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AI-Based Predictive Maintenance System for Industrial Machines (HVAC-R)

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Abstract

For industries like manufacturing, cold storage, and pharmaceuticals to maintain steady cooling, industrial HVAC refrigeration systems are essential. But because they are always in use, they are vulnerable to malfunctions that result in expensive downtime and inefficient use of energy. Conventional maintenance techniques are frequently inefficient or reactive. A low-cost, AI-based predictive maintenance system for small-to-medium-sized businesses is presented in this paper. The system tracks important parameters like temperature, vibration, and power consumption using real-time data from Internet of Things sensors that are connected to an ESP32 module. High accuracy fault prediction and anomaly detection are achieved by a hybrid machine learning model that combines an LSTM Autoencoder with a Random Forest classifier and regression. A chatbot and mobile app are part of the setup for easy-to-use monitoring. The solution can support more dependable and sustainable HVAC operations by lowering maintenance costs, improving energy efficiency, and reducing unplanned breakdowns.

Keywords: Predictive Maintenance; HVAC systems; IoT; Machine Learning; Fault Detection; LSTM Autoencoder; Random Forest; Sustainability

Introduction

The dependability and effectiveness of machinery are crucial in today's data-driven industrial environment to guarantee continuous operations in industries like manufacturing, cold storage, pharmaceuticals, and food processing. Among these devices, HVAC (heating, ventilation, and air conditioning) systems—in particular, industrial refrigeration units—are crucial for preserving environments that are sensitive to temperature changes. However, because of their mechanical complexity and constant operation, these systems are vulnerable to unanticipated malfunctions that can lead to high maintenance costs, product spoilage, and energy waste. Such failures are frequently not prevented by reactive, time-based maintenance procedures, particularly in small and medium-sized businesses (SMEs) that lack the funding for advanced monitoring. Because of costly commercial solutions or infrastructure requirements, predictive maintenance (PdM) is not as widely adopted in cost-sensitive environments as it could be. However, PdM offers a more proactive approach by identifying anomalies prior to failures.

The need for an affordable, easily accessible PdM solution specifically designed for industrial HVAC systems is addressed by this project. The suggested system seeks to democratize predictive maintenance for smaller industries by fusing machine learning methods, an intuitive user interface, and reasonably priced IoT hardware. To support smarter, more sustainable operations, the solution is designed to guarantee real-time monitoring, early fault detection, and minimal user intervention.

The contributions of this paper are threefold:

1. **Design and implementation of a prototype predictive maintenance system** using low-cost sensors and an ESP32 microcontroller.
2. **Development of a hybrid ML pipeline** tailored for time-series anomaly detection and fault classification using real-time data.
3. **Deployment of a mobile application** integrated with a chatbot to enable intuitive user interaction with live system diagnostics.

Literature Review

Recent studies have explored AI-based HVAC fault prediction using supervised and unsupervised learning models:

- **SVM and Decision Trees** have been effective but struggle with complex faults [1–3].
- **LSTM models** demonstrate strength in time-series analysis but are resource-heavy [4].
- **Random Forest and Gradient Boosting** offer robust classification in noisy environments [5,6].
- **Deep Reinforcement Learning** improves efficiency but lacks real-world deployment readiness [7].

Although several sophisticated predictive maintenance systems have demonstrated excellent fault detection capabilities, many of them depend on cloud infrastructure or proprietary hardware, which may restrict their affordability and real-time responsiveness for small-scale industries [1,6]. On the other hand, our system offers a responsive and affordable substitute that is appropriate for SME settings by utilizing open-source hardware and lightweight cloud services.

Methodology

A. Sensor Deployment and Data Acquisition

These sensors interface with an ESP32 microcontroller. Sensor readings are captured every 30 seconds and sent via HTTP POST requests to a cloud endpoint. Data is then stored in a Supabase PostgreSQL database.

Table 1. Market Survey

Service	Provider	Key Features	Limitations
Siemens Desigo CC	Siemens	Advanced diagnostics, energy monitoring	Expensive; requires proprietary hardware
IBM Maximo	IBM	Asset lifecycle management, AI-based PdM	Enterprise-tier only
Azure IoT + ML	Microsoft	Scalable, real-time analytics	Requires cloud infrastructure & expertise
Fiix by Rockwell	Rockwell Automation	CMMS with PdM capabilities	Subscription-based, limited hardware flexibility

Table 2. Component Survey

Sensor	Measured Parameter	Specs
DS18B20	Temperature	-55°C to 125°C
DHT22	Humidity	0–100% RH
ACS712	Current	Up to 30A
ZMTP101B	Voltage	Up to 250V
MQ-6	Gas (R134a, Ammonia, etc.)	ppm sensitivity
ADXL335	Vibration	± 3g

Table 3. Sensor Deployment

Sensor	Measured Parameter	Mounted On
DS18B20	Temperature	Evaporator Coil
DHT22	Humidity	Air Intake
ACS712	Current	Compressor Circuit
ZMTP101B	Voltage	Power Supply
MQ-6	Gas Leak	Near Refrigerant Lines
ADXL335	Vibration	Compressor Body

B. Cloud & Machine Learning Layer

1. Data Preprocessing

- Missing data is filled using linear interpolation.
- Outliers are replaced using median filtering.
- Data is normalized, and new features are derived (Power Consumption, Temperature Difference, etc.).

2. Model Architecture

- LSTM Autoencoder: Learns baseline behavior and flags anomalies based on reconstruction error.
- Random Forest Classifier: Assigns fault labels to detected anomalies using supervised learning.
- Random Forest Regressor: The Health Index Estimation Model estimates the equipment's health index as a

continuous value between 0 and 100.
- Multi-Class Classifier DLNN: The Part Risk Prediction Model predicts which component is most likely to fail and assesses its condition based on sensor data.

3. Training
- Models built in TensorFlow and Scikit-learn.
- Data split: 70% training, 15% validation, 15% test.
- Performance metrics: RMSE, F1-score, Precision, Latency (<1s).
- Synthetic faults added for robustness.

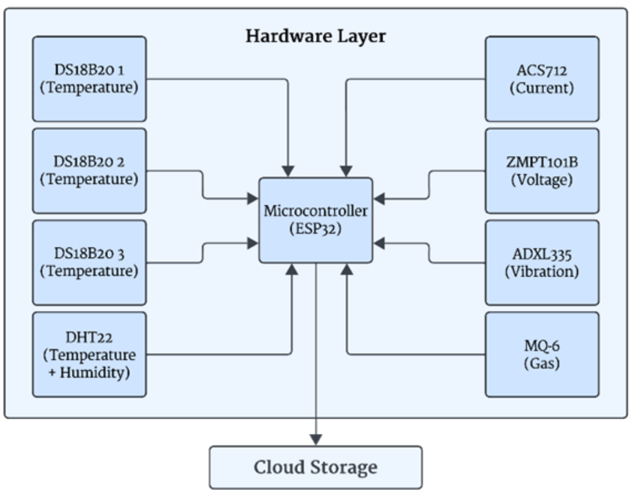

Fig 1. Hardware Layer

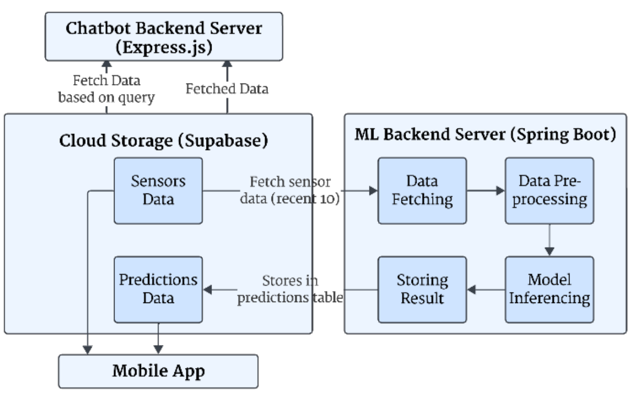

Fig 2. Cloud and ML Backend

C. User Interface Layer

C1. Mobile Dashboard:

The mobile app is built using React Native, supporting both Android and iOS platforms. It displays:

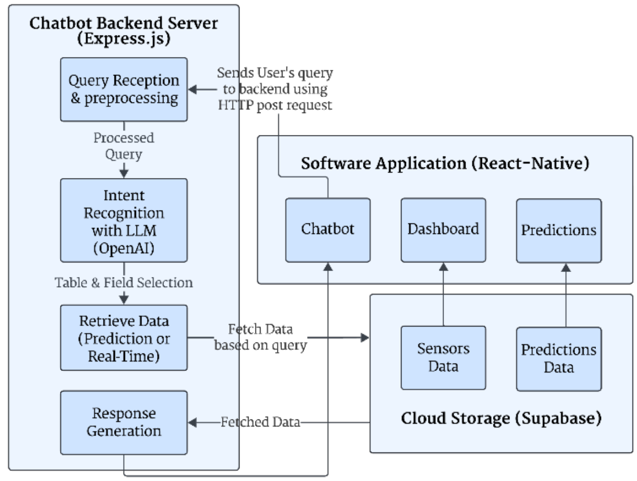

Fig 3. Chatbot Backend and Mobile App

- Live sensor readings (temperature, current, vibration, etc.).
- Fault probabilities and system health scores.
- Alerts and historical fault logs.

The app fetches data through secure HTTPS requests to cloud APIs and enforces user authentication using Supabase Auth. It supports role-based access, showing tailored views for administrators and technicians.

C2. Chatbot Interface:

To simplify access, a built-in chatbot allows users to ask questions like "Is the compressor working fine?" or "What faults were detected today?"

The chatbot runs on a backend built with Express.js and uses an LLM (Large Language Model) via OpenAI's API to interpret queries. It retrieves the latest data or predictions from the Supabase database and replies in plain language.

The backend uses a prompt-template wrapper for OpenAI GPT API to interpret the user's intent, executes appropriate REST queries to Supabase, constructs a response in natural language and sends it back to the app.

This interface enables non-technical users to interact with the system naturally, without needing to understand dashboards or charts.

D. Testing and Validation

The complete system was tested on real refrigeration units under various conditions—such as high humidity, power fluctuations, and simulated faults.

- The system successfully detected common faults (like refrigerant leaks and compressor inefficiencies) within 5 minutes.

- Prediction accuracy was validated against manually logged fault events.
- The app and chatbot were evaluated for usability by non-technical users, who were able to navigate the interface and understand the results with minimal guidance.

Results

The hybrid machine learning model, combining an LSTM Autoencoder for anomaly detection with a Random Forest classifier for fault identification, Random Forest Regressor for Health Estimation and a DLNN Multi-class classifier for component failure prediction was evaluated on data collected over 10 days. The LSTM effectively detected deviations from normal behavior, while the Random Forest classifier achieved high accuracy in categorizing faults—particularly for common issues like compressor short cycling. The model maintained consistent performance across validation folds and demonstrated fast inference times, confirming its suitability for real-time applications. These results validate the system's potential for reliable and responsive predictive maintenance.

The mobile dashboard provides a unified view of system data in real time (Figure 4). Key parameters like zone-wise temperature, compressor vibration, humidity, and power metrics are visualized to support quick diagnostics. This interface enables technicians to detect abnormalities without complex tools.

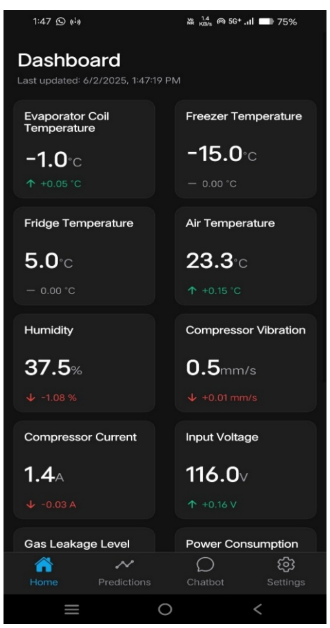

Fig 4. Dashboard depicting parameters for all components

Figure 5 highlights the NLP-powered chatbot integrated into the app. It allows users to query system health, request fault predictions, or interpret recent anomalies using conver-

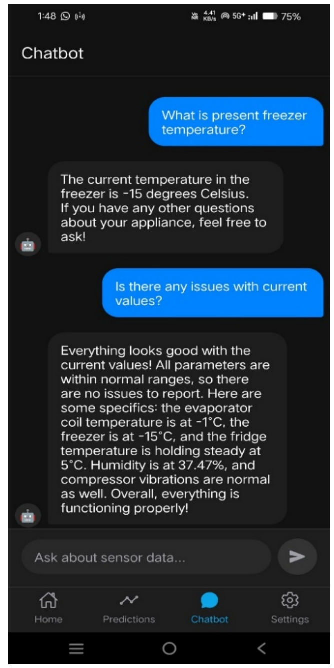

Fig 5. Chatbot section where user can ask his/her query

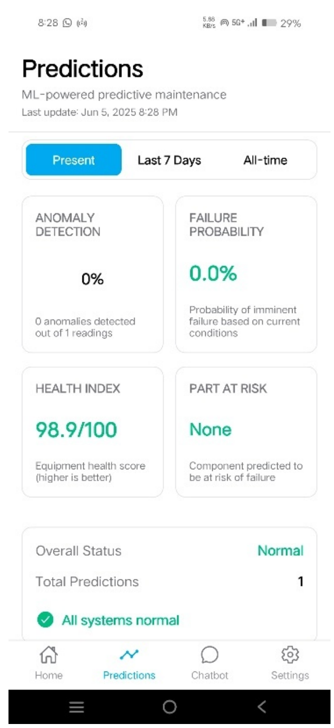

Fig 6. Predictions using ML model

sational input. The chatbot enhances accessibility for non-technical users.

Figure 6 demonstrates how the mobile application presents live prediction results from the ML pipeline. It displays system-level insights such as anomaly detection rate, component-level failure probability, overall health index, and component risk status. The app computes and visualizes this data in real time, helping users monitor system performance at a glance and take proactive action if needed.

Discussion

The findings show that the suggested system effectively combines machine learning, real-time data infrastructure, and inexpensive IoT hardware for HVAC predictive maintenance. The system's practicality and efficacy were enhanced by each of its parts.

Critical HVAC parameters like temperature, current, and vibration could be accurately monitored at high frequencies thanks to the sensor and ESP32-based hardware layer. Affordability was guaranteed without sacrificing data quality by using widely accessible, reasonably priced sensors. Consistent performance and robustness were demonstrated during testing under various operating conditions.

Fast and accurate fault detection, classification, and health evaluation were provided by the cloud storage and machine learning layer. The LSTM Autoencoder used reconstruction error to identify deviations as anomalies after learning baseline behavior patterns. A Random Forest Classifier, which used supervised learning to assign fault labels, was then used to classify the detected anomalies. A Random Forest Regressor calculated a continuous health index with a range of 0 to 100 to measure the overall health of the system, giving a useful overview of the state of the equipment. The component most likely to fail was also predicted using a multi-class deep learning model. With the use of real-time sensor data, this model evaluated the conditions of individual components, allowing for more focused maintenance choices. With low-latency inference appropriate for ongoing industrial monitoring, the combination of these models guaranteed both thorough system diagnostics and precise fault prediction.

System accessibility was greatly aided by the chatbot interface and mobile application. While the chatbot enabled non-technical users to ask questions about the status of the system using natural language, the dashboard gave technicians access to real-time system metrics and alerts. When combined, these interfaces facilitated speedier maintenance decisions and decreased the need for manual diagnostics. The system's functionality was confirmed by its performance in real-time tests. Predictions and manual fault logs showed a high degree of agreement, and faults were found within five minutes of occurrence. Deployment in other HVAC configurations is also made simple by the modular design.

But there are still certain difficulties. High-frequency data transmission revealed notification delays, indicating the need for additional backend optimization. Furthermore, even though the system was tested on domestic units, extensive industrial validation is necessary to guarantee wider scalability.

All things considered, the system fills a significant void in predictive maintenance tools for small and medium-sized businesses with an affordable and intuitive solution.

Conclusion

An AI-based predictive maintenance system designed specifically for HVAC refrigeration units is presented in this project. Early fault detection and real-time health monitoring are made possible by the system's integration of cloud infrastructure, inexpensive IoT hardware, and a hybrid machine learning model. Proactive maintenance decisions are supported by the chatbot interface and mobile application, which guarantee accessibility for both technical and non-technical users.

The system's responsiveness, dependability, and appropriateness for small-to-medium-sized businesses are all confirmed by test results. Future additions to other industrial equipment are possible due to its modular design. The solution has a great potential to decrease downtime, increase equipment lifespan, and boost energy efficiency in practical settings with additional validation and optimization.

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