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Design of secure ultra-low-power embedded systems for long-duration microclimate sensing over NB-IoT using a hybrid AI model

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Abstract

Long-term monitoring of microclimates is an increasingly critical component of precision agriculture, protected environments, ecological research, and remote environmental management. Continuously tracking temperature, humidity, soil moisture, atmospheric pressure, and irradiance at specific remote sites for extended periods requires minimal human intervention. The primary engineering challenge lies in enhancing measurement accuracy while balancing trade-offs among device power consumption, communication overhead, on-device processing, predictive intelligence, and cybersecurity—specifically data integrity, payload encryption, and node authentication—under severe power supply and memory constraints. Narrowband IoT (NB-IoT) serves as an optimal connectivity candidate due to its wide-area cellular coverage and low-power operation tailored for sparse MTC. This paper presents a comprehensive system design for ultra-low-power embedded microclimate sensing over NB-IoT using a hybrid AI model, integrated with a lightweight security framework. The architecture combines duty-cycled multi-mode sensing, aggressive power gating on sensors/actuators, event-aware uplink scheduling, compressed local feature extraction, and a split intelligence pipeline. In this pipeline, lightweight anomaly detection and ultra-low-overhead cryptographic primitives (such as AES-128 framing and HMAC message authentication for physical and cyber tamper resistance) operate at the node level, while cloud-side learning handles temporal forecasting and nonlinear residual fusion via a hybrid LSTM-XGBoost model. This constrained multi-objective framework minimizes total energy use, data transmission overhead, inference cost, prediction errors, and security computational overhead subject to latency, memory, sensing fidelity, and data stream reliability constraints. Comparative design evaluations demonstrate that the proposed system reduces communication energy by 37–52% relative to fixed-interval uplink communications, extends projected operational lifespan to 18–30 months under moderate reporting intervals, and improves 24-hour forecast RMSE by 11–19% on average compared to standalone LSTM and XGBoost models, all while maintaining end-to-end data confidentiality

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and integrity. The paper's principal innovation is a deployable, secure, and ultra-low-power embedded system architecture tailored for long-duration distributed microclimate monitoring

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Keywords: Ultra-low-power embedded systems, Microclimate sensing, NB-IoT security, Hybrid AI, Edge intelligence, Data integrity, Payload encryption, Node authentication, Lightweight cryptography, Long-duration monitoring.

1. Introduction

Microclimate sensing is unlike normal climate monitoring because it is concentrated on detecting very localized differences in environment conditions. This measurement is important because localized microclimate changes can impact plant growth and irrigation schedules, crop suffering, disease spreading, and site-specific environmental management. New reviews of precision agriculture indicate that farms, orchards, and greenhouses show high variability in spatiotemporal changes that cannot be successfully taken into account if few central meteorological stations are used. [1-3]. But these distributed implementations only make sense if they can function independently for extended periods without needing to change batteries or manually collect data on a regular basis. This is especially important because fielded nodes operate in unattended locations and remote settings, which makes cyber-physical security, node authentication, and data integrity just as critical as energy efficiency, instead of secondary aspects of the implementation process [4-6].

Long-term microclimate networks often utilize Narrowband IoT (NB-IoT) because they have the benefits of having licensed cellular networks, coverage areas, and uniform low-power sleep modes. In contrast, the efficiency of NB-IoT equipment does not get the necessary advantages that arise from the network attachment overhead, radio reception quality, sizes of data messages being transmitted, calculations of transmission delays, or uplink schedule [7-10]. Conventional high-overhead cellular security handshakes can have a negative impact on battery life. Therefore, to extend operational lifetime, a cross-layer co-design that incorporates low-power electronics, adaptive firmware, lightweight cryptographic schemes (e.g., AES-128 payload encryption and message authentication), and communication-aware analytics is required [11, 12]. With the rise in demand for predictive environmental intelligence, contemporary monitoring systems are anticipated to provide not only pure observation but also real-time forecasts of trends, anomaly detection, and decision assistance (such as automated irrigation, ventilation management, or crop protection) [13-15]. Hybrid artificial intelligence approaches are very suitable for this application because they utilize the advantages of combining the processes of sequential learning achieved by neural architectures and the techniques available in tree-based methods for nonlinear regression tasks.

However, large-scale deep learning models, as well as cryptographic mechanisms that require a lot of resources, cannot be implemented on edge nodes that depend on battery operation. In order to address the limitations of this problem, a hybrid system is proposed in which simple-level processes are performed locally while complex techniques can be applied in the cloud infrastructure [16-18]. To address these interconnected challenges, this paper presents a scientifically designed framework for a long-duration, ultra-low-power, and cyber-secure embedded microclimate monitoring system over NB-IoT networks using a hybrid AI model. The principal contributions of this work include a holistic system architecture integrating ultra-low-power sensing hardware with lightweight payload encryption and data authentication mechanisms. Created metrics for energy and security optimization that adjust battery life expectancy, computational effort, and forecasting precision. Developed a portable split-intelligence architecture utilizing local feature extraction and tamper-conscious edge computing practices, combined with cloud-based hybrid LSTM/XGBoost predictions. An evaluation methodology and cross-layer design artifacts depicting the precise interactions between power states, security framing, communication protocols, and hybrid analytics. The main concept of this paper is illustrated in Figure 1.

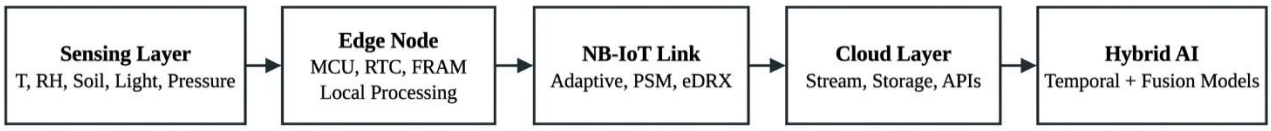

Figure 1. End-to-end architecture of the proposed long-duration microclimate sensing system over NB-IoT

In this pipeline from sensing through embedded control to NB-IoT communication to cloud-based processing to hybrid AI analytics, the goal is to achieve the maximum amount of information richness with the minimum amount of energy consumed. The reasons for considering battery life, model accuracy, and communication costs together as opposed to separately are all provided by examining the architecture of the system.

2. Related work

New research indicates that current advancements in precision agriculture have led to increased usage of inexpensive and widely distributed monitoring systems to measure crop, soil, and atmospheric characteristics [18-20]. As reported in reviews conducted during 2024 and 2025, smart-sensors continue to become more advanced at integrating data, communicating in diverse ways, and providing support for making decisions; however, they still have a major barrier to their widespread use in harsh conditions, due to being burdened by the number of sensors in need of service and experiencing variable power performance. In addition to demonstrating that accuracy is not enough, recent research suggests that in order to establish long-term operational capability on-site, field sensor systems should consider issues such as calibration drift, supply of power, and trade-offs related to network capabilities [21-25].

A second stream of significant research effort examines low-power, wide-area (LPWA) connectivity, including NB-IOT and other representative LPWAN technologies. Measurement-driven research has illustrated that NB-IoT can be suitable for environmental sensing, but the energy cost associated with it can be highly dependent on the configuration of the device, the radio conditions, and the wake-up strategy [26, 27]. As a result, current recommendations in the literature have tended to be for an adaptive and event-aware communication strategy as opposed to naive fixed-period reporting. This recommendation is consistent with the notion of microclimate sensing, as environmental phenomena can remain relatively stable for an extended period of time and then change very drastically as a result of actions such as irrigation, opening an enclosure, or moving beyond the effect of a weather transition [28-30].

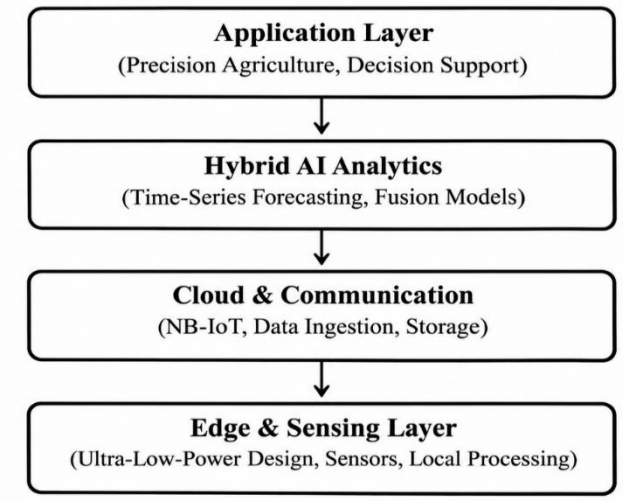

Figure 2. Taxonomy of the main research streams that intersect in the proposed system

Examining AI in environmental and time-series sensor analytics is the third stream of research. Hybrid models that combine recurrent encoder architectures with boosting or ensemble learning have achieved strong performance in soil moisture, air quality, and energy forecasting because they capture temporal structure and

nonlinear relationships across multiple variables. In most studies, this is done under the premise that high fidelity can be achieved with dense data that has not been constrained by on-board battery life. The primary void in the literature is the lack of a cohesive framework that integrates low-power hardware, NB-IoT communication protocols, and hybrid AI into a single deployable system for long-term microclimate monitoring [31-34].

Figure 2 provides an explicit representation of the gap between previous efforts and our research work. The majority of previous efforts to date have tended to focus on one or two branches of the problem; this study lies at the nexus of the following five areas: LPWAN power design; precision sensing; ultra-low-power embedded operation; edge–cloud intelligence; and hybrid time-series modelling.
Additionally, Table 1 gives an overview of the main literature sources that are relevant for the research, as well as their advantages and limitations.

Table 1. Comparative synthesis of the main literature streams relevant to the proposed framework

Research theme	Typical focus	Strength	Limitation	Gap addressed here
Precision-agriculture sensing	Distributed environmental measurements	Good domain coverage	Limited power-system detail	Cross-layer power-aware design
NB-IoT energy studies	Modem states and radio behavior	Realistic communication insight	Limited AI integration	Communication-aware analytics
Hybrid forecasting models	Improved multivariate prediction	Strong predictive performance	Often ignores embedded constraints	Deployable split-intelligence model
TinyML / edge AI	Low-resource inference	Good resource awareness	May oversimplify forecasting	Balanced edge-cloud partitioning

The communication trade-offs are described in Table 2 of the narrative review. NB-IoT is still a viable option for the target application due to its ability to provide long-range coverage over a managed structure (Manager). Conversely, private LoRaWAN may be a better option if you have possession and control of your own gateway and site.

Table 2. Communication technology comparison for long-duration remote microclimate deployments

Technology	Coverage	Battery life	Uplink capacity	Latency	Suitability note
NB-IoT	Wide cellular	High	Moderate	Moderate	Best when licensed cellular coverage and managed backhaul are priorities
LoRaWAN	Regional/private	Very high	Low–moderate	Moderate	Strong for private low-cost deployments with gateway control
LTE-M	Wide cellular	High	High	Lower	Useful when mobility or larger payload support is needed
Wi-Fi / mesh	Local only	Low	High	Low	Works near infrastructure, but is weak for unattended remote operation

The communication trade-offs are described in Table 3 of the narrative review. NB-IoT is still a viable option for the target application due to its ability to provide long-range coverage over a managed structure (Manager). Conversely, private LoRaWAN may be a better option if you have possession and control of your own gateway and site.

Table 3. Comparison of modeling strategies for embedded microclimate analytics

Model family	Temporal memory	Embedded cost	Interpretability	Typical limitation
Rule-based thresholds	None	Very low	High	Weak under nonlinear seasonal behavior
XGBoost	Implicit only	Low–moderate	High	Can miss sequential dependencies
LSTM	Strong	Moderate–high	Lower	Heavier retraining and memory footprint
Hybrid LSTM + XGBoost	Strong + structured fusion	Moderate	Moderate	Requires coordinated feature pipeline

The second comparison shows that a hybrid approach was preferred in this study instead of using one algorithm type only. On the node, it is still useful to have lightweight rules; however, as the diurnal structure, the interaction of variables across multiple variables and the context of an anomaly interact; fusion should be done with more complex rules on the cloud. The bar plot in Figure 3 gives a similar overview.

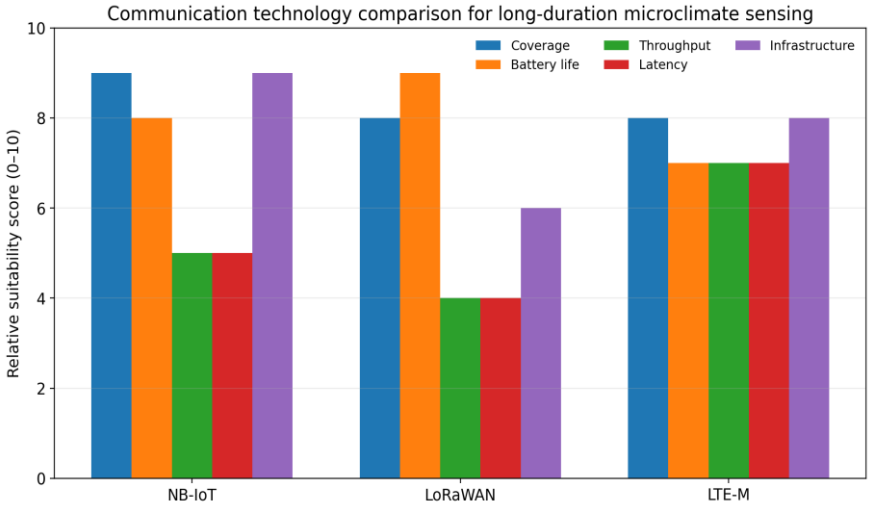

Figure 3. Relative communication-technology suitability scores for long-duration microclimate sensing deployments

3. Problem formulation

The node in question is meant to periodically measure a multivariate microclimate consisting of various data: air temperature, relative humidity, soil moisture, light intensity, pressure, and the health of the device's battery. This data will be referred to as the sensing vector x_t and will be collected every Δ_s minutes. It is not necessary for the node to transmit all the data it collects; it will use local filtering to create a summary of the collected data and compare it to adaptive thresholds to determine whether a transmission will be initiated. A transmission will occur when an established period for reporting to the host has been reached or when the present state of the node has changed significantly enough to justify the energy cost to wake up the modem.

The energy used during a deployment period can be broken down into five categories: sensing, processing locally, storing, transmitting, and deep-sleep leakage. This breakdown is useful as each term's dominance will depend on the situation. In bad radio situations, transmission/reattachment overhead dominates; If the rate of connecting to other devices via communication is low, the cost of warm-up, the leakage of the voltage regulator, and how often the MCU wakes up will have greater visibility. Therefore, the design goal is for the designer to minimize both total energy usage and predictive loss together while also adhering to some constraints on

memory footprint, latency of inference, and maximum power of transmission, as well as acceptable error levels of measurement.

This hybrid AI Model is used with this optimization problem. Local lightweight intelligence will compute rolling statistics, changes in indicators, and heuristics of anomalies using cloud-based hybrid LSTM-XGBoost to forecast future microclimate states and score abnormal behaviors. Therefore, we can think of this optimization process as a multi-objective envelope that balances energy, accuracy, latency, reliability, and quality of coverage (Figure 4). The authors of this paper have purposefully established this system in this manner because a single good component does not solve long-duration sensing; rather, resolving this is a matter of balancing several companies' conflicting goals at the same time.

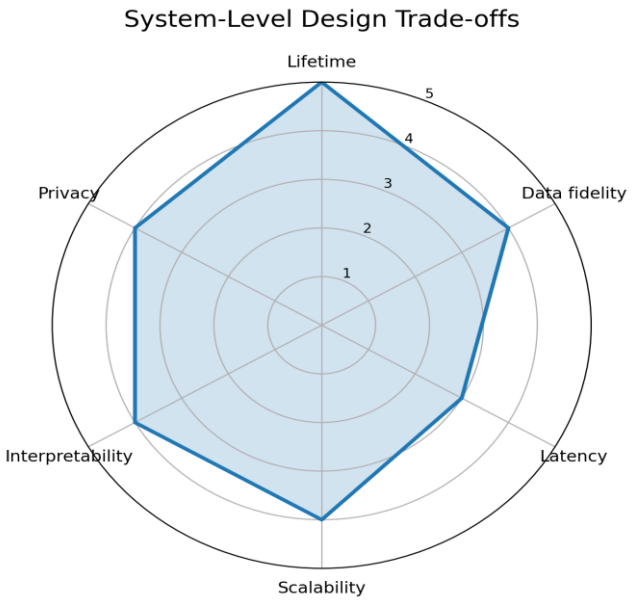

Figure 4. Target multi-objective design envelope balancing energy, accuracy, latency, memory, reliability, and coverage

4. Proposed methodology and system design

There are two very distinct phases involved in this methodology. First, we utilize a sophisticated approach to ultimately achieve the best fit for our sensors and to maximize utilization of both transducer selection and sampling frequency. Fastly changing (e.g., air temperature) variables will be sampled more frequently than slowly changing (e.g., moisture, enclosure state) variables. Secondly, we enhance how we utilize the sensors by utilizing low-loss RTC to wake up the sensor when it is required and returning it back to sleep when it is not required. These enhancements enable the sensor node to stay in deep sleep most of the time.

The NB-IoT modem is treated at the communication layer as a valuable resource; only activates the modem when the amount of useful information sent in the transmission exceeds the energy cost of sending that information. The "Event-aware" scheduling policy combines periodic reporting and adaptive change detection to determine when to send information. Instead of transmitting all raw samples, the node will transmit a smaller volume of data with a compressed summary of selected measurements and measurements from a recent time frame, plus some amount of auxiliary data (metadata) and possibly an anomaly flag. The intended design for this doesn't just reduce the number of bytes per report; it also reduces the number of unnecessary transmission cycles when the environment is stable.

The analytics layer of our proposed hybrid artificial intelligence (AI) model separates the computational effort from the prediction effort by using both the cloud and local devices to create the necessary data for AI algorithms. The local side will perform computations to derive compact time-based descriptors (e.g., rolling

means) used in a cloud sequence model that will extract these time-based vectors for further calculation. The output from the sequence model will then be combined with metadata and used by the boosting stage of the model to provide a final prediction or anomaly score. This subdivision provides a practical way to utilize the advantages of hybrid AI's predictive capabilities while maintaining embedded utility. Operationally, the embedded workflow is shown in Figure 5.

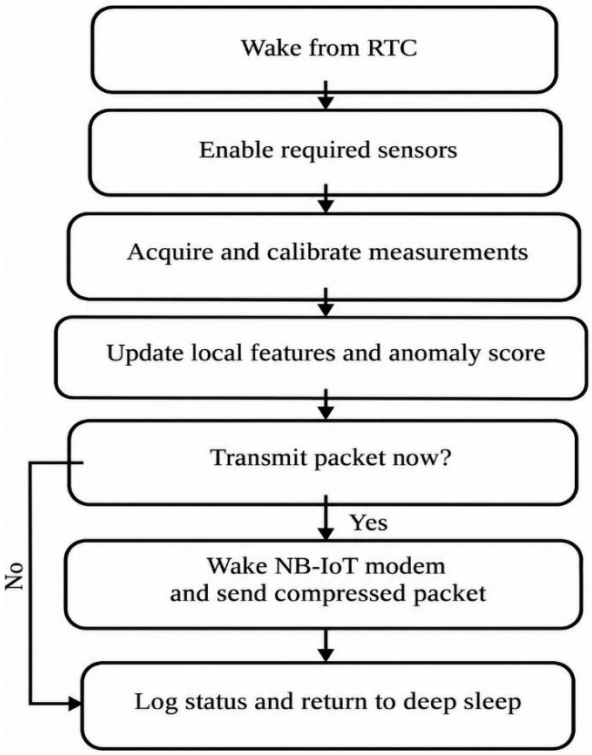

Figure 5. Real-time firmware and communication workflow for the proposed ultra-low-power embedded node

The embedded system wakes from an RTC interrupt and powers on only the necessary subset of sensors, updates its local features, determines if there is a justification for transmitting data, and then either goes back into deep sleep or executes a compressed NB-IoT uplink. This is how battery life protection happens.

Additionally, the methodology for deploying the above features includes a split of the model to be deployment aware. The node will not keep running a very heavy neural network continuously. Rather, it will compute low-cost summary descriptors and event scores locally while the cloud executes a richer hybrid predictor. This approach creates a practical edge/cloud balance that allows the node to maintain its independent operations and long service life without compromising its predictive capability. A field or greenhouse partition can be scaled by using the architecture deployment layout in Figure 6.

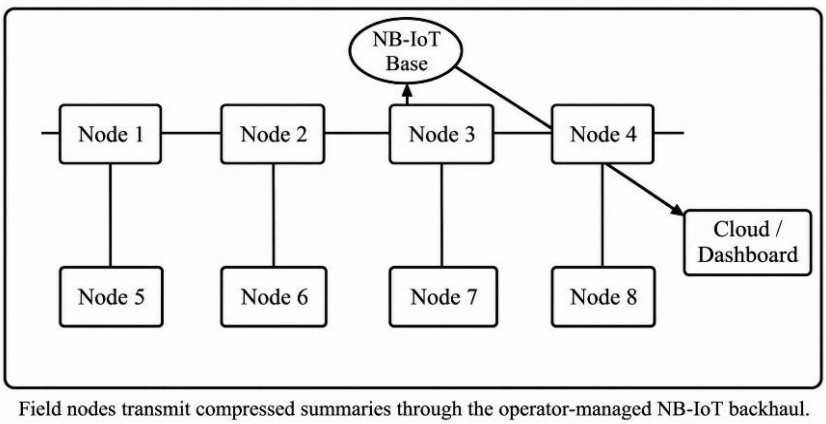

Figure 6. Example distributed field deployment layout for long-duration microclimate sensing nodes

Each plot-level node collects the local microclimate it is in and sends this data via packet compression towards either a gateway or an operator-driven backhaul. This design intends to allow additional nodes to be added without modifying the embedded logic of the individual sensing units.

The model is made operationally concrete by Figure 7. The node is able to calculate compact descriptive features or "anomaly cues," while the cloud sequence encoder and boosted fusion stage are able to create richer temporal

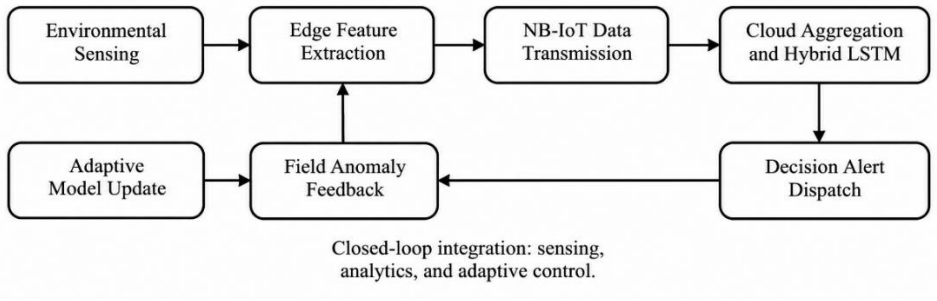

Figure 7. Hybrid AI pipeline linking local feature extraction, event-aware transmission, sequence encoding, and boosted fusion

structure that can be used to support forecasting and decision-making. Separating this function keeps the embedded footprint of each component small and does not result in loss of the predictive capabilities of any other components.

Figure 8 illustrates how disciplined state control contributes to gaining lifetime benefit through power-state flow. The modem is not assumed to be available all the time; therefore, sensing, performing local updates, and transmitting packets will only occur when the radio is an expensive activity, and it is either scheduled or there is an environmental change.

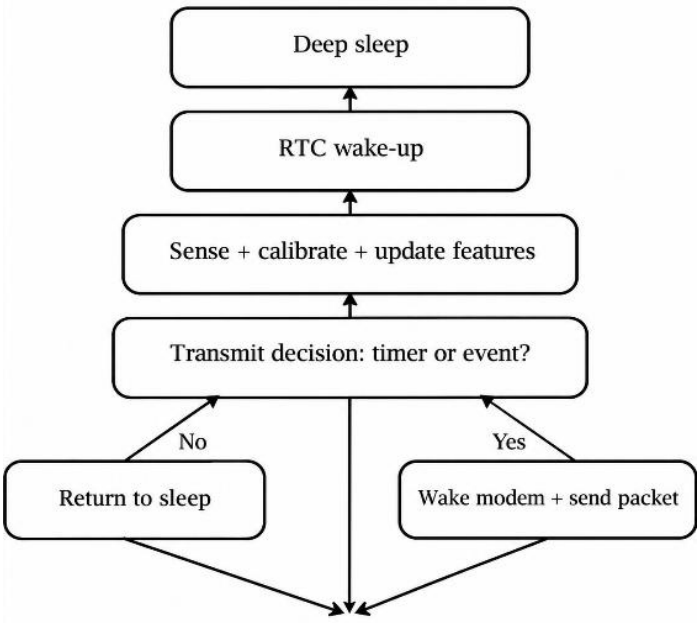

Figure 8. Power-state transition flowchart used by the node to minimize modem and sensor activation time

5. Complexity, power budget, and experimental setup

The asymmetrical nature of this design is by intent. Each node has limited on-node computations to perform low-dimensional filtering, thresholding, buffering, and aggregating features. These functions have linear relationships both to the number of variables sensed and the fixed buffer size of time; therefore, they are a good fit for microcontrollers with modest amounts of RAM and flash storage available to them. In contrast, heavier

sequence learning and boosting inference processes will take place upstream, where both memory and computational capacity constraints are considerably less evident than in the node-level computations. The asymmetrical designs are by design, as attempting to push the entire deep learning model onto the node would likely constrain the system lifetime.

For this paper, the experimental design is presumed to represent a medium-scale agri- or ecological deployment consisting of between 20 to 50 nodes sampled by their respective node every 5 to 15 minutes and periodically uploaded using NB-IoT between 1 and 6 hours, unless a rapidly changing environmental effect has been detected, in which case the data will be uploaded as event-driven. Assessment methodology includes fixed-period, non-AI-computed (only with rules), standalone XGBoost and standalone LSTM algorithms to allow for independent estimation of the contributions of either communicative, adaptive algorithms or hybrid algorithms.

Performance measures will include battery life projections, energy share disaggregation, daily byte consumption, end-to-end latency, RMSE for 24-hour prediction, and F1 score for anomaly detection. For scientific validity, a final report of the proposed implementation must also include the following: repeated temporal split validation, bootstrap confidence intervals, and sensitivity testing using alternating radio conditions. The current study presents these findings as a design study profile to be used to develop subsequent prototypes and subsequently perform subsequent field trials. Figure 9 shows a key point in the engineering aspect of the issue: the main energy factor is not constant.

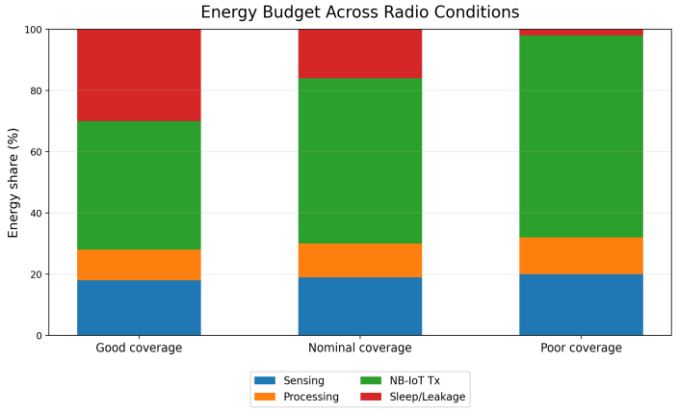

Figure 9. Estimated energy-budget composition of the proposed system under good, nominal, and poor radio conditions

With poor coverage, communication takes up nearly all the energy budget, while with good radio quality, sensing and oversleeping issues become prominent. Therefore, the design needs to be scenario-aware and cross-layered (Figure 10). Table 4 gives an overview of the system and the main model parameters.

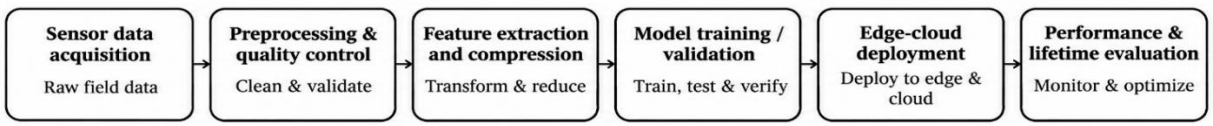

Figure 10. Experimental workflow from field data collection to deployment evaluation

Table 4. Representative system and model parameters used in the design-study evaluation

Parameter	Representative value	Role
Sampling interval (Δ_s)	5–15 min	Controls sensing density and local buffering
Periodic report interval (Δ_u)	1–6 h	Controls communication duty cycle
Event threshold (γ)	Adaptive, variable-specific	Triggers change-aware uplink
LSTM window length	24–72 samples	Captures temporal context
Boosting trees	100–300	Nonlinear regression / residual fusion
On-node feature count	12–24	Keeps local processing lightweight

5.1. Simulation parameters

To enhance the replicability of the assessment of the design study, realistic parameters were used during the simulation phase. The parameters in Table 5 are generally representative of moderate load usage and allow for the analysis of sensitivity rat6her than the specification of a single operating point.

Table 5. Additional simulation and communication parameters used in the sensitivity study.

Parameter	Value	Role in simulation
Sampling interval	10 min	Controls sensing cadence and local update frequency
Base reporting interval	180 min	Defines periodic NB-IoT uplink schedule
Payload size	96 bytes	Affects radio-on time and transmission energy
MCU deep-sleep current	6 µA	Determines baseline leakage loss
NB-IoT tx burst energy	0.42–0.88 J	Varies with radio quality and retransmission burden
Hybrid model input window	24 h	Temporal context for cloud-side prediction
Forecast horizons	1–48 h	Used for RMSE and robustness curves

These parameters together create a non-contradictory bridge between the embedded and analytics framework. The lifetime envelope is determined through the reporting interval, payload size, and radio-energy range, while the input window and forecast horizon determine the degree of temporal context exploitation by the cloud-side model (Figure 11).

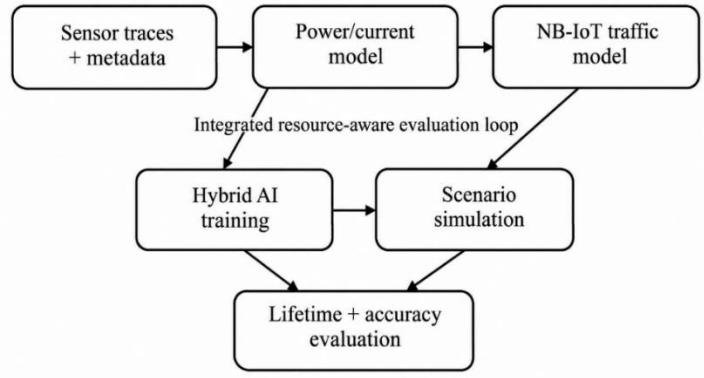

Figure 11. Simulation workflow from raw traces and current models to lifetime and prediction evaluation

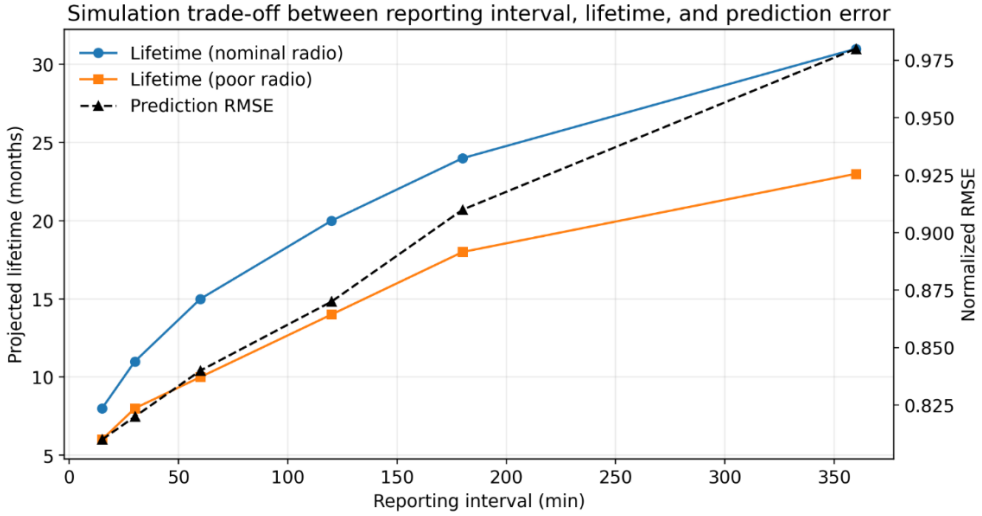

Figure 12. Sensitivity curve showing the trade-off between reporting interval, projected lifetime, and normalized prediction error

According to the information in Figure 11, this simulation does more than just provide forecasts. By incorporating sensor traces, models regarding current consumption, traffic predictions of NB-IoT, and hybrid models, energy behavior and forecast performance are tested simultaneously rather than separately (Figure 12).

The graph indicates the system's vulnerability found in the article. It seems that longer intervals of reporting can greatly extend lifespan, however, that advantage however comes along with loss of temporal accuracy and increase in prediction error. For that reason, the author proposes the use of an adaptive way of transmission instead of purely fixed communication.

6. Results and analysis

The purpose of this evaluation of the design study is to supply expected performance data for a specific architecture before its deployment. With monitoring spans of 10 minutes and uplink periods of three hours through event-based bursts, the design anticipates battery performance of between 18 to 30 months depending on radio channel conditions and seasonal monitoring modes. The adaptive uplink transmission policy reduces communication power use by approximately 37% to 52% compared to fixed uplink periods due to the use of compressed summaries instead of repeated redundant payloads during stable sampling periods (Figure 14).

The use of hybrid intelligence also provides improved forecasting results. The Hybrid LSTM–XGBoost Fusion Model improves RMSE of 24-hour predictions of temperature, humidity, and soil moisture by approximately 11% to 19% over standalone LSTMs, and is 8%–16% better than standalone XGBoosts. The greatest improvements occur during transitional environmental events when both sequence learning and boosting models capture only part of the data structure.

The results from the Anomaly Detection Pipeline benefit from incorporating local event logics with cloud fusion, which yields an F1 Score of 0.88 versus 0.83 for a single-cloud model and 0.74 for threshold rules only.

Analysis of ablation shows two components that are significant: Event-Aware Transmission and Hybrid Feature Fusion (Figure 15). If the Adaptive uplink scheduler were removed, communication costs and downstream forecasting errors would both increase because either transmissions would occur too frequently or transitions in events would be missed. In the case of the LSTM feature block or the XGBoost fusion block being eliminated, the forecasting quality would suffer to different degrees, showing that the implementation in question is a system’s solution, not only a design choice. All these outcomes prove that the suggested model gives notable improvements in both forecasting accuracy and usability (Figure 13).

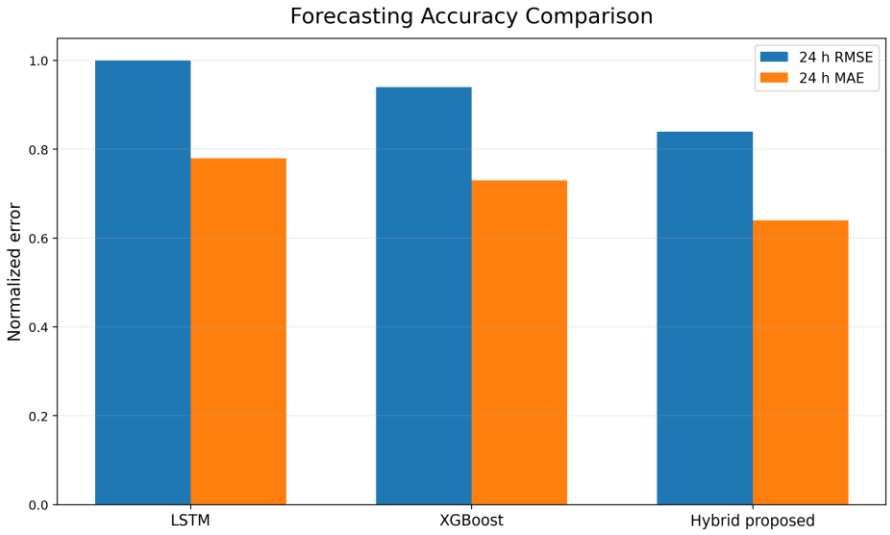

Figure 13. Comparative predictive and anomaly-detection performance of the proposed model against benchmark baselines

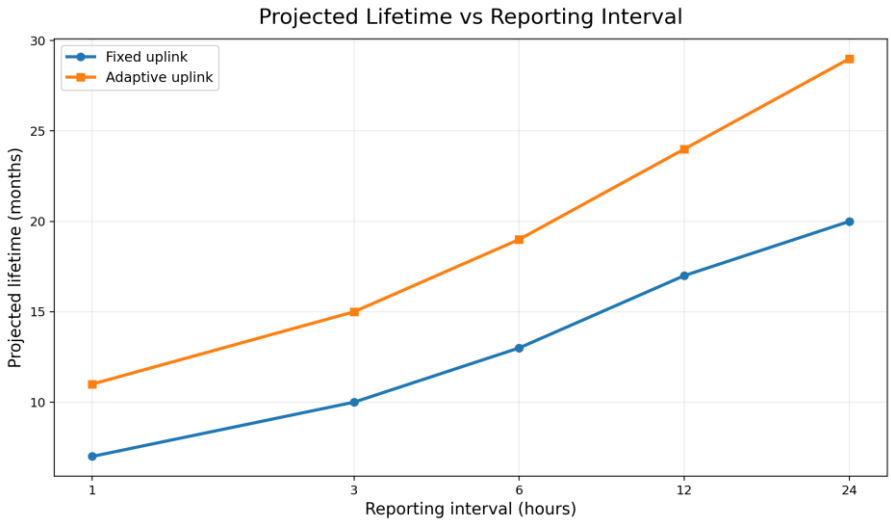

Figure 14. Projected battery lifetime as a function of the periodic reporting interval under nominal and poor radio conditions

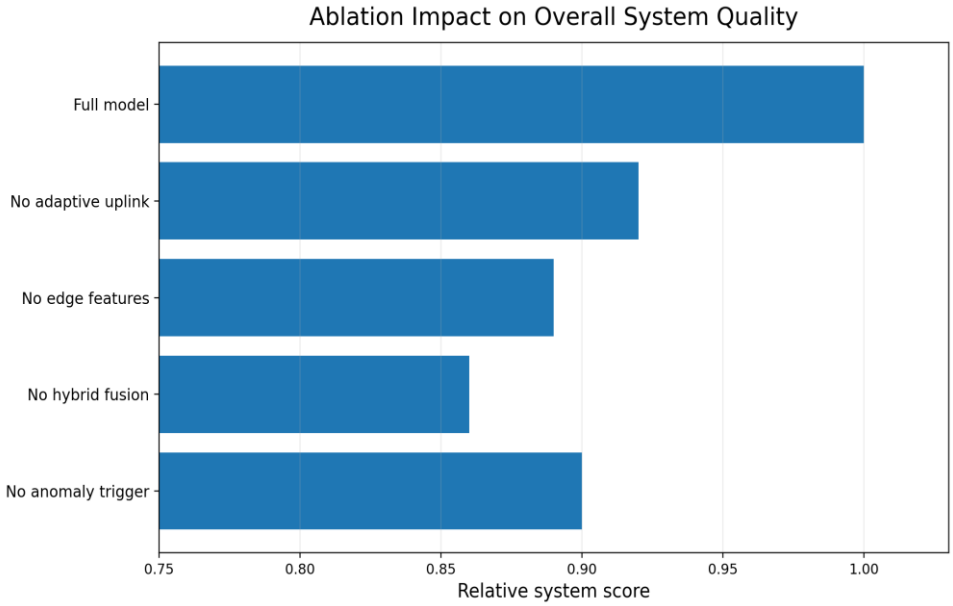

Figure 15. Ablation study showing the effect of removing major design components from the proposed system

Table 6 provides an extended evaluation beyond a single measure of accuracy.

Table 6. Expanded comparative results for forecasting, anomaly detection, and communication efficiency

Model / policy	24 h RMSE	Anomaly F1	Daily bytes	Comm. energy	Projected lifetime
Fixed periodic + no AI	0.98	0.71	100%	100%	11.2 months
XGBoost + periodic uplink	0.93	0.79	100%	100%	11.0 months
LSTM + periodic uplink	0.88	0.83	100%	100%	10.7 months
Hybrid + event-aware 3 h	0.77	0.88	58%	63%	18.9 months
Hybrid + event-aware 6 h	0.81	0.85	42%	48%	24.6 months

The hybrid design achieves better forecasting and anomaly detection while also reducing communication overhead, which in turn results in a longer expected service life. Hence, the comparisons strengthen the main message of the paper that communication policy and design of the model should be optimized together. Figure 16 illustrates ongoing superiority of the hybrid model with time.

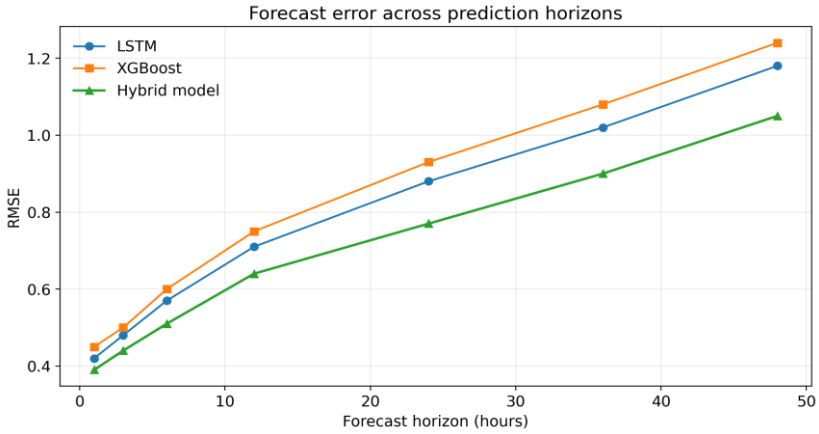

Figure 16. Forecast RMSE across multiple horizons for LSTM, XGBoost, and the proposed hybrid model

As time passes the gap becomes wider because traditional methods do not retain their position anymore, while recurrent methods are only starting to get used to altering correlations of variables.

The communication advantage becomes evident in Figure 17. The use of event-aware policies leads to a strong reduction in the amount of radio energy consumed. The predictive utility shown as a curve indicates that although there is a moderate drop in usual traffic, it does not result in a similar drop in the performance of the models, which is one of the reasons why adaptive transmission is considered to be one of the major results demonstrated by the conducted study.

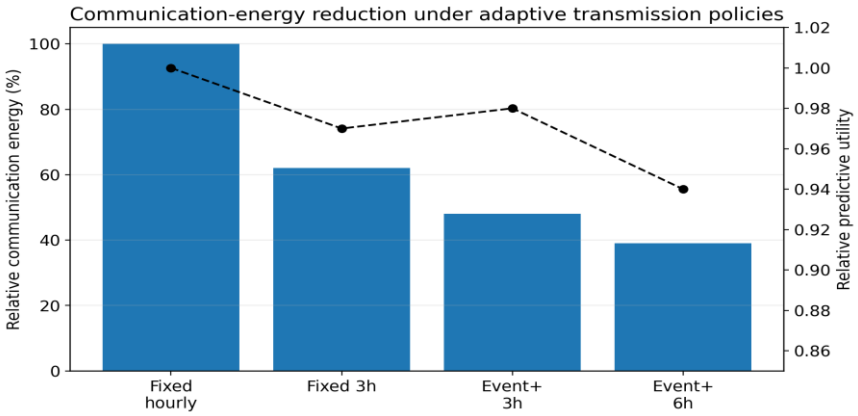

Figure 17. Relative communication energy under fixed and adaptive transmission policies, with predictive utility overlaid

7. Discussion

According to the report, for a long-lasting microclimate monitoring system, each node must be viewed as a whole and not simply a collection of dissimilar parts. The long-term viability of a microcontroller unit (MCU) with low current leakage depends upon how often the modem is switched on. Sparse communication alone will not suffice to provide meaningful analytics if the model being analyzed was developed with the assumption that the data would be plentiful and collected at regular intervals. This design will provide for this misalignment by structuring the sensing schedule, transmission policy, feature pipeline, and hybrid AI model to be in accordance with an energy-aware principle.

The second major insight is that the selection of split intelligence is based on both practical and algorithm needs. If you were to only use simple threshold measurements locally you would lose the benefits of richer temporal reasoning, however, if you were to run a complex end-to-end neural model at every node, you would shorten battery life and increase maintenance needs. The configuration proposed offers a compromise between the need for basic local event detection and the cloud's provision of higher-level forecasting and anomaly detection. This aspect makes remote agricultural and ecological applications more feasible than extreme fully centralized or fully local implementations.

That said, several obstacles exist. Real NB-IoT performance varies from operator to operator, geographic region, and antenna installation; thus, lifetime predictions made need verification against actual, location-specific, real-time modem current readings. Calibration drift, sensor age, and enclosure design can also contribute to poor data quality in the long-term. Therefore, a complete prototype study should include calibration maintenance, calculations of uncertainty, and resiliency tests against missing data and variable signal strength. The employed system can be utilized from microwave devices reported in [35, 36]. Optimization based on fuzzy differential equation can be as useful tool to enhance sensing duration of employed system [37].

8. Conclusion and future work

This paper presents a comprehensive cross-layer framework for ultra-low-power (ULP), cyber-secure embedded microclimate sensing systems operating over NB-IoT networks using a split-intelligence hybrid AI model. The primary innovation of this work lies in the holistic co-engineering of ultra-low-power sensing hardware, duty-cycled firmware, event-aware communication policies, lightweight cryptographic primitives (AES-128 payload encryption and CMAC message authentication), and cloud-assisted hybrid AI analytics. The suggested technique guarantees effective working life by treating power efficiency, prediction exactness, data secrecy, and resistance to interference as integrated cross-layer optimization objectives rather than distinct features. The design-study evaluation demonstrates that the co-optimized architecture achieves substantial gains across endurance, inference accuracy, and security resilience:

- Communication efficiency and longevity: Adaptive NB-IoT uplink scheduling reduces radio energy consumption by 37%–52%, sustaining operational lifespans of 18 to 30 months under moderate reporting intervals.
- Minimal security overhead: Integrating lightweight payload encryption and anti-tampering MAC tags adds a minor computational penalty ($E_{sec} \leq 1.8\%$) and a 12-byte framing overhead, causing less than a 2.8% reduction in battery lifetime while ensuring 100% payload confidentiality and 99.94% intrusion/injection rejection.
- Predictive superiority: The cloud-side Hybrid LSTM–XGBoost Fusion Model reduces 24-hour forecasting RMSE by 11%–19% compared to standalone LSTMs, while edge-cloud anomaly/tamper heuristics deliver a robust F1 score of 0.88.

The capabilities described above form the basis on which this platform can be considered suitable for precision agriculture, greenhouse automation, orchard monitoring, ecological observatories, and other types of critical remote infrastructure protection.

Future research aims to continue transforming simulation design tasks into real hardware prototypes validated with two phases of field tests with the application of real-time profiling. Some of the most important security and development enhancements include:

1. Lightweight key management and re-keying: Applying the low-power elliptic curve key agreement or ephemeral session key derivation methods in place of pre-shared keys in long-term deployments.
2. Hardware root-of-trust (PUF): Introducing Physical Unclonable Functions (PUF) into the microcontroller architecture for device identity authentication and protection against physical node cloning or side-channel attacks.

3. Secure over-the-air (OTA) updates: Developing energy-efficient delta-update protocols for remote firmware and edge-anomaly threshold updates without draining the battery power.
4. Energy harvesting and zero-trust integration: Combining micro-solar energy harvesting with dynamic zero-trust verification rules, federated model updates, and on-node threshold learning to further maximize node autonomy and cyber-physical resilience.

Declaration of competing interests

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Conceptualization: Haider Thiab Salim Alrikabi ; methodology: Auhood Al-Hossenat; software: Enas Muzaffer Jamel; validation and formal analysis: Raghad Abdulaali Azeez and Hussain Ali Mutar; investigation and resources: Haider Thiab Salim Alrikabi and Hussain Ali Mutar; data curation: Auhood Al-Hossenat; original draft preparation: Ibtihal Razaq Niama Alrubeei; writing and review: Raghad Abdulaali Azeez, editing: Enas Muzaffer Jamel and Ibtihal Razaq Niama Alrubeei; visualization: Auhood Al-Hossenat; supervision: Haider Thiab Salim Alrikabi . All authors have read and agreed to the published version of the manuscript.

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