

Autonomous Long-Range Climate Monitoring: Synergizing LoRa™ Connectivity and Edge Deep Learning

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Abstract– This study presents the design and implementation of an autonomous, IoT-enabled weather station engineered for real-time climate monitoring and high-precision forecasting. Addressing the need for localized meteorological tools in agriculture, urban planning, and environmental risk management, the system integrates diverse hardware and software technologies into a cohesive, portable unit. Data acquisition of key variables—including temperature, humidity, atmospheric pressure, and wind dynamics—is managed by Arduino™-based embedded systems, while a Raspberry® Pi facilitates localized edge computing. Central to its predictive capability is a multivariate Long Short-Term Memory (LSTM) deep neural network, trained to identify non-linear temporal patterns within climatic datasets. Experimental validation confirmed high operational reliability in data transmission and storage. The LSTM model achieved exceptional predictive accuracy, maintaining a Mean Squared Error (MSE) below 5%, thereby demonstrating its capacity to anticipate complex environmental trends. By synthesizing LoRa™ connectivity with edge-deployed Deep Learning, this research provides a low-uncertainty solution for hyper-local climate prediction. This architecture represents a significant advancement for data-driven decision-making, offering a scalable and efficient tool for sustainable resource management and smart city initiatives in climate-sensitive applications.

Keywords– Climate prediction, Edge computing, Long Short-Term Memory (LSTM), LoRa™ technology, Smart weather station.

I. INTRODUCTION

The spatiotemporal variability of climatic variables significantly influences environmental dynamics, urban development, agricultural productivity, and socioeconomic resilience. Accurate, continuous monitoring of parameters such as temperature, humidity, and solar radiation is essential for localized meteorological understanding and data-driven decision-making, particularly in hazard mitigation and food security contexts.

Conventional monitoring systems—typically centralized and manual—present limitations, including low spatial resolution, high maintenance costs, and restricted flexibility. Their reliance on fixed infrastructure constrains applicability in rural or remote regions where power and communication networks are scarce. Consequently, there is a demand for autonomous, energy-efficient paradigms capable of delivering high-resolution, real-time data.

A. Evolution of IoT and Edge Computing

Recent advances in the Internet of Things (IoT) and Artificial Intelligence (AI) have catalyzed next-generation environmental monitoring. While IoT architectures enable distributed sensing, many current solutions remain limited by high power consumption or dependence on high-bandwidth technologies [1 – 3].

Furthermore, although deep learning models have improved forecasting accuracy [4 – 6], they are predominantly cloud-based, requiring continuous data transmission and significant computational resources. Integrating these models into low-power devices via edge computing remains a critical challenge for long-term autonomous operation.

B. LPWAN and LoRa™ Integration

Modular architectures and compact embedded units have facilitated the emergence of cost-effective weather stations [7 – 13]. However, despite these advances, relatively few studies have addressed the practical deployment of such systems in rural or hard-to-reach environments, where ultra-low power consumption, portability, and long-range communication are essential design constraints [9].

Within this framework, Low-Power Wide-Area Network (LPWAN) technologies, specifically LoRa™, have surfaced as viable solutions for long-range data transmission with minimal energy requirements [14 – 23]. When combined with edge computing, LoRa™ connectivity offers a pathway toward fully autonomous systems capable of independent operation in geographically dispersed regions.

C. Proposed System and Contributions

While numerous IoT-based weather stations have enhanced localized monitoring capabilities, existing solutions exhibit significant limitations regarding energy autonomy, reliance on high-power or short-range networks, and a lack of integrated edge-computing intelligence.

In contrast, the proposed system introduces an innovative technological integration that addresses these challenges: (i) it leverages LoRa™ technology for long-range, low-power communication, which is critical for deployments in remote areas with limited infrastructure; (ii) it incorporates a multivariate Long Short-Term Memory (LSTM) deep learning model implemented directly on embedded hardware

(Raspberry® Pi), enabling real-time climatic predictions without requiring continuous cloud connectivity; and (iii) it employs a modular design that facilitates scalability and adaptability across diverse environmental scenarios and applications.

D. Experimental Validation and Objectives

The hardware architecture utilizes low-power embedded platforms equipped with atmospheric sensors and wireless modules designed for intermittent but reliable transmission [14 – 23]. On the software side, executing deep learning models at the edge reduces latency and bandwidth requirements while enhancing system resilience in connectivity-constrained settings [24 – 27].

The solution was experimentally validated through real-world deployment in a rural environment. Performance was assessed by comparing measurements and predictions against ground-based stations and satellite-derived models [23, 28, 29].

Accordingly, the main objectives of this research are threefold: (i) to design and integrate a compact, energy-efficient sensing and processing platform capable of accurately capturing atmospheric variables in real time using IoT technologies; (ii) to develop and deploy optimized deep learning models for climatic variable prediction on low-power edge hardware; and (iii) to validate the systems performance under field conditions, assessing its accuracy, autonomy, and practical utility across multiple application domains.

By addressing the gaps in current smart weather station research [30 – 32], this work provides a scalable tool for high-resolution climate observation, supporting sustainable development and climate resilience in marginalized regions..

II. PROPOSED METHODOLOGY FOR AUTONOMOUS CLIMATE MONITORING

This section details the methodological framework adopted for the design, implementation, and validation of the proposed autonomous long-range climate monitoring system. The methodology integrates low-power embedded hardware, long-range LoRa™ communication, and deep learning-based predictive analytics executed at the edge. The overall objective was to develop a robust, portable, and energy-efficient meteorological station capable of real-time monitoring and short-term forecasting of climatic variables in remote or infrastructure-limited environments. To ensure scientific rigor and reproducibility, the methodology was structured around four core components: (i) system architecture and hardware design, (ii) data acquisition, transmission, and storage, (iii) predictive modeling using deep learning at the edge, and (iv) experimental protocol and system validation.

E. Architecture of the Autonomous Climate Monitoring Platform

The proposed system was conceived as a hybrid and modular architecture that separates sensing, communication,

and computational tasks to optimize energy efficiency, scalability, and fault tolerance. This architectural choice aligns with the need for prolonged autonomous operation in remote deployments, as highlighted in the introduction. The system consists of two main subsystems: a data acquisition node and a processing and prediction node, interconnected through LoRa™ wireless communication.

The data acquisition subsystem is based on an Arduino™ UNO microcontroller, powered by an ATmega328P processor. This platform was selected due to its low power consumption, high reliability, extensive community support, and compatibility with a wide range of meteorological sensors. The Arduino™ UNO is responsible for continuous sensor sampling, basic data formatting, and wireless transmission.

The processing and analytics subsystem is implemented on a Raspberry® Pi 3 single-board computer, featuring an ARM-based system-on-chip (SoC). This unit performs data reception, local storage, real-time visualization, and execution of deep learning models for predictive analysis. Communication between both subsystems is achieved using LoRa™ Ra-02 (SX1278) transceiver modules. The overall system architecture is illustrated in Fig. 1.

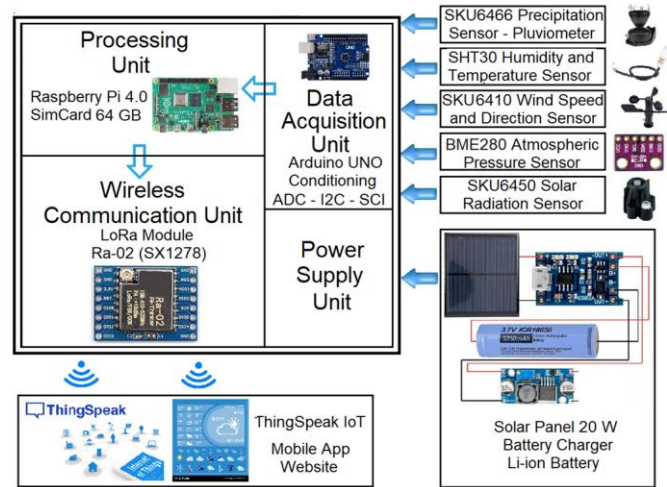


Fig. 1 LoRa™-Enabled Architecture – Autonomous Weather Station.

These modules operate within the 137–525 MHz frequency band and were selected for their long-range communication capabilities, low power requirements, and robustness against interference. The use of LoRa™ technology enables reliable data transmission over several kilometers with minimal energy consumption, making it particularly suitable for rural and remote climate monitoring applications.

The hardware components were selected based on measurement accuracy, operational range, environmental robustness, and compatibility with IoT data platforms such as ThingSpeak. The meteorological variables monitored by the station include temperature, relative humidity, atmospheric pressure, wind speed, wind direction, precipitation, and solar radiation. These variables were chosen due to their relevance for environmental monitoring, agricultural decision-making, and short-term climate forecasting.

Temperature and relative humidity are measured using an SHT30 digital sensor with an I2C interface. This sensor provides high accuracy (± 0.3 °C for temperature and $\pm 2\%$ for relative humidity) across a wide operating range, from -40 °C to 125 °C and $0 - 100\%$ RH, respectively. Atmospheric pressure measurements are obtained using a BME280 sensor, also interfaced via I2C, offering a precision of ± 1 hPa within a pressure range of $300 - 1100$ hPa.

Wind speed and direction are measured using the SKU6410 anemometer and wind vane assembly. Wind speed is detected through a solid-state magnetic sensor capable of measuring velocities from 0 to 60 m/s with a precision of ± 0.5 m/s. Wind direction is determined using a potentiometric sensor integrated into the wind vane, providing continuous angular measurements. Precipitation is quantified using a SKU6466 tipping bucket rain gauge, which generates a digital pulse for every 0.2 mm of accumulated rainfall. Solar radiation is recorded using a SKU6450 pyranometer, which employs a monocrystalline silicon photodiode to convert incident solar irradiance into an analog voltage signal proportional to solar intensity.

All sensors are connected to the Arduino™ UNO through a combination of analog and digital interfaces. The sampling frequency was set to one measurement every 10 seconds, providing a balance between temporal resolution and energy efficiency. Sensor calibration was conducted in a controlled laboratory environment prior to deployment, using reference instruments and standardized procedures to minimize systematic measurement errors.

To ensure durability and reliability in outdoor conditions, the electronic components were housed in a reinforced plastic enclosure coated with white anti-corrosion enamel. This coating reduces thermal absorption and protects against moisture, ultraviolet radiation, and corrosion. Internally, all components were mounted on a custom-designed printed circuit board (PCB) measuring $8\text{ cm} \times 15\text{ cm}$, developed using LiveWire and PCB Wizard software. The PCB was secured using stainless steel fasteners and coated with a dielectric varnish to prevent short circuits and environmental degradation.

The entire station was installed on a 2 m high support structure constructed from anodized aluminum and stainless steel, providing mechanical stability and resistance to weathering. Power is supplied by a rechargeable 12 V lithium-ion battery system, complemented by a 20 W photovoltaic solar panel. A dedicated charge controller and voltage regulation system provide stable 3.3 V and 5 V outputs required by the electronic components, ensuring uninterrupted autonomous operation.

F. Meteorological Data Collection and Management

The data acquisition process was implemented using firmware developed in C++ and deployed on the Arduino™ UNO. The firmware orchestrates periodic sensor polling, signal conditioning, and temporary data storage in the

microcontroller's internal memory. Each acquisition cycle results in a structured data packet containing ten floating-point values corresponding to the measured meteorological variables.

To optimize wireless transmission efficiency, the sensor data are serialized into a fixed-length 40-byte array before being transmitted via the LoRa™ module operating in transmission (TX) mode. The firmware was developed using established libraries such as Adafruit_Sensor and Adafruit_BME280 for sensor interfacing, and RH_RF95 for LoRa™ communication management.

On the receiving end, the Raspberry® Pi 3 operates in reception (RX) mode and runs a Python™-based software stack responsible for packet reception, decoding, storage, and visualization. The software leverages libraries including SX127x.LoRa for wireless communication, struct for binary data unpacking, pandas for data manipulation, datetime for timestamping, and MySQLdb for database interaction.

Upon reception, the binary payload is decoded into floating-point values and appended with a timestamp. A dual-storage strategy was adopted to ensure data integrity, traceability, and accessibility. First, the data are stored in comma-separated value (*.csv) files for long-term archival and offline analysis. Second, the data are simultaneously written to a MySQL relational database, enabling real-time visualization, querying, and integration with IoT dashboards.

This acquisition and storage pipeline operated continuously throughout a six-month experimental period, generating a high-resolution time series dataset. The redundancy provided by the dual-storage approach enhances fault tolerance and supports reproducibility, which is critical for training and validating predictive models.

G. Deep Learning Framework for Climatic Variable Prediction

To enable real-time forecasting capabilities, the system incorporates a deep learning - based predictive model implemented using a multivariate Long Short-Term Memory (LSTM) neural network. LSTM architectures are well suited for time-series prediction tasks due to their ability to capture long-term temporal dependencies and nonlinear relationships among variables.

Model training utilized two complementary data sources: a public benchmark dataset and data collected directly by the prototype. The primary dataset was the Jena Climate Dataset, which contains approximately 400,000 records of 14 meteorological variables recorded between January 2021 and August 2024. This dataset was selected for its high temporal resolution and data quality. To improve local adaptability, the public dataset was augmented with three months of data collected by the deployed weather station.

Prior to training, all data underwent a preprocessing pipeline that included normalization, outlier detection and removal, and handling of missing values. Min - Max normalization was applied to scale each variable into a

bounded numerical range, facilitating neural network convergence. The processed data were then segmented into sliding time windows of ten consecutive time steps, which served as input sequences for the LSTM model.

The complete dataset was partitioned into training (80%), validation (10%), and testing (10%) subsets to ensure unbiased performance evaluation. The LSTM architecture consists of a single recurrent layer with 64 hidden units, followed by two fully connected dense layers. Rectified Linear Unit (ReLU) activation functions were employed to introduce nonlinearity, while the Adam optimizer was used for training with a learning rate of 0.0001. Mean Squared Error (MSE) was selected as the loss function due to its suitability for regression tasks.

To reduce computational overhead on the embedded platform, the model was pre-trained on a higher-performance workstation equipped with an Intel Core i5-11300H processor. The trained model was then exported and deployed on the Raspberry® Pi 3 for real-time inference. Predicted values were subsequently denormalized to restore their original physical units, enabling meaningful interpretation and comparison with sensor measurements.

H. Field Evaluation and Validation Protocol

The complete system was validated through a six-month field deployment in a rural environment. During this period, continuous monitoring and prediction of meteorological variables were performed under diverse climatic conditions. Model predictions were compared against real-time sensor measurements to assess accuracy and reliability.

Performance evaluation employed standard statistical metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Additional analyses included residual distribution assessment and temporal error visualization. The LSTM model achieved a mean prediction error below 1.5 °C for temperature and 3% for relative humidity during cross-validation.

Robustness tests were also conducted to evaluate system stability under adverse conditions such as abrupt wind changes and intense precipitation events. The results demonstrate that the proposed architecture provides reliable long-term autonomous operation and accurate predictive performance, validating its suitability for decentralized climate monitoring applications.

III. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed autonomous climate monitoring system, focusing on both the performance of the embedded deep learning model and the operational reliability of the hardware platform under real-world conditions. The results are discussed in relation to the objectives defined in the methodological framework, emphasizing predictive accuracy, system robustness, and

suitability for long-range autonomous deployment using LoRa™ connectivity and edge computing.

A. System Implementation and Data Integrity Assessment

Following the completion of the system design and integration, the meteorological station was deployed and subjected to continuous operation in a real outdoor environment. Fig. 2 illustrates the finalized implementation of the sensing unit based on the Arduino™ UNO, the processing unit centered on the Raspberry® Pi, and the LoRa™-based wireless communication module, as well as the fully assembled weather station installed in the field. This configuration reflects the modular architecture described in the methodology, enabling independent validation of sensing, processing, and communication subsystems.

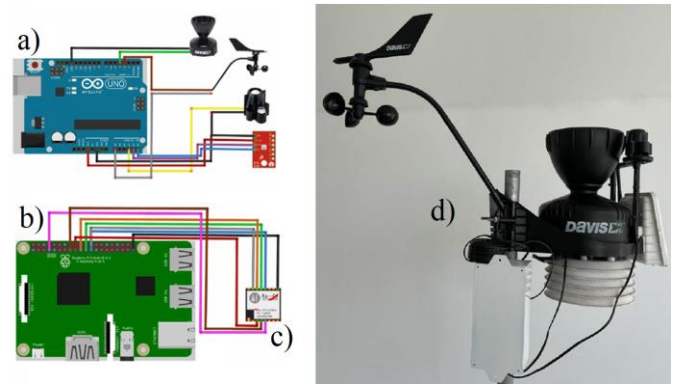


Fig. 2 Implemented architecture of the autonomous weather station, including: a) Data Acquisition Unit (Arduino™ UNO), b) Processing Unit (Raspberry® Pi), c) LoRa™ communication units, and d) Davis Weather Station.

Prior to predictive modeling, the integrity and consistency of the collected meteorological data were rigorously examined. Fig. 3 presents the temporal evolution of key atmospheric variables — temperature, atmospheric pressure, relative humidity, wind speed, and wind direction—recorded over a dataset comprising approximately 20,000 samples.

These records span several months and capture a wide range of climatic conditions, thereby providing a representative dataset for subsequent analysis. The time-series inspection confirmed that the measurements exhibited physically consistent behavior and realistic variability patterns. Temperature and atmospheric pressure displayed smooth diurnal and seasonal trends, while relative humidity exhibited inverse correlations with temperature, as expected from atmospheric thermodynamics. Wind speed and direction showed higher short-term variability, reflecting their inherently stochastic nature. Solar radiation and precipitation data (not shown in Fig. 3 for brevity) also demonstrated coherent temporal patterns consistent with local climatological expectations.

No systematic sensor drift or data acquisition anomalies were observed during this phase. Outliers were limited and predominantly associated with extreme environmental events, such as sudden wind gusts or transient precipitation, and were handled during preprocessing as described in the methodology. This validation step ensured that the dataset was suitable for training and evaluating deep learning models without introducing bias due to sensor malfunction or communication errors.

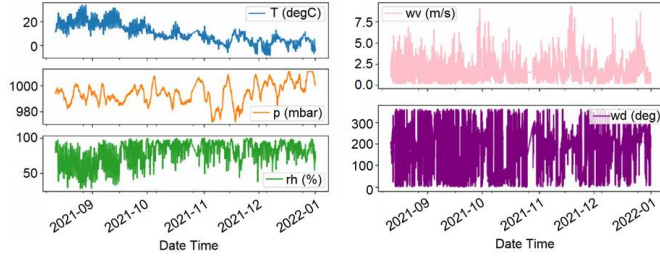


Fig. 3 Time-series records of key meteorological variables collected during the experimental period between 2021-09 and 2021-12.

B. Predictive Model Performance and Statistical Evaluation

The core analytical contribution of the proposed system lies in its ability to perform short-term climate prediction directly at the edge using a Long Short-Term Memory (LSTM) neural network. The predictive performance of the model was evaluated using a dataset exceeding 20,000 time-stamped samples, collected over a 12-month period and stratified across different temporal segments and climatic conditions. This stratification ensured that the evaluation encompassed both stable and highly variable meteorological regimes.

The LSTM model demonstrated strong predictive capability across multiple variables. Quantitatively, the model achieved a coefficient of determination (R^2) of 0.957 and a Mean Squared Error (MSE) of 0.0434. These results indicate a high degree of agreement between predicted and observed values and substantially exceed the predefined performance threshold of an MSE below 5%.

The low residual variance confirms the model's ability to capture the nonlinear temporal dependencies characteristic of atmospheric processes. To contextualize these results, a comparative analysis was conducted against alternative deep learning architectures, including a standard Recurrent Neural Network (RNN) and a Convolutional Neural Network (CNN).

The RNN model achieved an R^2 of 0.8815 with an MSE of 0.1189, while the CNN yielded a considerably lower R^2 of 0.6047 and a higher MSE of 0.4090. These findings underscore the limitations of conventional RNNs in retaining long-term dependencies and the relative unsuitability of CNNs for modeling temporal dynamics in meteorological time series.

Statistical significance testing using one-way Analysis of Variance (ANOVA) confirmed that the performance differences among the models were highly significant ($p <$

0.01), providing strong evidence in favor of the LSTM architecture. The superior performance of the LSTM is attributed to its gated memory mechanism, which effectively preserves long-range temporal information and mitigates the vanishing gradient problem that affects traditional recurrent models.

Fig. 4 illustrates a comparative visualization of predicted versus actual values for selected meteorological variables using the LSTM model. The close alignment between predicted and observed values for temperature, atmospheric pressure, relative humidity, and solar radiation demonstrates the model's high fidelity in capturing both trend and amplitude. While wind speed and direction exhibited larger deviations, the model successfully reproduced their general temporal behavior, which is notable given the chaotic and intermittent nature of wind-related phenomena.

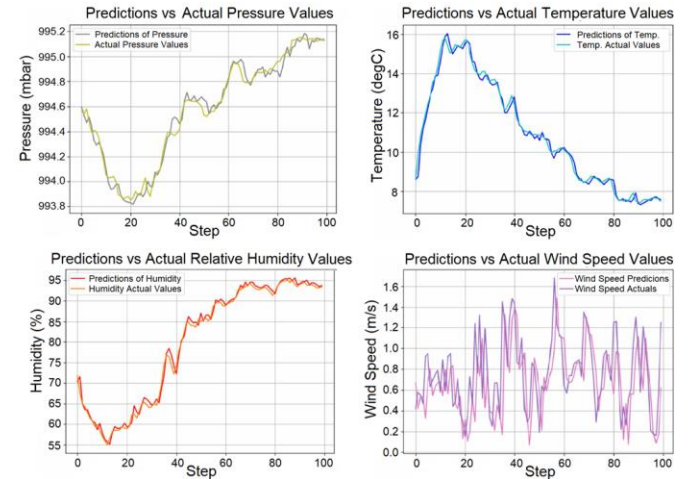


Fig. 4 Comparison between predicted and measured meteorological variables using the LSTM-based edge model.

To further assess robustness and generalization, a 10-fold cross-validation procedure was applied. The resulting performance metrics exhibited low variance across folds, indicating that the model's accuracy was not dependent on a specific subset of the data. This stability is critical for real-world deployment, where models must generalize reliably to unseen conditions.

Beyond regression accuracy, the system's capability to identify extreme meteorological events was also evaluated. Events such as intense precipitation and high solar radiation levels were treated as classification tasks, and performance was quantified using precision and recall metrics. The LSTM-based system achieved a precision exceeding 92% and a recall of approximately 89%, demonstrating strong discriminative power in detecting significant climatic events that are critical for risk management and decision support.

Receiver Operating Characteristic (ROC) analysis further confirmed this capability, with Area Under the Curve (AUC) values exceeding 0.95. The inclusion of 95% confidence intervals for all major metrics provides additional assurance regarding the statistical reliability of the results. Combined

with systematic outlier detection using residual analysis and standard deviation thresholds, these controls ensure that the reported performance is robust and not influenced by sampling artifacts or noise.

C. Hardware Validation and Operational Performance

In parallel with the evaluation of predictive accuracy, extensive field tests were conducted to validate the hardware reliability and operational stability of the system. Fig. 5 shows the installed weather station during field deployment. The LSTM model, previously trained on an external high-performance machine, was successfully synthesized and deployed on the Raspberry® Pi for real-time inference, demonstrating the feasibility of executing deep learning models on low-power edge devices.

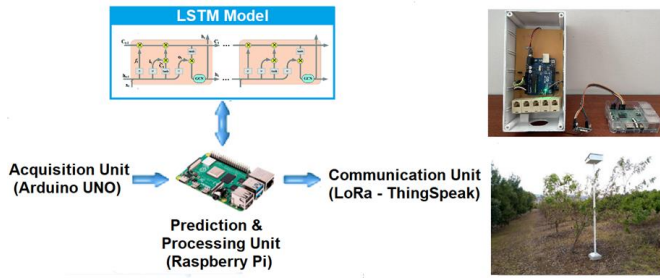


Fig. 5 Field deployment and installation of the proposed smart weather station.

Measurements collected by the prototype were compared against data from a commercial Davis Vantage Pro 2 weather station and a manually operated UPTC reference station. The comparison revealed minimal discrepancies, with error margins remaining within acceptable ranges for all measured variables. These results confirm the accuracy of the selected sensors and the effectiveness of the calibration procedures.

Wireless communication performance was evaluated by analyzing packet loss and transmission reliability under open-field conditions. The LoRa™ communication link remained stable up to a distance of 102 meters, with negligible data loss, validating its suitability for long-range environmental monitoring. While longer distances are theoretically achievable with LoRa™, this conservative validation demonstrates robust operation under typical deployment scenarios.

The adopted computational architecture—where training is performed offline and inference is executed locally—proved to be an effective compromise between computational efficiency and system portability. This approach minimizes energy consumption while preserving real-time predictive capabilities, a key requirement for autonomous operation in remote areas.

D. Data Visualization and Decision Support Capabilities

The integration of a MySQL database and Grafana-based visualization platform significantly enhanced the system's usability and analytical potential. Fig. 6 illustrates the real-

time visualization dashboard, which provides continuous access to meteorological data, historical trends, and predictive outputs from remote locations or mobile devices.

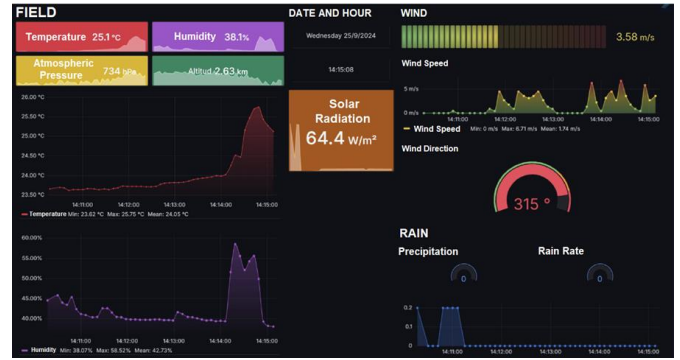


Fig. 6 Remote visualization and analysis dashboard for real-time meteorological monitoring.

This visualization framework supports informed decision-making by enabling users to monitor evolving climatic conditions and receive alerts when predefined thresholds are exceeded. The system's modular design allows additional analytical layers or alerting mechanisms to be incorporated with minimal effort, further increasing its adaptability to different application domains.

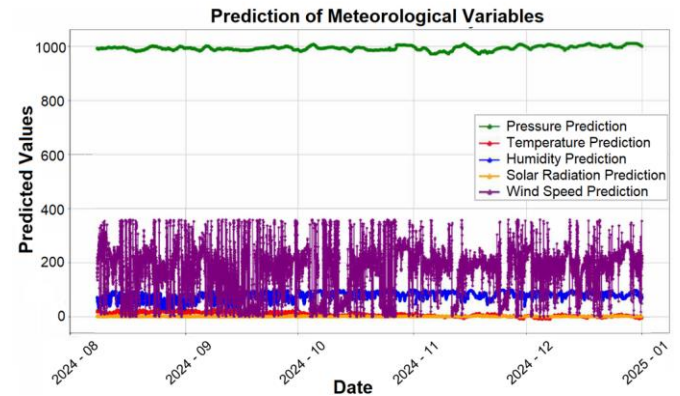


Fig. 7 Temporal evolution of predicted meteorological variables generated by the edge-based LSTM model.

Graphical logs generated during system operation offered an intuitive assessment of model behavior over time. These logs complement quantitative metrics by illustrating how predicted variables follow observed trends under real-world conditions. Fig. 7 presents a time-series log of predicted meteorological variables at 10-minute intervals from August to December 2024. The visual coherence between predicted trajectories and measured data reinforces the statistical findings and demonstrates the system's practical relevance for real-life climate-related decision-making.

E. Discussion and Implications

Overall, the results confirm that the proposed system successfully integrates long-range LoRa™ communication, edge-based deep learning, and autonomous sensing into a

cohesive and reliable climate monitoring architecture. The achieved predictive accuracy, characterized by low-power consumption and robust wireless connectivity, positions the system as a viable alternative to conventional weather stations, particularly in rural or infrastructure-limited regions.

The findings highlight the advantages of executing intelligent analytics at the edge, reducing dependency on continuous cloud connectivity while maintaining high-quality predictive performance. This work contributes to the growing field of intelligent environmental monitoring, demonstrating how the synergy integration between IoT, LPWAN technologies, and deep learning enhances climate resilience and data-driven decision-making.

Model robustness and generalization were verified through 10-fold cross-validation, which showed low variability across performance metrics. Furthermore, the classification capabilities of extreme weather events (e.g., intense precipitation or high solar radiation) were evaluated yielded a precision of over 92% and a recall of 89%.

This discriminative capacity was corroborated by the Receiver Operating Characteristic (ROC) curves, which achieved an Area Under the Curve (AUC) exceeding 0.95. Statistical reliability was ensured through 95% confidence intervals and rigorous data quality assurance protocols, including outlier detection via standard deviation and residual analysis, thereby mitigating sampling biases. Table I summarizes the results of the performance metrics of the implemented smart weather station.

TABLE I
SUMMARY OF THE PREDICTIVE AND STATISTICAL PERFORMANCE METRICS FOR THE INTELLIGENT WEATHER STATION

Metric Category	Evaluation Parameter	Performance Value / Range
Regression (Time Series)	Mean Squared Error (MSE)	LSTM: 0.0434 RNN: 0.1189 CNN: 0.4090
	Coefficient of Determination (R^2)	LSTM: 0.957 RNN: 0.8815 CNN: 0.6047
Classification (Extreme Events)	Precision	> 92%
	Recall	89%
	Area Under the Curve (AUC)	> 0.95
Statistical Validation	Cross-Validation	(10-fold) Low Variability
	Confidence Interval (CI)	95%

System integration with a MySQL database for structured storage and Grafana for real-time visualization provides a scalable platform for remote or mobile data analysis (See Fig. 6). Additionally, graphical logs generated by the LSTM model synthesized on the Raspberry® Pi provide a visual assessment of temporal trends.

As illustrated in Fig. 7, the 10-minute interval predictions from August to December 2024 demonstrate the model's ability to estimate meteorological variations accurately within operational ranges, facilitating informed climate-related decision-making in real-world scenarios.

IV. CONCLUSIONS

This study presented the design, implementation, and validation of an autonomous long-range climate monitoring system that synergistically integrates LoRa™ wireless connectivity with edge-based deep learning for real-time meteorological data acquisition and prediction. The proposed approach addresses key limitations of conventional weather monitoring infrastructures, particularly in remote or resource-constrained environments, by combining low-power sensing, long-range communication, and on-device intelligent analytics within a modular and scalable architecture.

The experimental results demonstrate that the developed IoT-enabled weather station achieves measurement accuracy and operational reliability comparable to that of high-end commercial meteorological systems. Field validation against reference stations confirmed the robustness of the sensing subsystem and the stability of LoRa™-based data transmission, ensuring consistent and high-quality data collection over extended deployment periods. The automated and high-frequency acquisition of meteorological variables produced a dense and reliable time-series dataset, which proved essential for effective machine learning – based climate prediction.

A central contribution of this work is the implementation and evaluation of a Long Short-Term Memory (LSTM) neural network for short-term climatic forecasting executed directly at the edge. Comparative analyses against alternative deep learning architectures, including Convolutional Neural Networks (CNNs) and traditional Recurrent Neural Networks (RNNs), confirmed the superior performance of the LSTM model in capturing the nonlinear temporal dependencies inherent in atmospheric processes. The achieved predictive accuracy — characterized by a high coefficient of determination (R^2), low Mean Squared Error (MSE), and stable cross-validation performance—highlights the suitability of LSTM architectures for time-series modeling of meteorological variables in decentralized monitoring systems.

The integration of edge computing within the proposed framework significantly enhances system autonomy by reducing dependence on continuous cloud connectivity and minimizing communication latency. This design choice not only improves energy efficiency but also increases system resilience in environments with intermittent or limited network infrastructure. Furthermore, the modular hardware and software architecture enables compatibility with a wide range of commercial sensors and facilitates future system expansion, positioning the platform as a flexible tool for both academic research and applied environmental monitoring.

From a broader perspective, this research advances the state of the art in autonomous climate monitoring by demonstrating the feasibility and effectiveness of coupling LoRa™ long-range communication with edge-based deep learning. The proposed system provides a practical pathway toward scalable, low-cost, and intelligent meteorological observation networks capable of supporting data-driven

decision-making in agriculture, environmental management, urban planning, and climate risk mitigation.

Future work will focus on extending the predictive framework to include additional atmospheric and environmental variables, integrating adaptive learning mechanisms to improve model performance under changing climatic conditions, and evaluating the system at larger spatial scales using multi-node deployments. Additionally, incorporating federated or collaborative learning approaches may further enhance prediction accuracy while preserving data locality and privacy. These directions aim to strengthen the role of edge intelligence and long-range IoT connectivity in next-generation climate monitoring infrastructures.

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