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# IIoT-Based Real-Time Monitoring and Predictive Maintenance System for Air Conditioning Ducting Systems

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***Abstract*** **—This paper presents an Industrial Internet of Things (IIoT)-based real-time monitoring and predictive maintenance system for air-conditioning ducting environments. The proposed system integrates a mobile robotic platform equipped with environmental sensors—BME280 and MQ135—and an ESP32 microcontroller, along with LoRa SX1278 modules for long-range wireless data transmission. The system visualises sensor data through a PyQt5-based graphical user interface. It utilises a deep learning model trained on the author's datasets to classify environmental conditions into 'Normal,' 'High Humidity,' or 'Fire.' Experimental results confirm the system's ability to operate reliably in metallic duct environments, ensuring secure data transmission and delivering accurate AI predictions. The study concludes with a discussion on system performance and future upgrades, including vision-based inspection.**

***Keywords—IIOT, HVAC, Predictive maintenance, LoRa, Deep learning, Real-time monitoring.***

## I. INTRODUCTION

Heating, Ventilation, and Air Conditioning (HVAC) systems are essential for maintaining comfort, indoor air quality, and energy efficiency in residential, commercial, and industrial environments.

Current HVAC maintenance strategies rely on scheduled inspections or wait until a fault disrupts operation. These approaches often lead to late detection of issues, unplanned downtime, or excessive maintenance. In large or complex ducting systems, especially those constructed of metallic materials, it can be challenging to monitor internal conditions without physically dismantling parts of the system.

With the growth of smart buildings and automation, traditional maintenance techniques such as reactive or scheduled servicing are increasingly inadequate. Failures in HVAC systems can lead to discomfort, health risks, and costly repairs or energy losses.

Furthermore, existing remote monitoring systems often rely on Wi-Fi or Bluetooth, which are ineffective in environments with metal that restricts signals. There is a pressing need for a compact, wireless, and intelligent monitoring solution that can operate reliably in such environments and identify potential problems in real time before they escalate.

To address these limitations, predictive maintenance methods that combine real-time sensor data and intelligent classification are gaining traction. The increasing use of the Industrial Internet of Things (IIoT) has enabled the deployment of networked sensor systems that collect environmental parameters, such as temperature, humidity, pressure, and gas concentration. When combined with machine learning or AI models, these systems can anticipate failures, detect anomalies, and enhance decision-making.

This paper introduces an end-to-end IIoT-based system for real-time monitoring and predictive maintenance of air-conditioning ducts. A robotic platform collects environmental data and transmits it via LoRa to a backend system developed for this study and a GUI that interprets and visualises the data. A Keras-based deep learning model classifies the environmental state, providing proactive insights and visual alerts. The system is designed to be modular, power-efficient, and highly responsive.



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The primary objective of the project is to design and implement a real-time monitoring and predictive maintenance system for air-conditioning duct environments, integrating IIoT and AI technologies. Specifically, the objectives are:

1. To implement a reliable wireless communication system using LoRa SX1278 modules and ESP32 microcontrollers to transmit data between the robot and a central processing unit.
2. To design a real-time GUI using PyQt5 that provides dynamic sensor data visualisation, a user control interface, and an AI-driven notification system.
3. To integrate a pre-trained deep learning model capable of classifying environmental conditions such as 'Normal,' 'High Humidity,' and 'Fire' using sensor data.
4. To validate system functionality in a metallic environment resembling actual ductwork conditions, ensuring robustness in signal transmission and classification accuracy.

## II. LITERATURE REVIEW

In the evolving field of HVAC system maintenance, the integration of real-time monitoring, IIoT, and AI has become increasingly vital for operational efficiency and safety. Traditional maintenance approaches—namely, corrective and preventive—have several limitations. Corrective maintenance, while straightforward, often leads to unexpected system failures and costly downtime [1, 2]. Preventive maintenance, although proactive, relies on static schedules and results in unnecessary servicing, increasing operational costs without considering the actual system condition [3].

To overcome these limitations, predictive maintenance (PdM) has emerged as a highly effective alternative. PdM leverages continuous monitoring, data analytics, and AI to assess the health of HVAC systems and predict faults before they occur [4, 5]. The study in [6] reports that AI-enabled PdM systems in HVAC can reduce equipment downtime by up to 70% and energy usage by 30%, demonstrating their significant operational benefits.

The Industrial Internet of Things (IIoT) is the cornerstone of modern PdM systems. IIoT involves deploying microcontrollers, wireless sensors, and embedded systems to collect and transmit data [7]. This architecture enables real-time communication and responsiveness. Furthermore, research in [8] indicates that IIoT-enabled monitoring systems may empower facilities to implement adaptive maintenance strategies that respond to actual wear patterns and environmental stressors. The author of [9] introduced the TIP4.0 framework, an IIoT-based predictive maintenance model that integrates sensor networks with centralised analytics. In HVAC applications, such architectures allow for modular scalability and decentralised intelligence.

In HVAC and building applications, LoRa (long-range) has repeatedly been shown to outperform short-range RF, Bluetooth, and Wi-Fi in coverage and robustness, especially in obstructed or metallic environments. LoRa's chirp spread spectrum modulation and exceptional receiver sensitivity, which is about 130 dBm, facilitate the decoding of signals up to ~20 dB beneath the noise level, hence enabling multi-kilometre connections and effective penetration through walls and barriers [10, 11].

In duct air-quality monitoring, prior Bluetooth and Wi-Fi deployments suffered severe range limits and cross-section disruptions because radio waves at 2.4 GHz cannot effectively penetrate metal, leading to frequent path loss in non-line-of-sight ducts [12]. Thus, LoRa communication is favoured over Bluetooth and Wi-Fi due to its superior penetration and long-distance transmission capabilities, especially in metallic environments such as air ducts [5, 13]. The study in [14] demonstrated that HVAC ducts can act as waveguides for low-frequency signals such as those used in LoRa communication, thereby enabling reliable transmission even in challenging environments.

Furthermore, LoRa is explicitly designed for ultra-low-power, with end devices able to operate for years on a battery because only small sensor payloads are transmitted at low bit rates. This makes LoRa suitable for distributed HVAC, agricultural, and industrial sensor applications [15, 16]. Additionally, LoRa's spread-spectrum modulation is robust against interference and fading, facilitating reliable connections even in non-line-of-sight (NLoS) and high-interference industrial environments. [11, 17]. Experiments in noisy IIoT conditions report around 90% reliability with proper configuration [17], and simulations show that coding and filtering further improve packet error rate in industrial channels [18].

Another critical element in PdM is AI and machine learning, where [6] evaluated Random Forest, SVM, and KNN models on HVAC datasets and found that Random Forest yielded the highest classification accuracy. In contrast, deep learning approaches, particularly neural networks, enable more flexible and scalable solutions for multi-class classification. In [19], the author implemented federated deep learning in HVAC fire prediction, improving both detection speed and privacy. Furthermore, AI-based methods do not rely on expert knowledge, achieve high fault detection and diagnosis accuracy, and can perform even when some sensors are missing, compared to physical model-based methods [20].

Furthermore, accurate monitoring depends on the effective use of environmental sensors [21]. The BME280 measures temperature, humidity, and pressure in a single compact unit, while the MQ135 is widely used for air quality monitoring due to its sensitivity to $CO_2$ and other harmful gases. The findings in [22] and [23] suggest that combining multiple sensor readings enhances AI model performance by increasing context specificity.

Finally, an essential component of real-time PdM systems is the graphical user interface (GUI). A GUI enables sensor data visualisation, alert display, and manual control. The study in [24] emphasised that intuitive GUI design enhances fault diagnosis and user interaction, particularly in telerobotic inspection systems. In the present study, a PyQt5-based GUI is implemented with features such as live plotting, history logging, and AI-based notifications.

## III. METHODOLOGY

The methodology for this project encompasses the systematic design and integration of hardware and software to realise an IIoT-based predictive maintenance system for HVAC duct inspection. It consists of several key stages: hardware architecture setup, communication design, software and GUI development, data acquisition, AI model training, and system integration for real-time operation. This methodology was chosen to ensure modularity, scalability, and operational reliability in metallic and enclosed environments.

### A. System Architecture Overview

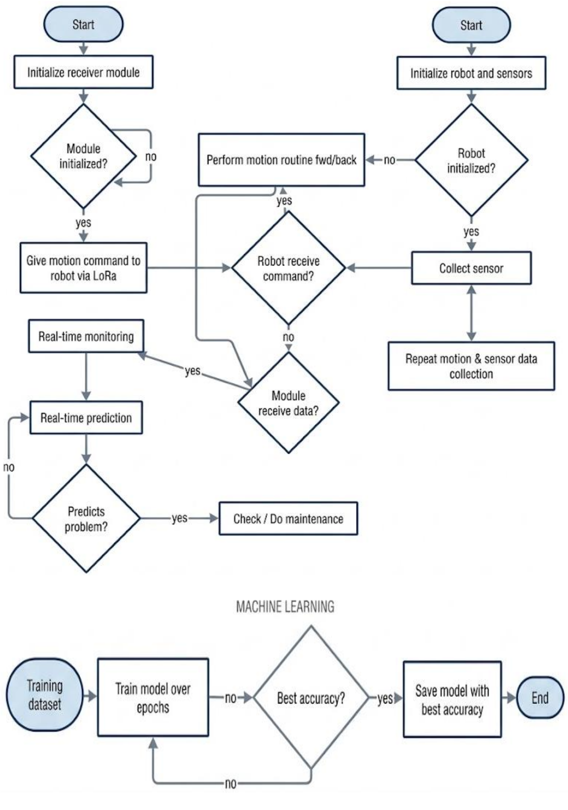



Fig. 1. Core workflow. (Author *et al.*., 2025).

The main components of the system are:

1. Two ESP32 microcontrollers: One acts as the transmitter on the mobile robot; the other serves as a receiver at the base station.
2. Sensors: BME280 (for temperature, humidity, and pressure) and MQ135 (for $CO_2$ and air quality).
3. Wireless module: LoRa SX1278, chosen for long-range, low-bandwidth, and obstacle-penetrating communication.
4. GUI host PC: Runs the PyQt5 application that reads incoming serial data, visualises it in graphs, performs AI inference, and logs data for historical review.

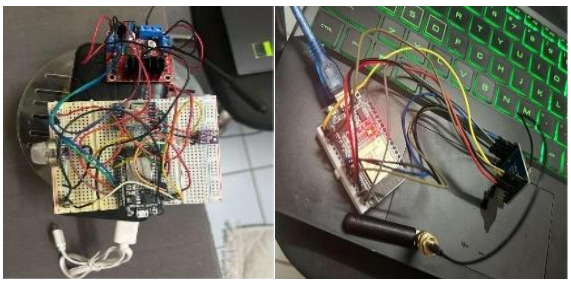
The overall architecture begins with a mobile robot equipped with multiple sensors that moves through HVAC ducting systems to collect real-time environmental data. The robot transmits sensor data via a LoRa SX1278 module to a base station, where the information is displayed in a PyQt5-based GUI and analysed using a deep learning model. The end-to-end workflow—from sensing to alert generation—ensures timely classification of duct conditions, including normal, high humidity, and fire. Figure 1 illustrates the core workflow between the robot, the receiver module, and the AI inference loop.

### B. Hardware Design and Justification

The ESP32 was selected for its dual-core 240 MHz processor, integrated Wi-Fi and Bluetooth connectivity, and 34 GPIO pins. Unlike the Arduino Uno, which has a single-core 16 MHz processor and lacks wireless capability, or STM32 boards that require external Wi-Fi modules, the ESP32 provides an all-in-one solution for IIoT applications. Its processing power enables real-time data processing, while its built-in wireless connectivity allows for effective data transfer. This combination provides a cost-effective and compact platform suitable for industrial IoT deployments.

The BME280 sensor integrates three environmental readings in a single package, significantly reducing wiring complexity and improving data synchronisation. MQ135 was selected for its responsiveness to a broad range of harmful gases, including those relevant to HVAC fire or chemical risks.

The LoRa SX1278 module operates at 433 MHz, a frequency well-suited to metallic environments such as HVAC ducts, offering better penetration and range than 2.4 GHz protocols. This frequency choice also aligns with the findings in [12] which confirmed the effectiveness of lower-frequency signals in duct-like structures. The transmitter and receiver modules are shown in Fig. 2. Meanwhile, the HVAC ducting assembly is shown in Fig. 3. The assembly incorporates an O-shaped structure to simulate the robot's movement at different angles and junctions.



Left Right

Fig. 2. System transmitter (left) and receiver (right). (Author *et al.*, 2025).

Fig. 3. HVAC ducting assembly. (Author *et al.*, 2025).

*C. Software Development*

The firmware for the robot's ESP32 was developed in the Arduino IDE using C++. It initialises sensors, performs $CO_2$ ppm calculations using Rs/Ro values from MQ135, and controls the robot's movement in a timed pattern. Every 10 seconds, the robot pauses, takes measurements, formats the data into a string, and transmits it via LoRa.

The receiver ESP32 continuously listens for incoming packets. Upon receiving data, it sends the data via serial USB to the GUI. This firmware is kept minimal to reduce latency and improve reliability. The PyQt5-based GUI on the host computer handles:

- Real-time graph plotting using PyQtGraph.
- Serial reading and sensor parsing.
- AI model inference and prediction display.
- Historical data logging into a CSV file.
- Manual robot control via serial commands.

This GUI supports tab-based navigation, with dashboards for each sensor, a control panel, and a prediction alert tab that changes colour when non-normal conditions are detected.

*D. AI Model Development*

For predictive classification, a deep neural network (DNN) was trained using Keras. The dataset was collected from real-world testing under different conditions:

- Normal: Hair dryer blowing into an enclosed metal box.
- High Humidity: Hair dryer and mist spray combined.
- Fire: Hair dryer and burning paper inside the box.

Data was labelled manually and split into training and test datasets. Preprocessing steps included:

- Dropping non-numeric fields (e.g., timestamp),
- Standard scaling with StandardScaler(),
- Label encoding with LabelEncoder(),
- One-hot encoding for multi-class training.

The DNN model consisted of:

- Input layer (4 neurons),
- Two hidden layers with ReLU and Dropout (to prevent overfitting),
- Output layer with softmax for multi-class classification.

Training used 50 epochs, a batch size of 16, and a 20% validation split. The model achieved approximately 100% accuracy on the test set and was saved in .h5 format for deployment.

Every third reading from the GUI was passed to the model. If the predicted label was not "Normal," the GUI highlighted the prediction in red.

*E. Signal Propagation Theory*

A crucial theoretical aspect of this system is LoRa communication within metallic ducts. Signal degradation is governed by:

$$\Delta S = -\alpha \Delta d \tag{1}$$

, where

- $\Delta S$ is the reduction in signal strength,
- $\alpha$ is the attenuation coefficient,
- $\Delta d$ is the distance travelled.

Equation (1) supports the system design, as metallic ducts tend to attenuate signals; however, LoRa's low-frequency modulation and long-range capability mitigate this loss.

## IV. RESULTS AND DISCUSSIONS

This section presents the key outcomes derived from the implementation and evaluation of the IIoT-based real-time monitoring and predictive maintenance system. The results are grouped into four core areas: (1) successful sensor data transmission and reception in metallic environments; (2) GUI performance and data logging behaviour; (3) AI model evaluation; and (4) comparative analysis between machine learning models. Each result is followed by an interpretation and its practical implications.

*A. Sensor Data Transmission in Metallic Environments*

One of the primary challenges addressed in this project was the reliable wireless transmission of sensor data through predominantly metallic HVAC ducts. These structures are known to cause signal reflection, absorption, and attenuation. Using the LoRa SX1278 module operating at 433 MHz, the system successfully transmitted environmental data (temperature, humidity, pressure and $CO_2$) from the mobile robot to the base station in real time, with no packet loss.

The viability of LoRa communication in constrained environments was confirmed. This result supports previous research reported in [12], which highlighted the waveguide-like properties of ducts. Empirical testing demonstrated stable communication even when the robot was placed inside closed metallic boxes, validating the project's theoretical model using Eq. (1). The ability to penetrate metal enclosures is critical for future deployment in real HVAC systems.

Figure 4, for instance, shows the real-time output received at the base station. The clearly delineated sensor readings—temperature, humidity, pressure, and air quality—validated data integrity over LoRa.

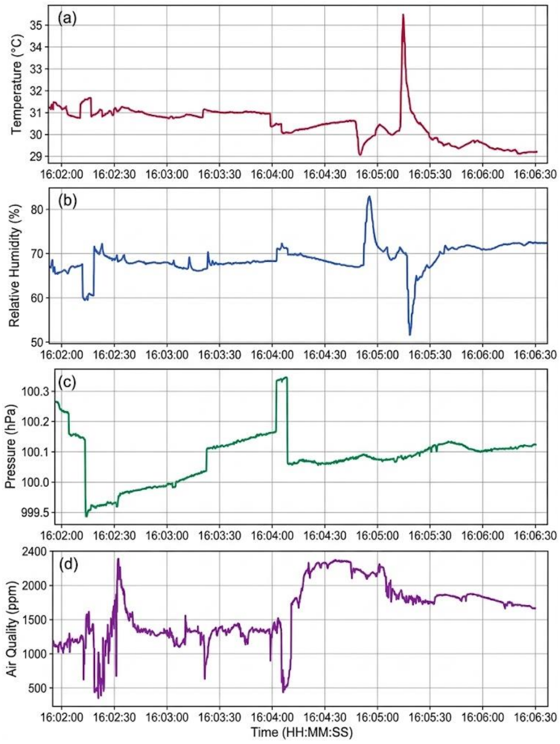



Fig. 4. Real-time output at base station. (Author *et al.*, 2025).

*B. GUI Monitoring, Visualisation, and Data Logging*

The GUI, developed using PyQt5 and PyQtGraph, functioned effectively throughout testing. It allowed for:

- Real-time graphing of four sensor readings.
- Auto-scaling and zoom/pan functionality.
- Manual reset of visualisation range.
- Manual control of the mobile robot (Start, Stop, Forward, Backwards).
- Periodic saving of data to sensor_history.csv.

The GUI dashboard is operational during a test run, with each graph updating every 2 seconds. The colour-coded curves helped operators visually identify anomalies, such as spikes in temperature or $CO_2$.

Additionally, the "Alert" tab in the GUI displayed a red visual indicator, and an icon appeared whenever the AI model classified abnormal readings. For example, in one trial, artificially elevated humidity triggered a "High Humidity" alert with clear time-stamped values. This feature enhanced operator responsiveness and improved real-time situational awareness.

The History tab retained the last 100 entries and allowed CSV export. This functionality is crucial for post-analysis and audit trails, particularly in regulated environments where historical sensor records may be required.

*C. Deep Learning Model Evaluation*

The DNN model, trained using Keras on custom dataset, showed impressive performance despite the modest dataset size. It was trained on three environmental conditions: Normal, High Humidity, and Fire. The training environment was carefully controlled. For instance:

- Normal: hair dryer alone inside a plastic-wrapped metal box.
- High Humidity: hair dryer with water spray.
- Fire: hair dryer with burning paper.

A "Blockage" condition was initially added but later removed due to model confusion with 'Normal.' The preprocessing steps included:

- Label encoding for target classes,
- Normalisation of input features (temperature, humidity, pressure, MQ135),
- One-hot encoding for categorical training,
- Splitting the data into 80% training and 20% test sets.

The initial dataset contained 577 samples with four features ('Temperature,' 'Humidity,' 'Pressure,' and 'AirQuality') and one 'Label' column. The data were split into training (461 samples) and testing (116 samples) sets, with labels encoded into three distinct numerical classes. Features were successfully scaled using StandardScaler, which was fitted only on the training data to prevent data leakage. A sequential neural network model was built with an input layer, two dense hidden layers (64 and 32 neurons with ReLU activation), and an output layer (3 neurons with 'softmax' activation). The model was compiled with the Adam optimiser and sparse categorical cross-entropy loss.

After 50 epochs of training, the model achieved final training and validation accuracies of 0.9946 and 1.0000, respectively. On the independent test set, the model demonstrated exceptional performance, achieving a test loss of 0.0096 and a test accuracy of 1.0000.

The loss and accuracy plots showed rapid convergence and stable performance, with both training and validation metrics quickly reaching optimal values, indicating a well-trained model without significant signs of overfitting or underfitting. Most importantly, the model reliably detected fire conditions, which are critical for safety applications.

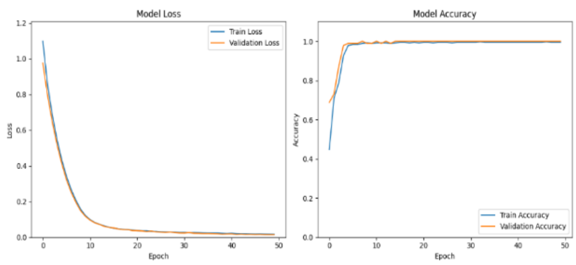



Fig. 5. Training learning curves. (Author *et al.*, 2025).

The final model was deployed in the GUI using load_model(). Every third reading from the serial interface was sent to the DNN for classification. The low inference time ensured no delay in user feedback.

### *D. Machine Learning Model Comparison (Random Forest, SVM, KNN)*

For benchmarking purposes, traditional ML classifiers—Random Forest, SVM, and KNN—were also trained on the same dataset. All three models achieved 100% accuracy on the test set. This unusually high performance was attributed to the small dataset and the controlled conditions, in which classes were well-separated.

Figure 6 and Fig. 7 show the classification reports and confusion matrices for these models. All models demonstrated perfect classification across all classes, with precision, recall, and F1-scores equal to 1.0. Random Forest emerged as the most robust model during minor noise injection tests.

```
Classification Report:
              precision    recall  f1-score   support

        Fire       1.00      1.00      1.00        11
  High Humid       1.00      1.00      1.00        20
      Normal       1.00      1.00      1.00        32

    accuracy                           1.00        63
   macro avg       1.00      1.00      1.00        63
weighted avg       1.00      1.00      1.00        63
```

Fig. 6. Classification report. (Author *et al.*, 2025).

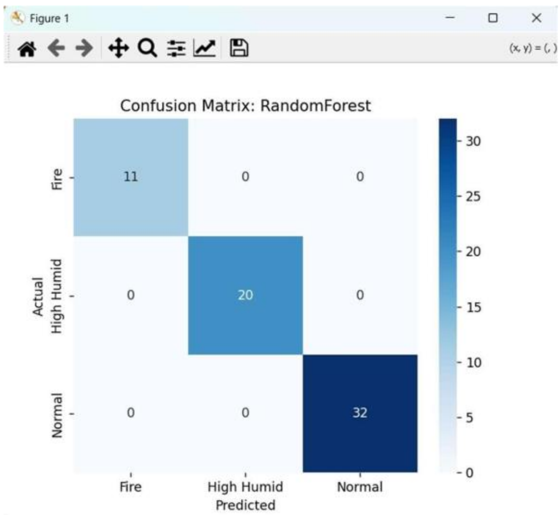



Fig. 7. Confusion matrix. (Author *et al.*, 2025).

However, such perfect results must be interpreted cautiously. Overfitting is a risk, especially with limited data. While SVM and KNN were accurate in tests, they may be less resilient in more diverse operational scenarios compared to ensemble methods like Random Forest.

### *E. Comparative Discussion of Model Performance*

All four models—DNN, RF, SVM, and KNN—performed excellently in controlled tests. Furthermore, DNN offers greater scalability and real-time edge deployment capabilities due to its ability to model complex nonlinear patterns. The accuracy and strengths of the AI models are shown in Table I.

Table I. Comparison of the Accuracy and Strengths of Different AI Models.

| Model | Accuracy | Strength Notes |
|---|---|---|
| DNN (Keras) | 100% | Shows slight generalisation loss |
| Random Forest | 100% | Robust and resistant to noise |
| SVM | 100% | Accurate but less scalable |
| KNN | 100% | Simple but sensitive to noise |

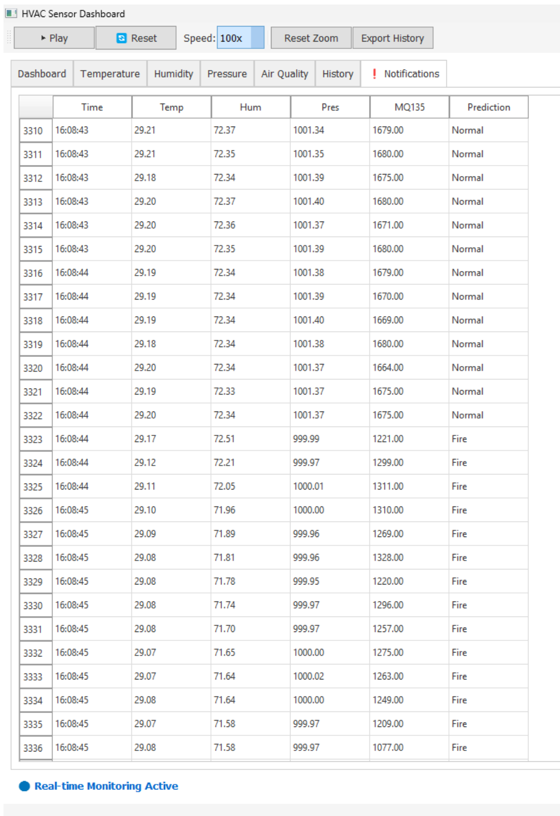
Ultimately, the DNN was chosen for integration due to its superior architecture for real-time streaming inference, low computational footprint, and ease of deployment in GUI applications.

### *F. Live AI Prediction and Alerting Results*

The system's real-time classification results were visually displayed in the GUI alert tab. During various live tests:

- "High Humidity" was detected when water was sprayed near the robot.
- "Fire" was correctly identified when smoke from burning paper entered the duct.
- "Normal" was consistently returned during clean air testing.

Figure 8 shows the classification logs including timestamps, sensor values, and predicted classes. The interface displayed alerts immediately upon abnormal detection, demonstrating the practical viability of the system.




| | Time | Temp | Hum | Pres | MQ135 | Prediction |
|---|---|---|---|---|---|---|
| 3310 | 16:08:43 | 29.21 | 72.37 | 1001.34 | 1679.00 | Normal |
| 3311 | 16:08:43 | 29.21 | 72.35 | 1001.35 | 1680.00 | Normal |
| 3312 | 16:08:43 | 29.18 | 72.34 | 1001.39 | 1675.00 | Normal |
| 3313 | 16:08:43 | 29.20 | 72.37 | 1001.40 | 1680.00 | Normal |
| 3314 | 16:08:43 | 29.20 | 72.36 | 1001.37 | 1671.00 | Normal |
| 3315 | 16:08:43 | 29.20 | 72.35 | 1001.39 | 1680.00 | Normal |
| 3316 | 16:08:44 | 29.19 | 72.34 | 1001.38 | 1679.00 | Normal |
| 3317 | 16:08:44 | 29.19 | 72.34 | 1001.39 | 1670.00 | Normal |
| 3318 | 16:08:44 | 29.19 | 72.34 | 1001.40 | 1669.00 | Normal |
| 3319 | 16:08:44 | 29.18 | 72.34 | 1001.38 | 1680.00 | Normal |
| 3320 | 16:08:44 | 29.20 | 72.34 | 1001.37 | 1664.00 | Normal |
| 3321 | 16:08:44 | 29.19 | 72.33 | 1001.37 | 1675.00 | Normal |
| 3322 | 16:08:44 | 29.20 | 72.34 | 1001.37 | 1675.00 | Normal |
| 3323 | 16:08:44 | 29.17 | 72.51 | 999.99 | 1221.00 | Fire |
| 3324 | 16:08:44 | 29.12 | 72.21 | 999.97 | 1299.00 | Fire |
| 3325 | 16:08:44 | 29.11 | 72.05 | 1000.01 | 1311.00 | Fire |
| 3326 | 16:08:45 | 29.10 | 71.96 | 1000.00 | 1310.00 | Fire |
| 3327 | 16:08:45 | 29.09 | 71.89 | 999.96 | 1269.00 | Fire |
| 3328 | 16:08:45 | 29.08 | 71.81 | 999.96 | 1328.00 | Fire |
| 3329 | 16:08:45 | 29.08 | 71.78 | 999.95 | 1220.00 | Fire |
| 3330 | 16:08:45 | 29.08 | 71.74 | 999.97 | 1296.00 | Fire |
| 3331 | 16:08:45 | 29.08 | 71.70 | 999.97 | 1257.00 | Fire |
| 3332 | 16:08:45 | 29.07 | 71.65 | 1000.00 | 1275.00 | Fire |
| 3333 | 16:08:45 | 29.07 | 71.64 | 1000.02 | 1263.00 | Fire |
| 3334 | 16:08:45 | 29.08 | 71.64 | 1000.00 | 1249.00 | Fire |
| 3335 | 16:08:45 | 29.07 | 71.58 | 999.97 | 1209.00 | Fire |
| 3336 | 16:08:45 | 29.08 | 71.58 | 999.97 | 1077.00 | Fire |

Fig. 8. Classification logs. (Author *et al.*, 2025).

## V. CONCLUSION

This project successfully developed an IIoT-based real-time monitoring and predictive maintenance system for HVAC duct environments. By integrating ESP32 microcontrollers, LoRa wireless communication, environmental sensors, and a PyQt5-based GUI with a deep learning model, the system was able to detect and classify air conditions into "Normal," "High Humidity," and "Fire" states. All components—including hardware, software, data transmission, and AI prediction—operated cohesively.

The results demonstrated reliable data transmission even in metallic environments, effective visualisation via a functional GUI, and accurate condition classification using both machine learning and deep learning models. Hence, the findings demonstrate the feasibility of deploying smart monitoring systems in real-world HVAC applications.

For future work, the system can be improved by collecting more real-world data, retraining the model with additional environmental scenarios, and integrating a camera for visual inspection, which would provide redundancy and better situational awareness.

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## AUTHOR CONTRIBUTIONS

Abd Halim Embong: Conceptualisation, Methodology, Supervision, Validation;
Syamsul Bahrin Abdul Hamid: Writing – Review & Editing, Supervision, Project Administration, Preliminary Review;
Muhammad Syahir Fathuddin Shukran: Writing – Review & Editing, Software, Validation, Analysis;
Nur Bidayatul Hidayah Abdul Kader: Writing – Review & Editing, Software, Validation;
Muhammad Arfan Zulkifli: Writing – Original Draft, Investigation, Data Collection.

## CONFLICT OF INTEREST

No conflict of interest was disclosed.

## ETHICS STATEMENT

Our publication ethics follow the guidelines of the Committee on Publication Ethics (COPE) https://publicationethics.org/. The research does not involve human participants, animal subjects, or any form of personal or sensitive data. Therefore, ethical approval and informed consent were not required for this project.

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