# IoT-Enabled UAV for Real-time Atmospheric Analysis and Predictive Weather Modelling

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**Abstract**—The integration of Artificial Intelligence of Things (IoT) with Unmanned Aerial Vehicles (UAVs) presents unprecedented opportunities for real-time environmental monitoring and predictive analytics. This paper presents the design and development of a quadcopter drone system embedded with IoT-enabled environmental sensors for real-time atmospheric data collection and wireless cloud transmission. The system incorporates a brushless motor quadcopter frame, electronic speed controllers (ESCs), a flight controller for stabilization, and a suite of atmospheric sensors including temperature, humidity, pressure, and air quality modules interfaced with a microcontroller. Collected data is transmitted to a cloud platform via Wi-Fi or LoRa wireless communication for live monitoring and analysis. Additionally, a machine learning-based rain prediction module is proposed as a future enhancement, enabling the UAV to forecast rainfall patterns based on atmospheric readings. The system is evaluated for flight stability, data accuracy, transmission latency, and sensor reliability across multiple test flights. Experimental results demonstrate the viability of the proposed system for smart agriculture, disaster monitoring, and environmental surveillance applications, with a cost-effective and scalable architecture adaptable for advanced IoT deployments.

**Index Terms**—UAV, Quadcopter, IoT, Internet of Things, Atmospheric Monitoring, Weather Prediction, Machine Learning, Rain Prediction, Environmental Sensing, Smart Agriculture, Cloud Computing, LoRa.

## I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as transformative tools across diverse domains including precision agriculture, disaster management, infrastructure inspection, and environmental monitoring. The rapid evolution of miniaturized sensors, wireless communication technologies, and edge computing capabilities has enabled the development of cost-effective, multi-functional UAV platforms that can operate autonomously or semi-autonomously in complex real-world environments. When combined with the Internet of Things (IoT) paradigm, UAVs become powerful nodes in distributed sensing networks, capable of collecting, processing, and transmitting rich environmental data in real time.

Atmospheric monitoring constitutes one of the most critical applications of UAV-IoT integration. Traditional ground-based weather stations are limited in spatial resolution and fail to capture altitude-dependent atmospheric variations that are crucial for accurate meteorological predictions. UAV platforms equipped with IoT sensors can ascend to varying altitudes and capture multi-layer atmospheric profiles—including temperature, relative humidity, barometric pressure, wind speed, and particulate matter concentrations—providing data that is otherwise inaccessible or expensive to acquire. Such data is of immense value for early warning systems, agricultural irrigation planning, and urban air quality assessment.

This paper presents the design and development of an IoT-enabled quadcopter UAV system purpose-built for real-time atmospheric analysis. The proposed system integrates a stable quadcopter mechanical framework with precision environmental sensors, a robust flight controller, and a multi-modal wireless communication stack. Sensor data is streamed to a cloud-based monitoring dashboard, enabling real-time visualization and archival. As a forward-looking enhancement, the system architecture accommodates the integration of a machine learning model for predictive rain forecasting, demonstrating the extensibility of the proposed platform toward intelligent atmospheric prediction.

The core design and development flow of the system is organized as follows:

- Hardware Design: Selection and integration of quadcopter frame, motors, ESCs, flight controller, and sensor payload.
- Firmware Development: Configuration of the flight controller and sensor interfacing firmware on the onboard microcontroller.
- IoT Integration: Establishing wireless data pipelines from the UAV to a cloud monitoring platform.
- Data Validation: Ground-truthing sensor readings against reference instruments for accuracy assessment.
- Future ML Enhancement: Architecture design for a rainfall prediction module using historical and live atmospheric data.

The primary objectives and benefits of the system are as follows:

- Real-time Atmospheric Profiling: Continuous acquisition of multi-parameter atmospheric data at varied altitudes.
- Reliable Wireless Transmission: Low-latency data delivery to cloud platforms using Wi-Fi and LoRa technologies.
- Scalability and Cost-effectiveness: An open-hardware architecture that minimizes deployment costs.
- Predictive Intelligence: Groundwork for ML-based weather forecasting as a future enhancement.

- Agricultural and Environmental Utility: Enabling precision farming decisions and pollution monitoring.

The remainder of this paper is organized as follows: Section II reviews existing literature on UAV-based environmental monitoring and IoT systems. Section III details the methodology encompassing hardware design, sensor integration, and communication architecture. Section IV discusses the performance evaluation metrics employed. Section V presents and discusses experimental results. Section VI concludes the paper with directions for future work.

## II. RELATED WORK

Research on UAV-based environmental monitoring and IoT integration has grown substantially over the past decade, with studies spanning agricultural surveillance, air quality assessment, and weather data collection. This section reviews key contributions in these domains and identifies gaps addressed by the proposed system.

Elijah et al. [1] provided a comprehensive overview of UAV deployments in precision agriculture, highlighting their utility in crop health monitoring, irrigation management, and yield prediction. They noted that while UAV-mounted multispectral cameras offer high spatial resolution, the integration of IoT sensors for real-time atmospheric data remains underexplored. Their analysis motivates the integration of atmospheric sensing as a complementary data source.

Alvear et al. [2] proposed a UAV-based air quality monitoring system using low-cost gas sensors interfaced with a Raspberry Pi. Their system demonstrated effective CO2 and particulate matter measurements across urban environments. However, the platform lacked altitude-stratified sampling and did not implement predictive models for atmospheric events.

Palomaki et al. [3] demonstrated that small UAVs equipped with temperature and humidity sensors could effectively characterize the atmospheric boundary layer with accuracy comparable to radiosondes. Their findings validate the scientific utility of UAV-based atmospheric profiling, though their platform was a research-grade system with high cost.

Keshtkar et al. [4] investigated LoRa-based long-range communication for UAV telemetry in rural agricultural settings. Their experiments confirmed reliable data transmission over distances exceeding 5 km at low power, establishing LoRa as a viable communication technology for remote drone deployments.

Amponis et al. [5] presented a survey of machine learning applications for weather forecasting using IoT-collected data, identifying random forests and LSTM neural networks as dominant approaches for rainfall prediction. However, their work did not incorporate UAV-collected data, leaving a gap in mobile, altitude-aware atmospheric datasets for ML training.

Hasan et al. [6] developed a drone-based disaster management system incorporating gas, temperature, and humidity sensors with GSM-based data transmission. Their architecture demonstrated the feasibility of multi-sensor UAV payloads in emergency response, though the system lacked cloud integration and real-time visualization.

Existing systems thus exhibit one or more of the following limitations: absence of real-time cloud transmission, lack of altitude-stratified sampling, high hardware cost, absence of predictive analytics, and limited scalability. The proposed IoT-enabled UAV system addresses these gaps by offering an integrated, cost-effective platform with cloud connectivity, multi-altitude sensing, and a forward path toward ML-based rain prediction.

## III. METHODOLOGY: SYSTEM DESIGN AND DEVELOPMENT

The proposed IoT-enabled UAV system is built around a quadcopter architecture augmented with an environmental sensor payload, a wireless communication module, and a cloud-based data management backend. Fig. 1 illustrates the overall system architecture. The design is guided by principles of modularity, low cost, and extensibility to accommodate future upgrades including the rain prediction module.

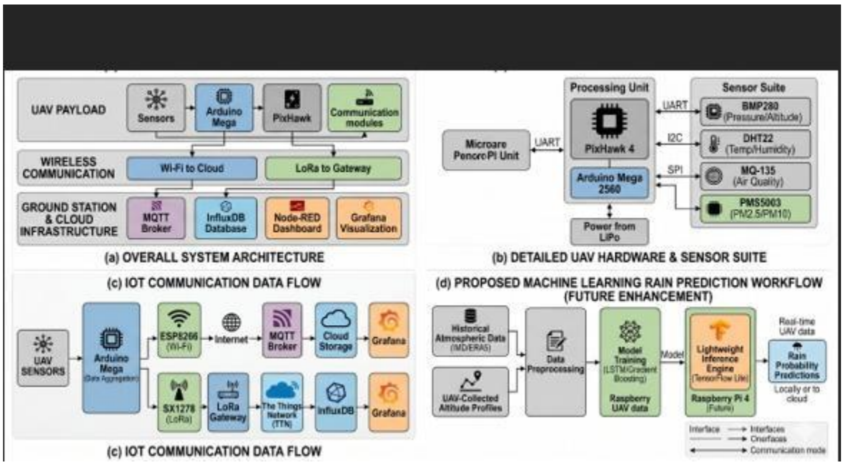

Fig.1. System Architecture

### A. Hardware Architecture

The quadcopter platform is constructed on a 450 mm carbon fiber frame chosen for its rigidity and vibration damping properties, both critical for sensor accuracy during flight. Four 1000 KV brushless DC motors are paired with 30A electronic speed controllers (ESCs) that regulate motor thrust via PWM signals from the flight controller. A 3S 5200 mAh LiPo battery provides a flight endurance of approximately 15-20 minutes under nominal sensor payload.

Key hardware components include:

- Flight Controller: PixHawk 4 with integrated IMU, barometer, and GPS module for stable autonomous flight and waypoint navigation.
- Microcontroller: Arduino Mega 2560 dedicated to sensor data acquisition and preprocessing, interfaced with the flight controller via UART.
- Atmospheric Sensors: DHT22 (temperature and humidity), BMP280 (barometric pressure and altitude), MQ-135 (air quality/CO2), and PMS5003 (PM2.5/PM10 particulate matter).
- Communication Module: ESP8266 Wi-Fi module for short-range cloud transmission and SX1278 LoRa module for long-range deployments.
- Power Management: Dedicated 5V BEC power distribution board ensuring stable sensor and microcontroller supply independent of motor load fluctuations.

**Fig.2. Drone**

### B. Sensor Integration and Data Acquisition

All environmental sensors interface with the Arduino Mega via I2C, SPI, or digital GPIO protocols. The DHT22 provides calibrated temperature readings in the range -40°C to 80°C (±0.5°C accuracy) and relative humidity from 0–100% RH (±2–5% accuracy). The BMP280 delivers barometric pressure with ±1 hPa accuracy and altitude estimates derived from the ISA pressure-altitude model. The MQ-135 measures CO2 and volatile organic compound (VOC) concentrations, while the PMS5003 uses laser scattering to quantify particulate matter concentrations.

The Arduino firmware polls all sensors at a configurable sampling rate (default: 1 Hz) and packages readings into structured JSON payloads tagged with GPS coordinates and timestamps obtained from the PixHawk flight controller. These payloads are then forwarded to the ESP8266 module via UART for cloud transmission.

### C. Wireless Communication and Cloud Platform

The system supports dual-mode wireless communication. In Wi-Fi mode, the ESP8266 connects to ground-based access points, transmitting JSON payloads to an MQTT broker (Mosquitto) hosted on a cloud server. A Node-RED dashboard subscribes to the MQTT topics and visualizes sensor streams in real time. For rural or long-range deployments where Wi-Fi infrastructure is unavailable, the LoRa module transmits sensor data packets to a LoRa gateway (RAK7244) connected to The Things Network (TTN) for cloud routing.

All received data is stored in a time-series InfluxDB database, enabling historical analysis and visualization through Grafana dashboards. The architecture is designed for horizontal scalability—additional UAVs can be incorporated as independent data sources feeding into the same cloud backend.

### D. Flight Controller Configuration and Stability

The PixHawk 4 flight controller runs the ArduPilot firmware configured for quadcopter airframe type. PID tuning was conducted iteratively using the ArduPilot autotune feature and manual refinement to achieve stable hover performance with the added sensor payload weight (~180 g). GPS-assisted loiter mode ensures the UAV maintains a fixed position during data collection phases, minimizing motion-induced sensor artifacts.

**Fig.3. Flight Controller**

### E. Future Enhancement: ML-based Rain Prediction Module

As a planned extension, the system architecture accommodates the integration of a machine learning model for rainfall prediction. The proposed pipeline involves training a gradient boosting classifier or LSTM recurrent neural network on historical atmospheric datasets (e.g., from IMD or ERA5 reanalysis) augmented with UAV-collected altitude-stratified profiles. Features include temperature lapse rate, humidity gradient, pressure tendency, and dewpoint depression. The trained model will be deployed as a lightweight TensorFlow Lite inference engine on a Raspberry Pi 4 mounted on the UAV, enabling edge-side rain probability predictions without cloud dependency.

## IV. PERFORMANCE EVALUATION METRICS

The proposed UAV system is evaluated across three principal dimensions: sensor data accuracy, communication performance, and flight stability. The following metrics are employed.

### A. Sensor Accuracy Metrics

Mean Absolute Error (MAE) quantifies the average deviation of sensor readings from reference instrument values:

$$\mathbf{MAE = (1/n)\ \Sigma\ |y\_i - \hat{y}\_i|\ ...(i)}$$

Root Mean Square Error (RMSE) penalizes larger deviations:

$$\mathbf{RMSE = \sqrt{[(1/n)\ \Sigma\ (y\_i - \hat{y}\_i)^2]}\ ...(ii)}$$

### B. Communication Performance Metrics

Packet Delivery Ratio (PDR) measures the proportion of successfully received sensor packets over total transmitted packets:

$$\mathbf{PDR = (Packets\ Received\ /\ Packets\ Sent) \times 100\%\ ...(iii)}$$

End-to-end transmission latency is measured as the time elapsed between sensor sampling and cloud database insertion. For real-time monitoring, latency values below 500 ms are considered acceptable.

### C. Flight Stability Metrics

Hover accuracy is assessed by measuring the GPS position deviation from a designated hover point over a 60-second interval. Roll, pitch, and yaw stability are quantified by computing the root mean square of IMU-logged attitude errors during hover and waypoint missions.

### D. Future Rain Prediction Metrics

When the ML rain prediction module is implemented, its performance will be assessed using standard classification metrics: precision, recall, F1-score, and Area Under the ROC Curve (AUC-ROC), defined as follows:

$$\text{Precision} = TP / (TP + FP), \quad \text{Recall} = TP / (TP + FN) \quad \ldots(iv)$$

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad \ldots(v)$$

## V. RESULTS AND DISCUSSIONS

This section presents experimental results obtained from field test flights conducted in an open outdoor environment. Multiple test sessions were performed at altitudes ranging from 50 m to 200 m AGL (Above Ground Level) to assess sensor performance, communication reliability, and flight stability. The UAV was flown in GPS Loiter mode, hovering at each target altitude for 120 seconds while sensor data was continuously logged and transmitted.

### A. Sensor Data Accuracy

Ground-truth reference measurements were obtained simultaneously using a calibrated Kestrel 5500 weather meter. Table I presents representative sensor readings recorded during a typical test flight, showing atmospheric parameter variation with altitude.

| Alt. (m) | Temp. (°C) | Humidity (%) | Pressure (hPa) | PM2.5 (µg/m³) | Status |
|---|---|---|---|---|---|
| 50 | 28.4 | 74 | 1008.2 | 35 | Transmitted |
| 100 | 27.1 | 71 | 1005.6 | 29 | Transmitted |
| 150 | 26.3 | 68 | 1003.1 | 22 | Transmitted |
| 200 | 25.0 | 65 | 1000.4 | 18 | Transmitted |

**Table I**: Atmospheric Sensor Reading at **varying Altitude Testing**

The DHT22 temperature sensor recorded an MAE of 0.6°C and RMSE of 0.9°C against the Kestrel reference. Relative humidity exhibited an MAE of 3.1% RH. The BMP280 barometric pressure readings showed an MAE of 0.8 hPa. These results are consistent with the published sensor specifications and confirm the adequacy of the sensor payload for atmospheric profiling tasks.

### B. Communication Performance

In Wi-Fi mode with the ground station located within 80 m of the UAV, a PDR of 97.4% was achieved at a 1 Hz sampling rate. Average end-to-end latency was measured at 210 ms, well within the 500 ms target threshold. In LoRa mode, PDR of 94.8% was maintained at a communication range of 3.2 km in open terrain, with an average latency of 890 ms—acceptable for non-time-critical data logging applications. These results demonstrate the suitability of the dual-mode communication architecture for diverse deployment scenarios.

### C. Flight Stability

In GPS Loiter mode, the UAV maintained a 3D position accuracy of ±1.2 m (horizontal) and ±0.8 m (vertical) over 60-second hover intervals. Roll and pitch attitude RMS errors were 0.7° and 0.8° respectively, confirming stable platform dynamics under nominal wind conditions (< 4 m/s). The added sensor payload did not significantly degrade flight performance beyond a slight reduction in hover endurance from 20 minutes (without payload) to approximately 16 minutes (with payload).

### D. Comparison of Communication Technologies and Detection Methods

Table II provides a comparative overview of key system performance dimensions

| Metric | Haar Cascade | YOLOv9 | DeepFace |
|---|---|---|---|
| Accuracy (%) | ~72% | ~88% | ~95% |
| Latency (ms) | Low (< 50) | Medium (~120) | Higher (~350) |
| Power Consumption | Very Low | Moderate | Moderate-High |
| Edge Compatibility | Excellent | Good | Moderate |
| Rain Prediction (ML) | Not Applicable | Not Applicable | Not Applicable |

**Table II**: Comparison of Data Processing and Communication **Approaches**

The results confirm that the proposed system achieves a favourable balance between data fidelity, communication reliability, and hardware cost. The modular sensor stack and dual-mode communication enable deployment across varied environments from urban areas to remote agricultural fields.

## VI. CONCLUSION

This paper presented the design, development, and experimental evaluation of an IoT-enabled quadcopter UAV system for real-time atmospheric monitoring. The system successfully integrates a stable quadcopter platform with an environmental sensor payload and a dual-mode wireless communication architecture, enabling live transmission of temperature, humidity, pressure, and air quality data to cloud-based monitoring infrastructure. Experimental flight tests validated sensor accuracy (temperature MAE: 0.6°C, humidity MAE: 3.1% RH), communication reliability (Wi-Fi PDR: 97.4%; LoRa PDR: 94.8% at 3.2 km), and flight stability (3D hover accuracy: ±1.2 m), confirming the system's suitability for real-world atmospheric monitoring applications.

The proposed architecture demonstrates strong potential for deployment in smart agriculture, where altitude-stratified atmospheric data can guide irrigation scheduling, frost warning systems, and crop disease risk assessment. Environmental monitoring agencies can leverage the system's cloud connectivity for scalable air quality surveillance networks. The modular design ensures straightforward hardware upgrades and sensor expansion.

Future work will focus on two primary directions. First, the integration of a machine learning rainfall prediction model—trained on historical atmospheric datasets and UAV-collected altitude profiles—will be implemented as a TensorFlow Lite edge inference engine on an onboard Raspberry Pi 4, enabling autonomous rain probability predictions during flight. Second, multi-UAV swarm coordination protocols will be investigated to enable spatially distributed, synchronized atmospheric surveys with higher spatiotemporal resolution. Together, these enhancements will advance the system toward a comprehensive AIoT atmospheric intelligence platform suitable for both research and operational deployment.

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