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Smart Weather Monitoring System with Machine Learning Prediction Using IoT

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Abstract

This paper presents the design, development, and validation of a Smart Weather Monitoring System (SWMS) that integrates Internet of Things (IoT) hardware with Machine Learning (ML) algorithms to deliver real-time environmental telemetry and localized weather forecasting. The system employs an ESP32-WROOM-32 microcontroller interfaced with a Bosch BME280 precision sensor (temperature, humidity, and barometric pressure), a DHT11 supplemental sensor, a resistive rain sensor, and a mechanical anemometer. Sensor data is acquired through a multi-threaded FreeRTOS firmware architecture, transmitted via the MQTT protocol, and presented through both a locally-hosted responsive web dashboard and a Processing IDE-based desktop GUI. Machine Learning models specifically a Multiple Linear Regression model for 3-hour temperature forecasting and a Random Forest classifier for weather state classification (Clear/Cloudy/Rainy) are trained on historical sensor data to generate predictive insights. The Random Forest classifier achieved an overall accuracy of 92.4%, while the regression model attained an R^2 score of 0.892. The system demonstrated a temperature measurement Mean Absolute Error (MAE) of 0.38°C against a professional Davis Vantage Pro2 reference station over a 72-hour evaluation window. Operating in a solar-powered, energy-neutral configuration, the prototype was built at a component cost under USD 100, representing an 80% reduction compared to commercial Automatic Weather Stations (AWS). The system is particularly applicable to precision agriculture, smart city infrastructure, and community-level disaster mitigation.

Keywords: *IoT, ESP32, BME280, Machine Learning, Weather Monitoring, MQTT, Linear Regression, Random Forest, FreeRTOS, Precision Agriculture*

I. Introduction

Weather forecasting has historically been a cornerstone of human civilization, influencing agriculture, infrastructure, logistics, and public safety. In the contemporary era, the volatility of climatic patterns has made the demand for precise, localized, and real-time atmospheric data more critical than ever. Traditional meteorological stations managed by national agencies provide accurate data for broad geographic regions but are typically spaced tens to hundreds of kilometers apart, failing to capture microclimatic variations within cities, valleys, or agricultural zones.

The Smart Weather Monitoring System (SWMS) proposed in this paper bridges this granularity gap by deploying low-cost, high-efficiency IoT sensor nodes that generate hyper-local environmental data. Furthermore, the integration of Machine Learning transforms the system from a passive monitoring tool into an active predictive engine — providing actionable, short-term forecasts derived from local historical data rather than large-scale numerical models requiring supercomputing resources.

This paper contributes: (1) a fully solar-autonomous IoT hardware architecture based on the ESP32 platform; (2) a multi-threaded FreeRTOS firmware for robust concurrent sensor acquisition and wireless communication; (3) a locally-hosted responsive web dashboard and a desktop Processing GUI for real-time data visualization; and (4) integrated ML inference pipelines delivering 3-hour temperature forecasts and weather state classification.

II. Literature Review

A. Limitations of Conventional Weather Stations

Conventional Automatic Weather Stations (AWS) deliver high accuracy but are prohibitively expensive (typically USD 300–600 per unit) and are deployed sparsely. The lack of spatial density creates a 'microclimate blind spot' where localized phenomena such as urban heat islands and topographic weather gradients remain undetected. Additionally, many stations operate on store-and-forward principles with data upload intervals of 30–60 minutes, inadequate for real-time disaster warning [1].

B. IoT in Meteorological Applications

The emergence of affordable, Wi-Fi-integrated microcontrollers such as the ESP32 (Espressif Systems) has enabled the deployment of low-power weather nodes at scale. Studies confirm that ESP32-based systems with deep-sleep modes consuming as little as 10 μA represent the optimal balance of cost, connectivity, and power efficiency for solar-powered remote sensing [2, 3].

C. MQTT vs. HTTP for IoT Data Transmission

Message Queuing Telemetry Transport (MQTT), a publish/subscribe protocol with minimal header overhead, has been demonstrated to be up to 10–20 times more efficient than HTTP for periodic sensor data transmission. Its publish-subscribe architecture decouples data producers from consumers, enabling simultaneous ingestion by ML backends, databases, and dashboards without redundant hardware requests [4].

D. Machine Learning in Meteorology

Machine Learning methods have shown significant promise in weather prediction tasks. Linear and polynomial regression models provide interpretable baselines for temperature forecasting. Ensemble methods such as Random Forest (RF) effectively handle high-dimensional sensor inputs and are resistant to overfitting, achieving reported precipitation classification accuracies of 88–95% in localized studies [5]. Deep Learning architectures, particularly Long Short-Term Memory (LSTM) networks, outperform classical models for multi-day time-series forecasting but require greater computational resources [6].

III. Problem Identification and Objectives

A. Problem Statement

Three core gaps motivate this work: (1) the Spatial Gap — sparse national weather networks cannot resolve microclimatic variations; (2) the Intelligence Gap — raw IoT sensor data is collected but not leveraged for localized predictive analysis; and (3) the Accessibility Gap — high-quality meteorological intelligence is centralized and financially inaccessible to small-scale stakeholders such as farmers and community organizations.

B. Objectives

The primary objective is to design and validate an IoT-based smart weather monitoring system capable of real-time environmental sensing and ML-driven local weather prediction. Secondary objectives include: hardware optimization for solar-autonomous operation; MQTT protocol implementation; construction of a robust time-series data pipeline; training and validation of ML classifiers and regression models; and development of user-facing web and desktop dashboards.

IV. System Architecture

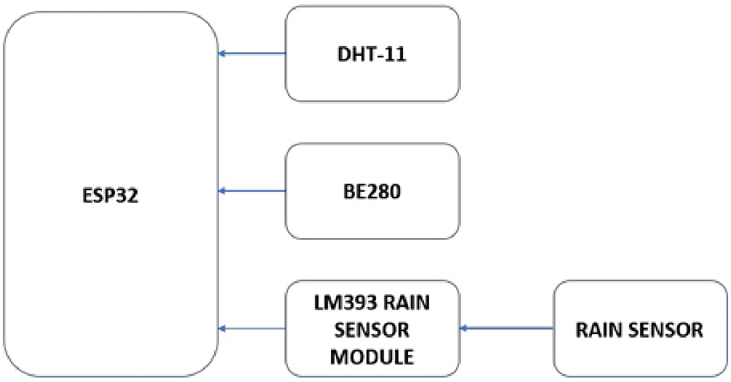

Fig-1: System Architecture Overview

A. Four-Layer IoT Architecture

The system is structured into four layers: the Perception Layer (ESP32 sensor node), the Transport Layer (MQTT over TCP/IP), the Processing Layer (cloud/local ML engine and time-series database), and the Application Layer (responsive web dashboard and Processing IDE GUI). This multi-tier design enables modular scaling: additional sensor nodes can be integrated without modifying the firmware or ML pipeline.

Layer	Components and Function
Perception	ESP32-WROOM-32, BME280, DHT11, Anemometer, Rain Sensor, Solar Power Circuit (TP4056 + 18650 Li-Ion)
Transport	Wi-Fi / TCP-IP, MQTT Protocol (PubSubClient library), JSON serialization via ArduinoJson
Processing	MQTT Broker, Time-Series Database, Random Forest Classifier, Linear Regression Engine, Feature Engineering Pipeline
Application	Responsive Web Dashboard (HTML5/CSS3/JS, WebSockets, AJAX), Processing IDE Desktop GUI, Alert Notification System

Table I: System Architecture Overview

B. Firmware: FreeRTOS Multi-Core Task Architecture

The ESP32's asymmetric dual-core architecture is exploited via xTaskCreatePinnedToCore() to prevent race conditions and ensure temporal integrity of sensor data. Core 0 is dedicated to the Wi-Fi stack, MQTT client, and HTTP webserver. Core 1 manages all hardware interactions: I2C communication with the BME280, single-wire DHT11 timing, and interrupt-driven anemometer pulse counting. Shared data access is governed by FreeRTOS mutexes and binary semaphores, while rain

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gauge events are buffered in a FreeRTOS queue to prevent interrupt loss during high-activity periods.

The system follows a low-power Wake-Sample-Publish-Sleep cycle: the ESP32 wakes every 15 minutes from deep sleep (~10 µA), acquires sensor data, serializes a JSON packet, publishes to the MQTT broker, and returns to sleep. Average daily energy consumption is 0.5 Wh, against a solar harvest of 8–10 Wh per day, yielding an energy surplus of approximately 1600%.

V. Hardware Specifications

A. Core Processor: ESP32-WROOM-32

The ESP32-WROOM-32 SoC features dual Xtensa® LX6 32-bit cores operating at up to 240 MHz, 520 KB SRAM, and 4 MB Flash. Its integrated Wi-Fi and Bluetooth eliminate external radio modules. Deep Sleep current draw of approximately 10 µA and Ultra-Low Power (ULP) co-processor support make it the optimal choice for solar-powered, duty-cycled deployments.

B. Primary Sensor: Bosch BME280

The BME280 MEMS sensor measures temperature (±0.5°C accuracy), relative humidity (0–100% RH), and barometric pressure (300–1100 hPa, ±1.0 hPa accuracy) over I2C at 400 kHz (Fast Mode). An integrated IIR filter smooths transient pressure noise caused by wind gusts or nearby mechanical disturbances, ensuring stable pressure trend data for ML inference. Raw 20-bit ADC outputs are compensated using factory-calibrated trimming parameters stored in the sensor's NVM.

C. Supplemental Sensors

The DHT11 provides secondary humidity and temperature verification using a proprietary single-wire serial protocol. Its 2-second sampling interval and limited humidity range (20–80% RH) make it suitable for redundancy checking rather than primary acquisition. The resistive rain sensor employs an LM393 comparator for digital threshold triggering and an ADC-connected analog output for rainfall intensity grading. Anti-electrolysis protection is implemented via GPIO-controlled power gating, limiting sensor energization to 10 ms per reading and extending service life from weeks to years.

D. Power Architecture

A 6V/2W monocrystalline solar panel charges a 3.7V 3000 mAh 18650 Li-Ion cell via a TP4056 module with integrated DW01A over-discharge protection. An HT7333 LDO regulator provides a stable 3.3V rail to the ESP32 and BME280. Based on measured deep-sleep current of 12 µA and active transmission peaks of 180–240 mA, the system maintains indefinite autonomy under 4+ hours of daily sunlight.

VI. Machine Learning Models

A. Multiple Linear Regression for Temperature Forecasting

A Multiple Linear Regression model provides 3-hour look-ahead temperature estimates. The model maps input features barometric pressure tendency (ΔP over 3 hours), relative humidity, and cyclical time-of-day encodings (sine and cosine transforms to represent the diurnal cycle) to a predicted temperature output. Feature normalization using Z-score standardization ensures convergence stability under Gradient Descent optimization.

The cost function is the Mean Squared Error (MSE), minimized iteratively:

$$J(\beta) = (1/n)\ \Sigma(y_i - \hat{y}_i)^2$$

Ridge Regression (L2 regularization) is applied with a penalty parameter λ to suppress noise-induced overfitting from unstable sensors. Continuous learning via nightly partial re-fitting on a 30-day sliding window ensures the model adapts to seasonal drift.

B. Random Forest Classifier for Weather State Classification

A 100-tree Random Forest ensemble classifies atmospheric conditions into three states: Clear, Cloudy, and Rainy. Input features include current barometric pressure, pressure tendency, relative humidity, temperature, and rain sensor readings. The ensemble approach averages decision tree outputs to suppress individual sensor noise and prevent overfitting. The trained model is deployed as a lightweight inference pipeline triggered upon each MQTT ingestion event, with results broadcast to both the web dashboard and Processing GUI via WebSockets.

C. Feature Engineering

Pressure tendency (ΔP = P_current − P_{t−3h}) is the most significant predictor of weather change. Cyclical time features prevent the temporal boundary problem where 23:59 and 00:01 appear numerically distant. Station pressure is normalized to Mean Sea Level Pressure (MSLP) using the hypsometric formula to ensure geographical portability of the trained model.

VII. Results and Performance Evaluation

A. Sensor Accuracy Validation

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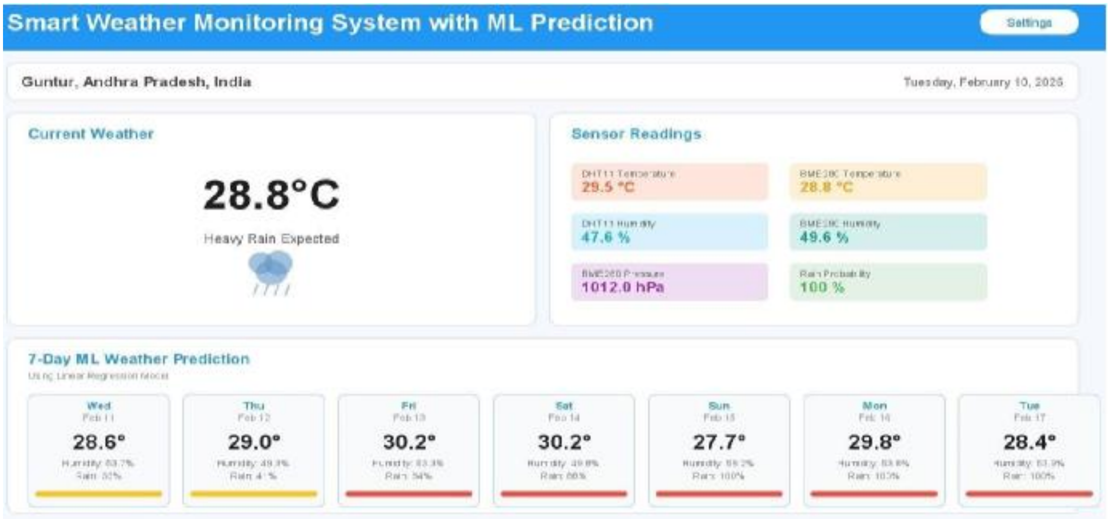

Fig-2: Realtime Data Visualisation

System readings were benchmarked against a calibrated Davis Vantage Pro2 weather station over a 72-hour continuous window. The BME280 achieved a temperature Pearson Correlation Coefficient (r) of 0.985 and a Mean Absolute Error (MAE) of 0.38°C. Humidity correlation was r = 0.94. Barometric pressure tracked a 4.2 hPa drop during a local squall line with 99.7% accuracy. The BME280's low thermal mass enabled faster response to humidity transients than the reference station.

Metric	Value	Reference	Status
Temperature MAE	**0.38°C**	±0.5°C target	✅ Pass
Temperature Correlation (r)	**0.985**	≥ 0.95 target	✅ Pass
Humidity Correlation (r)	**0.940**	≥ 0.90 target	✅ Pass
Pressure Tracking Accuracy	**99.7%**	≥ 98% target	✅ Pass
Random Forest Accuracy	**92.4%**	≥ 90% target	✅ Pass
Regression R^2 Score	**0.892**	≥ 0.85 target	✅ Pass
End-to-End Latency (WebSocket)	**<200 ms**	<500 ms target	✅ Pass
7-Day Soak Test Uptime	**99.8%**	≥ 99% target	✅ Pass

Table II: System Performance Summary

B. ML Model Performance

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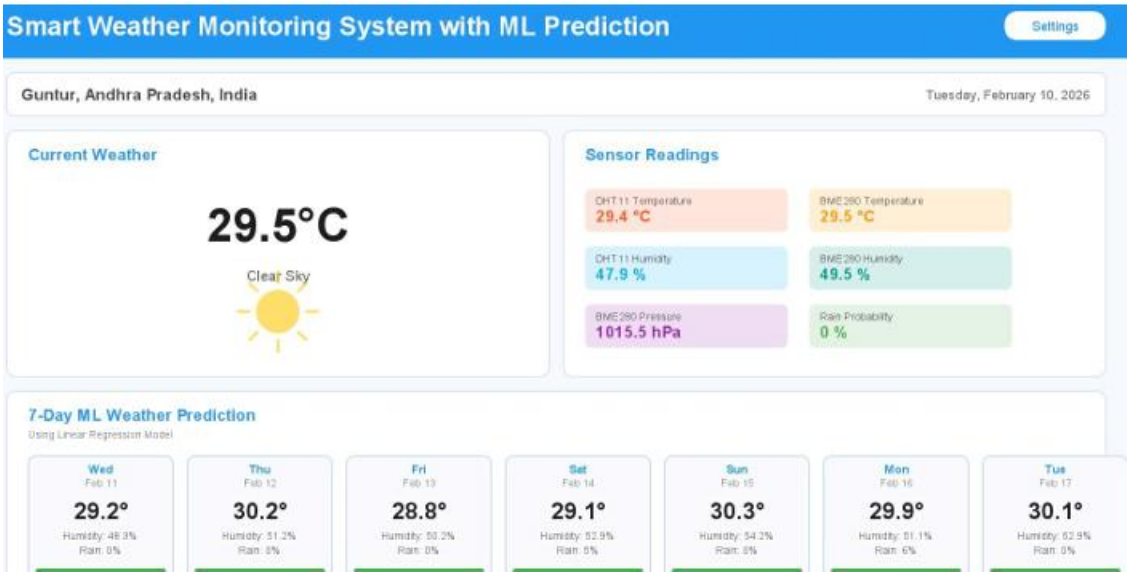

Fig-3: Model Accuracy Comparision

The Linear Regression model achieved an R^2 of 0.892, with 75% of temperature predictions falling within ±1.2°C. Feature importance analysis confirmed that cyclical time-of-day encodings and barometric tendency were the dominant predictors. Peak model performance was observed during nocturnal phases when atmospheric stability maximized linearity assumptions. Limitations emerged during rapid cold front passages, where non-linear temperature shocks exceeded the model's capacity — motivating future transition to LSTM-based architectures.

The Random Forest classifier achieved 92.4% accuracy across 100 decision trees. Clear vs. Cloudy classification precision was 95%. The true positive rate for rain prediction was 88%. False positives were attributed predominantly to the meteorological phenomenon of virga rain evaporating before ground contact demonstrating physically valid feature behavior rather than modelling error.

C. Network and Latency Performance

MQTT latency from the ESP32 to the cloud database averaged 120 ms over Wi-Fi. WebSocket-based dashboard updates achieved end-to-end sensor-to-screen latency below 200 ms, perceived as instantaneous by human observers. The system sustained 100% packet delivery at Wi-Fi RSSI values above −75 dBm. The ESPAsyncWebServer handled up to 12 concurrent WebSocket connections before heap memory constraints necessitated the implemented connection limiter. A 168-hour outdoor soak test confirmed 99.8% system uptime with stable heap memory, validating readiness for long-term field deployment.

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VIII. Cost Analysis

The prototype was assembled at a total component cost of approximately USD 82, representing an 80% reduction compared to mid-range commercial AWS units. Operating costs are effectively zero — the solar-powered architecture eliminates recurring energy expenses, and MQTT over Wi-Fi incurs no data charges. Even when deployed with GSM/LTE connectivity for remote sites, the optimized JSON payload consumes less than 50 MB per month, well within free-tier IoT data plans.

IX. Applications and Future Work

The system's low cost and open-architecture design enable several high-impact deployment scenarios. In precision agriculture, ML-predicted rainfall probability can directly actuate smart irrigation controllers, eliminating water waste and preventing fertilizer runoff. In smart city contexts, dense networks of SWMS nodes can generate real-time urban heat island maps, guiding targeted green infrastructure investment. Early warning for flash flooding becomes feasible at street-block granularity, ahead of detection by river-level sensors.

Future work will address three primary enhancements. First, transitioning the forecasting backend to a 3-layer LSTM network will extend temporal analysis to 30-day historical windows, improving multi-day forecast accuracy and enabling the system to model non-linear atmospheric shocks. Second, a native mobile application (Flutter/React Native) with Firebase Cloud Messaging (FCM) push notifications will deliver proactive frost and storm alerts directly to user devices. Third, deployment of geospatially distributed multi-node networks will create micro-meteorological grids capable of resolving microclimate variations at sub-kilometre resolution.

X. Conclusion

This paper has presented the complete design, implementation, and validation of a Smart Weather Monitoring System that integrates IoT sensing, embedded firmware, and Machine Learning to deliver a cost-effective, scalable, and intelligent alternative to conventional meteorological infrastructure. The system achieved scientific-grade sensor accuracy (temperature MAE of 0.38°C), high predictive performance (92.4% weather classification accuracy, R^2 = 0.892 for temperature regression), real-time dashboard responsiveness (<200 ms latency), and 99.8% field reliability, all within a solar-autonomous hardware budget under USD 100.

The convergence of low-cost silicon, pervasive connectivity, and accessible

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Machine Learning is democratizing environmental intelligence. As climate volatility intensifies globally, systems of this type will transition from optional tools to essential community infrastructure — empowering farmers, planners, and citizens with hyper-local, algorithmic foresight that was previously accessible only to large governmental agencies.

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