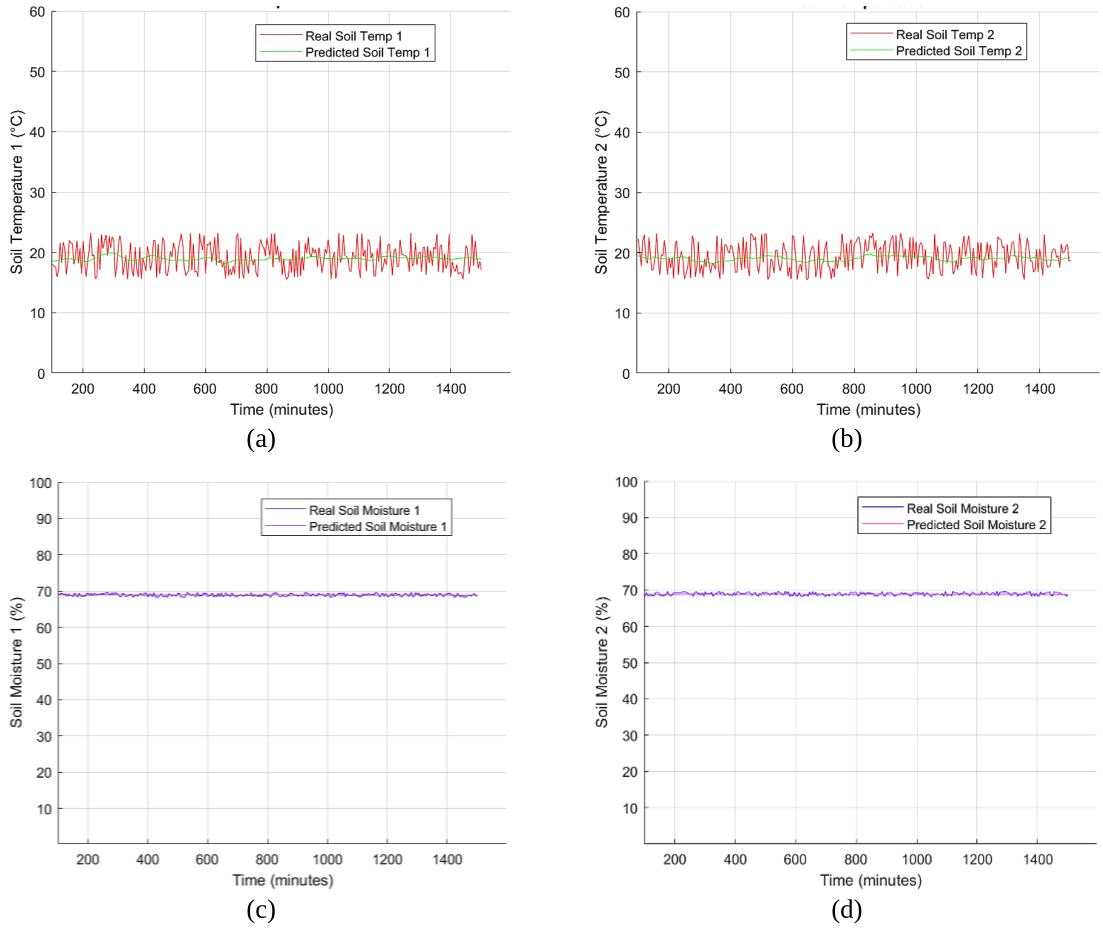


Figure 1. Real and predicted sensor readings of (a), (b) soil temperature, and (c), (d) soil moisture

4.1. Results discussion

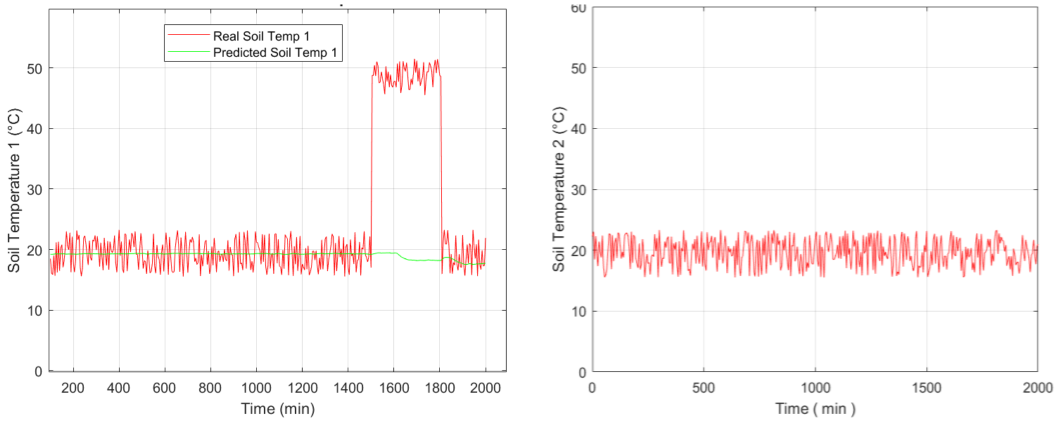
To evaluate the effectiveness of the LSTM model in detecting sensor faults, abnormal values were intentionally introduced into the dataset at specific intervals. These intervals are as follows: soil temperature 1 experienced faults between 1500 minutes and 1800 minutes, while soil moisture 1 encountered faults between 1600 minutes and 1800 minutes. By analyzing the model's response to these injected anomalies, we can assess its capability to detect and identify sensor faults accurately.

By comparing the LSTM-predicted values with the actual sensor readings, deviations indicative of faults was identified at $t = 1500\,min$. Figure 5(a) illustrates a representative example of fault injection, showing the divergence between predicted and actual sensor data. This figure clearly demonstrates the model’s ability to maintain accurate predictions under normal conditions while effectively highlighting anomalies caused by the injected faults.

To evaluate the effectiveness of our proposed fault detection approach, we conducted a series of experiments using real-world sensor data. Figure 5(b) illustrates a comparison between a healthy and a faulty soil temperature sensor. The model accurately predicted normal behavior for the healthy sensor while correctly identifying anomalous patterns in the faulty sensor's readings.

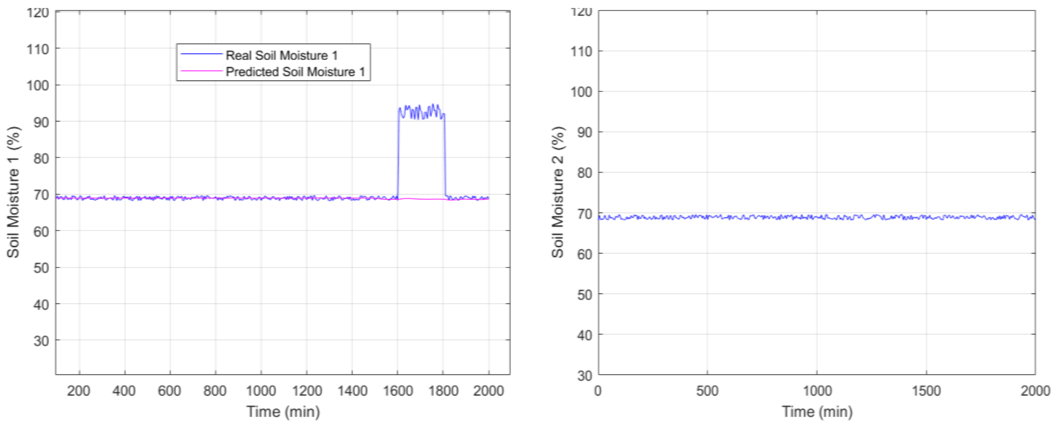
Similarly, Figure 6(a) and 6(b) depict the model's performance in detecting faults in a soil moisture sensor. By intentionally introducing anomalies into the dataset, we assessed the model's sensitivity to faulty readings. The model successfully identified the injected faults, demonstrating its ability to distinguish between normal and anomalous behavior.

The results demonstrate the effectiveness of our proposed LSTM-based fault detection model in accurately identifying faulty sensor nodes in WSNs. By capturing temporal dependencies within sensor data, the model can effectively detect subtle anomalies that may be overlooked by traditional methods. The model's ability to accurately classify sensor readings as normal or faulty contributes to the reliability and integrity of WSN-based systems. While the proposed model shows promising results, it is important to acknowledge its limitations. The model's performance may be influenced by factors such as data quality, sensor noise, and the complexity of the underlying physical processes.



(a) (b)

Figure 2. Real and predicted soil temperature data, (a) sensor soil temperature 1; real soil temperature data and its predicted data in faulty situation and (b) sensor soil temperature 2; real soil temperature data and in normal conditions



(a) (b)

Figure 3. Real and predicted soil temperature data, (a) sensor soil temperature 1; real soil temperature data and its predicted data in faulty situation and (b) sensor soil temperature 2; real soil temperature data in normal conditions

5. CONCLUSION

This study presents a novel LSTM network-based method for WSNs to enhance fault detection in WSNs for precision agriculture applications. By leveraging the power of deep learning, specifically LSTM networks, our model effectively captures temporal dependencies within sensor data, enabling accurate prediction of normal sensor behavior and precise detection of anomalies. This approach surpasses traditional fault detection techniques, which often struggle with the complexity and dynamism of real-world internet of things (IoT) environments. The ability to promptly identify and address faults is crucial for maintaining the integrity of IoT systems and ensuring reliable data collection.

Our findings demonstrate the potential of this approach to improve the accuracy and efficiency of fault detection in WSNs. By addressing the limitations of existing methods, our work opens up new possibilities for optimizing various precision agriculture applications. Future research directions may involve exploring the impact of varying data quality and noise levels on the performance of the proposed model, as well as investigating its applicability to different types of sensors and environmental conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Jamal El Abbadi		✓		✓		✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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