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Anomaly Detection for Enhanced Safety in Chemical Warehouses using ESP8266, Sensor Fusion, and Firebase Realtime Database

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***Abstract*— Chemical warehouses require continuous monitoring of environmental conditions to ensure safety and prevent potential hazards. This paper proposes a real-time anomaly detection system for chemical warehouses using a combination of Internet of Things (IoT) devices, sensor fusion, and Machine Learning (ML). The system leverages an ESP8266 microcontroller to collect data from sensors like DHT22 (temperature and humidity) and MQ-135 (gas concentration). Firebase Realtime Database provides a platform for storing sensor data. An Isolation Forest (IF) model, trained on historical sensor data, identifies anomalies in real time, enabling early detection of potential safety issues. The paper presents the system design, implementation details, and experimental results, demonstrating its effectiveness in anomaly detection for improved chemical warehouse safety.**

***Keywords*—Chemical Warehouse, Anomaly Detection, ESP8266, Sensor Fusion, Firebase Realtime Database, Isolation Forest, Machine Learning.**

I. INTRODUCTION

Chemical warehouses store hazardous materials, requiring stringent environmental controls for safety and compliance. Traditional monitoring systems, relying on manual inspections and fixed-location sensors, can be time-consuming and prone to human error, potentially failing to provide timely alerts about hazardous conditions. ESP8266 Microcontroller: A low-cost, low-power microcontroller with Wi-Fi capabilities, that collects real-time data from environmental sensors. Sensor Fusion: Integrating data from DHT22 (temperature and humidity) and MQ-135 (gas concentrations) sensors to enhance accuracy and reliability. Firebase Realtime Database: A cloud-based platform for real-time data storage and retrieval, offering scalability and ease of integration. Isolation Forest (IF) Model: An unsupervised ML algorithm for anomaly detection, trained on historical sensor data to establish normal environmental conditions.

II. OBJECTIVE

The primary objective of this research is to design, implement, and evaluate an IoT-based real-time anomaly detection system for chemical warehouses.

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The system aims to improve safety by providing timely alerts about abnormal environmental conditions that could indicate potential hazards. By leveraging the capabilities of the ESP8266 microcontroller, sensor fusion, Firebase Realtime Database, and the Isolation Forest model, the proposed solution seeks to enhance the reliability, accuracy, and efficiency of environmental monitoring in chemical warehouses.

III. CONTRIBUTIONS

The key contributions of this paper include:

A. System Design

A detailed architecture for integrating IoT devices, sensors, cloud storage, and ML models to monitor chemical warehouse environments in real time.

B. Implementation Details

Step-by-step procedures for deploying the system, including hardware and software components, data acquisition, and cloud integration.

C. Experimental Results

Empirical evaluation of the system's performance, demonstrating its effectiveness in detecting anomalies and providing early warnings of potential hazards.

IV. SIGNIFICANCE

The proposed system addresses critical challenges in chemical warehouse management by offering a scalable, cost-effective, and reliable solution for continuous environmental monitoring. By leveraging advanced technologies, this system has the potential to significantly reduce the risk of incidents, enhance safety, and streamline operations in chemical warehouses. The insights gained from this research can also be applied to other industrial settings where real-time monitoring of environmental conditions is crucial for safety and efficiency.

V. SYSTEM DESIGN

The proposed real-time anomaly detection system for chemical warehouses is structured into three main components: Sensor Network, Data Storage and Management, and Anomaly Detection and Alerting System. Each component plays a crucial role in ensuring the efficient monitoring and early detection of potential hazards.

A. Sensor Network

The Sensor Network is the system's foundation, continuously collecting environmental data within the warehouse.

ESP8266 Microcontroller

The ESP8266 microcontroller acts as the core of the system, responsible for acquiring sensor data and transmitting it to the Firebase Realtime Database. Its built-in Wi-Fi capability allows seamless communication with the cloud, enabling real-time data collection. The ESP8266 continuously reads data from the DHT22 and MQ-135 sensors and preprocesses it by formatting the readings into structured JSON objects, which are then transmitted to Firebase.

Sensors

The selection of sensors was based on the critical need to monitor both the temperature/humidity levels and gas concentrations in chemical ware houses

The DHT22 sensor was chosen due to its high accuracy in measuring temperature (±0.5°C) and humidity (±2%), making it ideal for detecting environmental deviations that could affect chemical safety.

The MQ-135 sensor was selected because of its capability to detect harmful gases like ammonia, sulfur, benzene, and smoke. These gases are common in chemical warehouses and could indicate leaks or unsafe air quality. The MQ-135's fast response time and wide detection range make it an optimal choice for continuous gas monitoring.

Data Collection

The data acquisition process begins with the ESP8266 reading sensor values at configurable intervals. The DHT22 sensor measures temperature and humidity, while the MQ-135 sensor monitors gas concentration levels.

These readings are then timestamped and transmitted via Wi-Fi to the Firebase Realtime Database. To ensure data reliability, error-checking mechanisms are implemented in the ESP8266 code to handle sensor failures, such as retrying readings in case of inconsistent values. Data is stored in Firebase with an efficient schema, where each reading is associated with a specific timestamp, enabling easy retrieval for historical analysis and model training.

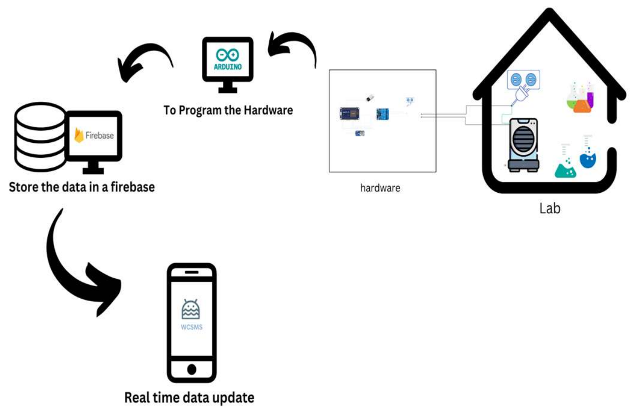

Fig 1. System Architecture Diagram

B. Data Storage and Management

Efficient storage and management of sensor data are crucial for real-time monitoring and historical analysis.

Firebase Realtime Database:

- Sensor readings are transmitted from the ESP8266 to the Firebase Realtime Database, a cloud-based platform that supports real-time data synchronization and storage.
- Firebase is chosen for its scalability, reliability, and real-time capabilities, making it suitable for continuous monitoring applications.

Database Structure:

- The database is structured to efficiently store sensor data, including timestamps and corresponding readings for temperature, humidity, and gas concentration.
- A well-designed database schema ensures quick access and retrieval of data for anomaly detection and visualization purposes.
- Data is organized in a manner that facilitates historical analysis, enabling the training of the Isolation Forest model on comprehensive datasets.

C. Anomaly Detection and Alerting System

The anomaly detection process is handled by the Isolation Forest (IF) model, which is trained on historical sensor data. The process starts by collecting data from the DHT22 (temperature and humidity) and MQ-135 (gas concentration) sensors, which is stored in Firebase. The IF algorithm isolates anomalies by randomly selecting subsets of features (temperature, humidity, and gas levels) and creating decision paths. Shorter paths signify anomalies. Each new sensor reading is assigned an anomaly score, which measures the deviation from normal environmental conditions. When this score exceeds a predefined threshold, an alert is triggered, notifying warehouse personnel about the potential hazard. The contamination parameter, representing the expected percentage of anomalies, is fine-tuned to suit the specific safety requirements of chemical warehouses.

Model Training:

- The Isolation Forest model was selected for its efficiency in high-dimensional anomaly detection and its ability to perform well with limited data. Compared to other unsupervised learning models such as One-Class SVM or Local Outlier Factor (LOF), the Isolation Forest is less computationally intensive and well-suited for real-time systems. One-Class SVM requires more tuning and can be computationally expensive, while LOF may struggle with detecting global anomalies in varying sensor data. The Isolation Forest offers robustness in handling the diverse conditions of chemical warehouses while maintaining simplicity in implementation.

Model Deployment:

- Once trained, the Isolation Forest model can be deployed in the cloud or potentially on the ESP8266 microcontroller, depending on the computational requirements and capabilities of the device.

Real-Time Anomaly Detection:

- The Isolation Forest model calculates anomaly scores for each new sensor reading. These scores indicate how much a reading deviates from the established baseline of normal conditions.

Alerting Mechanism:

If an anomaly score exceeds a predefined threshold, the system triggers an alert. This threshold is determined based on the sensitivity required for detecting potential hazards in the warehouse environment.

D. Dashboard and Visualization

- A monitoring dashboard provides a real-time visual representation of the warehouse environment, displaying current sensor readings and highlighting any detected anomalies.

VI. IMPLEMENTATION

The implementation of the real-time anomaly detection system for chemical warehouses involves a series of steps, including hardware setup, software development, and integration of various components. This section details the process of building and deploying the system.

A. Hardware Setup

Components Used

- ESP8266 Microcontroller: A low-cost, low-power microcontroller with built-in Wi-Fi capabilities.
- DHT22 Sensor: Measures temperature and humidity.
- MQ-135 Sensor: Detects various gases such as ammonia, sulfur, benzene, and smoke.

Assembly

- Connect the DHT22 sensor to the ESP8266. The DHT22 has four pins: VCC, GND, Data, and a non-connected pin. Connect VCC to the 3.3V pin on the ESP8266, GND to the ground pin, and Data to a digital input pin (e.g., D2).
- Connect the MQ-135 sensor to the ESP8266. The MQ-135 has four pins: VCC, GND, Analog Output (A0), and Digital Output (D0). Connect VCC to the 3.3V pin on the ESP8266, GND to the ground pin, and A0 to an analogue input pin (e.g., A0).

Schematic Diagram

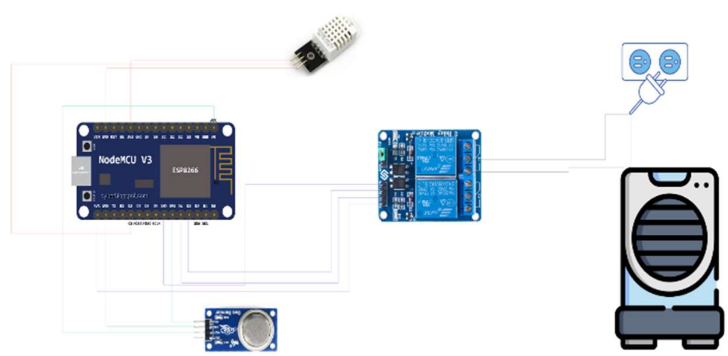

Fig 2. IOT Hardware

- Provide a detailed schematic diagram showing the connections between the ESP8266, DHT22, and MQ-135 sensors. This diagram helps in replicating the setup.

B. Software Development:

Programming the ESP8266:
Environment Setup

- Use the Arduino IDE for programming the ESP8266. Install the necessary libraries, such as DHT for the DHT22 sensor and ESP8266WiFi for Wi-Fi connectivity.

Code for Data Collection:

```
void loop() {
float h = dht.readHumidity();
float t = dht.readTemperature();
int gas = analogRead(MQ135PIN);
if (isnan(h) || isnan(t)) {
Serial.println("Failed to read from DHT sensor!");
return;
}
Firebase.pushFloat("/sensor_data/humidity", h);
Firebase.pushFloat("/sensor_data/temperature", t);
Firebase.pushInt("/sensor_data/gas", gas);
delay(2000);
}
```

Firebase Realtime Database:

To set up Firebase, start by creating a Firebase project and configuring the Realtime Database. Afterward, obtain the database URL along with the secret key required for authentication. When organizing the database, structure the data to include both timestamps and sensor readings to ensure accurate tracking and retrieval of sensor data.
Example structure:

```
{
 "sensor_data": {
   "timestamp": {
     "temperature": value,
     "humidity": value,
     "gas": value
   }
 }
}
```

C. Cloud Integration:

Training the Isolation Forest Model:

- Use Google Colab for training the Isolation Forest model on historical sensor data.
- Preprocess the data to handle missing values and normalize the readings.
- Train the model using the scikit-learn library.

Data Of Sensors

```
//code
# Define the base timestamp
base_timestamp = pd.Timestamp("2024-04-04 00:00:00")
# Descriptive statistics
print("Descriptive Statistics:")
print(df.describe())  # Print summary statistics for all numeric columns
plt.plot(df.index, df[col], label=col)
plt.xlabel("Time")
plt.ylabel("Sensor Reading")
plt.title("Sensor Readings Over Time")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
X_train shape: (80, 4)
X_test shape: (20, 4)
Sample X_train data:
[[ 1.43576297  0.49664097  0.25140406 -0.21948309]
 [ 0.04088586  1.354324    0.87627799 -1.45663084]]
```

Fig 3. Scaling And Splitting

Isolation Forest

```
//code
# Train the Isolation Forest model
model = IsolationForest(contamination=0.1, random_state=42)
model.fit(X_train)
# Predict anomalies on the testing set
y_pred = model.predict(X_test)
anomaly_indices = np.where(y_pred == -1)[0]
# Get indices of predicted anomalies
```

Data Scaling and Splitting

```
//code
# Scale sensor readings (excluding timestamps)
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)  # All columns are numeric now
# Split data into training and testing sets (80/20 split)
X_train, X_test = train_test_split(scaled_data, test_size=0.2, random_state=42)
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
# You can also print a few samples of the training data
print("Sample X_train data:")
print(X_train[:2])
```

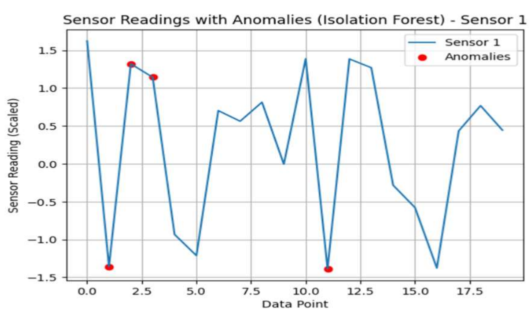

Fig 4. Sensor 1 IF Anomaly plot

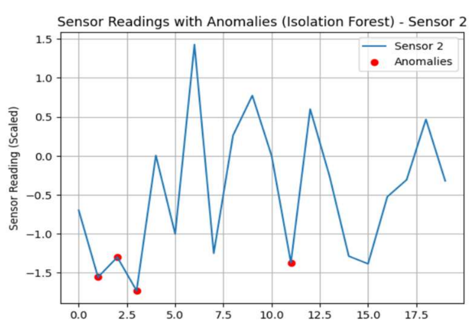

Fig 5. Sensor 2 IF Anomaly plot

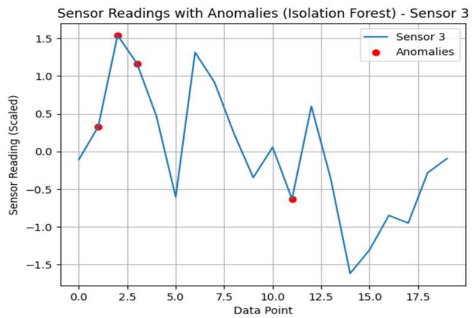

Fig 6. Sensor 3 IF Anomaly plot

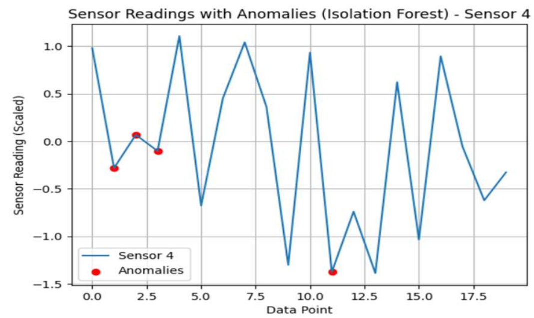

Fig 7. Sensor 4 IF Anomaly plot

```
X_train shape: (160, 4)
X_test shape: (40, 4)
```

Fig 8. IF Performance

```
//code
# Calculate precision, recall, and F1 score using the true labels and predicted anomalies
precision = precision_score(true_labels, y_pred, pos_label=-1)
recall = recall_score(true_labels, y_pred, pos_label=-1)
f1 = f1_score(true_labels, y_pred, pos_label=-1)
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

Real-Time Anomaly Detection

```
# Fetch the service account key JSON file contents
cred= credentials.Certificate('/content/wcsms-146bb-firebase-adminsdk-ox908-9bb733a0f5.json')
# Initialize the app with a service account, granting admin privileges
firebase_admin.initialize_app(cred,{'databaseURL': 'https://wcsms-146bb-default-rtdb.firebaseio.com/'
})
# As an admin, the app has access to read and write all data, regardless of Security Rules
ref = db.reference('data/NH3/live/value')
# Fetch data from Firebase
rs = ref.get()
print(rs)
```

D. Dashboard and Visualization

Our system includes a robust web-based dashboard developed using Angular. Leveraging the Firebase Realtime Database, the dashboard provides continuous updates on sensor readings and anomaly alerts within the chemical warehouse environment. Real-time visualization of sensor readings such as temperature, humidity, and gas levels using interactive charts. For comprehensive environmental analysis and decision-making support, the system offers powerful tools for historical data exploration and reporting.

VII. Result and Discussion

Our implemented Isolation Forest model demonstrated robust performance in detecting anomalies within the chemical warehouse environment. Evaluation metrics yielded the following results:

A. Real-Time Monitoring Effectiveness

Our developed dashboard provided intuitive visualization of real-time sensor data, facilitating proactive monitoring of environmental conditions. Warehouse personnel found the dashboard effective. Alerts and visual cues enabled quick identification of abnormal sensor readings by Immediate Anomaly Detection.

```
X train shape: (80, 4)
X test shape: (20, 4)
Sample X train data:
[[ 1.43576297 0.49664097 0.25140406 -0.21948309]
 [ 0.04088586 1.354324   0.87627799 -1.45663084]]
```

Fig 9. IF Result

Our developed dashboard provided intuitive visualization of real-time sensor data, facilitating proactive monitoring of environmental conditions. Warehouse personnel found the dashboard effective. Alerts and visual cues enabled quick identification of abnormal sensor readings by Immediate Anomaly Detection.

B. Cost and Resource Savings

The system contributed to cost savings by optimizing maintenance schedules and resource allocation based on predictive insights.

- Maintenance Optimization
- Resource Allocation

VIII. RECOMMENDATIONS AND IMPLEMENTATION PLAN

To enhance the system’s performance, several optimizations can be implemented. First, adjusting the sensor data acquisition frequency can reduce latency while maintaining real-time monitoring. Additionally, incorporating edge computing by deploying lightweight anomaly detection models directly on the ESP8266 would reduce dependence on cloud-based analysis and improve response times. From a machine learning perspective, exploring advanced models like Autoencoders or LSTM (Long Short-Term Memory) networks could significantly improve the system’s ability to detect complex anomalies. Fine-tuning the Isolation Forest's hyperparameters (e.g., contamination rate) could further optimize the model’s accuracy.

IX. FUTURE DEVELOPMENTS AND EMERGING TECHNOLOGIES

For future developments and emerging technologies related to your project on real-time anomaly detection systems for chemical warehouses, consider the following:To improve the system’s accuracy, several approaches can be considered. First, calibration of sensors should be conducted regularly to ensure the precision of the DHT22 and MQ-135 readings. Additionally, implementing data normalization and scaling during the preprocessing stage will enhance the performance of the machine-learning model. Advanced feature engineering, such as deriving additional features like the rate of change in gas levels, can also improve model accuracy. Tuning the hyperparameters of the Isolation Forest model, particularly the number of trees and contamination level, can further refine anomaly detection accuracy. Lastly, validating the model with a separate test set of data can help prevent overfitting and ensure generalization.

X. CONCLUSIONS

In conclusion, the development and implementation of a real-time anomaly detection system for chemical warehouses represent a significant advancement in ensuring operational safety, efficiency, and compliance with regulatory standards. By leveraging sensor data from devices like the ESP8266 microcontroller, DHT22, and MQ-135 sensors, coupled with advanced machine learning techniques such as the Isolation Forest algorithm, the system effectively monitors environmental conditions and detects anomalies indicative of potential hazards or operational irregularities. In essence, the project underscores the importance of leveraging IoT, cloud computing, and machine learning technologies to enhance industrial safety, operational efficiency, and regulatory compliance in chemical warehouses.

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