Proactive Link Failure Early Warning for Ultra-Long-Range Maritime 5G via Edge Intelligence and Random Forest

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***Abstract*—In the Maritime Internet of Things (MIoT), the link stability of 5G communications is a critical bottleneck for the reliable execution of mission-critical tasks by autonomous ships and maritime mobile robots. As an integral component of intelligent sensing infrastructures, proactive link failure early warning serves as a cross-layer perception mechanism, providing essential connectivity for robust navigation and situational awareness in extreme environments. However, traditional physical-layer hardware enhancement strategies exhibit diminishing returns when addressing nonlinear, stochastic signal fading in Beyond-Line-of-Sight (B-LoS) scenarios. To address this challenge, this paper proposes an embedded communication-aware framework for robot perception. By treating Channel State Information (CSI) as virtual sensing data, temporal features are dynamically extracted via a sliding window mechanism, and an intelligent sensor data interpretation model is constructed using a Random Forest (RF) algorithm to achieve proactive awareness of interruption risks. Validation performed on field-test data collected from a 341 km voyage of the "Sansha No. 2" supply ship demonstrates that the model achieves a prediction accuracy of 94.95%. Results indicate that the algorithm effectively balances millisecond-level inference latency with predictive precision, thereby fulfilling the strict real-time processing requirements of embedded platforms under resource-constrained conditions. This research provides a methodological reference for integrating adaptive sensing strategies into maritime autonomous systems to enhance navigation resilience.**

Keywords-Maritime Internet of Things; robot perception; Random Forest; link failure prediction; edge intelligence.

I. INTRODUCTION

The rapid evolution of the Maritime Internet of Things (MIoT) has made autonomous ships and maritime mobile robots essential to the global blue economy. In typical maritime scenarios, such as multi-vessel coordinated scheduling, marine scientific observation, and autonomous navigation, constructing high-reliability and high-bandwidth wireless communication networks is a primary objective in both academia and industry [1]. Although terrestrial cellular networks have achieved robust coverage in coastal regions, ensuring end-to-end Quality of Service (QoS) under long-distance and highly dynamic sea conditions remains a major technical challenge in maritime communications [2].

Figure 1 illustrates the maritime 5G topology and communication scenarios. The figure depicts terrestrial base stations, experimental vessels, and signal propagation paths influenced by the Earth's curvature and sea-surface reflection.

These propagation challenges become particularly pronounced as the offshore distance exceeds 60 km. Due to Line-of-Sight (LoS) blockage caused by the Earth's curvature and multipath reflection effects induced by complex sea-surface fluctuations, signal amplitudes exhibit deep-fading characteristics [3]. As shown in Figure 1, the sea surface acts as an irregular reflector where reflected and direct waves superimpose coherently at the receiver, leading to severe nonlinear signal fluctuations. Related 5G channel measurement studies indicate that these complex propagation characteristics render traditional terrestrial propagation models inapplicable in maritime scenarios, resulting in a significant stability deficit for communication links in the open sea [4].

Consequently, both academia and industry often adopt enhanced hardware deployment strategies. However, empirical analysis in this study reveals that while pure hardware gain enhancements can improve the Reference Signal Received Power (RSRP), they cannot fundamentally suppress the stochastic drops in the Signal-to-Interference-plus-Noise Ratio (SINR). During an ultra-long-distance test of 341 km, enhanced terminals still experienced frequent instantaneous link crashes, demonstrating a clear stability bottleneck in physical-layer-only enhancement schemes. Existing research suggests that anomaly behavior recognition and tracking for dynamic spectrum environments can provide new technical pathways for securing and stabilizing communication links [5]. Deploying lightweight intelligent algorithms at edge nodes to proactively predict link risks offers a viable alternative to redundant hardware design, thereby improving the robustness of maritime communications.

To meet the link maintenance requirements of ultra-long-range maritime 5G communication, the primary contributions of this paper are as follows:

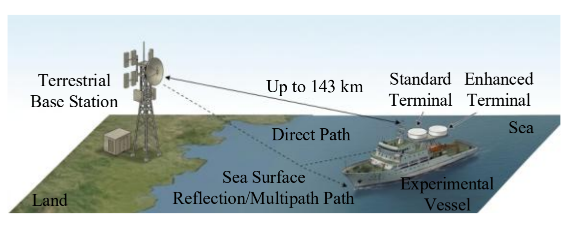

Figure 1. Maritime 5G topology and communication scenario.

- Construction of a scarce deep-sea field-test dataset: Based on the “Sansha No. 2” measurement platform, full-dimensional channel performance data were acquired for dual terminals at distances of up to 143 km from terrestrial base stations. These data provide empirical evidence for the Beyond-Line-of-Sight (B-LoS) coverage research of terrestrial 5G base stations in the open sea.
- Proposal and validation of a lightweight edge early-warning scheme: Addressing the computational resource constraints of MIoT routers, the effectiveness of a Random Forest (RF) algorithm for link failure early warning was verified. Field-test results indicate that this scheme achieves a real-time prediction accuracy of 94.95% for failure risks, providing empirical support for the construction of adaptive and intelligent MIoT.

The remainder of this paper is structured as follows: Section II reviews related work. Section III describes the methodology, including data preprocessing and classifier design. Section IV presents and analyzes the experimental results. Section VI provides a detailed discussion, and Section VI concludes the paper and discusses future work.

II. Related work

Accurate characterization of maritime channel features is a prerequisite for constructing a high-reliability MIoT. Although existing research has performed extensive measurements on 5G communication propagation characteristics across various scenarios [4], empirical studies in ultra-long-range maritime environments remain scarce. Wang et al. systematically reviewed maritime wireless channel models, identifying multipath fading and sea-surface reflection as the dominant factors affecting link stability [3]. However, most current maritime experiments are concentrated in near-shore areas within 20–40 km of the coast; consequently, there is a lack of authentic and continuous experimental data for long distance exceeding 100 km that cross the LoS boundary. Because signal propagation at long distance is further complicated by the combined effects of the Earth’s curvature and tropospheric refraction, existing near-shore empirical models exhibit significant limitations in describing the stochastic link failure behavior of deep-sea links.

Since traditional deterministic models struggle to characterize the nonlinear fluctuations of wireless channels, Machine Learning (ML) and Artificial Intelligence (AI) technologies are increasingly utilized for wireless network optimization [6]. Kibria et al. noted that the utilization of big data analytics and ML algorithms can significantly enhance resource scheduling and link management efficiency within complex heterogeneous networks [6]. Regarding the processing of highly dynamic channel variations, Liang et al. proposed an ML framework for vehicular network environments, demonstrating that reinforcement learning and ensemble learning possess superior generalization capabilities in addressing signal fading prediction caused by high-speed terminal mobility [7]. Applying ML algorithms to maritime networks, which share dynamic characteristics similar to vehicular networks, is a promising approach to mitigate stochastic signal drops.

As the scale of Internet of Things (IoT) networks grows, the latency and bandwidth limitations of traditional cloud-centric processing become more apparent. This challenge is particularly evident in maritime operational environments: real-time early warning of maritime communication link quality imposes millisecond-level requirements on the inference latency of prediction algorithms; however, the satellite backhaul links between shipborne edge nodes and remote cloud servers often fail to meet these constraints. Consequently, migrating intelligent analysis functions from the cloud to edge nodes (e.g., shipborne routers) provides a practical solution.

For instance, Sudharsan et al. proposed adaptive communication strategies that rely on lightweight algorithms to locally optimize real-time communication quality for IoT edge devices [8]. Nevertheless, MIoT terminals are generally constrained by limited computational capacity and storage volume. Thus, further compressing model computational complexity and memory footprint while maintaining high prediction accuracy remains a key challenge for the practical deployment of edge intelligence in maritime scenarios.

III. Methodology

This section details the experimental design and the machine learning architecture, spanning from physical layer perception to edge-side decision-making.

A. Experimental Setup and Hardware Parameters

Field-test data were acquired using the “Sansha No. 2” supply ship during a 341 km voyage. The route reached a maximum offshore distance of 143 km, approaching the B-LoS coverage limits of terrestrial base stations. The complex meteorological and dynamic sea states provide an authentic environment for evaluating 5G stability. As shown in Figure 2, standard and enhanced terminals with distinct radio frequency gains were deployed on the main deck.

B. Data Preprocessing and Management of Missing Values

Regarding the non-stationary time-series data, this study did not employ conventional interpolation for filling gaps. All illegal observations containing non-numeric characters were removed to ensure the arithmetic validity of the input vectors. During large-scale disconnection intervals of the standard terminal, the state was labeled as “Out-of-Service” to preserve the authentic physical characteristics of channel collapse. To eliminate the influence of different physical dimensions on

Figure 2. Terminal installation location.

model convergence speed, Min-Max normalization was applied to RSRP, Reference Signal Received Quality (RSRQ), SINR.

After preprocessing and sliding window transformation, the refined dataset comprises 2271 valid temporal samples, featuring a class distribution of 1590 (70.01%) normal states and 681 (29.99%) warning states (defined as SINR < 0 dB). To ensure rigorous evaluation and prevent data leakage, the samples were chronologically partitioned into a training set (80%, 1816 samples) and an independent testing set (20%, 455 samples).

C. Feature Engineering: Time-Series Sliding Window Mechanism

Wireless signal fading processes exhibit significant temporal dependency; deterioration in signal quality at the current moment is typically a precursor to imminent link interruption. To precisely capture these dynamic evolutionary patterns, this study introduces a sliding window mechanism to reconstruct the time-series signals and mine the temporal correlation features of channel states [9], as shown in Figure 3.

Let the raw feature vector at time t be defined as:

$$S_t = [RSRP_t, RSRQ_t, SINR_t]^T, \tag{1}$$

where the window length is set to n, the channel states of the past n consecutive moments are aggregated into the current model input vector. In this experiment, $n = 5$ was selected to integrate the observation sequence of the previous 5 seconds. The mathematical expression is:

$$X_t = \{S_{t-n}, S_{t-n+1}, ..., S_t\}. \tag{2}$$

This methodology transforms the traditional static point-to-point classification problem into a pattern recognition problem based on temporal context. By incorporating temporal dimension observations, the model can capture the slope features of severe SINR fluctuations and the instantaneous jitter trends of RSRQ, thereby identifying microscopic physical layer anomalies before a complete link interruption occurs.

D. Random Forest Classifier Design

This study employs the RF ensemble learning framework proposed by Breiman as the prediction algorithm [10], as shown in Figure 3. Compared to deep learning models with high computational overhead, such as Long Short-Term Memory (LSTM) networks, RF strikes a superior balance between algorithmic performance and feasibility for edge engineering deployment [11–13].

The RF algorithm constructs multiple decision trees via bootstrap sampling and selects only a random subset of features during the node-splitting process of each tree. This dual randomness enhances the model's generalization and mitigates overfitting when processing noisy and highly stochastic maritime channel data. Model training uses Gini impurity as the optimization criterion for node splitting; this index can effectively quantify the marginal contribution of different channel features (such as RSRQ fluctuation amplitude and SINR trend) to link failure time. Its mathematical expression is as follows:

$$Gini(D) = 1 - \sum_{k=1}^{2} p_k^2, \tag{3}$$

where p_k denotes the probability that a sample belongs to the k^{th} category (Normal or Warning). In highly dynamic fluctuation scenarios of maritime channels, the advantage of the Gini criterion lies in its superior computational efficiency and robust tolerance to outliers. Specifically, the algorithm traverses all features within the sliding window (e.g., the variation slope of SINR) to identify the optimal splitting threshold that minimizes node impurity. By minimizing node impurity, this screening mechanism allows the model to decouple genuinely predictive SINR perturbation features from the power compensation effects of RSRP. While

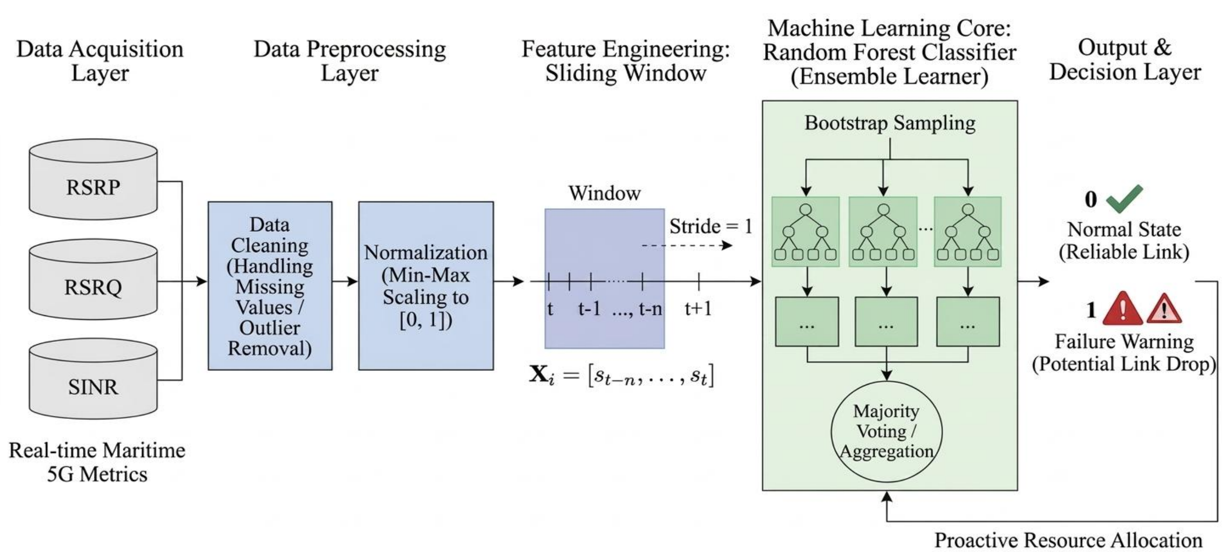

Figure 3. Proposed Edge-AI link prediction framework based on sliding window feature engineering and random forest classifier.

information entropy (Information Gain) is also a standard splitting criterion [14], the Gini index avoids complex logarithmic computations, making it more amenable for deployment on resource-constrained edge routers [14–15]. This low-complexity decision mechanism ensures the real-time inference performance of the algorithm on shipborne edge gateways.

Table I benchmarks the proposed RF model against Extreme Gradient Boosting (XGBoost), LSTM, and Gated Recurrent Unit (GRU) using the same sliding window configuration. While recurrent neural networks like LSTM and GRU exhibit high recall, their significantly lower precision would trigger excessive false alarms in autonomous maritime navigation. In contrast, the RF model achieves superior overall performance with an accuracy of 0.95. The selection of RF is further justified by its architectural suitability for edge intelligence. Unlike the complex tensor operations and high computational overhead associated with deep learning models, the RF algorithm relies on parallel logical decision trees that ensure millisecond-level inference latency on resource-constrained shipborne gateways without GPU support. Specifically, the model is configured with 100 estimators and a maximum tree depth of 10 to prevent over-fitting while optimizing efficiency. By utilizing the Gini index, the algorithm avoids the complex logarithmic computations required by information gain, facilitating seamless deployment on System on Chip (SoC) based edge devices.

IV. EXPERIMENTAL RESULTS

The field-test dataset is quantitatively analyzed across two dimensions: physical-layer transmission characteristics and algorithmic prediction efficacy. This evaluation reveals the degradation patterns of 5G links in long-distance maritime environments and validates the proposed early-warning model.

A. *Physical Layer Performance Analysis and Hardware Bottleneck Observations*

To further quantify the actual contribution of hardware enhancement to link performance, Cumulative Distribution Functions (CDFs) are used to statistically model the field-test dataset. The spatial distribution of link failures and the corresponding ship trajectories are visualized in Figure 4(a) for the standard terminal and Figure 4(b) for the enhanced terminal. As illustrated in the SINR and RSRP CDF curves in Figures 4(c)–(d), high-gain hardware effectively extends the coverage radius. Specifically, the enhanced terminal reduces the proportion of sampling points in the “weak coverage zone” (below –105 dBm) to less than 5%. However, as shown in the SINR CDF curve in Figure 4(c), a non-negligible proportion of samples for the enhanced terminal still fall within the failure interval where SINR < 0 dB due to stochastic maritime multipath fading. These statistical results reveal an inherent “power-quality paradox”: relying solely on hardware-level power gain cannot fundamentally resolve nonlinear signal fluctuations, necessitating the introduction of intelligent prediction algorithms for proactive link maintenance.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT PREDICTION MODELS

Model	Accuracy	Precision	Recall	F1-score
RF	0.95	0.93	0.90	0.94
XGBoost	0.92	0.87	0.88	0.91
LSTM	0.87	0.71	0.96	0.86
GRU	0.87	0.73	0.91	0.85

B. *Quantitative Summary of Network Performance Indicators*

We statistically analyzed the communication indicators collected by both terminals across the entire 341 km voyage. As presented in Table II, the average network throughput of the enhanced terminal is nearly four times higher than that of the standard terminal. However, its average communication latency remains constrained by the physical laws governing long-distance electromagnetic wave propagation and has not undergone significant improvement.

C. *Performance Evaluation of the Random Forest Early Warning Model*

Following the identification of the performance limitations of hardware enhancement schemes, this section evaluates the actual early-warning performance of the RF prediction model based on temporal sliding window feature engineering. The core of this model is to learn microscopic fluctuation precursors of signal quality to achieve proactive warning of link failure events (defined as SINR < 0 dB).

Figure 5(a) presents the confusion matrix of the RF classifier on the test set, achieving an overall prediction accuracy of 94.95%. Quantitative evaluation results show that the model recall and F1-score are 90% and 94%, respectively, indicating that the algorithm can effectively identify the vast majority of potential channel drop events and significantly reduce the risk of data transmission interruption caused by false negatives. Under edge computing constraints, the RF model exhibits robust performance, effectively filtering non-stationary channel noise induced by maritime multipath

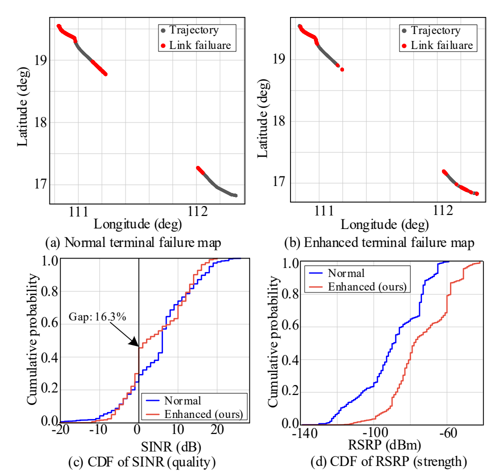

Figure 4. Comprehensive performance evaluation of maritime communication links.

TABLE II. SUMMARY OF NETWORK PERFORMANCE INDICATORS

Metric	Standard Terminal	Enhanced Terminal
Average RSRP	-103.5 dBm	-82.9 dBm
Average RSRQ	-13.5 dB	-11.9 dB
Average SINR	5.4	4.4
Average Network Latency	98.56 ms	86.93 ms
Average Downlink Rate	3.73 Mbps	13.11 Mbps
Average Uplink Rate	0.71 Mbps	2.76 Mbps
Link Failure Rate	48%	12%

effects and precisely capturing channel degradation trends with clear physical significance.

D. Feature Importance Analysis and Physical Interpretation

To interpret the model's decision-making mechanism, the Gini Importance index was employed to quantify the contribution weights of the input features.

Figure 5(b) illustrates the contribution weight distribution of each feature indicator to the prediction results. Analysis results indicate that the temporal variation rate of SINR and the fluctuation magnitude of RSRQ are the dominant factors determining link stability. From a physical mechanism perspective, while RSRP characterizes absolute signal strength, its sensitivity as an indicator for instantaneous link interruption is lower than that of SINR in maritime propagation environments where background noise and multipath interference effects are significant. Feature importance ranking further confirms that the first-order difference of SINR within the sliding window (i.e., the variation trend) accounts for the highest proportion, which corroborates the physical law that link failure follows a progressive degradation pattern. By extracting the fluctuation characteristics of RSRQ and SINR, the RF model can effectively identify complex nonlinear interference patterns, which is the primary reason its prediction performance surpasses traditional fixed-threshold decision methods.

V. DISCUSSION

Field test results across the 341 km voyage confirm that hardware-centric strategies encounter physical limitations in highly dynamic maritime environments. While enhanced terminals extend coverage, relying solely on antenna gain introduces additional multipath interference and creates “perception blind spots” for robot navigation. In contrast, the proposed RF-based early-warning scheme offers a more efficient alternative. By leveraging edge intelligence, this soft-hardware co-design improves link stability with minimal computational overhead, providing a predictive diagnostic layer for resilient MIoT deployment.

Maritime communication imposes stringent real-time requirements where network latencies exceeding 1000 ms can lead to complete interruption. Edge computing meets these ultra-low latency demands by offloading tasks [16]. Deploying a lightweight RF model within maritime gateways embeds the prediction logic directly into edge processing units.

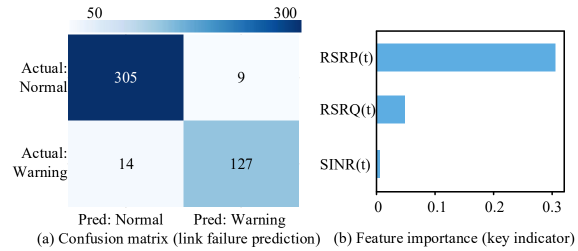

Figure 5. Classification Performance Evaluation of the Random Forest Classifier.

Since RF consists of logical condition judgments without complex tensor operations, it achieves true millisecond-level warning. This “algorithmic sinking” alleviates backhaul bandwidth pressure and provides a critical safety buffer, allowing robots to execute fail-safe maneuvers well before total link loss occurs.

The consistency of high performance in RF underscores its generalization potential. By capturing relative evolutionary trends through the sliding window rather than absolute thresholds, the model perceives degradation patterns that are universal across different sea states. While current results are based on a 341 km voyage, this methodology provides a baseline for future cross-scenario validation in extreme climates. Future research could integrate online or federated learning to perform adaptive parameter fine-tuning for specific deep-sea environments. Furthermore, this edge framework can be migrated to 6G Non-Terrestrial Networks (NTN) to compensate for atmospheric scintillation and deep fading, contributing to resilient global ocean sensing networks.

VI. CONCLUSION AND FUTURE WORK

Based on the “Sansha No. 2” field-test platform, this paper systematically investigated 5G link stability mechanisms in extreme maritime conditions across an ultra-long-distance route. Our findings indicate that while hardware-centric enhancement strategies extend coverage boundaries, they exhibit diminishing marginal returns in addressing nonlinear, stochastic signal fluctuations. This confirms that power compensation alone cannot fundamentally resolve deep-sea 5G interruptions, necessitating an active link-aware mechanism at the software level.

The proposed lightweight early-warning scheme, integrating sliding window feature extraction with RF, achieved a prediction accuracy of 94.95% with millisecond-level inference overhead on a real-world dataset. This approach transitions maritime communication from passive failure recovery to proactive predictive maintenance, demonstrating the practical value of edge intelligence for MIoT robustness. Ultimately, integrating edge intelligence with physical-layer perception is critical for high-reliability deep-sea connectivity. Future research will focus on adaptive federated learning mechanisms and migrating this framework to 6G NTN to support resilient global ocean sensing networks.

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REFERENCES

[1] J. Wang, Y. Li, X. Zhang, and Z. Chen, "Wireless channel models for maritime communications," IEEE Access, vol. 6, pp. 68070–68088, Nov. 2018, doi: 10.1109/ACCESS.2018.2879653.

[2] R. He, X. Gao, L. Chen, Y. Li, and J. Zhang, "A survey of 5G channel measurements and models," IEEE Commun. Surveys Tuts., vol. 23, no. 3, pp. 1588–1616, Aug. 2021, doi: 10.1109/COMST.2021.3090193.

[3] T. Zhao, S. Sarkar, Y. Tian, and D. Cabric, "Anomaly transmitter recognition and tracking," in Proc. IEEE Int. Symp. Dynamic Spectrum Access Networks (DySPAN), May 2024, pp. 357–364, doi: 10.1109/DySPAN61131.2024.10547477.

[4] T. Yang, Z. Cui, R. Wang, J. Zhao, Z. Su, and R. Deng, "A multivessels cooperation scheduling for networked maritime fog-ran architecture leveraging SDN," Peer-to-Peer Netw. Appl., vol. 11, no. 4, pp. 808–820, Jul. 2018, doi: 10.1007/s12083-017-0610-8.

[5] Y. Xu, "Quality of service provisions for maritime communications based on cellular networks," IEEE Access, vol. 5, pp. 23881–23890, Nov. 2017, doi: 10.1109/ACCESS.2017.2764003.

[6] M. G. Kibria, K. Nguyen, G. P. Villardi, O. A. Dobre, and S. J. Bae, "Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks," IEEE Commun. Surveys Tuts., vol. 20, no. 4, pp. 3238–3274, Fourth Quart. 2018, doi: 10.1109/COMST.2018.2845765.

[7] L. Liang, H. Ye, and G. Y. Li, "Toward intelligent vehicular networks: A machine learning framework," IEEE Internet Things J., vol. 6, no. 1, pp. 124–135, Feb. 2019, doi: 10.1109/JIOT.2018.2846263.

[8] B. Sudharsan, J. G. Breslin, and M. I. Ali, "Adaptive strategy to improve the quality of communication for IoT edge devices," in Proc. IEEE 6th World Forum Internet Things (WF-IoT), Jun. 2020, pp. 1–6, doi: 10.1109/WF-IoT48130.2020.9221151.

[9] Y. Yu, L. Huang, and X. Wang, "Time series outlier detection based on sliding window prediction," Math. Probl. Eng., vol. 2014, pp. 1–10, Jul. 2014, doi: 10.1155/2014/879736.

[10] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.

[11] M. Krichen and A. Mihoub, "Long short-term memory networks: A comprehensive survey," AI, vol. 6, no. 9, Art. no. 215, pp. 1–18, Sep. 2025, doi: 10.3390/ai6090215.

[12] J. P. P. M. Yucra, D. J. C. Quina, G. A. E. Espinoza, M. A. V. Solis, D. D. Y. A. Cardenas, and A. O. Salazar, "Design and implementation of an LSTM model with embeddings on MCUs for prediction of meteorological variables," Sensors, vol. 25, no. 12, Art. no. 3601, pp. 1–16, Jun. 2025, doi: 10.3390/s25123601.

[13] G. Maor, A. M. Abdelrahim, and R. Berkovich, "An FPGA implementation of stochastic computing-based LSTM," in Proc. IEEE 37th Int. Conf. Comput. Design (ICCD), Nov. 2019, pp. 1–6, doi: 10.1109/ICCD46524.2019.00012.

[14] J. R. Quinlan, "Induction of decision trees," Mach. Learn., vol. 1, no. 1, pp. 81–106, Mar. 1986, doi: 10.1007/BF00116251.

[15] L. E. Raileanu and K. Stoffel, "Theoretical comparison between the Gini index and information gain criteria," Ann. Math. Artif. Intell., vol. 41, no. 1, pp. 77–93, May 2004, doi: 10.1023/B:AMAI.0000018580.96245.c6.

[16] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet Things J., vol. 3, no. 5, pp. 637–646, Oct. 2016, doi: 10.1109/JIOT.2016.2579198.

[17] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing," Proc. IEEE, vol. 107, no. 8, pp. 1738–1762, Aug. 2019, doi: 10.1109/JPROC.2019.2918951.