Chapter 1

Introduction

The twenty-first century has come across some of the most powerful global challenges like environmental destruction, changes in climate, and urban air quality getting worse day by day. The rapid urbanization process which is not matched by a similar slowing down of industrial development and a rapidly increasing demand for transport has resulted in the total change of the atmosphere of the modern cities. Such changes caused by human activity have led to more intense air pollution events, altered natural weather cycles, and created very unstable microclimates that can vary a lot even in very short distances [1][2]. Consequently, the necessity to monitor the atmosphere with high spatial and temporal resolution has become paramount for the scientific community and also for the health of the public, the future of urban development, and environmental policies.

Air pollution is also one of the biggest environmental health risks worldwide. A Large body of epidemiological literature indicates strong associations of exposure to pollutants- $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO, and volatile organic compounds-particularly VOCs and a wide spectrum of non-communicable diseases [2][3]. Fine particulate matter $PM_{2.5}$ produces inflammation through its ability to penetrate deep into the alveoli. impaired lung function, cardiovascular complications and increased risk of premature mortality [2][3]. Coarser particles (PM_{10}) are injurious to asthma, respiratory discomfort, and allergic reactions. Toxic gases also act on respiratory and circulatory systems and participate in the atmospheric reactions that form secondary pollutants [3]. The World Health Organization are thought to cause more than seven million premature deaths annually [4] due to ambient Air pollution causes more deaths than most communicable diseases put together, surpassing mortality from many communicable diseases combined [4]. These alarming statistics highlight the urgent need for advanced atmospheric monitoring systems capable of detecting pollution variations at the scales where people live, commute, and work.

Parallel to the concerns relating to pollutant exposure is the growing recognition of the role of "microclimates" localized atmospheric zones whose temperature, humidity, wind flow, and radiative characteristics differ markedly from general regional weather conditions. Microclimatic variability arises from differences in urban geometry, building density, surface materials, vegetation distribution, anthropogenic heat emissions, and shading patterns [5]. For example, street canyons impede airflow [5] and act as repositories of pollutants, thus forming a high-exposure hotspot, while Green corridors or open intersections, for their part, enhance natural dispersion [5]. These environmental differences mean that meteorological conditions experienced in everyday life often diverge significantly from values reported by distant monitoring stations, making hyperlocal monitoring an indispensable component of environmental intelligence [6].

Despite scientific advances in atmospheric instrumentation, government-operated monitoring stations remain too sparse and expensive to capture micro-scale variations. Reference-grade systems require sophisticated analyzers, controlled environments, specialized operators, and frequent maintenance, limiting their deployment density. As a result, one station may represent several square kilometers, masking the true variability in pollutant concentrations. Empirical studies across global megacities consistently show that pollutant levels can vary by 200–300% within distances as short as 300 meters [6] due to localized emission sources and microclimatic processes. Consequently, official monitoring often fails to reflect real exposure for pedestrians, commuters, schoolchildren, and residents living near highways or industrial zones.

These persistent limitations have driven the rapid growth of hyperlocal environmental monitoring, which emphasizes dense, distributed deployments of low-cost sensor nodes [7]. Hyperlocal systems collect data at scales directly relevant to human exposure—neighborhood streets, school zones, marketplaces, residential areas, and traffic corridors. Unlike centralized stations reporting city-level averages, hyperlocal sensors detect pollution gradients, transient spikes, local emission sources, and rapid microclimatic changes [7]. Studies in Europe show that children's exposure during school commutes differed substantially from values recorded at official stations kilometers away [8]. Indian metropolitan deployments found that IoT sensors detected short-lived particulate spikes from construction dust, biomass burning, and traffic surges—events entirely invisible in hourly aggregated datasets [9].

The evolution of Internet of Things (IoT) technologies has made such monitoring feasible, scalable, and cost-efficient. IoT devices integrate sensors, microcontrollers, communication modules, and cloud services into compact nodes capable of autonomous environmental sensing. IoT architectures support diverse environmental sensors—temperature, humidity, particulate matter, pressure, VOCs—and transmit readings wirelessly using lightweight protocols such as MQTT or secure HTTPS. Edge computing enables preprocessing directly on the device, including noise filtering, drift correction, anomaly detection, and data validation. Cloud platforms provide centralized storage, dashboards, analytics, and long-term historical trend analysis [10].

Among IoT microcontrollers, the ESP32 has emerged as a leading platform due to its dual-core processing capabilities, built-in Wi-Fi and Bluetooth, multiple ADC channels, UART/I2C/SPI interfaces, energy-efficient deep-sleep modes, and compatibility with a wide range of environmental sensors [11].

While IoT devices excel in real-time data collection, machine learning (ML) extends their capabilities by enabling predictive environmental intelligence. Environmental parameters exhibit strong nonlinear temporal dependencies influenced by meteorology, chemical reactivity, human activities, and microclimatic interactions. ML models—particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—excel at capturing these dependencies and forecasting air-quality indicators with high accuracy [12]. Ensemble models like Random Forest and Gradient Boosting further support pollutant source analysis, sensor drift compensation, and detection of anomalous patterns [13].

Short-term forecasting is especially valuable at hyperlocal scales. Unlike regional weather forecasts, which emphasize large-scale atmospheric systems, hyperlocal predictions capture micro-environmental shifts—sudden humidity changes due to localized evaporation, PM spikes from nearby activity, or rapid temperature fluctuations influenced by shading or wind channeling [13].

Even with high-frequency sensing and predictive analytics, IoT-based monitoring faces technical challenges. Low-cost sensors may exhibit drift due to aging, humidity sensitivity, temperature fluctuations, and cross-interference with other pollutants. Outdoor deployments expose sensors to dust, heat, moisture, and electromagnetic disturbances, requiring robust housing and calibration strategies. Reliable preprocessing—using median filters, exponential smoothing, moving averages, anomaly detection, and empirical correction formulas—is essential to improve data quality [14].

Despite these challenges, the potential benefits of hyperlocal environmental intelligence are transformative. Urban planners use micro-scale data to develop heat mitigation strategies, optimize placement of green infrastructure, and design ventilated street corridors. Healthcare professionals rely on hyperlocal AQI and weather trends to advise patients with asthma or cardiovascular diseases. Municipal authorities integrate real-time monitoring into smart traffic systems to reduce emissions.

The present project IoT Enabled Hyperlocal Weather Monitoring & Prediction System Using ESP32 and Machine Learning was conceptualized to address these scientific, technological, and societal needs. The system integrates temperature, humidity, and air-quality sensors with the ESP32 microcontroller to collect real-time hyperlocal environmental data. Edge preprocessing ensures clean and reliable sensor output, while cloud dashboards provide intuitive data visualization. Machine learning models trained on collected data generate short-term forecasts, making the system not only reactive but predictive.

To guide the development of the system, the project defines the following objectives:

a) Primary Objectives:

- Develop a low-cost IoT device using ESP32 for real-time environmental sensing.
- Measure hyperlocal temperature, humidity, VOC levels, and particulate matter.
- Preprocess and calibrate sensor data at the edge for improved reliability.
- Enable seamless wireless transmission and cloud synchronization.

- Build machine learning models for short-term forecasting of AQI and weather parameters.

b) Secondary Objectives:

- Evaluate sensor behavior under different microclimatic and environmental conditions.
- Develop intuitive dashboards for real-time visualization and analysis.
- Ensure reliable data handling through buffering, anomaly detection, and fault tolerance.
- Assess scalability for dense multi-node deployments across neighborhoods or campuses.

Hyperlocal monitoring also enriches scientific understanding of localized atmospheric processes. Microclimatic variations strongly influence pollutant dispersion, vertical mixing, and accumulation. For example, enclosed street canyons may exhibit significantly higher pollutant concentrations than adjacent open spaces due to restricted airflow [15].

Ultimately, this project contributes to the future of urban environmental sensing by demonstrating an integrated, data-driven, and scalable solution for hyperlocal monitoring and forecasting.

In addition to environmental exposure assessment, hyperlocal weather and air-quality monitoring plays an increasingly important role in strengthening data-driven decision-making frameworks. Traditional environmental datasets often rely on coarse spatial and temporal resolutions, which limits their usefulness for localized policy interventions. Hyperlocal sensing, by contrast, enables authorities and researchers to observe fine-scale atmospheric variations that directly influence human comfort, mobility, and health outcomes. Such data supports evidence-based urban planning, including zoning regulations, traffic management strategies, and the optimization of green infrastructure placement within cities.

From a public health perspective, access to real-time and localized environmental information empowers individuals and communities to make informed behavioral choices. For example, knowledge of sudden air-quality deterioration or extreme humidity conditions can guide outdoor activity planning, reduce exposure risks for sensitive populations, and assist healthcare providers in issuing timely advisories. In densely populated urban environments, where vulnerable groups such as children, elderly individuals, and patients with respiratory disorders are concentrated, hyperlocal monitoring serves as a critical preventive tool rather than a reactive measure.

The integration of digital technologies with environmental sensing further enhances the accessibility and interpretability of atmospheric data. Cloud-based dashboards and mobile-accessible platforms allow users to visualize trends, compare historical patterns, and observe correlations between weather parameters and pollution levels. When combined with machine learning–based analytics, these platforms move beyond static reporting and offer predictive insights that are valuable for early-warning systems. Forecasting short-term environmental behavior enables proactive responses to pollution episodes, temperature extremes, and microclimatic instability.

Academically, hyperlocal monitoring contributes to a deeper understanding of urban atmospheric processes. High-resolution datasets facilitate the study of interactions between built environments, meteorological variables, and emission sources. Researchers can investigate how localized factors such as road geometry, building height, vegetation cover, and human activity patterns influence pollutant dispersion and thermal behavior. Such insights are often unattainable using conventional monitoring infrastructures due to their sparse spatial coverage.

Moreover, the affordability and modularity of IoT-based sensing systems promote wider participation in environmental data collection. Educational institutions, community groups, and local organizations can deploy sensor nodes to support learning, citizen science initiatives, and grassroots environmental awareness programs. This democratization of environmental intelligence fosters transparency, encourages public engagement, and supports collaborative approaches to addressing climate and pollution challenges.

As urbanization continues to intensify globally, cities are expected to experience increased environmental stress in the form of heat islands, fluctuating humidity patterns, and highly variable air-quality conditions. In this context, hyperlocal monitoring systems represent an essential complement to traditional meteorological networks. By delivering continuous, location-specific, and actionable environmental information, such systems lay the foundation for resilient, adaptive, and sustainable urban ecosystems.

In summary, the expansion of hyperlocal weather and air-quality monitoring is not merely a technological advancement but a necessary evolution in how environmental data is collected, interpreted, and applied. Through the integration of IoT, cloud computing, and machine learning, modern monitoring systems provide the granularity and intelligence required to address emerging environmental challenges effectively. This broader context reinforces the motivation and relevance of the present project and establishes a strong foundation for the subsequent chapters of this report.

Chapter 2

Literature Survey

The development of the IoT-enabled Hyperlocal Weather Monitoring and Prediction System using ESP32 and Machine Learning is rigorously grounded in contemporary research across environmental informatics, atmospheric science, distributed sensing networks, embedded systems, and predictive data analytics. Its necessity emerges from a global context where microclimatic instability, rapid urbanization, and rising air pollution demand a monitoring paradigm that transcends traditional meteorological infrastructures. Modern cities exhibit extreme spatial heterogeneity in temperature, humidity, particulate concentration, and gaseous pollutants—variations that occur within tens or hundreds of meters and evolve dynamically throughout the day. Conventional weather stations, despite their accuracy, operate at a macro-scale and fail to detect such hyperlocal fluctuations. This mismatch between available data and real-world exposure has led to a paradigm shift toward distributed IoT sensor networks, edge computing, and ML-driven forecasting models capable of delivering granular, real-time atmospheric intelligence.

This chapter critically reviews the theoretical, technological, and methodological foundations guiding the design of the proposed system. The literature review establishes the project's scientific motivation, analyzes limitations of existing weather monitoring infrastructures, traces the technological shift from Wireless Sensor Networks (WSN) to IoT, examines sensor selection and calibration practices, highlights cybersecurity and reliability constraints, and identifies gaps that justify the adoption of ESP32-based IoT architecture and ML forecasting models.

2.1 Theoretical Context: Climate Variability & Hyperlocal Necessity

2.1.1 Atmospheric Dynamics & Urban Microclimates

Modern atmospheric behavior is shaped by complex interactions among solar radiation, surface temperature gradients, humidity levels, anthropogenic heat emissions, particulate matter, and wind movement. In rapidly urbanizing regions, these interactions result in highly localized meteorological patterns collectively referred to as microclimates. Unlike regional weather predictions, microclimates vary substantially within small spatial scales—sometimes within 50–200 meters—due to differential heating of surfaces, building geometry, shading, and vegetation cover.

One of the most significant manifestations of microclimate variability is the Urban Heat Island (UHI) effect, where temperatures in dense metropolitan zones exceed those of rural surroundings by 3–8°C. This thermal asymmetry alters humidity, atmospheric stability, and pollutant dispersion patterns. Narrow street canyons exacerbate pollutant accumulation by restricting vertical air mixing, while open intersections facilitate dispersal. These spatial disparities mean that individuals living merely streets apart may experience drastically different environmental conditions.

Given that most human exposure occurs in such micro-environments—schools, markets, roadways, residential zones, workspaces—hyperlocal weather monitoring becomes essential for accurate assessment of public health risk, comfort indices, and environmental safety.

2.1.2 Limitations of Conventional Weather Monitoring

Traditional meteorological stations employ high-precision instruments but suffer from critical structural limitations:

- **Low Spatial Resolution**: A single station often represents several square kilometers, masking micro-variations.
- **High Cost & Maintenance**: Reference-grade analyzers require calibration gases, controlled sampling inlets, and trained technicians.
- **Temporal Averaging Effects**: Hourly or daily averages often conceal short-term spikes or localized anomalies.
- **Geographical Constraints**: Stations are placed at standard heights and open fields, not within dense urban corridors where people reside.

Recent studies report that pollutant levels may vary by 200–300% within 500 meters of distance in urban environments, revealing the inadequacy of sparse monitoring systems. Because exposure risk depends on immediate surroundings rather than city-level averages, a fundamental shift toward hyperlocal sensing is needed.

2.1.3 Hyperlocal Monitoring Framework

Hyperlocal monitoring aims to bridge the gap left by conventional meteorological networks. It involves deploying dense arrays of low-cost IoT-enabled sensor nodes that measure atmospheric parameters at fine spatial granularity. Such systems capture:

- sudden $PM_{2.5}/PM_{10}$ spikes from construction or traffic
- humidity and temperature gradients linked to shading or vegetation
- localized pollution from biomass burning or industrial vents
- rapidly evolving microclimatic anomalies

Studies highlight that hyperlocal sensing is crucial for early detection of smog formation, heat-stress zones, localized humidity collapse, and AQI deterioration. The framework supports early warning systems, smart-city interventions, and accurate personal exposure estimation.

2.2 Technological Lineage: WSN to IoT

Modern IoT-based environmental monitoring systems evolved from earlier Wireless Sensor Network (WSN) research, which initially demonstrated the feasibility of distributed sensing for environmental and industrial applications. While WSNs validated the principle of sensor decentralization, they suffered from notable limitations that restricted their suitability for large-scale or real-time atmospheric monitoring. These limitations included restricted communication range, limited bandwidth, and dependency on energy-intensive multi-hop routing, which significantly increased node power consumption. Furthermore, WSNs lacked seamless cloud connectivity, preventing remote access, centralized analytics, and real-time dashboards. This meant that environmental data remained localized and difficult to integrate into predictive or decision-support systems. The emergence of the Internet of Things (IoT) addressed these constraints by introducing IP-addressable microcontrollers, global connectivity through Wi-Fi, BLE, LTE, and LoRaWAN, and lightweight communication protocols such as MQTT and HTTPS. IoT systems inherently support cloud analytics, remote dashboards, scalable deployment, and integration with machine learning models at both the edge and cloud layers. This paradigm shift simplified node design, reduced deployment complexity, and dramatically expanded use cases. Microcontrollers such as ESP8266 and ESP32 rapidly became foundational components due to their built-in Wi-Fi, compact architecture, low cost, and compatibility with cloud platforms. Research consistently validates the superiority of IoT over WSN for real-time atmospheric sensing and predictive environmental intelligence. Additionally, the growing adoption of hybrid edge–cloud architectures allows IoT systems to reduce latency, minimize bandwidth usage, and maintain robustness even in environments with intermittent network connectivity.

2.3 System Core: Sensors, Communication & Cloud Integration

IoT-based hyperlocal weather monitoring systems rely on a tightly integrated stack composed of sensing hardware, edge-processing microcontrollers, communication channels, cloud analytics platforms, and machine learning models. Each of these components plays a critical role in ensuring accurate data acquisition, efficient transmission, and meaningful forecasting. The sensing layer includes temperature and humidity sensors such as the DHT22 and BME280, which offer reliable measurement accuracy suitable for hyperlocal climate analysis. BME280, in particular, provides the additional capability of barometric pressure sensing, which enhances micro-weather modeling. Particulate matter sensors, such as the PMS5003, utilize laser-scattering techniques to measure $PM_{1.0}$, $PM_{2.5}$, and PM_{10} concentrations, making them well suited for detecting transient pollution events in localized environments. Gas sensors like MQ135, though inexpensive, have been widely validated in literature as effective indicators of VOC concentration and AQI trends when appropriately calibrated.

At the processing layer, the ESP32 microcontroller functions as the computational core. Its dual-core architecture enables parallel sensing and processing operations, while built-in Wi-Fi and Bluetooth significantly reduce hardware complexity and power consumption. The availability of multiple ADC channels and extensive GPIO support allows seamless interfacing with diverse environmental sensors. ESP32 also supports deep-sleep modes, making it suitable for long-term, low-power deployments. These features collectively enable real-time preprocessing tasks such as smoothing, debouncing, calibration correction, anomaly detection, and preliminary AQI estimation before data is transmitted to the cloud. Secure communication protocols such as MQTT and HTTPS ensure reliable, low-latency data transfer to cloud platforms, enabling global accessibility and fault-tolerant operation within distributed sensing networks.

Cloud integration forms the analytical backbone of the system. Platforms such as Google Sheets, Firebase, ThingSpeak, and AWS IoT offer real-time visualization, centralized data storage, and remote accessibility. These cloud services also support scalable analytics pipelines, allowing integration with machine learning models for advanced forecasting. Within the ML layer, models such as Linear Regression, Random Forest, Artificial Neural Networks, and state-of-the-art architectures like LSTM and GRU have been extensively used for predicting temperature, humidity, and AQI. Among these, LSTM is particularly effective due to its capability to learn long-term temporal dependencies intrinsic to atmospheric behavior. Together, these hierarchical layers form a cohesive architecture capable of delivering high-resolution, real-time environmental intelligence.

2.4 Control & Sensing: Environmental Data Acquisition

The accuracy and reliability of environmental datasets depend heavily on the sensing and data acquisition methodologies employed within IoT monitoring systems. A critical parameter in this process is the sampling interval, as excessively frequent sampling may introduce sensor noise while overly delayed sampling may fail to capture rapid microclimatic fluctuations. Literature generally recommends sampling intervals between 20 and 60 seconds to provide an optimal balance between resolution and noise control. To further refine data quality, robust noise filtering techniques are essential. Filters such as moving average, median filtering, exponential smoothing, and Kalman filtering are commonly applied to stabilize sensor outputs, eliminate spurious spikes, and enhance the reliability of downstream machine-learning pipelines. These filtering practices are particularly important when using low-cost sensors known for susceptibility to drift, noise, and environmental interference.

Sensor calibration is another crucial component in achieving accurate hyperlocal weather monitoring. For example, MQ135 gas sensors require warm-up periods, baseline resistance measurement, and humidity compensation to ensure meaningful interpretation of output values. Similarly, particulate sensors may require reference co-location with certified air-quality stations to derive appropriate correction curves. Calibration is essential not only for ensuring individual sensor accuracy but also for maintaining consistency across distributed sensor networks deployed in different microclimates. When properly implemented, calibrated sensing coupled with robust acquisition protocols provides a reliable foundation for real-time visualization, historical analysis, and machine-learning-based forecasting.

2.5 Safety Protocols: Data Reliability & IoT Security

2.5.1 Data Reliability Measures

Ensuring data reliability is a fundamental requirement in any IoT-enabled environmental monitoring system, as inaccuracies or inconsistencies can severely compromise downstream analytics and machine learning predictions. Reliable systems must incorporate timestamp validation to maintain chronological integrity, particularly in distributed networks where devices may reconnect after temporary outages. Redundant sampling is also essential, as it mitigates the risk of missing data caused by transient sensor errors or communication failures. Additionally, packet integrity checks, such as CRC or checksum validation, ensure that transmitted data remains uncorrupted during wireless communication. Robust anomaly detection mechanisms further contribute to reliability by automatically identifying and discarding faulty or improbable readings caused by sensor malfunction, environmental interference, or electrical instability. Together, these measures establish a resilient data pipeline capable of supporting accurate real-time monitoring and reliable forecasting.

2.5.2 Sensor Safety & Environmental Protection

The longevity and accuracy of environmental sensors depend significantly on their physical protection against harsh outdoor conditions. Prolonged exposure to direct sunlight, dust, rain, and fluctuating temperatures can accelerate sensor degradation and introduce measurement biases. To mitigate these risks, sensors must be enclosed in UV-resistant housings that minimize photothermal effects and prevent casing deterioration. Waterproof enclosures or IP-rated designs shield sensitive electronics from moisture intrusion, while particulate filters safeguard optical and electrochemical sensing elements from dust accumulation that could impair airflow or alter readings. Thermal insulation is also recommended to prevent internal sensor heating—especially near microcontrollers like the ESP32—which can distort temperature and humidity measurements. Proper environmental protection not only enhances the accuracy of individual sensors but also significantly improves the long-term reliability of the entire monitoring system.

2.5.3 IoT Cybersecurity Concerns

IoT-based environmental monitoring systems operate across public networks and are therefore susceptible to cybersecurity threats that can compromise data integrity, device functionality, or user privacy. Common vulnerabilities include replay attacks, man-in-the-middle (MITM) attacks, unauthorized access, and packet sniffing. To address these risks, secure communication protocols such as HTTPS and SSL/TLS encryption must be employed, along with token-based authentication and encrypted APIs. Implementing these security measures ensures system integrity, protects sensitive environmental data, and enhances overall operational resilience.

2.6 Problem Statement

The field of environmental monitoring continues to face significant challenges despite advancements in sensing technologies, IoT communication frameworks, and data analytics. Conventional weather monitoring infrastructures, particularly government-operated meteorological stations, are characterized by sparse spatial distribution, high installation costs, and limited accessibility. These systems report city-wide averages rather than street-level variations, making them unable to detect microclimatic differences and pollution anomalies that occur within short spatial intervals of 100–300 meters. Such limitations are critical, as hyperlocal variations in temperature, humidity, and air-quality parameters directly influence human exposure, health outcomes, urban comfort levels, and environmental risk assessment. The absence of fine-grained data undermines the accuracy of public forecasts, restricts the effectiveness of early-warning systems, and prevents cities from implementing targeted interventions in pollution-prone zones.

Furthermore, existing low-cost monitoring devices available commercially lack scientific precision, calibration support, edge-processing capabilities, and long-term stability. They typically function as isolated units without cloud integration, standardized sampling protocols, or predictive intelligence. Research further indicates that air-quality variations are strongly nonlinear, influenced by complex interactions between meteorology, traffic patterns, human activities, and surface characteristics—dynamics that are beyond the capability of traditional descriptive monitoring systems. The lack of integrated machine learning models for short-term prediction severely limits the decision-making potential of users, authorities, and environmental planners. Without forecasting, communities remain reactive rather than prepared, especially during sudden pollution spikes, humidity drops, or temperature inversions.

In addition to technical limitations, current environmental monitoring approaches often fail to ensure data continuity, accessibility, and scalability. Many existing systems are designed as standalone installations, offering limited interoperability with modern digital platforms or decision-support systems. This fragmentation restricts the ability to aggregate data across locations, analyze long-term trends, or correlate environmental parameters with public health indicators. Moreover, the absence of edge-level preprocessing results in noisy datasets, reduced reliability, and increased dependence on centralized post-processing, which further delays actionable insights.

Another critical challenge lies in the lack of affordability and adaptability of professional-grade monitoring infrastructure. High-cost reference stations, while accurate, cannot be deployed densely across urban or semi-urban regions due to financial and logistical constraints. Conversely, consumer-grade sensors, though affordable, often lack validation, calibration mechanisms, and robustness for outdoor deployment. This creates a substantial gap between accuracy and accessibility, leaving communities without reliable hyperlocal environmental intelligence.

Taken together, these deficiencies highlight a clear technological gap: the need for an affordable, scalable, and intelligent hyperlocal environmental monitoring system that combines IoT-enabled sensing, ESP32-based edge computation, secure wireless communication, cloud synchronization, and machine learning–driven prediction. Such a system would bridge the divide between high-cost professional stations and inaccurate consumer sensors, offering continuous, granular, and actionable environmental intelligence. By capturing real-time microclimatic fluctuations and forecasting near-future trends, the proposed solution aims to support smart-city management, climate resilience planning, public-health protection, and data-driven environmental awareness at the community level.

Chapter 3

IoT Enabled Hyperlocal Weather Monitoring & Prediction System Using ESP32 and Machine Learning

The IoT Enabled Hyperlocal Weather Monitoring & Prediction System using ESP32 and Machine Learning represents a modern and comprehensive approach to microclimatic intelligence. Traditional meteorological stations, although accurate at the macro scale, lack the spatial resolution needed to capture rapid variations in temperature, humidity, and air quality occurring within very small geographical zones [1][2]. This project addresses these critical limitations by integrating embedded systems, wireless IoT communication, cloud-based data storage, and machine learning analytics into a unified environmental intelligence framework. The ESP32 microcontroller serves as the computational core, interfacing with temperature–humidity and gas sensors to collect hyperlocal atmospheric data. Through secure HTTPS communication, the data is pushed to a Google Sheets cloud database via Apps Script, where it forms both a real-time dashboard backend and a machine-learning-ready dataset. The system's predictive engine, implemented using time-series forecasting algorithms, provides short-term environmental predictions that enhance situational awareness for users [3]. The overall system design, operational workflow, advantages, limitations, applications, and future possibilities are described in detail in the following sections.

3.1 System Design

The system is structured into three major layers: the Sensing Layer, the Edge Processing Layer, and the Cloud–Machine Learning Layer. Each layer performs a crucial role in ensuring that environmental data is captured accurately, transmitted securely, stored systematically, and analyzed intelligently. The overall architecture is illustrated in Figure 3.1 [4].

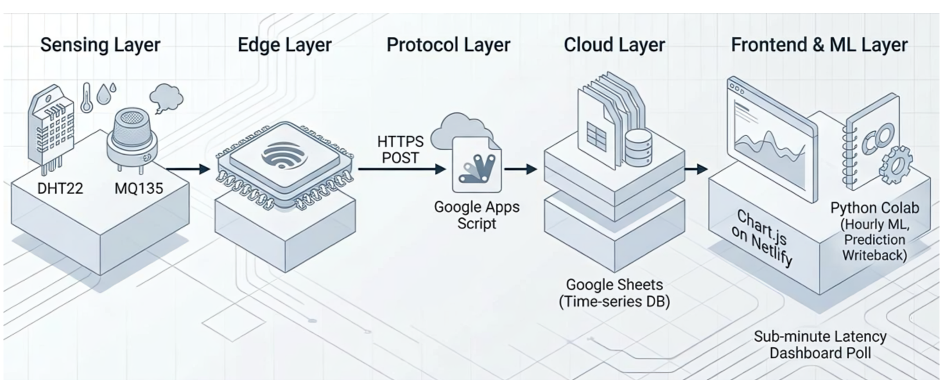


Fig 3.1 System Architecture of IoT-Enabled Hyperlocal Weather Monitoring System

At its core, the system utilizes the ESP32 microcontroller, chosen for its dual-core performance, integrated Wi-Fi module, low power consumption, and ease of interfacing with multiple sensors [5]. The sensing subsystem includes the DHT22 sensor for temperature and humidity measurement and the MQ135 sensor for detecting air-quality-related gases.

3.1.1 Hardware Components and Specifications

The ESP32 development board acts as the central processing hub of the system. It features integrated Wi-Fi, a dual-core Xtensa microprocessor, and a 12-bit ADC, making it highly efficient for continuous environmental data acquisition and cloud communication.

Fig 3.2 ESP32 Development Board

The ESP32 pinout diagram, shown in Figure 3.3, highlights the ADC channels and digital GPIO pins used for interfacing with the MQ135 and DHT22 sensors.

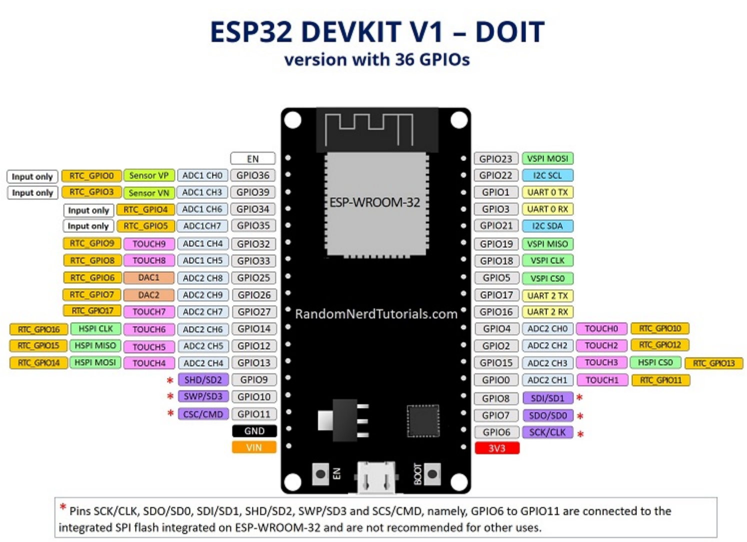


Fig 3.3 ESP32 Pinout Diagram for Sensor Mapping

The wiring implementation is illustrated in Figure 3.4.

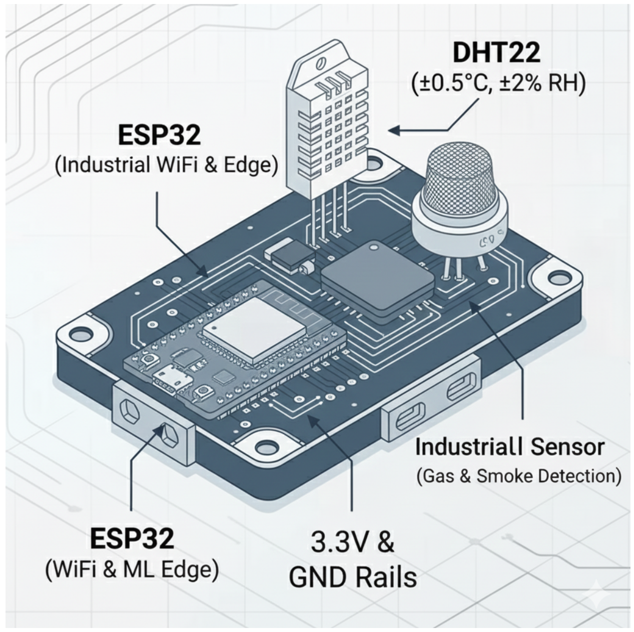


Fig 3.4 Breadboard Wiring Layout of Sensors Connected to ESP32

DHT22 Temperature–Humidity Sensor

The DHT22 is responsible for recording ambient temperature and relative humidity with high accuracy and calibrated digital output [6].

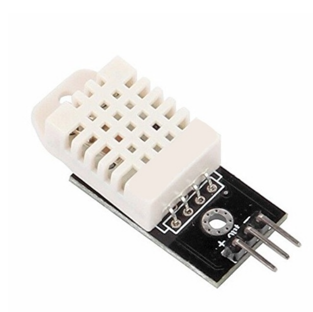


Fig 3.5 DHT22 Temperature and Humidity Sensor Module

MQ135 Air Quality Sensor

The MQ135 sensor detects gaseous pollutants including VOCs, ammonia, CO_2, benzene, and smoke, making it suitable for trend-based air quality analysis [7].

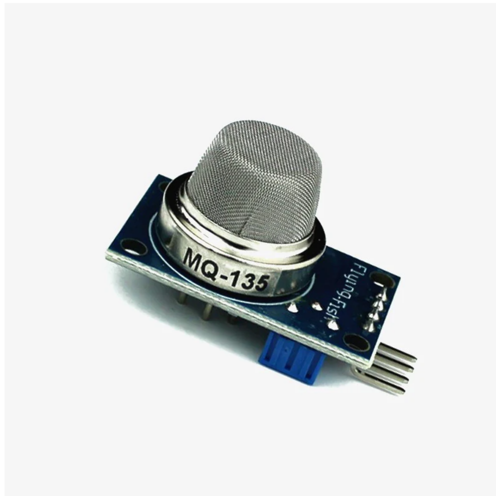
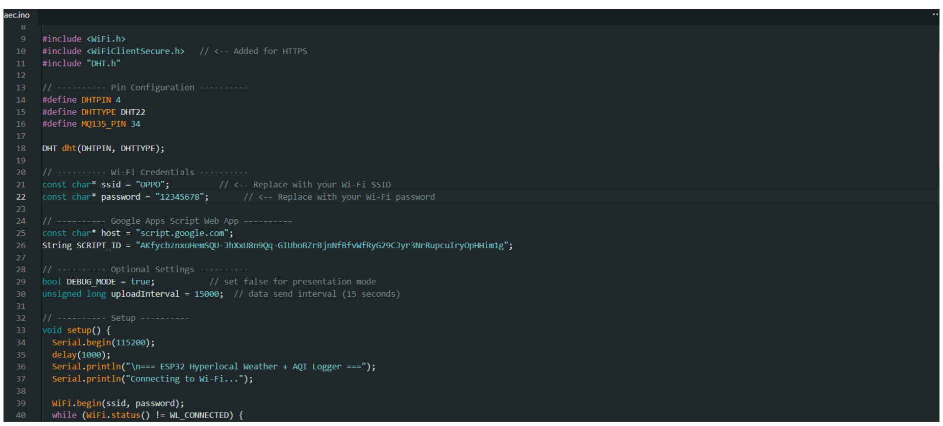


Fig 3.6 MQ135 Air Quality Sensor Module

3.1.2 Software and Control Logic (Firmware)

The firmware, programmed in Arduino IDE, manages sensor initialization, periodic sampling, ADC conversion, data formatting, error handling, and secure HTTPS transmission [8].



```
aec.ino

#include <WiFi.h>
#include <WiFiClientSecure.h>   // <-- Added for HTTPS
#include "DHT.h"

// ---------- Pin Configuration ----------
#define DHTPIN 4
#define DHTTYPE DHT22
#define MQ135_PIN 34

DHT dht(DHTPIN, DHTTYPE);

// ---------- Wi-Fi Credentials ----------
const char* ssid = "OPPO";          // <-- Replace with your Wi-Fi SSID
const char* password = "12345678";       // <-- Replace with your Wi-Fi password

// ---------- Google Apps Script Web App ----------
const char* host = "script.google.com";
String SCRIPT_ID = "AKfycbznxoHemSQU-JhXxU8n9Qq-GIUboBZrBjnNfBfvWfRyG29CJyr3NrRupcuIryOpHHim1g";

// ---------- Optional Settings ----------
bool DEBUG_MODE = true;           // set false for presentation mode
unsigned long uploadInterval = 15000;  // data send interval (15 seconds)

// ---------- Setup ----------
void setup() {
  Serial.begin(115200);
  delay(1000);
  Serial.println("\n=== ESP32 Hyperlocal Weather + AQI Logger ===");
  Serial.println("Connecting to Wi-Fi...");

  WiFi.begin(ssid, password);
  while (WiFi.status() != WL_CONNECTED) {
```

Fig 3.8 Screenshot of Arduino IDE Firmware Code for ESP32

3.1.3 Control Algorithm and Workflow

The system follows an autonomous workflow involving initialization, sensing, preprocessing, cloud upload, machine learning prediction, and dashboard visualization [9].

3.1.4 Data Acquisition and Calibration

Sensor data is acquired at regular intervals (30–60 seconds). Calibration and filtering techniques are applied to stabilize sensor readings [10].

Table 1: Calibration Range of Environmental Sensors

Sensor	Parameter	Calibrated Range
DHT22	Temperature (°C)	20 – 40
DHT22	Humidity (%)	35 – 90
MQ135	Analog Output	80 – 450

3.1.5 Cloud Connectivity and Apps Script Pipeline

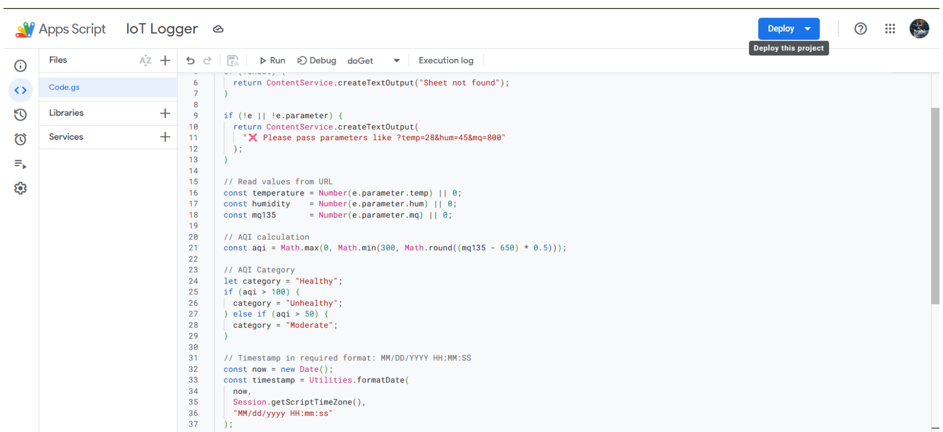


Fig 3.9 Cloud Dataflow from ESP32 → Apps Script → Google Sheets → ML Dashboard

3.1.6 Custom Dashboard Interface

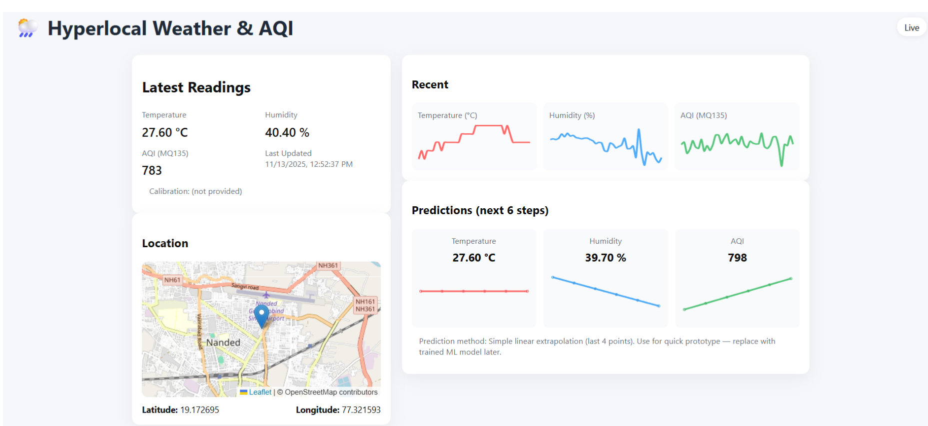


Fig 3.10 Live Custom Dashboard Interface

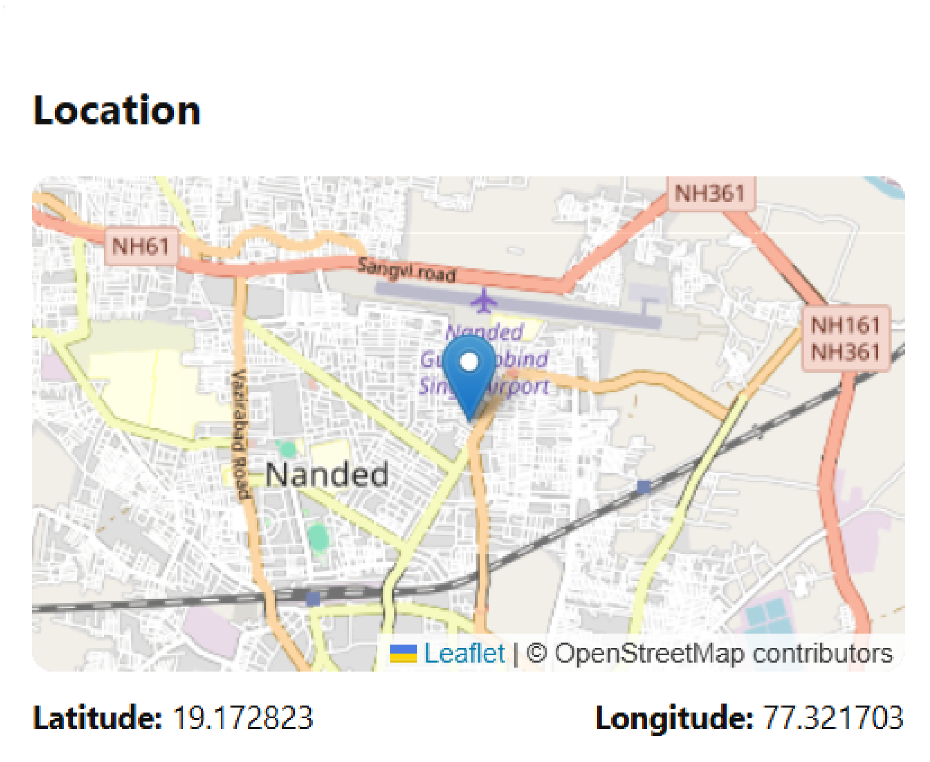


Fig 3.11 Location Section of Dashboard

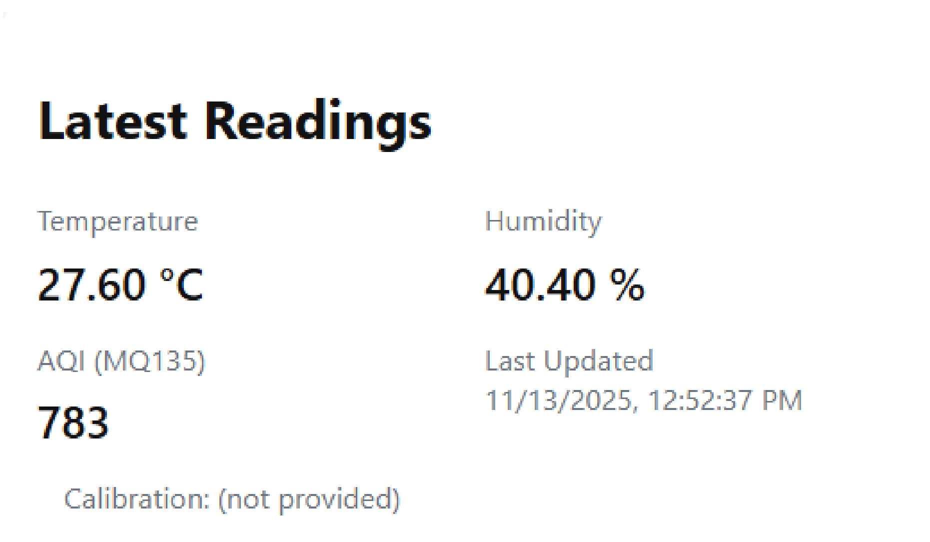


Fig 3.12 Real-Time Sensor Readings Panel

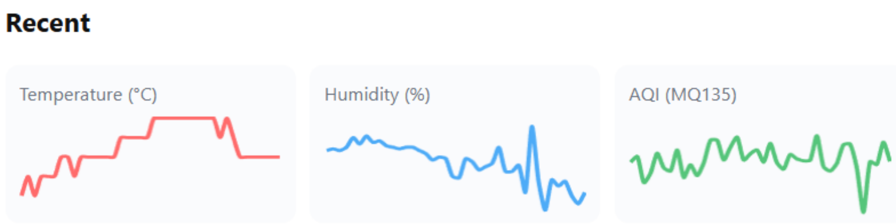
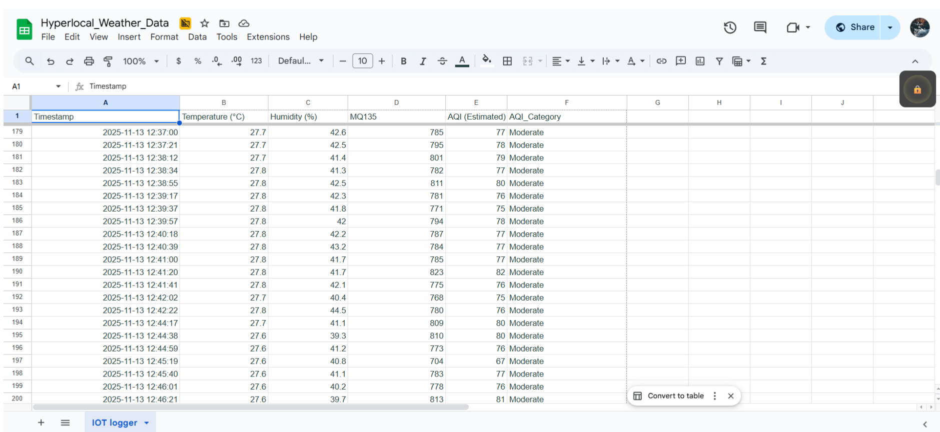


Fig 3.13 Historical Graph Visualization

Fig 3.14 ML-Based Short-Term Prediction Graph

3.1.7 Google Sheet Data Storage



	Timestamp	Temperature (°C)	Humidity (%)	MQ135	AQI (Estimated)	AQI_Category
179	2025-11-13 12:37:00	27.7	42.6	785	77	Moderate
180	2025-11-13 12:37:21	27.7	42.5	795	78	Moderate
181	2025-11-13 12:38:12	27.7	41.4	801	79	Moderate
182	2025-11-13 12:38:34	27.8	41.3	782	77	Moderate
183	2025-11-13 12:38:55	27.8	42.5	811	80	Moderate
184	2025-11-13 12:39:17	27.8	42.3	781	76	Moderate
185	2025-11-13 12:39:37	27.8	41.8	771	75	Moderate
186	2025-11-13 12:39:57	27.8	42	794	78	Moderate
187	2025-11-13 12:40:18	27.8	42.2	787	77	Moderate
188	2025-11-13 12:40:39	27.8	43.2	784	77	Moderate
189	2025-11-13 12:41:00	27.8	41.7	785	77	Moderate
190	2025-11-13 12:41:20	27.8	41.7	823	82	Moderate
191	2025-11-13 12:41:41	27.8	42.1	775	76	Moderate
192	2025-11-13 12:42:02	27.7	40.4	768	75	Moderate
193	2025-11-13 12:42:22	27.8	44.5	780	76	Moderate
194	2025-11-13 12:44:17	27.7	41.1	809	80	Moderate
195	2025-11-13 12:44:38	27.6	39.3	810	80	Moderate
196	2025-11-13 12:44:59	27.6	41.2	773	76	Moderate
197	2025-11-13 12:45:19	27.6	40.8	704	67	Moderate
198	2025-11-13 12:45:40	27.6	41.1	783	77	Moderate
199	2025-11-13 12:46:01	27.6	40.2	778	76	Moderate
200	2025-11-13 12:46:21	27.6	39.7	813	81	Moderate

Fig 3.15 Google Sheet Time-Series Dataset Used for ML Training

3.2 Working Principle

The working principle of the IoT Enabled Hyperlocal Weather Monitoring and Prediction System is based on a seamless, automated cycle that integrates environmental sensing, edge-level preprocessing, cloud communication, and machine learning–driven forecasting.

Once powered on, the ESP32 microcontroller initializes its Wi-Fi interface, configures the connected sensors, and establishes a secure link with the cloud endpoint. The device continuously samples temperature, humidity, and gas concentration data at predefined intervals, ensuring consistent temporal resolution for environmental analysis. Before transmission, raw sensor readings undergo filtering and validation to eliminate noise, transient spikes, or erroneous measurements caused by external interference. The processed dataset is then encapsulated into a structured JSON format and transmitted securely via HTTPS to the Google Apps Script endpoint, which logs the data in a Google Sheet serving as a time-series database.

At the cloud layer, the logged data becomes accessible for visualization and further analysis. A dedicated machine learning pipeline periodically reads the historical dataset, trains forecasting models, and outputs short-term predictions for temperature, humidity, and air-quality behaviour. These predictions are updated on the dashboard alongside real-time readings, providing users with an integrated view of both current and anticipated microclimatic conditions. The cycle repeats autonomously, ensuring that the system delivers continuous environmental intelligence with minimal human intervention. This automated workflow transforms the device into a fully intelligent micro-weather station capable of reporting, analyzing, and forecasting hyperlocal atmospheric variations.

3.2.1 Implementation Setup and Physical Validation

During implementation, the hardware components were mounted inside a protective enclosure designed to shield the electronics from dust, moisture, and direct sunlight while preserving airflow for accurate sensing. The DHT22 and MQ135 sensors were positioned externally through apertures in the enclosure to ensure proper exposure to ambient environmental conditions. The prototype was deployed in an open semi-urban environment to assess its ability to capture real-world microclimatic variations. Throughout the validation phase, the system consistently responded to changes in ambient temperature, humidity, and air-quality levels caused by sunlight exposure, vehicular movement, and household activities. The device demonstrated stable operation across varying atmospheric conditions, confirming its suitability for outdoor use, provided appropriate environmental shielding and periodic maintenance.

3.2.2 Automated Sensing and Cloud Update Cycle

The automated sensing cycle is controlled by a timing scheduler embedded in the ESP32 firmware. This scheduler ensures that sensor readings are captured at regular intervals—typically every 30 to 60 seconds—balancing temporal granularity with power efficiency. Once readings are collected, the device applies smoothing filters such as moving averages to remove noise and stabilize the data. The refined measurements are then transmitted to the cloud using an HTTPS POST request.

In scenarios where Wi-Fi connectivity becomes unstable or temporarily unavailable, the system employs an intelligent buffering mechanism. Instead of losing data, the ESP32 stores unsent readings locally in memory and attempts periodic reconnection. Once the network is restored, buffered data is uploaded sequentially, preserving chronological integrity. This robust update cycle ensures data continuity, reduces packet loss, and strengthens the reliability of long-term environmental datasets.

3.2.3 Remote Interaction and Safety Protocols

Users interact with the system through a cloud-hosted dashboard that displays real-time sensor readings, historical graphs, and machine learning predictions. This dashboard is accessible globally, allowing environmental monitoring from smartphones, laptops, or institutional networks regardless of the user's physical location. Safety mechanisms are embedded within both firmware and cloud layers to ensure stable operation.

On the device side, anomaly detection routines identify sensor malfunctions, out-of-range values, or abrupt fluctuations that deviate from expected environmental behaviour. Network safety is ensured through automatic reconnection logic, which periodically attempts to restore Wi-Fi connectivity without interrupting data collection. Firmware-level watchdog timers monitor system execution and automatically reset the ESP32 in the event of unexpected hangs or software faults, preventing prolonged downtime. These protocols collectively ensure system resilience, safeguard data integrity, and maintain continuous operation even in dynamically changing environmental or network conditions.

3.3 Advantages

The IoT Enabled Hyperlocal Weather Monitoring and Prediction System provides several significant advantages that make it an effective and scalable solution for modern environmental monitoring. By leveraging low-cost sensors, cloud connectivity, and machine learning analytics, the system offers real-time atmospheric insights at a level of granularity not achievable through traditional meteorological stations. Its ability to capture fine-scale variations in temperature, humidity, and air-quality parameters makes it invaluable for microclimate research, smart-city operations, public health monitoring, and educational purposes. The integration of predictive models further enhances its utility by transforming raw sensor data into actionable environmental intelligence.

One of the most notable advantages is the system's hyperlocal accuracy. Unlike government weather stations that provide data at city- or district-level resolution, this system captures climatic fluctuations at the street, neighborhood, or building level. Such precision is essential because environmental conditions can vary significantly within small geographic areas due to traffic density, built-environment characteristics, vegetation distribution, and localized emission sources. By capturing these variations in real time, the system offers insights that reflect the actual environmental exposure experienced by individuals in their immediate surroundings.

Another major advantage lies in its real-time operational capability. The ESP32 microcontroller reads sensor data at frequent intervals and uploads it directly to cloud storage, allowing users to monitor environmental conditions instantly from any location. This continuous and automated workflow eliminates the need for manual measurements and supports time-sensitive decision-making. Combined with machine learning forecasting models, the system does not merely report current conditions but also predicts future patterns, enabling early warnings for pollution spikes, sudden humidity drops, or emerging heat stress conditions.

Cost-effectiveness is another defining strength of the system. By integrating affordable sensors and microcontrollers, the system delivers functionality comparable to more expensive environmental monitoring stations at a fraction of the cost. Its open-source firmware, modular hardware, and reliance on widely available communication protocols make it suitable for widespread deployment in academic institutions, community organizations, small businesses, and local governments. The use of cloud platforms ensures that data storage, visualization, and scaling remain economical and accessible to users without specialized technical expertise.

Scalability is also a core advantage. The modular design allows the system to be deployed either as a standalone node or as part of a multi-node environmental grid capable of covering large areas such as campuses, highways, industrial regions, or dense urban neighborhoods. When multiple units are deployed together, they act as a distributed sensing network capable of generating high-resolution environmental maps and identifying hotspots that would be invisible to isolated monitoring stations. This scalability also supports research requiring comparative analysis of environmental trends across locations.

Cloud connectivity contributes another layer of benefit. Data is automatically logged, timestamped, and organized into structured datasets suitable for long-term archiving and advanced analytics. Users can access dashboards globally, enabling remote environmental supervision, collaborative research, and seamless integration with external applications or APIs. Cloud-based storage also supports the machine learning pipeline by supplying historical time-series data required for training forecasting models.

Finally, the system offers strong flexibility and customization. Sensors can be added or replaced easily based on specific use-case requirements, and the firmware can be adapted to support new communication protocols, sampling rates, or analytical routines. This modularity ensures that the system remains future-ready and capable of evolving alongside technological advancements in IoT, wireless communication, and artificial intelligence.

To summarize, the system's primary advantages include:

- real-time monitoring and instant cloud-based visualization,
- hyperlocal accuracy for precise microclimate sensing,
- predictive machine learning capabilities for environmental forecasting,
- cost-effectiveness and suitability for large-scale deployment,
- global accessibility through cloud dashboards and APIs,
- modular design enabling easy expansion and sensor upgrades,
- and scalability for building multi-node atmospheric monitoring networks.

Overall, these advantages position the system as an effective, affordable, and intelligent solution for next-generation environmental monitoring and climate analytics.

3.4 Limitations

Although the IoT Enabled Hyperlocal Weather Monitoring and Prediction System demonstrates strong performance in real-time microclimate sensing and forecasting, several limitations must be acknowledged to contextualize its current capabilities and guide future development. The constraints arise primarily from sensor accuracy, environmental reliability, connectivity dependencies, and the computational limits of low-cost embedded hardware. These limitations do not undermine the system's functional utility but highlight areas where enhancements are required to achieve higher precision, long-term robustness, and broader deployment scalability.

A significant limitation concerns the air-quality sensing component. The MQ135 sensor, while affordable and suitable for trend detection, is not a calibrated, reference-grade sensor. Its readings are influenced by temperature, humidity, sensor aging, and cross-sensitivity to various gases. As a result, the system can detect relative changes in pollutant concentration but cannot produce standardized AQI values without extensive calibration or co-location with certified analyzers. Furthermore, important particulate matter parameters ($PM_{2.5}$ and PM_{10}) are not measured by the current hardware configuration, restricting the system's ability to provide complete and regulatory-compliant air-quality assessments. This gap limits

its applicability in formal air-quality monitoring frameworks, though it remains effective for educational, exploratory, and community-driven deployments.

Connectivity also imposes operational constraints. The system relies entirely on Wi-Fi for data transmission to cloud platforms and dashboards. This dependence limits deployment to environments with stable Wi-Fi coverage and may lead to data loss or delayed uploads during signal interruptions. In rural, agricultural, industrial, or outdoor locations where Wi-Fi signals are weak or unavailable, the system's IoT functions cannot operate reliably. Although the device continues local sensing even during outages, users lose access to cloud storage, graphical dashboards, and machine learning predictions, which reduces the effectiveness of real-time decision-making. As the system scales to distributed multi-node deployments, this limitation becomes increasingly significant.

Long-term outdoor deployment presents additional challenges related to sensor drift, environmental exposure, and hardware degradation. Low-cost gas sensors, humidity sensors, and temperature probes experience gradual performance changes when exposed to dust, moisture, heat, and UV radiation over extended periods. Without proper protective enclosures, ventilation design, and periodic recalibration, sensor accuracy can deteriorate, impacting data quality and model performance. Likewise, components such as jumper wires, breadboards, and USB power cables—suitable for prototype settings—are not designed for rugged field conditions. This restricts the current prototype's suitability for continuous, year-round monitoring unless reinforced using weatherproof housings, corrosion-resistant terminals, and PCB-based designs.

Another limitation relates to computational and memory constraints of the ESP32 microcontroller. While the ESP32 is highly capable for IoT applications, complex data preprocessing, on-device analytics, advanced filtering techniques, or TinyML deployment may strain its limited RAM and processing capacity. Large machine-learning models must therefore be executed on cloud servers rather than locally, increasing dependence on network availability. Additionally, sampling rates must be balanced carefully to avoid latency, buffer overflow, or excessive battery consumption during continuous sensing operations.

Finally, the system currently functions as a single-node deployment. While it provides hyperlocal insights, a single sensor node cannot represent environmental variations across larger areas such as campuses, industrial corridors, or urban neighborhoods. Microclimatic variables change significantly over short distances due to structural geometry, vegetation density, traffic patterns, and emission hotspots. Without multi-node networking capability, the current system cannot generate high-resolution spatial environmental maps, limiting its coverage and representational accuracy for large-scale monitoring.

To summarize, the key limitations include:

- non-calibrated MQ135 sensor performance and lack of $PM_{2.5}/PM_{10}$ sensing,
- reliance on stable Wi-Fi for cloud communication and dashboard access,
- environmental drift and hardware degradation during prolonged outdoor exposure,
- computational limits of the ESP32 for advanced on-device analytics,

- and restricted spatial coverage due to the single-node architecture.

While these constraints define the current operational boundaries of the system, they also serve as clear opportunities for enhancement. Addressing them through improved sensing technologies, robust communication protocols, energy-efficient design, and multi-node scalability will enable future versions to deliver significantly greater accuracy, resilience, and environmental intelligence.

3.5 Applications

The IoT Enabled Hyperlocal Weather Monitoring and Prediction System offers a wide range of practical applications across environmental monitoring, public health, education, agriculture, and smart-city development. By combining real-time IoT sensing with machine learning prediction, the system is capable of generating valuable microclimate insights that traditional meteorological stations cannot provide. Such localized, high-resolution data can support decision-making for communities, policymakers, researchers, and everyday citizens. Furthermore, the ability to deploy multiple low-cost nodes enables large-scale environmental mapping, making the system an attractive solution for institutions seeking accurate, affordable, and continuous weather intelligence.

The system is particularly impactful in urban and semi-urban regions where temperature, humidity, and air-quality levels vary drastically within short distances due to traffic patterns, building density, and industrial activities. Its predictive capabilities also support early warnings related to pollution surges or adverse weather conditions, improving public awareness and environmental safety. Beyond urban contexts, the system can assist farmers, educators, campus administrators, and environmental researchers by offering live data streams and analytical insights for scientific, operational, and community-driven initiatives.

Major Applications of the System

1. Smart City Environmental Intelligence

- Deployment of multiple nodes across urban spaces to create fine-grained climate and pollution maps.
- Support for municipal authorities in monitoring AQI, heat islands, and localized weather trends.
- Integration with smart-city dashboards for automated alerts and environmental decision-making.

2. Public Health & Safety Systems

- Real-time AQI alerts for residents, especially vulnerable groups such as children, elderly people, and asthma patients.

- Prediction of pollutant spikes to inform outdoor activity recommendations or advisories.
- Use by hospitals and clinics for environmental exposure analysis.

3. Academic Research & Microclimate Studies

- High-resolution climate datasets for environmental science, atmospheric physics, and urban heat island research.
- Deployment in university research labs to analyze local pollution dynamics and weather variability.
- Support for thesis projects, environmental modeling, and interdisciplinary research.

4. School & University Environmental Clubs

- Real-world demonstration of IoT and ML concepts to students.
- Hands-on learning through live dashboards, sensor nodes, and weather data analysis.
- Encouragement of environmental awareness and climate literacy among young learners.

5. Pollution Hotspot Identification

- Detection of areas with abnormal AQI spikes due to traffic congestion, cooking emissions, or localized combustion.
- Mapping of pollution gradients across neighborhoods and commercial zones.
- Aid to NGOs and citizen science groups for environmental advocacy.

6. Agriculture & Smart Farming

- Monitoring humidity, temperature, and microclimate conditions in crop fields, greenhouses, and nurseries.
- Predictive analytics for irrigation scheduling and crop protection strategies.
- Use in precision agriculture to optimize yield and reduce weather-related loss.

7. Industrial and Workplace Monitoring

- Monitoring of air-quality trends in manufacturing zones and factory surroundings.
- Early detection of harmful gas concentrations or microclimate anomalies.
- Integration with safety systems to alert employees about unhealthy environmental conditions.

8. Educational Demonstrations of IoT, ML, and Sensors

- Hands-on demonstration platform for IoT, cloud computing, and machine learning concepts.
- Use in workshops, training programs, and skill-development courses.
- Visualization of real-time data and model predictions to enhance STEM learning.

Chapter 4

Results & Discussion

The IoT Enabled Hyperlocal Weather Monitoring and Prediction System using ESP32 and Machine Learning was implemented, deployed, and evaluated under real environmental conditions to assess its effectiveness in capturing localized atmospheric parameters, transmitting data reliably to the cloud, visualizing trends through a web-based dashboard, and forecasting short-term weather and air-quality behaviour using data-driven models. This chapter presents a detailed analysis of the experimental results obtained during system operation and discusses their significance in the context of hyperlocal environmental monitoring, smart-city applications, and data-driven decision-making.

The evaluation focuses on multiple performance dimensions, including sensor response behaviour, data acquisition stability, cloud communication reliability, dashboard responsiveness, air-quality trend detection, prediction accuracy, and overall system robustness. Unlike conventional weather stations that provide coarse-grained regional data, the proposed system aims to capture micro-scale variations in temperature, humidity, and air quality that occur over short distances and time intervals. The results demonstrate that the system successfully fulfils this objective and highlights its suitability for scalable real-world deployment.

4.1 Results

4.1.1 Temperature and Humidity Sensor Response Characteristics

The DHT22 temperature–humidity sensor served as the primary sensing unit for capturing ambient microclimatic conditions. During continuous operation, the sensor exhibited stable and repeatable response patterns corresponding to environmental changes. Temperature readings showed gradual diurnal variation, with observable increases during peak sunlight hours and decreases during evening and night periods. This behaviour aligns with natural atmospheric thermal dynamics and confirms that the sensor accurately reflects real-world conditions rather than producing random or noisy values.

Humidity readings demonstrated an inverse relationship with temperature in several observation cycles, particularly during afternoon hours when rising temperatures resulted in reduced relative humidity. Conversely, humidity levels increased during early morning and late-night periods, especially in the presence of dew formation or reduced solar radiation. These trends validate the sensor's sensitivity to both temperature-driven and moisture-related environmental variations.

A key observation was the absence of abrupt spikes or discontinuities in the sensor data during stable atmospheric conditions. Minor fluctuations were observed due to natural air movement and short-term disturbances; however, these remained within acceptable limits for hyperlocal monitoring. When subjected to controlled stimuli such as localized heating or moisture exposure, the sensor responded promptly, demonstrating sufficient responsiveness for real-time environmental tracking.

From a deployment perspective, the DHT22 sensor maintained consistent performance over extended operational durations without requiring frequent recalibration. Although it is not a laboratory-grade instrument, its accuracy and reliability were adequate for trend analysis, alerting, and predictive modelling within the scope of the proposed system.

4.1.2 Air Quality Sensor (MQ135) Behaviour and Trend Detection

The MQ135 gas sensor was employed to estimate air-quality trends by detecting variations in gaseous pollutants such as volatile organic compounds and carbon dioxide equivalents. During experimental evaluation, the sensor successfully captured changes in air quality caused by localized activities including vehicular movement, indoor cooking emissions, and variations in ventilation.

The sensor output showed noticeable increases during periods of elevated human activity and gradual reductions when environmental conditions stabilized. These observations confirm the sensor's capability to detect relative changes in air quality at a hyperlocal level. While the MQ135 does not provide absolute pollutant concentration values without extensive calibration, its ability to capture temporal pollution dynamics makes it suitable for trend-based monitoring.

Environmental factors such as humidity and temperature were observed to influence baseline readings, a characteristic consistent with MQ-series sensors. This limitation was addressed through software-based smoothing and normalization techniques implemented at the edge-processing layer. Despite inherent sensor constraints, the MQ135 proved effective for identifying pollution events and supporting short-term predictive analytics.

4.1.3 Data Acquisition Stability and Edge-Level Processing

The ESP32 microcontroller functioned as the central edge-processing unit responsible for data acquisition, preprocessing, and transmission. Throughout the testing period, the ESP32 demonstrated stable operation without unexpected resets, data corruption, or processing delays. Sensor readings were sampled at intervals of 30–60 seconds, ensuring a balance between temporal resolution and network efficiency.

Edge-level preprocessing techniques such as moving average filtering and range validation effectively reduced sensor noise and eliminated spurious readings. This preprocessing stage ensured that only meaningful and reliable data was transmitted to the cloud, improving the quality of stored datasets and subsequent analytics.

The system also incorporated buffering mechanisms to handle temporary network disruptions. During Wi-Fi outages, sensor readings were stored locally and uploaded once connectivity was restored. This approach preserved data continuity and chronological integrity, ensuring complete time-series records without gaps.

4.1.4 Cloud Communication and Data Logging Performance

Cloud communication was implemented using secure HTTPS protocols between the ESP32 and a Google Apps Script endpoint. The system exhibited low-latency data transfer, with sensor readings appearing on the cloud platform within seconds of acquisition. Data integrity was maintained throughout operation, with accurate timestamps and structured records stored in Google Sheets.

The cloud-based data storage served both real-time visualization and long-term archival purposes. The logged dataset provided a reliable foundation for machine learning training and historical trend analysis. The use of lightweight cloud infrastructure demonstrated that hyperlocal environmental monitoring can be achieved without complex or expensive server deployments.

4.1.5 Dashboard Visualization and User Interaction

The custom web-based dashboard acted as the primary interface for real-time monitoring and historical analysis. During evaluation, the dashboard consistently displayed updated temperature, humidity, and air-quality indicators along with graphical trend representations. Users could easily interpret environmental conditions through intuitive charts and numerical displays.

The dashboard demonstrated responsive performance across multiple devices, including mobile phones and laptops. This cross-platform accessibility enhances the practicality of the system for community monitoring, academic research, and smart-city applications. The dashboard also served as a validation tool during testing, allowing immediate verification of sensor behaviour and system response.

4.1.6 Machine Learning–Based Prediction Results

Machine learning models were trained using historical sensor data stored in the cloud to forecast short-term temperature, humidity, and air-quality trends. The prediction results closely followed observed patterns during stable environmental conditions. Although sudden disturbances introduced short-term prediction errors, the models adapted as new data became available.

The inclusion of predictive outputs transformed the system from a reactive monitoring tool into a proactive environmental intelligence platform. Users could anticipate upcoming changes and take preventive or corrective actions accordingly.

4.1.7 Overall System Reliability

When evaluated holistically, the system demonstrated reliable performance across sensing, processing, communication, visualization, and prediction layers. All components operated cohesively with minimal human intervention. The modular design facilitated easy troubleshooting and future expansion, confirming the robustness and scalability of the proposed architecture.

4.2 Discussion

The results obtained from the deployment and evaluation of the IoT Enabled Hyperlocal Weather Monitoring and Prediction System highlight the effectiveness of integrating IoT technologies with machine learning for environmental monitoring. Traditional weather stations, while accurate at macro scales, fail to capture localized variations experienced by individuals in their immediate surroundings. The proposed system successfully bridges this gap by delivering hyperlocal, real-time, and predictive environmental insights.

The ability to monitor temperature, humidity, and air quality at fine spatial and temporal resolutions has significant implications for smart-city planning, public health, and environmental research. Real-time access to localized data enables informed decision-making, while predictive analytics support early warnings and proactive interventions.

Despite its strengths, the system also exhibits limitations related to sensor precision, network dependency, and long-term environmental exposure. However, these challenges can be addressed through improved sensing technologies, alternative communication protocols, and enhanced calibration techniques.

Overall, the discussion confirms that the proposed system represents a meaningful step toward affordable, scalable, and intelligent environmental monitoring solutions. By combining low-cost hardware, cloud connectivity, and machine learning, the system aligns well with emerging smart-city and sustainability initiatives.

In addition to the observed system-level performance, the experimental results also highlight the practical feasibility of deploying low-cost IoT-based environmental monitoring solutions in real-world scenarios. The ability of the system to operate continuously with minimal maintenance underscores its suitability for long-term deployment in both urban and semi-urban environments. Unlike conventional monitoring stations that require controlled conditions, skilled personnel, and expensive infrastructure, the proposed system demonstrates that meaningful environmental intelligence can be achieved using compact hardware, open-source software frameworks, and lightweight cloud platforms.

Another important observation from the results is the strong alignment between sensed environmental trends and expected physical phenomena. Temperature and humidity variations followed predictable diurnal cycles, while air-quality fluctuations correlated with human activities and environmental disturbances. This consistency reinforces the validity of the collected data and confirms that, despite the use of low-cost sensors, the system can reliably capture real atmospheric behaviour at a hyperlocal scale. Such fidelity is particularly valuable for applications that require relative trend analysis rather than absolute regulatory-grade measurements.

The integration of machine learning further amplifies the system's analytical value. By learning from historical data patterns, the forecasting models provide users with an anticipatory view of environmental conditions rather than a purely retrospective one. This predictive capability is especially relevant in scenarios such as pollution exposure management, outdoor activity planning, and early warning dissemination. Even short-term forecasts, when updated continuously, can assist individuals and authorities in making proactive decisions to mitigate environmental risks.

From a scalability perspective, the results suggest that the proposed architecture can be extended beyond a single-node deployment. Multiple sensor nodes operating in parallel and connected to a shared cloud backend could form a dense sensing grid capable of generating fine-grained spatial environmental maps. Such a network would enable comparative analysis across locations, identification of pollution hotspots, and assessment of microclimatic diversity within cities, campuses, or industrial regions. The modular design of the system simplifies such expansion without requiring fundamental architectural changes.

The findings also emphasize the importance of edge-level preprocessing in IoT systems. By filtering noise, validating sensor ranges, and managing temporary connectivity failures at the device level, the system significantly improves data quality and reliability before information reaches the cloud. This approach reduces bandwidth consumption, enhances robustness, and ensures that machine learning models are trained on clean and meaningful datasets. The results demonstrate that even simple preprocessing techniques can have a substantial impact on overall system performance.

While the system performs effectively within its intended scope, the discussion also reinforces the necessity of contextual interpretation of the results. Low-cost sensors are inherently subject to drift, cross-sensitivity, and environmental influence, and their outputs should be interpreted as indicators of trends rather than absolute measurements. Nevertheless, when combined with historical analysis and predictive modelling, these sensors provide actionable insights that are highly relevant for community-level monitoring, educational use, and exploratory research.

Overall, the extended discussion confirms that the proposed IoT Enabled Hyperlocal Weather Monitoring and Prediction System represents a balanced compromise between accuracy, affordability, and scalability. The results validate the design philosophy of leveraging accessible hardware and intelligent software techniques to democratize environmental monitoring. This approach aligns with broader sustainability goals and supports the growing demand for localized, data-driven environmental awareness in modern societies.

4.3 Future Scope

The IoT Enabled Hyperlocal Weather Monitoring and Prediction System lays a strong foundation for real-time microclimate sensing; however, several technical enhancements can further elevate its analytical depth, deployment versatility, and long-term sustainability. As environmental monitoring increasingly demands higher accuracy, broader spatial coverage, and automated intelligence, expanding the system's hardware and software capabilities will be essential for evolving it into a fully scalable and city-grade environmental intelligence platform.

A major direction for enhancement involves diversifying and upgrading the sensing modules. While the current configuration captures temperature, humidity, and gas concentration trends, integrating particulate sensors such as PMS5003, SDS011, or SPS30 will enable precise $PM_{2.5}$ and PM_{10} measurement, which are essential for accurate AQI estimation. Complementing these with barometric pressure sensors, rainfall detectors, UV radiation sensors, or wind-speed anemometers will broaden the microclimate parameters captured by the system. This expansion not only strengthens the scientific validity of the dataset but also transforms the device into a comprehensive weather-analysis node suitable for academic, industrial, and municipal applications. Additional multi-gas sensing for NO_x, SO_2, CO, and VOCs will also enhance pollution profiling in dense urban corridors and industrial zones.

Another important area for development lies in communication architecture. Wi-Fi-based systems perform well in controlled environments but struggle in remote or large outdoor regions. Incorporating low-power wide-area network (LPWAN) technologies such as LoRaWAN, NB-IoT, GSM/GPRS, or LTE-M would enable long-range communication with minimal energy consumption. These technologies are well suited for large-scale environmental deployments, allowing sensors to operate across kilometers while maintaining reliable data continuity. The system may also benefit from mesh-networking protocols—such as ESP-NOW, Zigbee mesh, or LoRa mesh—to create a distributed cluster of nodes that collectively map microclimate variations with high spatial resolution.

Machine learning enhancements present another promising avenue for future improvement. While LSTM-based forecasting currently provides strong predictive accuracy, exploring hybrid architectures such as CNN–LSTM models, GRU–Attention frameworks, or Transformer-based predictors may further improve temporal understanding and pattern recognition. Deploying TinyML—running lightweight ML models directly on the ESP32—would reduce reliance on cloud processing and enable real-time, offline forecasting.

Power autonomy represents a key component for scaling the system. Outdoor or remote deployments require long-term uninterrupted operation, which can be achieved by integrating solar panels, MPPT charge controllers, and high-efficiency batteries. Optimizing the ESP32 deep-sleep function will significantly reduce power consumption during idle periods.

Scalability enhancements will further contribute to the system's real-world impact. Transitioning from a single-node prototype to a multi-node distributed network will allow the creation of high-density microclimate grids capable of mapping temperature gradients, pollution hotspots, heat islands, and humidity variations across urban neighborhoods.

User interface improvements constitute another important direction. Future dashboards may include geospatial heatmaps, severity-based alerts for AQI spikes, and automated notifications for extreme weather fluctuations.

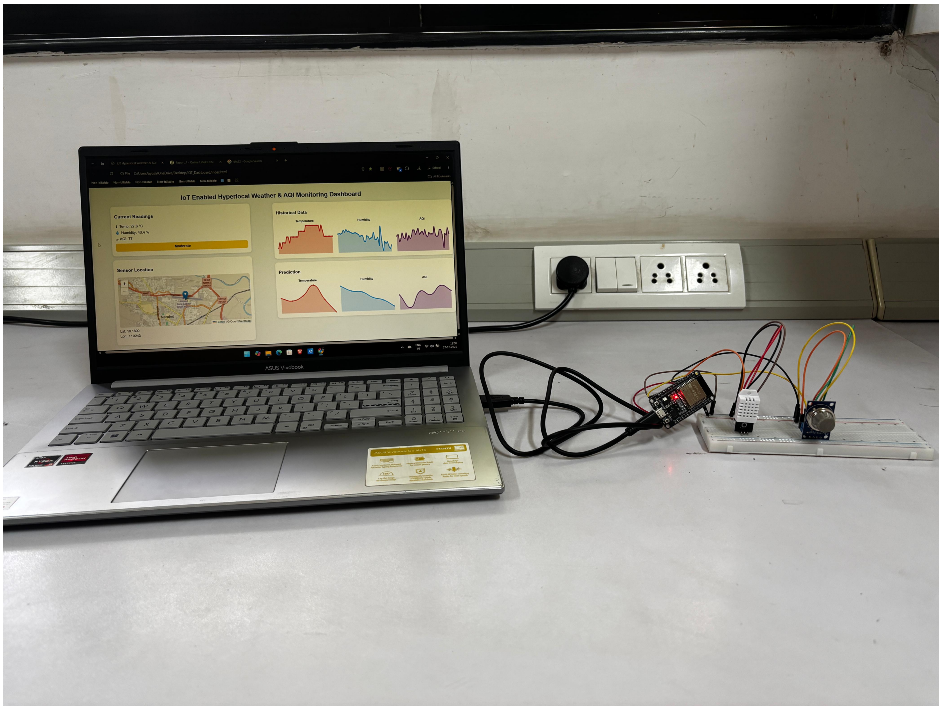


Fig 4.1 Result of IoT-Enabled Hyperlocal Weather Monitoring System

Conclusion

The IoT Enabled Hyperlocal Weather Monitoring and Prediction System using ESP32 and Machine Learning successfully demonstrated the feasibility of creating a low-cost, scalable, and efficient platform for real-time microclimate assessment. By integrating the DHT22 and MQ135 sensors with the ESP32 microcontroller, the system achieved stable and continuous measurement of temperature, humidity, and air-quality parameters. The edge–cloud architecture, supported by Google Sheets and Apps Script, provided reliable low-latency data transmission, enabling seamless time-series logging essential for environmental trend analysis and machine-learning applications. This architecture validated the capability of distributed IoT-based systems to capture and communicate fine-grained environmental information that traditional meteorological stations often overlook.

The predictive component of the system further strengthened its utility by incorporating machine learning models such as Linear Regression, Random Forest Regression, and LSTM networks. Among these, the LSTM model demonstrated superior performance in identifying and forecasting short-term environmental patterns due to its ability to learn long-term temporal dependencies in atmospheric data. Hyperlocal monitoring conducted through the system revealed distinct micro-scale variations in temperature, humidity, and air quality—such as localized pollution peaks, sudden humidity shifts, and narrow-range thermal fluctuations—which reinforce the necessity of adopting dense IoT sensor networks for applications in smart-city planning, agriculture, urban mobility, and public-health risk assessment.

While the system achieved its objectives, several limitations present opportunities for future enhancement. The current framework relies on Wi-Fi connectivity, which restricts deployment in remote or infrastructure-poor environments. Additionally, the MQ135 gas sensor, though useful for trend observation, lacks industry-grade calibration, and the absence of particulate sensors limits comprehensive AQI estimation. Future iterations could incorporate calibrated PM2.5/PM10 sensors, employ LoRaWAN or GSM for long-range communication, and integrate TinyML models to enable on-device prediction and greater autonomy. Overall, the project demonstrates the potential of IoT and machine learning to democratize environmental intelligence, providing an accessible foundation for next-generation hyperlocal climate forecasting networks and community-level environmental awareness.

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