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# An IoT-Based LSTM System for Early Fire Detection in Wood Waste Warehouses

Vanya Nindya Chandra[1], Safwati Ismail[1,*], Asmaa Mahfoud Hezam Al-Hakimi[1]

[1] Faculty of Information Sciences and Engineering, Management and Science University, Section 13, 40100 Shah Alam, Selangor, Malaysia

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**ABSTRACT**

High global fire frequencies and the inherent vulnerability of industrial wood waste storage demand advanced monitoring solutions to prevent catastrophic loss. This research develops an Internet of Things-based early fire detection system specifically designed for wood waste warehouses. The system is grounded in recurrent neural network theory, utilising multivariate Long Short-Term Memory architectures to model long-term temporal dependencies between thermal and gas variables. Following experimental research design and the iterative Spiral Model, the study utilises a technical sample of 5,280 sensor records and a user sample of 30 warehouse personnel. Data gathered in a simulated warehouse setting were processed using a 15-step sliding window and Synthetic Minority Over-sampling Technique to generate a balanced training set of 52,800 sequences. The Long Short-Term Memory model achieved a weighted average accuracy of 98.6% and an F1-score of 98.1%. The system delivered alerts with a best-case end-to-end latency of 3.23 seconds, and statistical tests confirmed no significant difference in usability scores between different personnel roles. The detection logic misclassified 0 Danger events as Normal states, proving the reliability of the multivariate temporal approach. This study provides a novel application of sliding-window multivariate recurrent networks to the specific slow-evolving thermal signatures of dense organic waste; consequently, warehouse operators should integrate temporal predictive modelling into fire safety frameworks to reduce response latencies below the levels of traditional threshold-based alarms.

## 1. Introduction

Structural fires represent a major portion of global fire statistics, with residential fires alone accounting for 32.2% of all structural incidents according to recent data from 34 countries. Global fire incident records show an average of 3.8 million fire events annually, posing a persistent threat to life, property, and economic stability [1]. Within industrial contexts, wood waste storage facilities exhibit extreme vulnerability due to high organic material accumulation and a critical lack of continuous monitoring during off-peak operational hours [2]. The rapid evolution of urban and industrial landscapes intensifies the need for resilient systems that can provide more than just

* *Corresponding author.*
*E-mail address: safwati@msu.edu.my*

reactive shelter. Traditional fire safety infrastructure often fails to meet contemporary demands, showing significant limitations in large-scale facilities where early detection is paramount to preventing catastrophic loss. These societal stakes necessitate a shift toward more intelligent, proactive urban and industrial safety frameworks [3].

Modern fire safety is currently undergoing a transformation through the integration of the Internet of Things (IoT) and deep learning architectures. Prevailing literature emphasizes the use of multi-sensor fusion, utilizing sensors like the MQ-2 for gas and DHT22 for temperature and humidity to create comprehensive environmental profiles. Long Short-Term Memory (LSTM) models have become a standard for time-series forecasting due to their unique ability to handle sequential data and learn long-term dependencies through gating mechanisms. These models frequently achieve predictive accuracy levels exceeding 90%, offering a substantial advantage over traditional threshold-based systems. Furthermore, the deployment of cloud-based platforms like ThingSpeak and communication protocols such as MQTT enables real-time data storage, visualization, and immediate emergency notification via SMTP [4]. Such integrated solutions allow for the transition from simple detection to predictive analysis of incipient combustion signatures.

The progression from basic threshold detection to intelligent temporal pattern recognition remains problematic in specialized industrial environments. Wood waste storage areas present a complex scenario where early combustion often begins as slow smoldering, generating subtle thermal signatures that are easily obscured by background environmental noise. A significant mechanism-based puzzle persists because existing detection frameworks struggle to interpret the non-linear transition between stable storage conditions and incipient ignition [5]. Rather than capturing the interdependent evolution of temperature and gas concentrations, current models often process environmental inputs as discrete, unrelated data points. This inability to analyze the continuous temporal sequences characteristic of organic waste fire development results in a fundamental failure to differentiate between transient operational fluctuations and genuine fire hazards. Without a more sophisticated understanding of these temporal dependencies, systems remain prone to either dangerous response latencies or unmanageable rates of false alerts [6].

This study develops an IoT-based early fire detection system tailored for wood waste warehouse environments using a multivariate LSTM architecture. Grounded in recurrent neural network theory, the research employs an experimental design that utilizes the Spiral Model for iterative system development and risk mitigation. The research setting consists of a simulated warehouse environment specifically designed to mimic the high-density storage of wood waste. This site is a theoretically informative test site because the specific material density and airflow constraints produce slow-evolving, complex thermal patterns that represent a stress test for predictive deep learning models [7]. The analytical approach processes 5,280 sensor records into 52,800 time-series sequences using a 15-step sliding window and SMOTE-based class balancing to ensure stability and accuracy during danger-state classification [8].

This study extends the current literature on temporal pattern recognition by demonstrating how sliding-window LSTM models can detect incipient fires in dense organic materials. Furthermore, it refines environmental monitoring methodologies by establishing a robust approach for managing imbalanced sensor data in safety-critical industrial applications [9]. Finally, the research challenges the reliance on static threshold methods by proving that a multivariate predictive framework significantly improves response times in wood waste facilities. The remainder of this manuscript details the IoT hardware configuration and sensing layers, the iterative development process using the Spiral Model, the comprehensive evaluation of the LSTM model's performance metrics, and a concluding discussion on operational reliability and future field deployment [10].

## 2. Methodology

The research follows an experimental research design, utilizing a quantitative approach to develop and evaluate an IoT-based early fire detection system for wood waste. The system architecture is structured across four layers: the edge network layer (sensing), the fog network layer (gateway), the cloud computing layer (data storage and processing), and the data presentation layer (visualization and alerting) [11].

### *2.1 System Development Lifecycle*

The development process adheres to the Spiral Model, an iterative framework specifically chosen for its risk-driven nature in safety-critical applications. The model proceeds through four primary cycles: (i) planning and requirements definition, (ii) risk analysis and prototype development including Failure Mode and Effects Analysis (FMEA) to reduce Risk Priority Numbers (RPN), (iii) system implementation integrating IoT hardware with the LSTM model, and (iv) comprehensive evaluation and refinement [12].

### *2.2 IoT Hardware and Sensing Layers*

Environmental data is captured using an ESP32 microcontroller integrated with a multi-sensor array. This sensing layer includes the DHT22 for temperature (26–32°C normal range) and humidity (58–72% normal range), the MQ-135 for gas concentration (100–180 ppm normal), and a specialized flame sensor to detect direct combustion signatures. Sensors are calibrated to ensure stability over continuous 72-hour operation, with noise filtered to maintain data integrity.

### *2.3 Data Acquisition and Feature Engineering*

The system processes 5,280 initial sensor records, which are cleaned via Z-score analysis to remove anomalies. To address the inherent class imbalance in fire datasets, where Normal records significantly outnumber Danger events, SMOTE is applied to generate a balanced training set of 52,800 sequences. Features are organized using a 15-step sliding time window to capture the temporal dependencies essential for incipient fire signatures [13].

### *2.4 LSTM Model Architecture*

The core predictive engine is a multivariate LSTM network developed in TensorFlow/Keras. Unlike univariate models, this architecture learns the interdependent relationships between temperature, humidity, and gas concentrations over time. The model utilizes forget, input, and output gates to manage long-term information retention and prevent vanishing-gradient problems characteristic of traditional recurrent networks.

### *2.5 Evaluation and User Acceptance*

System performance is quantified using precision, recall, F1-score, and ROC-AUC metrics. A user acceptance, as presented in table 1. Evaluation was conducted using a structured questionnaire administered to 30 respondents, including warehouse personnel and system administrators. Items were rated on a 7-point Likert scale to assess system usefulness, warning clarity, and confidence in the LSTM-driven logic [14].

**Table 1**
Candidate user-acceptance measurement instruments

| Scale | Developer, year, DOI | Items | Format and anchors | Reliability | Validated populations | License |
|---|---|---|---|---|---|---|
| TAM | Davis, 1989; 10.2307/249008 | 6 | 7-point Likert; strongly disagree–agree | α = 0.98 | Professionals and students (USA) | Free |
| SUS | Brooke, 1986 | 10 | 5-point Likert; strongly disagree–agree | α = 0.85 | General technology users (UK/USA) | Free |
| DBQ | Reason et al., 1990; 10.1016/0001-4575(90)90044-P | 27* | 6-point Likert; never–nearly always | α > 0.80 | General public; older drivers (China/EU) | Permission |

*Items count is based on the validated revision cited in the draft. SUS and TAM are commonly used for dashboard efficacy and system adoption. TAM may oversimplify user behaviour by omitting environmental and social influences, while DBQ may be affected by social-desirability bias in self-reporting. Adapted instruments should use forward-backward translation, expert review, and pilot testing. System usability and overall satisfaction may overlap and should be assessed for discriminant validity [15].

## 3. Results

### *3.1 Response Rate and Analytical Sample*

The user acceptance evaluation utilized a final analytical sample of 30 respondents. The technical evaluation phase was conducted using a total dataset of 5,280 sensor records obtained from a simulated warehouse environment.

### *3.2 Sample Profile*

The respondent sample comprised warehouse workers, security personnel, and system administrators. Specific demographic distributions for the 30 participants were not available in the supplied evidence table. Detailed technical dataset characteristics are provided in Table 2.

### *3.3 Common Method Bias Assessment*

Common method bias assessment was not reported in the provided source tables.

### *3.4 Measurement Model: Reliability and Validity*

Data preprocessing results are summarized in Table 2. Cleaning via Z-score analysis removed 47 records, accounting for 0.89% of the total dataset. Convergent validity for the sensing layer was verified through stable 72-hour DHT22 operation and 100% flame-sensor detection accuracy across 50 test exposures. The final training dataset reached 52,800 sequences after SMOTE and windowing [15].

### *3.5 Descriptive Statistics and Correlations*

The dataset included 3,200 Normal records, 1,280 Warning records, and 800 Danger records. Temperature, humidity, and gas concentration were used as the model's independent input variables [16].

### *3.6 Structural Model and Hypothesis Tests*

The LSTM performance is presented in Table 3. The hypothesis that the system achieves high predictive accuracy was supported (accuracy = 98.6%; F1-score = 98.1%). The hypothesis that the model differentiates fire-risk states was also supported: Danger-condition recall was 97.9% and precision was 98.6%. No Danger condition was classified as Normal. The latency hypothesis was supported, with an average LSTM inference latency of 78 ms [17-19].

### *3.7 Mediation and Moderation Results*

Mediation and moderation analyses were not conducted in this study.

### *3.8 Explanatory and Predictive Power*

The LSTM model achieved a weighted average ROC-AUC of 0.995. Communication reliability is indicated by MQTT transmission with 0% packet loss across 500 payloads.

### *3.9 Robustness Checks*

The system maintained 99.2% uptime over 168 hours of continuous operation. Notification delivery achieved a 98.6% success rate across 500 alerts. End-to-end delays ranged from 3.23 s to 4.80 s, while user acceptance indicated high agreement on usefulness and overall satisfaction (mean = 6.3 for each). Table 2. Presents the dataset measurements and results, while table 3 presents the LSTM.

**Table 2**
Dataset, sensing, and operational characteristics

| Measure | Result |
|---|---|
| Initial sensor records | 5,280 |
| Records removed by Z-score cleaning | 47 (0.89%) |
| Class distribution | Normal: 3,200; Warning: 1,280; Danger: 800 |
| Normal operating ranges | Temperature: 26–32°C; humidity: 58–72%; gas: 100–180 ppm |
| Sliding-window length | 15 steps |
| Final balanced training set | 52,800 sequences |
| DHT22 stability test | 72 hours |
| Flame-sensor detection test | 100% across 50 exposures |
| MQTT packet loss | 0% across 500 payloads |
| System uptime | 99.2% across 168 hours |
| Notification success | 98.6% across 500 alerts |

**Table 3**
LSTM predictive and latency performance

| Metric | Result |
|---|---|
| Weighted average accuracy | 98.6% |
| Weighted average F1-score | 98.1% |
| Danger precision | 98.6% |
| Danger recall | 97.9% |
| Danger classified as Normal | 0 |
| Weighted average ROC-AUC | 0.995 |
| Average LSTM inference latency | 78 ms |
| End-to-end latency | 3.23–4.80 s |

## 4. Discussion

The research successfully implemented an IoT-based early fire detection system using an LSTM architecture. The discussion situates the findings within the supplied scholarly comparison set, evaluates reported discrepancies, and addresses theoretical implications.

### *4.1 Predictive Performance*

The model achieved high predictive performance for early fire signatures in wood waste (accuracy = 98.6%; F1-score = 98.1%). This level of classification stability is consistent with several deep-learning benchmarks in surveillance and industrial safety, although cross-study comparisons should be interpreted cautiously because settings, inputs, and outcome measures differ. Table 4 presents the comparative analysis of predictive accuracy.

**Table 4**
Comparative analysis of predictive accuracy

| Study | DOI | Country/industry | Design | N | Statistic |
|---|---|---|---|---|---|
| Pravesh and Sahana (2025) | 10.1016/j.rineng.2025.106330 | India/ Surveillance | Experimental | 15,960 images | 98.1% accuracy |
| Zhang *et al.*, (2026) | 10.1016/j.ijtst.2025.10.011 | China / Transport | Simulation | 32 subjects | 97.49% accuracy |
| Chen *et al.*, (2022) | 10.1016/j.compeleceng.2022.108046 | Global / Building | Experimental | N/A | 99.83% accuracy |
| Yuvaraj *et al.*, (2025) | 10.1016/j.csite.2025.107159 | Unknown / Safety | Experimental | 1,671 images | 97.0% accuracy |
| Morchid *et al.*, (2025) | 10.1016/j.sciaf.2025.e02559 | Morocco/ Agriculture | Field | 7 cases | 100.0% accuracy |
| Elvas *et al.*, (2020) | 10.1016/j.atech.2023.100358 | Portugal / Smart city | Experimental | N/A | 60.0% accuracy |
| Rodriguez *et al.*, (2021) | 10.3390/s21082614 | Spain / Responder | Experimental | N/A | <90.0% accuracy |
| Ibrahim *et al.*, (2021) | 10.1109/ismsit52890.2021.9604650 | Egypt / Energy | Experimental | N/A | 20.5% MAPE |
| Alhussein *et al.*, (2020) | 10.1109/access.2020.3028281 | Saudi / Energy | Experimental | N/A | 44.0% MAPE |
| Perez Cortes (2024) | 10.1016/j.bspc.2023.105381 | Global / Biological | Experimental | N/A | 12.1% MAPE |

The lower accuracy reported for Elvas et al. was attributed in the draft to conventional data-mining methods rather than LSTM architectures. Rodriguez-Sanchez et al. reported lower accuracy in a setting affected by moving-camera noise, whereas the present design uses stationary sensors. Higher error rates in household-load studies may reflect greater signal complexity than the thermal patterns of wood-waste storage.

### *4.2 Response Latency*

The best-case end-to-end delay of 3.23 s is operationally important for incipient fire detection. Unlike local-only detection measurements, this figure represents the full path through sensing, cloud processing, and notification. Table 5. Presents the comparative analysis of response latency.

**Table 5**
Comparative analysis of response latency

| Study | DOI | Country/industry | Design | N | Reported latency |
|---|---|---|---|---|---|
| Maltezos *et al.*, (2022) | 10.3390/info13040164 | Greece / Building | Experimental | N/A | 32 ms detection |
| Morchid *et al.*, (2025) | 10.1016/j.sciaf.2025.e02559 | Morocco/ Agriculture | Field | 7 | 2 s response |
| Yuvaraj *et al.*, (2025) | 10.1016/j.csite.2025.107159 | Unknown / Safety | Experimental | N/A | 51 ms inference |
| Hasan (2025) | 10.1016/j.meaene.2024.100033 | Iraq / Residential | Experimental | 10,500 | 142 cycles |
| Present study (2026) | N/A | MSU / Warehouse | Experimental | 5,280 | 3.23 s delay |
| Morchid *et al.*, (2025) | 10.1016/j.sciaf.2025.e02559 | Morocco/ Agriculture | Field | 4 tests | 9.16 s receive |
| Chowdhury *et al.*, (2025) | 10.1016/j.atech.2025.101512 | Bangladesh / Agro | Field | N/A | Late alerts |

The draft attributes the longer 9.16 s receiving time in one Morchid et al. test to SMTP email, which is slower than web-push and MQTT mechanisms. It further distinguishes the 32 ms local detection reported by Maltezos et al. from the present end-to-end metric, and notes that network infrastructure was controlled in the simulated setting.

### *4.3 User Perception*

No significant difference was found in satisfaction across personnel groups ($p > .05$; mean satisfaction = 6.3/7.0). The result suggests that the interface may be usable across operational roles, though the small sample means that group-specific differences may not have been detectable. The high agreement may indicate that Warning and Danger thresholds were sufficiently clear for security and administrative users without being unduly intrusive.

## 5. Conclusions

This investigation examined whether multi-sensor IoT networks combined with iterative recurrent neural-network modelling could accurately flag early-stage combustion markers in dense organic-waste storage. The findings confirm that a multivariate modelling approach identified ignition risks with high reliability while preventing Danger events from being overlooked by the system logic. The sensing and cloud layers delivered alerts with minimal delay, providing a functional window for proactive intervention. Testing with organizational personnel indicated that the monitoring interface was perceived as usable and effective regardless of job responsibility. The research contributes to computational safety theory by showing that long-term temporal dependencies between thermal and gas variables can differentiate genuine hazards from background noise in industrial settings. Warehouse operators should move beyond simple alarm triggers and adopt predictive frameworks that interpret the continuous progression of environmental data. Future work should deploy the system in the field to test reliability under unpredictable airflow patterns and high humidity in large-scale storage facilities.

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