IoT-Based Smart Freezer Monitoring Using Artificial Intelligence and Computer Vision

Abstract

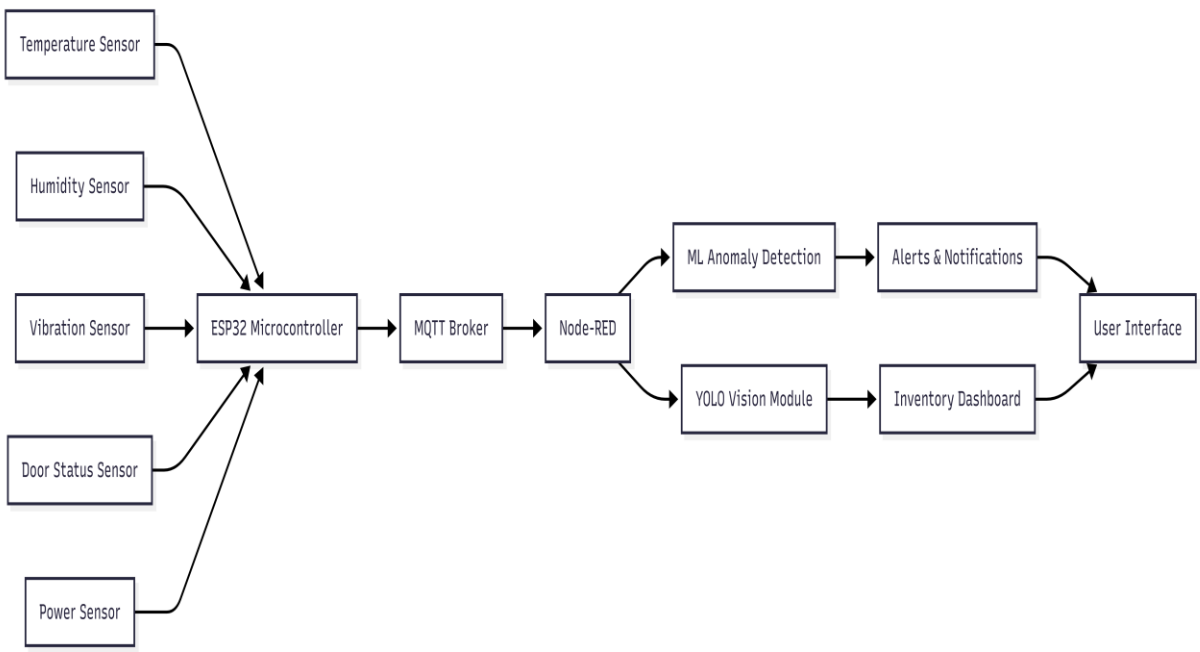
Cold storage systems play a critical role in food preservation, pharmaceuticals, and retail industries. Conventional freezer monitoring relies heavily on manual inspection and threshold-based alarms, which are insufficient for early fault detection and scalable inventory management. This project presents an IoT-based smart freezer monitoring system integrated with machine learning and computer vision techniques. The proposed system continuously monitors environmental and operational parameters using sensors interfaced with an ESP32 microcontroller. Anomaly detection is performed using an unsupervised machine learning model, while inventory monitoring is achieved through real-time object detection using YOLO. The system provides real-time visualization, alerts, and intelligent decision-making, offering a scalable and automated alternative to traditional freezer monitoring systems.

Introduction

Cold storage freezers are essential for maintaining product quality and safety in various industries. Failures such as temperature rise, prolonged door opening, abnormal vibration, or excessive power consumption can lead to product spoilage and financial losses. Additionally, inventory verification inside freezers is often performed manually, which is time-consuming and prone to human error.

Recent advances in IoT and artificial intelligence enable intelligent monitoring systems capable of real-time sensing, fault detection, and automation. This project aims to develop a smart freezer monitoring system by combining IoT-based data acquisition, machine learning-based anomaly detection, and computer vision-based inventory management.

Overall System Architecture



The proposed system follows a modular and layered architecture, enabling scalability and easy integration of AI components. The architecture is divided into four major phases:

1. Data collection using IoT sensors
2. Anomaly detection using machine learning
3. Alerting and decision logic
4. Vision-based inventory management

2.1 System Architecture Description

Sensor data is collected using multiple sensors connected to an ESP32 microcontroller. The ESP32 publishes sensor readings to an MQTT broker. Node-RED subscribes to these MQTT topics for data ingestion, visualization, and alert generation. Machine learning models process the incoming data streams to detect anomalies, while a computer vision module performs inventory detection using a camera feed.

3. Phase 1: Data Collection and Ingestion

3.1 Objective

The objective of this phase is to continuously acquire reliable, structured, and timestamped data suitable for machine learning analysis.

3.2 Hardware Components and Sensors

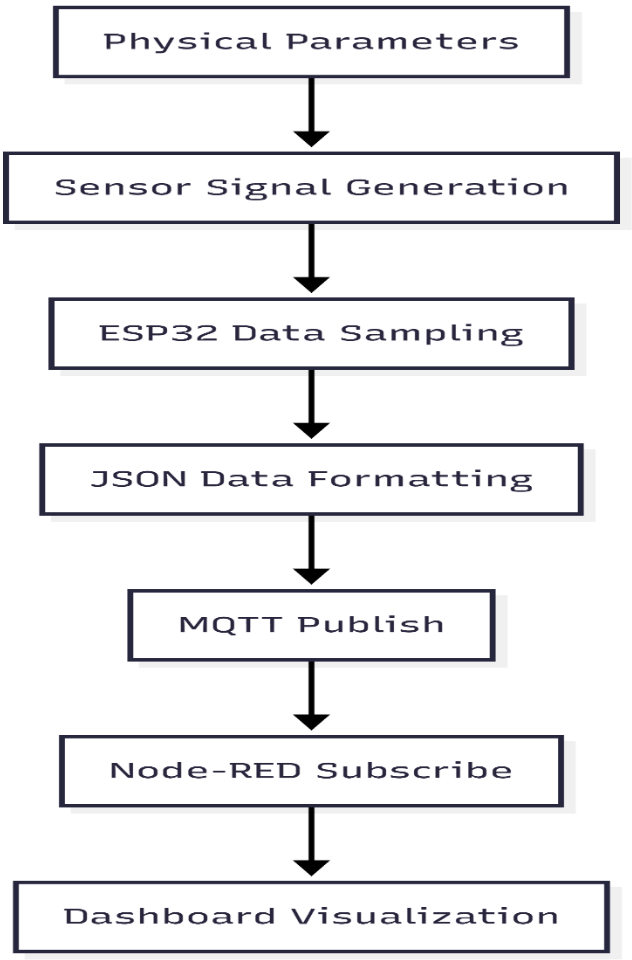
The following parameters are monitored:

- Freezer temperature
- Humidity level
- Door open/close status
- Vibration (compressor health)
- Power consumption (real or simulated)

Each sensor is interfaced with the ESP32 using appropriate digital, analog, or I^2C interfaces.

3.3 Data Flow and Communication

The ESP32 samples sensor data at fixed intervals and formats the readings into JSON payloads. These payloads are transmitted using the MQTT protocol, chosen for its lightweight and low-latency characteristics suitable for IoT applications. Node-RED subscribes to the MQTT topics and acts as the central data ingestion and visualization platform.



3.4 Importance of This Phase

High-quality data is the foundation of any AI-based system. Consistent sampling, accurate timestamps, and structured data formats ensure reliable machine learning model performance in later phases.

Phase 2: Anomaly Detection Using Machine Learning

4.1 Objective

The goal of this phase is to automatically detect abnormal freezer behaviour without relying on manually defined fault conditions.

4.2 Machine Learning Model

An **Isolation Forest** algorithm is used for anomaly detection. It is an unsupervised learning technique well-suited for scenarios where labelled anomaly data is unavailable.

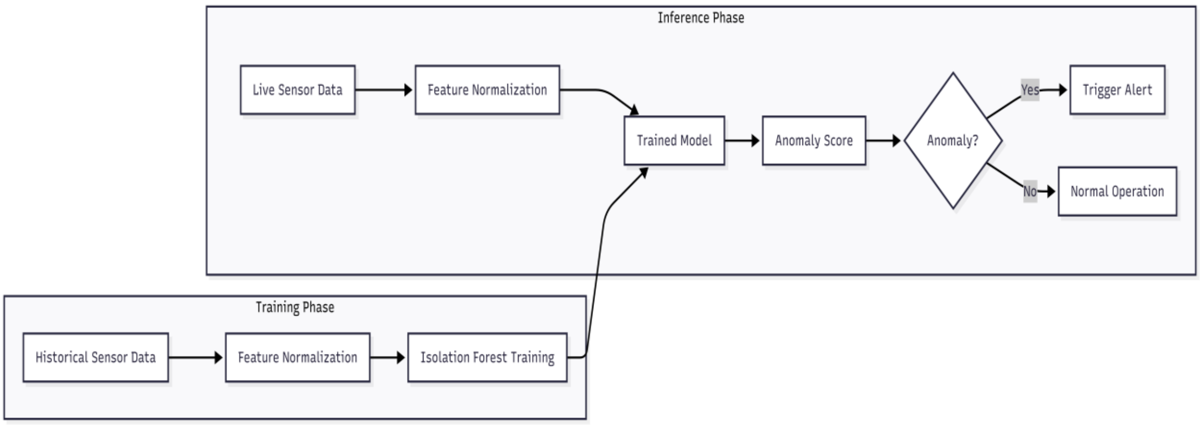
4.3 Feature Selection

The model operates on the following features:

- Temperature
- Vibration
- Power consumption
- Humidity

4.4 Anomaly Detection Logic

The Isolation Forest model learns the normal operating patterns of the freezer from historical data. Data points that significantly deviate from learned patterns are isolated and flagged as anomalies.



4.5 Significance of AI Usage

Unlike threshold-based systems, the model adapts to operational behavior and identifies unseen fault patterns, enabling predictive maintenance.

Phase 3: Alerting and Decision Logic

5.1 Objective

This phase converts detected anomalies and abnormal sensor readings into actionable alerts for users.

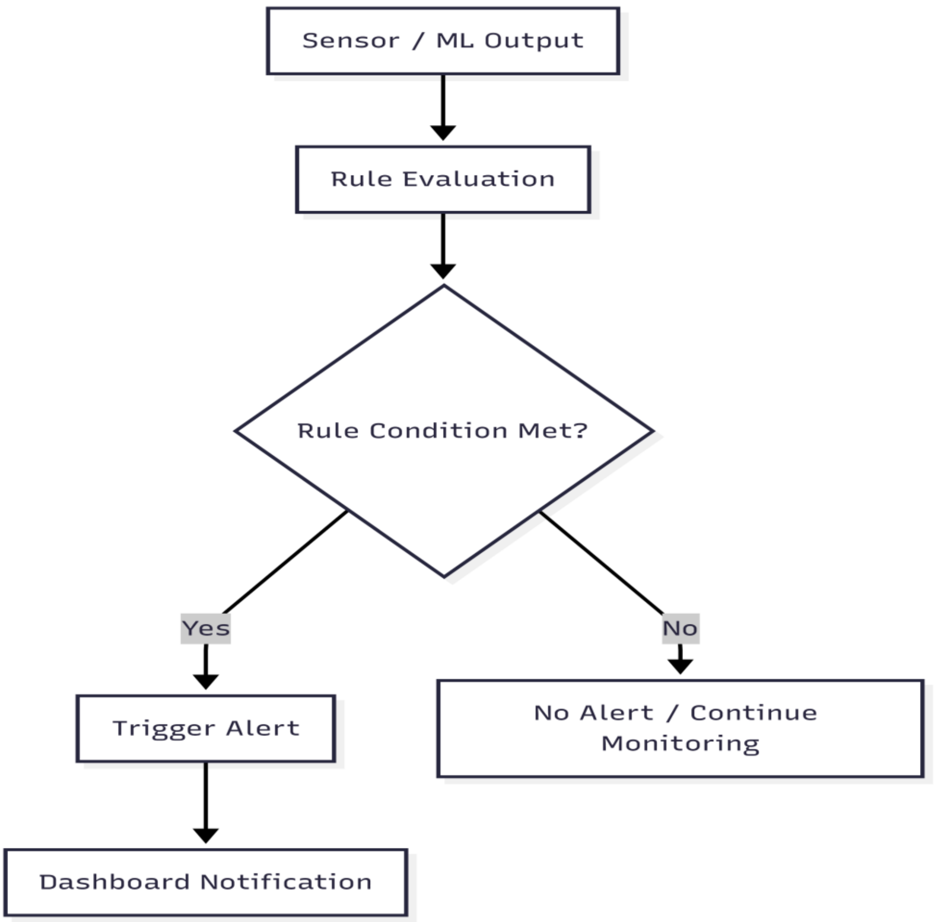
5.2 Decision Strategy

A rule-based decision layer is implemented on top of machine learning outputs. This hybrid approach ensures fast response, interpretability, and safety.

5.3 Example Alert Conditions

- Temperature exceeding safe limits
- Door remaining open beyond a threshold duration
- Excessive vibration indicating mechanical issues
- Power consumption exceeding rated limits

5.4 Alert Flow



Phase 4: Vision-Based Inventory Management

6.1 Objective

The objective of this phase is to automate inventory monitoring using computer vision techniques, eliminating manual inspection.

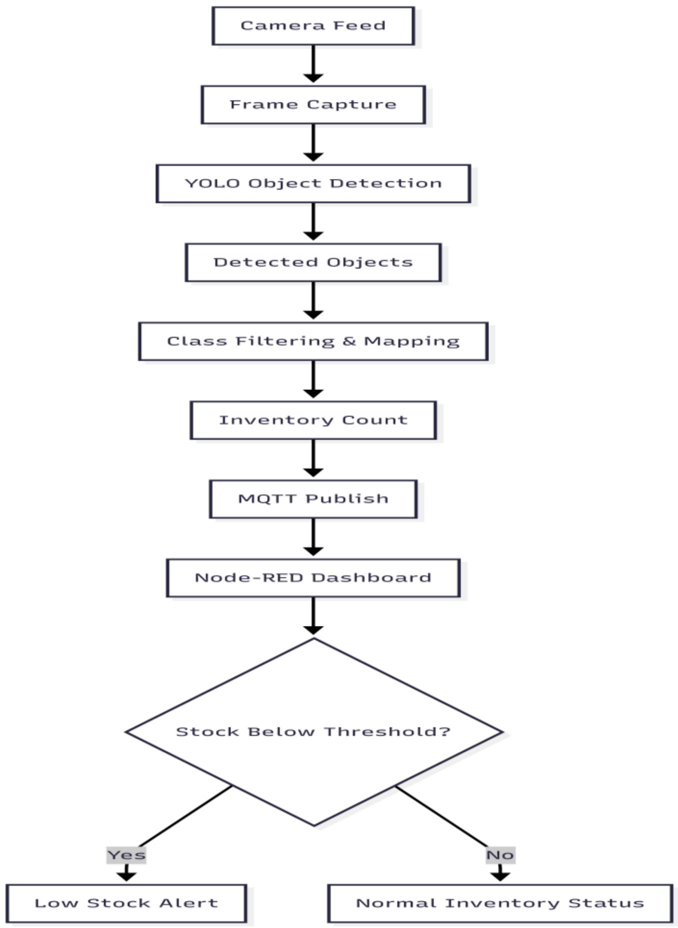
6.2 Computer Vision Model

The system uses **YOLOv8 (You Only Look Once)** for real-time object detection due to its high speed and low inference latency.

6.3 Design Constraint and Mapping Strategy

YOLOv8 pretrained models are trained on the COCO dataset, which does not include an ice-cream class. Instead of retraining, a semantic mapping approach is adopted. Detected container-like objects such as bowls or cups are logically mapped as ice-cream inventory units. This approach is widely used in proof-of-concept and real-time deployments.

6.4 Inventory Detection Flow



Validation of the AI Approach

The proposed system is validated through:

- Use of industry-standard pretrained models
- Real-time inference without cloud dependency
- Modular and scalable architecture
- Integration of IoT, ML, and CV in a single pipeline

This architecture closely resembles real-world industrial monitoring systems.

Future Enhancements

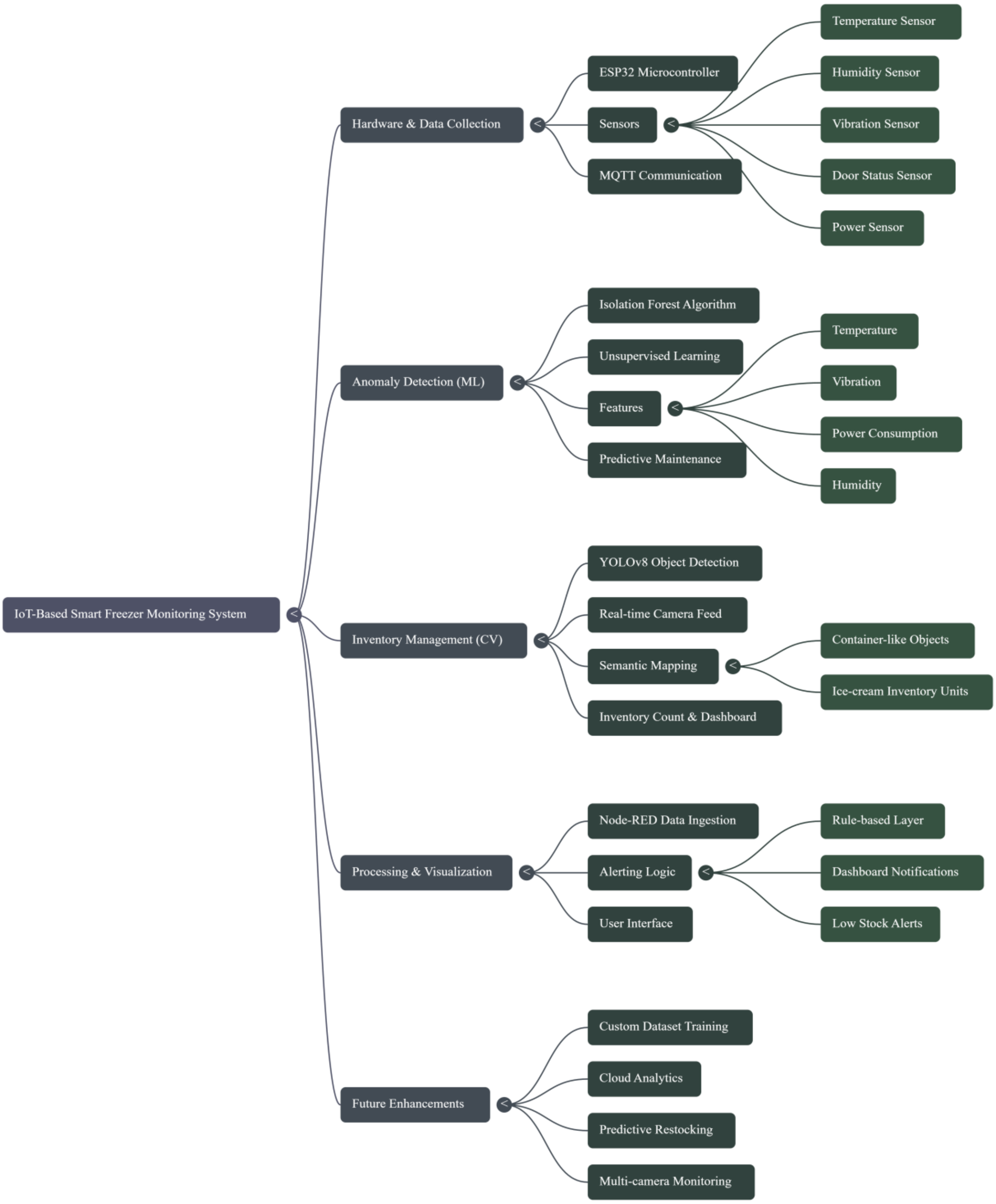
Potential improvements include:

- Custom YOLO training with ice-cream datasets
- Enhanced low-light vision performance
- Predictive restocking using inventory trends
- Multi-camera freezer monitoring
- Cloud-based analytics and long-term insights

Conclusion

This project presents a comprehensive IoT-based smart freezer monitoring system integrating sensor-based data acquisition, machine learning-based anomaly detection, and computer vision-based inventory management. The system enables real-time monitoring, predictive fault detection, automated alerts, and intelligent inventory tracking. The modular design ensures scalability and makes the solution suitable for real-world industrial deployment.

SUMMARY


IoT-Based Smart Freezer Monitoring System
Hardware & Data Collection
ESP32 Microcontroller
Sensors
MQTT Communication
Temperature Sensor
Humidity Sensor
Vibration Sensor
Door Status Sensor
Power Sensor
Anomaly Detection (ML)
Isolation Forest Algorithm
Unsupervised Learning
Features
Predictive Maintenance
Temperature
Vibration
Power Consumption
Humidity
Inventory Management (CV)
YOLOv8 Object Detection
Real-time Camera Feed
Semantic Mapping
Inventory Count & Dashboard
Container-like Objects
Ice-cream Inventory Units
Processing & Visualization
Node-RED Data Ingestion
Alerting Logic
User Interface
Rule-based Layer
Dashboard Notifications
Low Stock Alerts
Future Enhancements
Custom Dataset Training
Cloud Analytics
Predictive Restocking
Multi-camera Monitoring