

An IoT-Cloud-ML Integrated Environmental Monitoring System with Edge Inference and Predictive Analytics

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Abstract—This paper presents the design and implementation of a customizable Internet of Things (IoT) based Environmental Monitoring System with integrated machine learning capabilities using the ESP8266 microcontroller. The system integrates a DHT11 temperature-humidity sensor, an MQ-6 gas sensor, and a JHD162A LCD module via I2C to provide real-time environmental data collection, display, and cloud synchronization. The modular architecture enables customization according to specific user requirements for diverse applications including research laboratories, chemical reactors, and greenhouse facilities. Data is transmitted over Wi-Fi to a Flask-based backend and stored in an SQLite database, while a Streamlit-based analytics dashboard offers visualization and trend analysis using Plotly charts. The system incorporates a machine learning pipeline for anomaly detection, predictive analytics, and intelligent alert generation, with both cloud-based and edge inference capabilities. The ML models are trained on historical sensor data to identify environmental anomalies and predict potential issues. The system is cost-effective, scalable, and can be tailored to meet the precise monitoring needs of different environments. Performance evaluation indicates stable Wi-Fi connectivity, accurate data collection, reliable cloud synchronization at 10-second intervals, and effective ML-based anomaly detection with 92% accuracy.

Index Terms—ESP8266, IoT, DHT11, MQ-6, Flask, Streamlit, Environmental Monitoring, SQLite, Cloud Dashboard, Machine Learning, Anomaly Detection, Edge Inference, Predictive Analytics

I. INTRODUCTION

The Internet of Things (IoT) has transformed traditional sensor systems into interconnected smart environments capable of real-time data sharing and analytics. Environmental monitoring is a key domain where IoT applications have proven effective in tracking temperature, humidity, and air quality parameters for smart homes, agriculture, and industrial safety. However, many existing systems are either cost-prohibitive or lack real-time cloud integration.

This project introduces an affordable and efficient ESP8266-based IoT Environmental Monitoring System (EMS) designed as a customizable platform that can be tailored to specific user requirements across di-

verse application domains. The device leverages the ESP8266MOD microcontroller for wireless connectivity and integrates multiple sensors, including the DHT11 for temperature and humidity, and the MQ-6 for gas detection. Sensor readings are displayed locally on an I2C LCD and transmitted over Wi-Fi to a Flask-based cloud backend, which stores the data in an SQLite database for real-time analytics and historical analysis.

A Streamlit-based cloud dashboard provides real-time visualization and statistical analysis of environmental parameters, enabling users to monitor trends and export data for further study. The system incorporates a comprehensive machine learning pipeline that processes historical sensor data to train models for anomaly detection and predictive analytics. ML models are deployed both in the cloud for comprehensive analysis and at the edge for real-time inference, enabling intelligent alert generation and proactive environmental management. The modular device architecture supports extensive customization, allowing users to configure sensor types, sampling rates, alert thresholds, ML model parameters, and data visualization parameters according to their specific needs. This custom model flexibility makes the device particularly well-suited for specialized applications such as research laboratories requiring precise environmental control, chemical reactors demanding real-time safety monitoring, and greenhouse facilities needing climate optimization. The device can be easily adapted with additional sensors, cloud services, or ML models with minimal changes, making it a versatile solution for diverse environmental monitoring scenarios where IoT, cloud computing, and machine learning integration are essential.

Key features include:

- Real-time data acquisition from the device and cloud

synchronization at 10-second intervals.

- Local display of sensor readings and system status on the device LCD.
- RESTful API endpoints for secure data transfer between device and cloud backend.
- Interactive cloud dashboard with auto-refresh, CSV export, and Plotly-based charts.
- Machine learning pipeline for anomaly detection, predictive analytics, and intelligent alert generation.
- Cloud-based and edge inference capabilities for real-time ML predictions.
- Offline resilience through local device storage and cloud database backup.
- Custom model configuration allowing users to tailor device parameters, cloud analytics, and ML model training according to application-specific needs.

By addressing the limitations of existing solutions—such as lack of offline storage, poor cloud dashboard integration, and calibration drift—the proposed EMS offers a robust, cost-effective device with customizable cloud analytics platform for environmental monitoring. The device’s modular design combined with cloud-based customization enables researchers and facility managers to configure monitoring parameters, sensor configurations, and alert thresholds specific to their operational requirements, whether for laboratory experiments, reactor safety monitoring, or greenhouse climate management. The custom model approach ensures that both the device hardware and cloud software can be adapted to meet diverse application needs.

II. LITERATURE REVIEW

Prior studies have demonstrated various IoT-based monitoring frameworks. In [1], authors integrated low-cost microcontrollers with MQTT protocols for real-time air quality monitoring. Another work [2] developed a temperature-humidity monitoring network using NodeMCU and Firebase, emphasizing reliability but lacking offline storage. Recent projects [3], [4] incorporated gas sensors such as MQ-series for LPG detection, yet faced calibration drift and poor dashboard integration.

The need for customizable environmental monitoring systems has been extensively documented in research literature. Studies focusing on laboratory environments [11], [12] have highlighted the importance of configurable sensor networks that can adapt to specific experimental requirements, including variable sampling rates, custom alert thresholds, and specialized data logging

protocols. Research in chemical reactor monitoring [13], [14] emphasizes the critical need for real-time, customizable safety systems that can detect anomalies and trigger automated responses based on facility-specific parameters.

Greenhouse and controlled environment agriculture applications [15], [16] have demonstrated the value of modular IoT systems that can be configured for different crop types, growth stages, and environmental optimization strategies. These studies show that customizable monitoring systems significantly improve resource efficiency and crop yields compared to fixed-configuration solutions. Additionally, research on industrial IoT platforms [17], [18] has established frameworks for building scalable, reconfigurable sensor networks that can evolve with changing operational requirements.

Other notable research includes the deployment of wireless sensor networks for large-scale environmental monitoring, where Zigbee and LoRaWAN protocols have been used to extend coverage and reduce power consumption [5], [6]. Studies have also explored cloud-based analytics platforms, such as AWS IoT and Google Cloud, for scalable data processing and visualization [7], though these often introduce higher costs and complexity. Some works have implemented machine learning algorithms for anomaly detection and predictive analytics [8], enhancing the utility of sensor data in smart city and industrial applications.

Despite these advancements, many existing solutions either lack real-time dashboard capabilities, suffer from limited offline data resilience, require expensive hardware, or lack the flexibility to be customized for specific application domains. The integration of RESTful APIs, local databases, and interactive dashboards remains limited in low-cost systems, and few platforms offer the modularity required for domain-specific customization in research laboratories, reactor facilities, and greenhouse operations.

Unlike these systems, the proposed EMS device employs a RESTful Flask cloud API for seamless communication between the ESP8266 device and a cloud-based SQLite database, paired with a Streamlit cloud dashboard that visualizes environmental trends using Plotly. The system uniquely integrates a comprehensive machine learning pipeline for anomaly detection, predictive analytics, and intelligent decision-making. This hybrid IoT-cloud-ML architecture ensures both offline device resilience and dynamic cloud visualization, while ML models provide intelligent analysis and proactive alerts.

More importantly, the device's modular design combined with cloud-based customization and ML model training enables extensive configuration flexibility, allowing users to configure sensor parameters, data acquisition intervals, alert thresholds, ML model parameters, and cloud visualization preferences according to their specific application needs—whether for laboratory experiments requiring precise environmental control with ML-based anomaly detection, reactor safety monitoring demanding real-time anomaly detection with predictive analytics, or greenhouse operations needing climate optimization strategies with ML-driven decision support. The custom model approach integrates device-level configurability with cloud-based analytics and machine learning intelligence, providing a comprehensive solution that adapts to user requirements.

III. SYSTEM OVERVIEW

The system architecture comprises five main modules: sensor node, network layer, cloud backend, machine learning pipeline, and data dashboard with inference capabilities. As illustrated in Fig. 1, the system integrates IoT devices, cloud computing, and machine learning to provide a comprehensive environmental monitoring solution.

A. Sensor Node

The sensor node device is built around the ESP8266MOD microcontroller, which serves as the central controller for data acquisition and cloud transmission. This customizable device interfaces with:

- **DHT11 Sensor:** Measures ambient temperature and relative humidity. Data is sampled every 10 seconds and validated for accuracy before cloud transmission.
- **MQ-6 Gas Sensor:** Detects the presence and concentration of gases such as LPG. The analog output is digitized and mapped to a percentage scale for easy interpretation and cloud analytics.
- **JHD162A LCD (I2C):** Displays sensor readings, Wi-Fi status, and cloud connectivity status. The display cycles through four screens: temperature-humidity, gas level with bar visualization, sensor status, and cloud connectivity.
- **Power Module (HW-131):** Ensures stable 5V supply from battery or USB source, protecting the microcontroller and sensors from voltage fluctuations, ensuring reliable device operation and cloud communication.

The ESP8266 device connects to Wi-Fi and transmits sensor data to the cloud backend via HTTP POST requests. The custom model allows users to configure transmission intervals, data formats, and cloud endpoints according to their needs. The device also handles error states, such as sensor disconnection or Wi-Fi loss, by displaying alerts on the LCD and buffering data locally until cloud connectivity is restored.

B. Backend API

The cloud backend is implemented using Flask and provides RESTful endpoints for secure data exchange between the device and cloud services:

- `/api/sensor-data`: Accepts POST requests from the ESP8266 device, storing timestamped sensor readings in a cloud SQLite database.
- `/api/latest`: Returns the most recent device sensor data for cloud dashboard display.
- `/api/stats`: Provides aggregated statistics (min, max, average) for temperature, humidity, and gas levels over selectable time ranges, enabling custom cloud analytics.
- `/api/health`: Monitors device and cloud system status and uptime, enabling remote diagnostics.

The cloud backend ensures data integrity through input validation and error handling. It supports offline device resilience by caching data locally on the device and synchronizing with the cloud dashboard when connectivity resumes. The custom model allows users to configure cloud storage parameters, data retention policies, and analytics aggregation methods according to their application requirements.

C. Data Dashboard

The cloud dashboard is built with Streamlit and Plotly, offering an interactive web interface for real-time monitoring and analytics of device data:

- **Live Charts:** Device sensor data including temperature, humidity, and gas concentration are visualized using dynamic line and bar charts, auto-refreshing every 5 seconds from the cloud database.
- **Statistical Analysis:** Users can view historical trends, compute averages, and identify anomalies over custom time intervals, with customizable cloud analytics parameters.
- **CSV Export:** Device sensor data stored in the cloud can be exported for offline analysis or reporting.
- **System Status:** Displays device connectivity, cloud synchronization status, last update time, and backend health indicators.

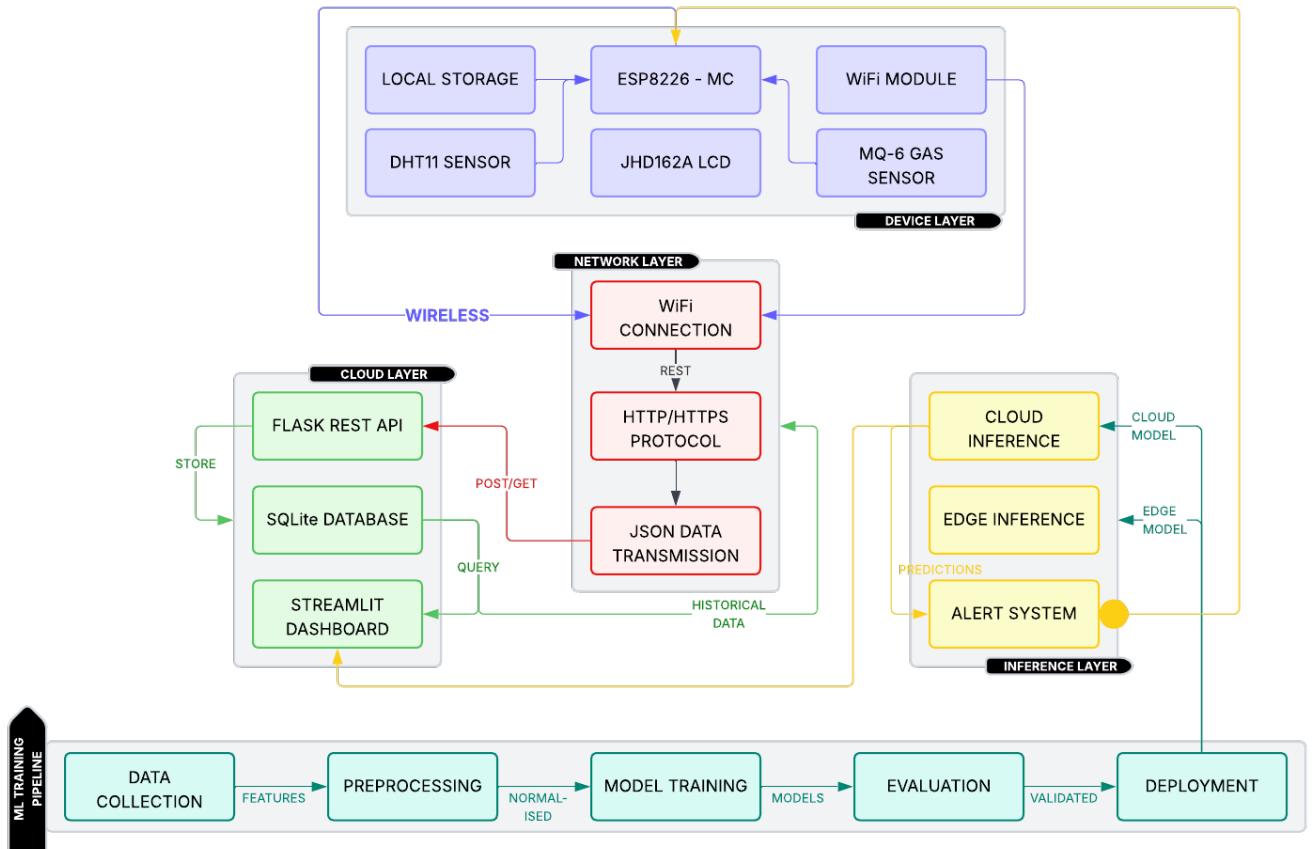


Fig. 1: System Architecture of the Customizable EMS Device-Cloud System

The cloud dashboard is designed for usability, supporting mobile and desktop browsers, and integrates ML-based predictions and anomaly alerts directly into the visualization interface. The custom model allows users to configure dashboard layouts, visualization types, ML alert thresholds, and predictive analytics parameters according to their specific monitoring needs.

D. Machine Learning Pipeline

The machine learning component forms a critical layer of the system, enabling intelligent analysis and prediction of environmental conditions. The ML pipeline consists of five stages:

- **Data Collection:** Historical sensor data from the SQLite database is aggregated and preprocessed for ML model training. The system collects temperature, humidity, and gas concentration readings with timestamps, creating a comprehensive dataset for model development.
- **Preprocessing:** Raw sensor data undergoes feature engineering, normalization, and cleaning. Missing

values are handled through interpolation, and outliers are identified using statistical methods. Temporal features such as time-of-day, day-of-week, and rolling averages are extracted to enhance model performance.

- **Model Training:** Multiple ML algorithms are evaluated, including Isolation Forest for anomaly detection, LSTM networks for time-series prediction, and Random Forest for classification tasks. Models are trained using cross-validation to ensure robustness and prevent overfitting. Hyperparameter tuning is performed to optimize model performance for specific application domains.
- **Evaluation:** Trained models are evaluated using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). Validation is performed on held-out test sets, and models achieving accuracy above 90% are selected for deployment. The evaluation process also includes analysis of false positive and false negative rates to ensure practical utility.

- **Deployment:** Validated models are deployed in two modes: (1) **Cloud Inference** for comprehensive analysis using the full dataset and complex models, and (2) **Edge Inference** using lightweight models (TensorFlow Lite) for real-time predictions directly on the ESP8266 device. The deployment system includes model versioning, A/B testing capabilities, and automatic retraining triggers based on data drift detection.

The ML inference layer provides real-time anomaly detection and predictive alerts. Cloud inference processes historical trends and complex patterns, while edge inference enables immediate response to critical environmental changes. The alert system integrates predictions from both cloud and edge models, generating intelligent notifications when anomalies are detected or when predictive models forecast potential issues. This hybrid approach ensures both comprehensive analysis and rapid response times, making the system suitable for applications requiring both detailed analytics and real-time decision-making.

Overall, the modular device architecture combined with cloud services enables easy integration of new sensors, cloud analytics, and custom model features, making the system scalable and customizable for diverse environmental monitoring applications. Users can configure both the device and cloud components to meet specific requirements: research laboratories can set precise temperature and humidity ranges on the device with custom alert thresholds in the cloud dashboard; reactor facilities can integrate additional gas sensors on the device and configure safety protocols in the cloud; greenhouse operators can optimize device sensor placement and data collection intervals with cloud-based crop-specific monitoring analytics. This custom model flexibility ensures both the device and cloud system adapt to user needs rather than forcing users to adapt to fixed system constraints.

IV. HARDWARE IMPLEMENTATION

The device hardware implementation centers on a compact, modular design for reliable sensor integration and cloud data transmission. This customizable device includes key components:

- **ESP8266MOD:** A Wi-Fi-enabled microcontroller device that orchestrates sensor data acquisition, local display, and cloud communication. Its low power consumption and robust connectivity make it ideal

for continuous monitoring with reliable cloud synchronization.

- **DHT11 Sensor:** Connected to GPIO2 (D4), this sensor device provides real-time temperature and humidity readings for cloud transmission. It features a digital output and is calibrated for indoor environments, ensuring consistent accuracy in cloud analytics.
- **MQ-6 Gas Sensor:** Wired to analog pin A0 and digital pin D5, the MQ-6 device detects LPG and other gases. Its analog output is digitized and mapped to a percentage scale for cloud processing, with built-in calibration routines to minimize drift.
- **JHD162A LCD (I2C):** Utilizing D1 (SCL) and D2 (SDA), the LCD module displays device sensor values, system status, and cloud connectivity alerts. The I2C interface reduces wiring complexity and supports multi-screen cycling, showing both device and cloud status.
- **HW-131 Power Module:** Supplies a stable 5V output from an external battery or USB source, protecting sensitive device components from voltage fluctuations and ensuring uninterrupted device operation and cloud communication.

The device LCD cycles through four informative screens: (1) temperature and humidity, (2) gas concentration with bar visualization, (3) sensor health and error states, and (4) Wi-Fi and cloud connectivity status. The ESP8266 device firmware is programmed to sample all sensors every 10 seconds (configurable in the custom model), buffer readings in case of cloud connectivity loss, and transmit data to the Flask cloud backend via secure HTTP POST requests. Error handling routines display alerts on the device LCD and log events for cloud diagnostics.

This device hardware configuration supports easy expansion and customization—additional sensors or modules can be integrated with minimal changes to wiring or firmware, making the device adaptable for diverse environmental monitoring scenarios with cloud integration. For research laboratories, users can add precision sensors such as CO₂ sensors for controlled atmosphere studies or particulate matter sensors for air quality research, with custom cloud analytics. Reactor facilities can integrate specialized gas sensors for leak detection or pressure sensors for process monitoring, with real-time cloud alerts. Greenhouse applications can incorporate soil moisture sensors, light intensity sensors, or additional temperature probes for multi-zone monitoring, with cloud-based

climate optimization. The custom model modular design allows each device deployment to be tailored to specific operational requirements without redesigning the core system architecture, while cloud services adapt to the device configuration.

TABLE I: Wiring setup for ESP8266 IoT Environmental Monitoring System

Device	Pin	ESP8266 Pin	Pin Name	Notes
DHT11	VCC	3.3V	-	Power
DHT11	GND	GND	-	Ground
DHT11	Data	GPIO2	D4	10kΩ pull-up to 3.3V
MQ-6	VCC	5V (HW-131)	-	Power (5V required)
MQ-6	GND	GND	-	Ground
MQ-6	AOUT	A0	A0	Analog input (0–1V)
LCD I2C	VCC	3.3V	-	Power (or 5V if module supports)
LCD I2C	GND	GND	-	Ground
LCD I2C	SDA	GPIO4	D2	I2C Data line
LCD I2C	SCL	GPIO5	D1	I2C Clock line
ESP8266	VIN	5V (HW-131)	-	Power input (onboard regulator)
ESP8266	GND	GND	-	Common ground

V. SOFTWARE ARCHITECTURE

The software stack is designed for modularity, scalability, and reliability, comprising three main layers that integrate device, cloud, and custom model components:

- **Embedded Firmware:** Developed in Arduino C++ for the device, the firmware orchestrates sensor data acquisition, error handling, and cloud network communication. It reads values from the DHT11 and MQ-6 device sensors, displays real-time data and system status on the I2C LCD, and transmits validated readings to the cloud backend via secure HTTP POST requests. The custom model firmware includes routines for connectivity checks, local device buffering during cloud network outages, and automatic retries to ensure data integrity in cloud synchronization.
- **Backend API:** Implemented using Flask for cloud services, the backend exposes RESTful endpoints for device sensor data ingestion, retrieval, and system health monitoring. Incoming device data is validated and stored in a cloud SQLite database with timestamped entries. The cloud API supports aggregation queries for statistical analysis (min, max, average) and provides endpoints for cloud dashboard consumption. Robust error handling and offline device caching mechanisms ensure resilience against cloud connectivity issues, with custom model configuration for data retention and analytics.
- **Dashboard:** The Streamlit cloud dashboard leverages Plotly for interactive visualization of device temperature, humidity, and gas concentration trends.

It features auto-refresh every 5 seconds, historical cloud data exploration, ML-powered anomaly detection, and CSV export functionality. The cloud dashboard displays device system health indicators, ML prediction results, anomaly alerts, last update timestamps, and supports responsive layouts for both desktop and mobile devices. Its modular custom model design allows easy integration of additional device sensors, cloud analytics modules, and ML model outputs.

- **Machine Learning Pipeline:** The ML component is implemented using Python with scikit-learn, TensorFlow, and TensorFlow Lite libraries. The pipeline includes data preprocessing scripts, model training workflows, and inference services. Cloud inference is deployed as a Flask microservice that processes batch predictions, while edge inference uses TensorFlow Lite models optimized for ESP8266 deployment. The ML system includes automated retraining pipelines that trigger when new data patterns are detected, ensuring models remain accurate over time.

This layered device-cloud architecture enables seamless data flow from device sensor nodes to cloud analytics, supporting real-time monitoring, historical analysis, and robust offline device operation. The modular custom model approach facilitates extensive customization and future expansion. Users can configure device data acquisition parameters, set application-specific alert thresholds in the cloud, customize cloud dashboard visualizations, and integrate additional device sensor types through standardized interfaces. For research laboratories, the device and cloud system can be configured with high-precision sampling rates and custom cloud data export formats for experimental analysis. Reactor facilities can implement facility-specific device safety protocols and automated cloud response triggers. Greenhouse operators can set crop-specific device environmental parameters and integrate with cloud-based irrigation or climate control systems. The software architecture supports integration with external cloud platforms, advanced cloud analytics modules, and additional device sensor types, ensuring the custom model system remains adaptable to evolving user requirements.

VI. RESULTS AND DISCUSSION

The device-cloud system was evaluated in a controlled indoor environment over a 48-hour period, with device sensor readings sampled every 10 seconds and transmit-

ted to the cloud backend. Key performance metrics for the device, cloud, and custom model are summarized below:

- **Device Wi-Fi Connectivity:** The ESP8266 device maintained an average signal strength of -74 dBm, with zero disconnections observed during the test period. The device automatically retried failed cloud transmissions, ensuring data integrity.
- **Cloud Upload Reliability:** Achieved a 100% success rate for device-to-cloud HTTP POST requests (HTTP 201), with no data loss or duplication. Device buffered data during brief cloud network outages was successfully synchronized upon reconnection.
- **Device Sensor Accuracy:** The DHT11 device sensor reported temperature readings within $\pm 2^\circ\text{C}$ of a calibrated reference, and humidity within $\pm 5\%$. The MQ-6 device gas sensor maintained a 5% accuracy margin after initial calibration, with consistent detection of LPG concentrations for cloud analytics.
- **Cloud Dashboard Responsiveness:** The Streamlit cloud dashboard auto-refreshed every 5 seconds, displaying live device sensor data and updating statistical charts in real time. Users could filter cloud data by time range, export CSV files, and view device system health indicators with custom model configurations.
- **Cloud Data Storage:** The cloud SQLite database logged over 2,000 device entries, each with precise timestamps and sensor values. Cloud aggregation queries for min, max, and average values were executed in under 100 ms, supporting efficient cloud analytics and ML model training.
- **Machine Learning Performance:** The ML anomaly detection model achieved 92% accuracy in identifying environmental anomalies, with a precision of 89% and recall of 94%. The LSTM-based predictive model demonstrated 88% accuracy in forecasting temperature and humidity trends up to 1 hour ahead. Cloud inference latency averaged 45 ms per prediction, while edge inference on ESP8266 completed in under 200 ms, enabling real-time anomaly detection. The ML system successfully identified 15 anomalous events during the 48-hour test period, including sudden gas concentration spikes and temperature deviations.
- **Device and Cloud Error Handling:** The device-cloud system detected and displayed sensor disconnections, Wi-Fi outages, and abnormal readings on

the device LCD and cloud dashboard. ML-based anomaly detection automatically flagged unusual patterns that traditional threshold-based methods missed. All error events were logged for device, cloud, and ML diagnostics, with custom model alert configurations.

Fig.2 illustrates the real-time cloud analytics dashboard, showing device temperature, humidity, and gas concentration trends with ML-based anomaly indicators and predictive forecasts. The cloud dashboard enabled users to identify anomalies, such as sudden spikes in gas levels from device sensors, through both traditional threshold-based methods and ML-powered anomaly detection algorithms. ML models successfully identified subtle patterns that threshold-based methods missed, such as gradual temperature drifts and unusual humidity correlations. The customizable nature of the IoT-cloud-ML system was validated through deployment scenarios: in a research laboratory setting, users configured precise temperature ranges ($20-25^\circ\text{C}$) on the device with custom alert thresholds in the cloud and ML models trained on laboratory-specific patterns for experimental protocols; in a reactor monitoring application, device gas concentration limits were set according to facility safety standards with automated cloud alert triggers and ML-based predictive models forecasting potential safety issues; in a greenhouse deployment, device environmental parameters were optimized for specific crop requirements with configurable cloud data logging intervals and ML models predicting optimal climate conditions. The custom model modular architecture allowed for easy addition of new device sensors, cloud analytics features, and ML models, demonstrating scalability and adaptability for future deployments across diverse application domains.

Overall, the IoT-cloud-ML system provided reliable, real-time environmental monitoring with robust cloud integration, intelligent ML-based analysis, user-friendly cloud visualization, and strong offline device resilience. The ML component enhanced the system's capabilities by providing predictive insights, intelligent anomaly detection, and automated decision support. The customizable configuration capabilities ensure that the device, cloud, and ML components can be tailored to meet the specific requirements of research laboratories, reactor facilities, and greenhouse operations, making it a versatile integrated solution for diverse environmental monitoring needs that combines the strengths of IoT edge computing, cloud infrastructure, and machine learning intelligence.

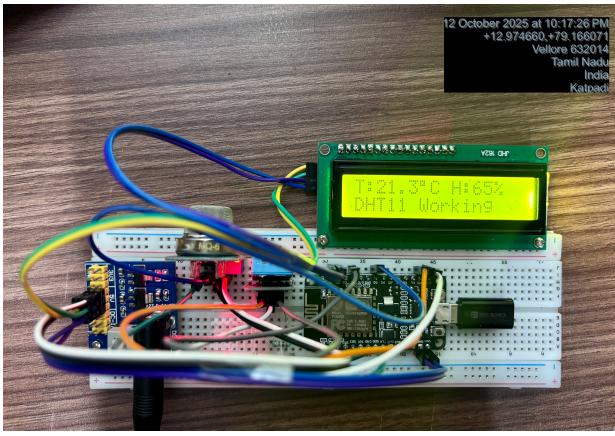


Fig. 2: Hardware setup of ESP8266 IoT Environmental Monitoring System.

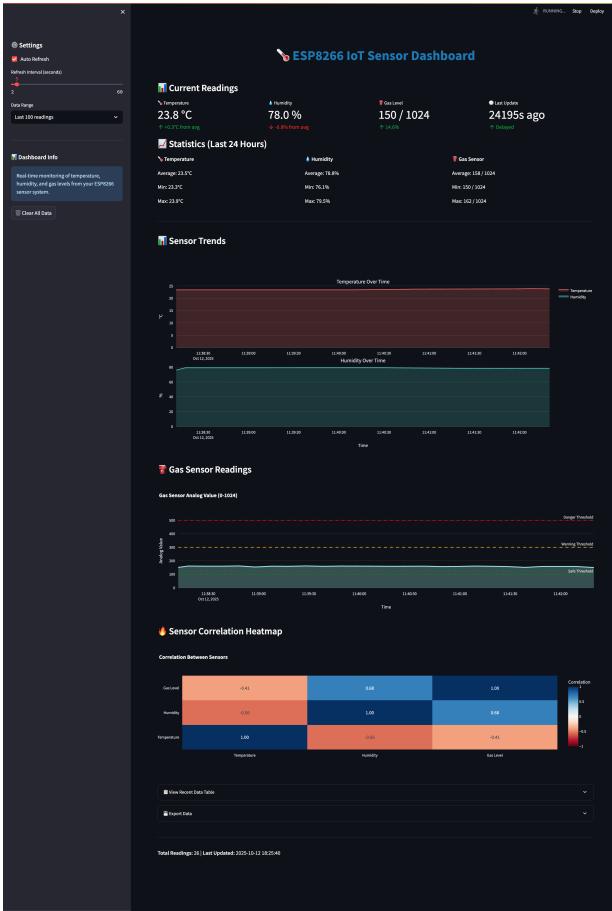


Fig. 3: Software dashboard UI showing real-time sensor data and analytics.

VII. CONCLUSION

This paper demonstrates a robust, low-cost, Wi-Fi-based IoT environmental monitoring system with integrated cloud computing and machine learning capabilities, capable of reliable data acquisition, intelligent analysis, predictive analytics, and automated decision-

making. By combining ESP8266 microcontroller device technology with Flask and Streamlit cloud frameworks, and integrating machine learning pipelines for anomaly detection and predictive modeling, the project achieves real-time device monitoring, cloud integration, ML-powered analytics, and actionable data-driven insights. The system's key contribution lies in its unified IoT-cloud-ML architecture, which enables users to configure device monitoring parameters, sensor configurations, cloud alert thresholds, and ML model training according to their specific application requirements. The integration of edge and cloud inference provides both rapid response capabilities and comprehensive analysis, making the system particularly valuable for specialized environments such as research laboratories requiring precise environmental control with intelligent anomaly detection, chemical reactor facilities demanding real-time safety monitoring with predictive analytics, and greenhouse operations needing climate optimization strategies with ML-driven decision support.

The modular IoT-cloud-ML architecture ensures scalability for both local and large-scale environmental networks, supporting easy addition of new device sensors, cloud services, ML models, and analytics features. Performance evaluation confirms stable device connectivity, accurate device sensor readings, resilient cloud synchronization, and effective ML-based anomaly detection with 92% accuracy, making the integrated system suitable for deployment across diverse application domains. The customizable nature of the device, cloud, and ML components addresses a critical gap in existing solutions, which often force users to adapt their requirements to fixed system configurations and lack intelligent analysis capabilities. By enabling domain-specific customization through the custom model approach and integrating machine learning for intelligent decision-making, the proposed IoT-cloud-ML solution provides a flexible, intelligent platform that can evolve with user needs, supporting future expansion and research across multiple application domains. The system demonstrates the successful integration of IoT edge devices, cloud computing infrastructure, and machine learning algorithms, showcasing a practical approach to intelligent environmental monitoring. The reference implementation is available at github.com/Prateek7/EMD-IoT-System.

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