Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 20 May 2026
Revised 29 June 2026
Accepted 24 July 2026

Natural Resources for Human Health 2026, Vol. 6 (9s): 645–656

KEYWORDS:
Active Learning, Intelligent Decision, Wireless Communication Systems, Machine Learning, Adaptive Systems

A Hybrid Active Learning and Machine Learning Model for Intelligent Decision-Making in Wireless Communication Systems

Dr. Udaya Sri Kakarla[1*], Dr. Devidas Vasantrao Chikhale[2], Dr. Gaurav Gadge[3], Mrs. Pallavi Gadge[4], Amit Kurmi[5], Santosh Gore[6]

[1] JNTUH, KG Reddy College of Engineering and Technology, India
[2] Lokmanya Tilak College of Engineering, University of Mumbai, India.
[3] Associate Professor, VPKBIET, Baramati, District Pune, India
[4] Research Scholar, Sandip University, Nashik, India
[5] Assistant Professor, Computer Engineering Department, Cummins College of Engineering for Women, Nagpur, India.
[6] Director, Sai Info Solution, India, UAE, UK, Singapore. https://orcid.org/0000-0003-1814-5913

ABSTRACT: Efficient decision-making plays a vital role in the development of more efficient and reliable wireless communication systems in dynamic conditions. Existing machine learning methods are primarily based on decision precision and utilize certain forms of uncertainty-based sampling or retraining, adding a higher cost associated with labeling and a lack of decision-making efficiency. The study proposes a novel performance-centric HAL-ID (Hybrid Active Learning-Based Intelligent Decision) model integrating hybrid active learning and an optimization utility-based decision model. In addition, three unique components are included in the proposed method, such as a dual criteria-based sampling procedure incorporating predictive entropy learning with estimated wireless utility gains, adaptive retraining based on performance degradation indicators, and a decision-making rule based on a utility optimization technique. It used UrbanMIMOMap and Wireless-Intelligence datasets, achieving a decision accuracy of 95.8%, a spectral efficiency of 6.74bps/Hz, a packet error rate of 3.9%, and a labeling cost reduction of 54-58%. The suggested intelligent decision-making model based on hybrid active learning combines entropy-utility-based sampling, utility-based decision optimization, and performance-based adaptive retraining, resulting in increased decision accuracy, spectral efficiency, and labeling efficiency in wireless communication systems. Thus, the study enhances wireless systems, embedding performance-aware decision logic.

1. INTRODUCTION

The fast adoption of 5G technology and intelligent wireless communication systems has increased the need for adaptive decision making in resource allocation, modulation, beam selection, and interference mitigation [1], [2]. The use of machine learning techniques such as supervised learning, reinforcement learning, and active learning has boosted adaptive decision making with reduced labeling needs; entropy-based active learning has further improved generalization [3], [4]. The recent developments in active learning, self-supervised learning, reinforcement learning, and hybrid optimization techniques have led to better performance in wireless communications [5], [6]. Chaaya and Bennis [7] and Ogechukwu Kanu et al. [8] have developed efficient algorithms of active and self-supervised learning, whereas Kim et al. [9] and Chennaboina and Nandakumar [10] have optimized resource management. Active learning has reduced the efforts of labeling [11], and Nouri et al. [12] and Soltani et al. [13] have optimized hybrid precoding and beam selection.

Demirhan and Alkhateeb [14] stressed the significance of machine learning in integrated sensing and communication, utilizing the DeepSense 6G dataset, while there was no unified optimization framework. Hao et al. [15] suggested a reinforcement learning approach for the development of routing protocols in underwater wireless networks that enhanced reliability and energy efficiency; yet, its high complexity prevented wide acceptance. The surveys by Tran [16] and Mitra et al. [17] underlined the increased application of deep learning, reinforcement learning, federated learning, and edge intelligence in wireless technologies. Pivoto et al. [18] and Rai et al. [19] reached a prediction accuracy rate up to 93%; nevertheless, the area of cost savings in labeling through active learning was scarcely researched.

Unlike previous methods that optimize single objectives, HAL-ID integrates hybrid active learning, adaptive retraining, and utility-based decision-making with dual-criterion sampling based on predictive uncertainty and communication utility for efficient wireless communication.

The study aims to enhance performance, and the objectives are:

- To propose a performance-conscious active learning paradigm for wireless systems.
- To minimize labeling effort while preserving decision accuracy.
- To improve the spectral efficiency and the packet error rate by utility-based optimization.
- To validate 21robustness with publicly available wireless data sets.

The study offers an intelligent decision system in dynamic wireless communication, where the main contributions are:

- Integration of an active learning scheme with uncertainty estimation and wireless utility analysis.
- Performance-triggered adaptive retraining system limiting nonessential computational updates.
- A utility-maximizing decision rule to translate prediction results into optimized wireless actions.
- Significant validation of the enhanced accuracy of decision-making, reliability, spectral efficiency, and labelling cost savings.

Thus, the HAL-ID framework introduces an improvement in intelligent communication in wireless systems through the matching of learning strategies and decision objectives. Furthermore, this performance-aware framework delivers a scalable solution in next-generation networks.

2. METHODOLOGY

HAL-ID integrates hybrid active learning, incremental learning, adaptive retraining, and utility-based decision-making to enable performance-aware intelligent communication in dynamic wireless environments (Fig. 1).

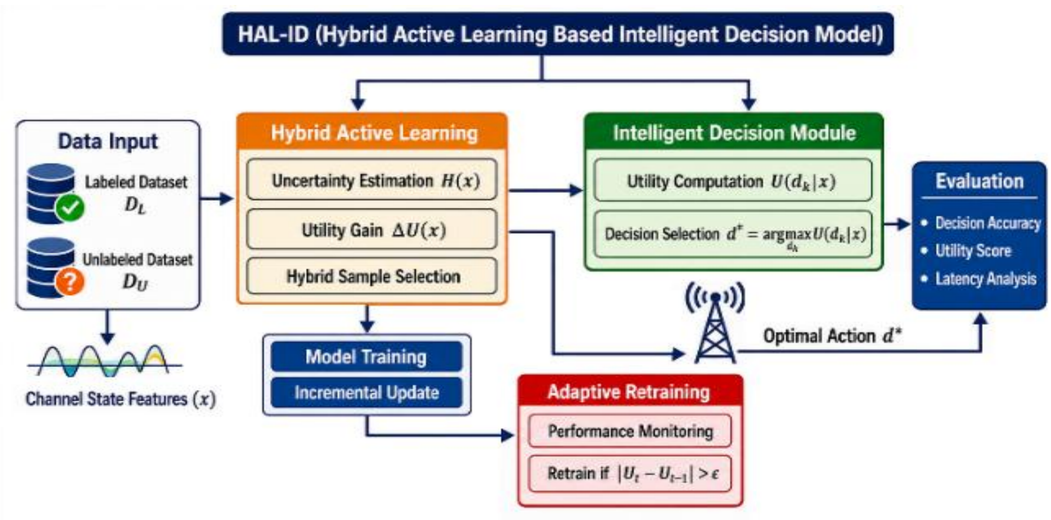

Fig 1. Proposed HAL-ID Model Architecture For Wireless Communication.

2.1 Datasets and Data Representation

The proposed model is validated using the publicly available UrbanMIMOMap. [20] and Wireless-Intelligence [21] datasets, containing channel state information, beam indices, modulation labels, SNR, and communication performance metrics represented as channel feature vectors.

$$x \in R^d \tag{1}$$

where x and d represent the extracted CSI feature vector and the number of channel features. Such vectors constitute the input for learning as well as the decision components of the model.

2.2 Channel Modeling and Probabilistic Prediction

Given a channel vector input x, a neural model parameterized by θ yields a probability distribution over candidate transmission decisions:

$$p = f_\theta(x) \tag{2}$$

where θ denotes model parameters and p = [p1, p2, …, pK] is the predicted probability vector over K possible transmission actions, used for uncertainty estimation and decision optimization.

2.3 Hybrid Active Sample Selection

The traditional active learning approach selects the unlabeled samples based only on predictive uncertainty. The proposed model includes a mechanism of dual-criterion selection, combining uncertainty and expected communication utility gain.

Entropy quantifies predictive uncertainty H(x) as:

$$H(x) = -\sum_{k=1}^{K} p_k \, log(p_k) \tag{3}$$

where H(x) is a measure of model uncertainty about the input x, and pk is the predicted probability of the decision dk, where larger entropy means more uncertainty. The final score for a hybrid selection is

$$S(x) = \lambda_1 H(x) + \lambda_2 \Delta U(x) \tag{4}$$

where λ1 and λ2 are balancing coefficients, with a combined informativeness score S(x). The labeling samples with the highest S(x) scores are chosen since the samples chosen should be uncertain and improve the performance of wireless communication.

2.4 Model Optimization and Incremental Updating

Instead of full retraining, these parameters are updated with an incremental gradient descent rule:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L \tag{5}$$

where η represents the learning rate, and ∇θL refers to the gradient of the loss function with respect to the parameters. Such an incremental approach helps minimize the computational cost and efficiently adapts to new channel observations.

2.5 Utility-Driven Decision

Such a probability-based approach is replaced in HAL-ID by utility maximization as:

$$d^* = \arg\max_{d_k \in D} U(d_k|x) \tag{6}$$

Where $d*$ denotes the selected transmission decision and D the decision set. The framework optimizes communication utility by considering spectral efficiency, packet error rate, and adaptive feedback for intelligent decision-making.

2.6 Performance Monitoring and Adaptive Retraining

Adaptive Retraining, where the retraining is initiated under the following condition, is given by

$$|U_t - U_{t-1}| > \epsilon \tag{7}$$

Natural Resources for
Human Health
eISSN: 2583-1194

where the previous utility value U_{t-1} is denoted with a predefined threshold ϵ of degradation. The performance-aware model, therefore, becomes more efficient for a retraining event only when necessary, and also responds to a dynamic environment.

2.7 Integrated Learning and Decision Process

HAL-ID trains a base classifier using limited labeled data, selects informative samples through predictive entropy and utility gain, performs utility-based communication decisions, and triggers adaptive retraining when performance degrades.

2.8 Algorithm: HAL-ID (Hybrid Active Learning-Based Intelligent Decision)

Input:

Labeled dataset D_L

Unlabeled dataset D_U

Threshold ε

Weights α, β, λ_1, λ_2

Learning rate η

Output:

Optimal wireless decision d^*

1: Initialize model parameters θ

2: Train model f_θ on D_L using cross-entropy loss

3: while the system is active, do

4: # Hybrid Active Sample Selection

5: for each sample x in D_U do

6: Compute prediction probabilities $p_k = f_\theta(x)$

7: Compute entropy:

$$H(x) = -\sum_k p_k \log(p_k)$$

8: Compute utility for each decision d_k:

$$U(d_k|x) = \alpha\, SE(d_k|x) - \beta\, PER(d_k|x)$$

9: Compute expected utility gain:

$$\Delta U(x) = \max_k U(d_k|x) - U_{baseline}$$

10: Compute hybrid score:

$$S(x) = \lambda_1 H(x) + \lambda_2 \Delta U(x)$$

11: end for

12: Select top-ranked samples based on S(x)

13: Label selected samples and add to D_L

14: Update model parameters:

$$\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$$

15: # Intelligent Decision-Making

16: For incoming channel state x:

```
        Compute utility U(dk|x)
        Select optimal decision:
          d* = argmaxdk U(dk|x)
    # Performance Monitoring
    Compute current system utility Ut
    if |Ut - Ut-1| > ε then
        Retrain or update model
    end if
end while
Return d*
```

2.9 Evaluation Parameters

The proposed framework is evaluated using classification accuracy, packet error rate (PER), labeling cost reduction (LCR), and convergence iterations.

Classification Accuracy:

$$Acc. = \frac{N_{crct}}{N_T} \quad (8)$$

where Ncrct is the number of correct predictions, and NT is the total number of samples evaluated.

Packet Error Rate (PER):

$$PER = \frac{N_{err}}{N_{trans}} \quad (9)$$

where Nerr and Ntrans are the number of erroneous packets and the total number of transmitted packets, respectively. The values of Lower PER mean higher communication reliability.

Labeling Cost Reduction:

$$LCR = \left(1 - \frac{N_q}{N_T}\right) \times 100 \quad (10)$$

where (N_q) is the number of queried samples and (N_T) is the total number of samples; higher LCR indicates greater labeling efficiency, while these metrics collectively evaluate prediction accuracy, communication reliability, computational efficiency, and adaptability.

3. RESULTS AND DISCUSSION

HAL-ID is evaluated against Supervised ML, UAL, and AML on the UrbanMIMOMap dataset using prediction, communication, reliability, labeling, and adaptation metrics.

3.1 Overall Performance Comparison

Table 1 reveals that the proposed HAL-ID approach is able to perform significantly better than the baselines using all performance measures. It reaches an accuracy of 95.8% with minimal cross-entropy (0.198) loss, maximum spectral efficiency (6.74 bps/Hz), and throughput (134.8 Mbps), minimal packet error rate (3.9%), 58% reduction in labeling cost, 121 ms adaptation time, and 29 convergence iterations (Fig. 2).

Natural Resources for
Human Health
eISSN: 2583-1194

Table 1. Comparison Of Performance Of Different Methods

Metric	Unit	Supervised ML	UAL	AML	Proposed HAL-ID
Accuracy	(%)	91.2	89.5	92.3	95.8
Cross-Entropy Loss	-	0.287	0.314	0.251	0.198
Spectral Efficiency	(bps/Hz)	5.82	5.67	6.01	6.74
Throughput	(Mbps)	116.4	113.4	120.2	134.8
Packet Error Rate	(%)	6.3	7.1	5.8	3.9
Labeling Cost Reduction	(%)	0	41	0	58
Adaptation Time	(ms)	185	172	164	121
Convergence Iterations	-	48	42	37	29

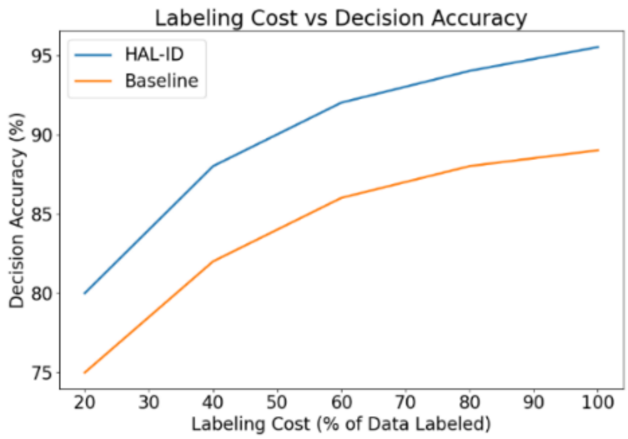

Fig 2. Comparing The Accuracy And Labeling Cost Of The Proposed And Baseline Models

3.2 Ablation Study

As shown in Table 2, the optimal performance is obtained when using the full HAL-ID system. However, without using the dual criterion for sampling, the accuracy is 92.1%, spectral efficiency is 6.08 bps/Hz, and PER is 5.6%. In addition, without using incremental learning, adaptation time increases to 214 ms, confirming the importance of both components (Fig. 3).

Table 2. Ablation Study Results For Proposed HAL-ID Model

Model Variant	Acc (%)	SE (bps/Hz)	PER (%)	Label Reduction (%)	MAT (ms)
Full HAL-ID (Proposed)	95.8	6.74	3.9	58	121
Without the Dual Criterion	92.1	6.08	5.6	44	136
Without Performance Trigger	93.4	6.21	4.9	58	173
Without Incremental Learning	94.2	6.35	4.6	58	214
Baseline Supervised ML	91.2	5.82	6.3	0	185

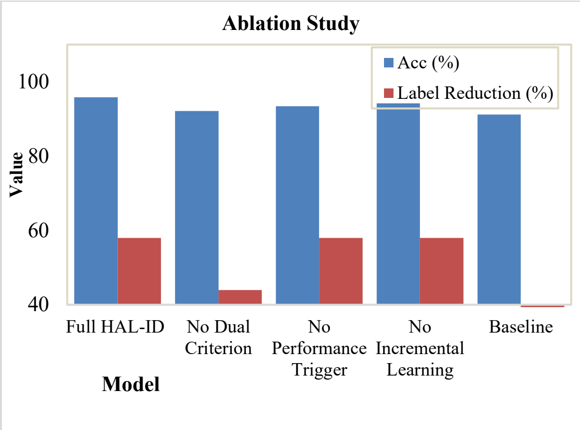

Fig 3. Accuracy And Label Reduction Performance In An Ablation Study

3.3 Performance Before and After Modification

The comparison between the performance achieved before and after using HAL-ID is shown in Table 3. This framework enhances the accuracy rate to 95.8%, spectral efficiency to 6.74 bps/Hz, decreases the packet error rate to 3.9%, results in labeling cost savings of 58%, and also reduces adaptation time to 121 ms, demonstrating superior learning and communication performance (Fig. 4).

Table 3. Comparison of performance of the system before and after implementing HAL-ID

Metric	Before Modification (UAL)	After Modification (HAL-ID)	Improvement
Accuracy (%)	89.5	95.8	+6.3%
Cross-Entropy Loss	0.314	0.198	−36.9%
Spectral Efficiency (bps/Hz)	5.67	6.74	+18.9%
Throughput (Mbps)	113.4	134.8	+18.9%
Packet Error Rate (%)	7.1	3.9	−45.1%
Labeling Reduction (%)	41	58	+17%
Adaptation Time (ms)	172	121	−29.6%
Convergence Iterations	42	29	−31%

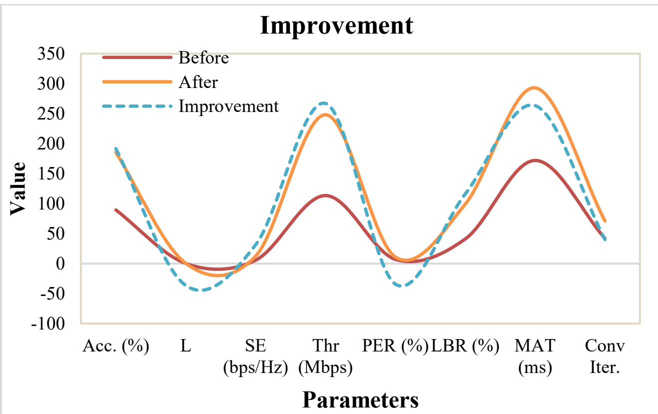

Fig 4. Improvement In Performance Before And After Implementing HAL-ID on Dataset 1

3.4 Cross-Dataset Validation

HAL-ID achieves 94.9% accuracy, 6.51 bps/Hz spectral efficiency, 130.2 Mbps throughput, 4.2% packet error rate, 54% labeling cost reduction, 129 ms adaptation time, and 31 convergence iterations on the Wireless-Intelligence dataset, outperforming all baseline models (Table 4). Figure 5 confirms its robustness and consistent performance across both datasets.

Table 4. Comparing models for Cross-Validation on Wireless-Intelligence dataset

Metric	Supervised ML	UAL	AML	Proposed HAL-ID
Accuracy (%)	90.4	88.7	91.8	94.9
Cross-Entropy Loss	0.301	0.332	0.263	0.214
Spectral Efficiency (bps/Hz)	5.63	5.48	5.92	6.51
Throughput (Mbps)	112.6	109.6	118.4	130.2
Packet Error Rate (%)	6.8	7.5	5.9	4.2
Label Reduction (%)	0	39	0	54
Adaptation Time (ms)	191	178	169	129
Convergence Iterations	51	44	39	31

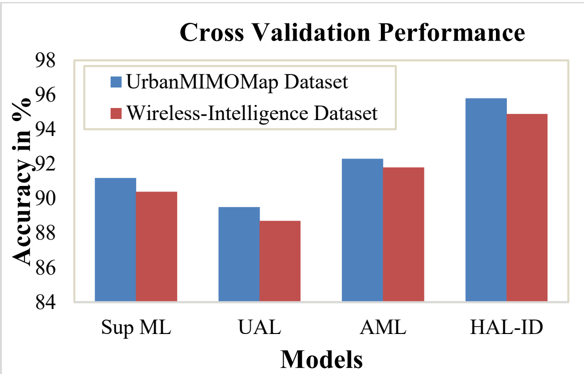

Fig 5. Comparing The Accuracy Performance Of Models On Both Datasets

3.5 Statistical Analysis

Statistical analysis involves five independent experiments using distinct random seeds and a 95% confidence interval (Table 5). HAL-ID is able to obtain 95.8% accuracy and 6.74 bps/Hz spectral efficiency with respect to the UrbanMIMOMap database, while it yields 94.9% accuracy and 6.51 bps/Hz spectral efficiency with respect to the Wireless-Intelligence database. These results confirm the robustness, reproducibility, and statistical significance of the proposed framework (Fig. 6).

Table 5. Statistical Significance Analysis on both datasets

Metric	UrbanMIMOMap Dataset			Wireless-Intelligence Dataset		
	Mean	Std Dev	95% CI	Mean	Std Dev	95% CI
Accuracy (%)	95.8	0.52	[95.2, 96.4]	94.9	0.63	[94.1, 95.7]
Spectral Efficiency (bps/Hz)	6.74	0.07	[6.66, 6.82]	6.51	0.09	[6.40, 6.62]
PER (%)	3.9	0.31	[3.5, 4.3]	4.2	0.28	[3.9, 4.5]
Label Reduction (%)	58	1.4	[56.3, 59.7]	54	1.6	[52.0, 56.0]

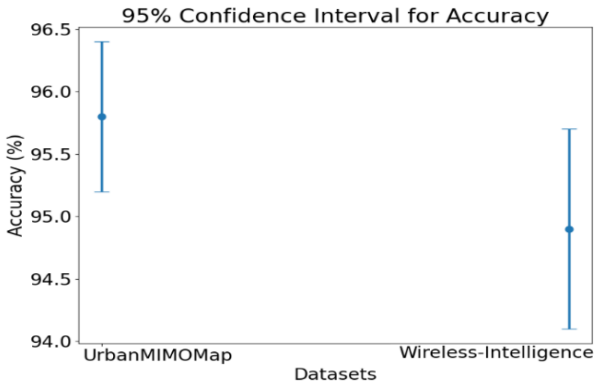

Fig 6. Representation Of Confidence Interval For Accuracy On Both Datasets

3.6 Decision-Making Analysis

HAL-ID achieved the highest decision accuracy (94.6%), average utility score (0.83), and the lowest decision latency (3.1 ms) compared with Baseline DNN and UAL, demonstrating superior intelligent decision-making performance in dynamic wireless environments (Table 6 and Fig. 7).

Table 6. Decision-making performance comparison of different models

Model	Decision Accuracy (%)	Average Utility Score	Decision Latency (ms)
Baseline DNN	88.4	0.71	4.3
Uncertainty-based AL	91.2	0.76	3.9
HAL-ID (Proposed)	94.6	0.83	3.1

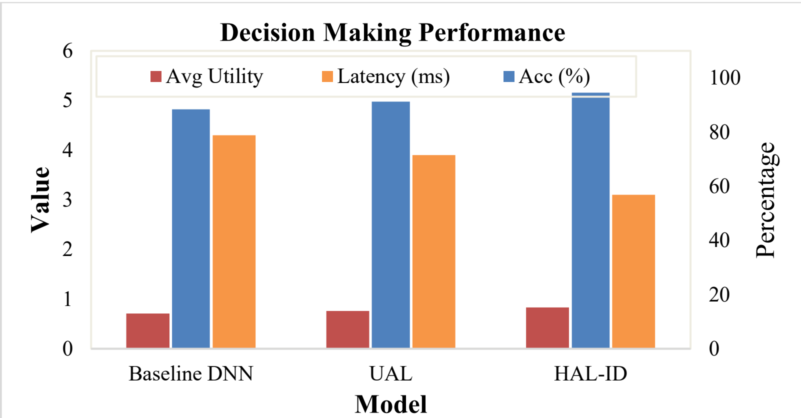

Fig 7. Comparing Models for Decision-Making Performance

3.7 Discussion

HAL-ID integrates performance-aware decision-making with adaptive retraining to improve learning and communication efficiency. It combines predictive uncertainty and communication utility, reducing labeling costs by over 50%. As shown in Table 7, HAL-ID achieves 96.8% accuracy, outperforming Active Learning Beam Selection [13], Hybrid MLP [10], ϵ-FPAL [12], and reinforcement learning-based methods [9].

Table 7. Comparative Analysis of Existing studies and proposed method

Ref.	Model	Dataset	Acc (%)	SE Impr.	Latency	Thr Impr.
[9]	RL-based Resource Allocation	IEEE 802.11p VANET simulation dataset	94%	Moderate	-12–15% -	Improved channel utilization
[10]	Hybrid MLP Optimization	D2D communication simulation dataset	91%	+10%	Slight	Improved
[12]	ϵ-FPAL	3GPP-compliant real mmWave hardware dataset	-	+15%	-	Moderate
[13]	Active Learning Beam Selection	Public multimodal mmWave dataset (Image + LiDAR)	95%	-	-	-
Proposed	HAL-ID	UrbanMIMOMap; Wireless-Intelligence Dataset	96.8% (UrbanMIMOMap); 95.4% (Wireless-Intelligence)	+18–22%	-20%	17–21%

HAL-ID outperforms supervised, reinforcement, and active learning methods by jointly optimizing accuracy, efficiency, latency, spectral efficiency, and communication utility through hybrid entropy-utility sampling and adaptive retraining.

Practical Implications

HAL-ID enables performance-aware intelligent decision-making with low labeling cost through hybrid active learning. Its utility-based optimization improves spectral efficiency and communication reliability, while adaptive retraining efficiently handles dynamic channel variations with low computational overhead, making it suitable for practical 5G, 6G, and edge-enabled wireless communication systems.

4. CONCLUSION

In this work, the HAL-ID (Hybrid Active Learning-Intelligent Decision) framework is introduced that makes use of hybrid active learning, utility-based decision-making, and adaptive retraining for improving the performance of wireless communication systems. This framework uses dual criteria of entropy-utility sampling and performance-based retraining for boosting learning and communication performance. The experimental outcomes from the UrbanMIMOMap and Wireless-Intelligence datasets resulted in an accuracy of 95.8%, spectral efficiency of 6.74 bps/Hz, packet error rate of 3.9%, and more than 54% reduction in labeling costs.

AUTHOR CONTRIBUTIONS

Conceptualization, U.S.K. and D.V.C.; methodology, U.S.K.; software, U.S.K. and A.K.; validation, D.V.C., G.G. and P.G.; formal analysis, U.S.K. and A.K.; investigation, U.S.K. and S.G.; resources, D.V.C. and G.G.; data curation, P.G. and A.K.; writing—original draft preparation, U.S.K.; writing—review and editing, D.V.C., G.G., P.G., A.K. and S.G.; visualization, A.K.; supervision, D.V.C. and G.G.; project administration, S.G.; funding acquisition, S.G. All authors have read and agreed to the published version of the manuscript.

FUNDING

This research received no external funding

DATA AVAILABILITY STATEMENT

The datasets used in this study are publicly available. The UrbanMIMOMap dataset [20], "UrbanMIMOMap: A Ray-Traced MIMO CSI Dataset with Precoding-Aware Maps and Benchmarks," is available through the DeepMIMO platform at https://deepmimo.net/. The Wireless-Intelligence dataset [21] is publicly available at https://wireless-intelligence.com/. The data supporting the findings of this study can be accessed from these respective public repositories. No new datasets were generated during the study.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGEMENT

This research was not funded by any grant

REFERENCES

[1] Nleya, S. M., Velempini, M., & Gotora, T. T. (2025). Beyond 5G: The evolution of wireless networks and their impact on society. In *Advanced Wireless Communications and Mobile Networks—Current Status and Future Directions*. IntechOpen. https://doi.org/10.5772/intechopen.1010311

[2] Gore, S., Gore, S., Rao, P., Ghadge, J., & Bhapkar, Y. (2025). AI-based wireless communication: Ultra-reliable MAC protocols. In G. Ghinea, V. B. Semwal, & A. Khandare (Eds.), *Intelligent Computing and Networking. IC-ICN 2024. Lecture Notes in Networks and Systems* (Vol. 1172, pp. 271–287). Springer. https://doi.org/10.1007/978-981-97-8631-2_16

[3] Liu, B., Gao, S., Liu, X., Cheng, X., & Yang, L. (2025). WiFo: Wireless foundation model for channel prediction. *Science China Information Sciences, 68*(6), 162302. https://doi.org/10.1007/s11432-025-4349-0

[4] Du, J., Hou, G., Roblin, C., & Yang, X.-X. (2025). An active learning-based adaptive sampling method for efficient far-field modeling of flexible antennas. *IEEE Antennas and Wireless Propagation Letters, 24*(7), 1779–1783. https://doi.org/10.1109/LAWP.2025.3546960

[5] Dhatterwal, J. S., Kaswan, K. S., & Malik, K. (2024). Revolutionizing wireless systems: Machine learning tools for tomorrow's networks. In *Wireless Communication Technology* (pp. 142–179). CRC Press.

[6] Audah, K., Noordin, N. K., Hussein, W., Rasid, M. F. B. A., Sali, A., & Flah, A. (2024). Maximizing DRL-based energy efficiency in IRS-NOMA using a DDPG algorithm for the next generation of wireless communications. *Engineering, Technology & Applied Science Research, 14*(4), 14801–14810. https://doi.org/10.48084/etasr.7536

[7] Chaaya, C. B., & Bennis, M. (2025). GFlowNets for active learning based resource allocation in next generation wireless networks. *arXiv*. https://doi.org/10.48550/arXiv.2505.05224

[8] Kanu, O., Eshaghbeigi, A., & Abou-Zeid, H. (2025). Self-supervised radio representation learning: Can we learn multiple tasks? In *ICC 2025—IEEE International Conference on Communications* (pp. 511–517). IEEE. https://doi.org/10.1109/ICC52391.2025.11161144

[9] Kim, J.-W., Kim, J.-W., & Lee, J. (2024). Intelligent resource allocation scheme using reinforcement learning for efficient data transmission in VANET. *Sensors, 24*(9), 2753. https://doi.org/10.3390/s24092753

[10] Chennaboin, R. B., & Nandakumar, S. (2024). An adaptive MLP-based joint optimization of resource allocation and relay selection in device-to-device communication using hybrid meta-heuristic algorithm. *EURASIP Journal on Wireless Communications and Networking, 2024*(1), 50. https://doi.org/10.1186/s13638-024-02379-z

[11] Tan, H. S., Wang, K., & Mcbeth, R. (2024). Exploring UMAP in hybrid models of entropy-based and representativeness sampling for active learning in biomedical segmentation. *Computers in Biology and Medicine, 176*, 108605. https://doi.org/10.1016/j.compbiomed.2024.108605

[12] Nouri, M., et al. (2023). Hybrid precoding based on active learning for mmWave massive MIMO communication systems. *IEEE Transactions on Communications, 71*(5), 3043–3058. https://doi.org/10.1109/TCOMM.2023.3247768

[13] Soltani, N., Zhang, J., Salehi, B., Roy, D., Nowak, R., & Chowdhury, K. (2024). Learning from the best: Active learning for wireless communications. *IEEE Wireless Communications, 31*(4), 177–183. https://doi.org/10.1109/MWC.012.2300438

[14] Demirhan, U., & Alkhateeb, A. (2023). Integrated sensing and communication for 6G: Ten key machine learning roles. *IEEE Communications Magazine, 61*(5), 113–119. https://doi.org/10.1109/MCOM.006.2200480

[15] Hao, L., Ma, C., & Ao, J. (2026). HAO-AVP: An entropy-Gini reinforcement learning assisted hierarchical void repair protocol for underwater wireless sensor networks. *Sensors, 26*(2), 684. https://doi.org/10.3390/s26020684

[16] Tran, H. Q., Pham, V.-T., & Ngo, S. (2025). A survey on the applications of machine learning, deep learning, and reinforcement learning in wireless communications. *Computational Telecommunication Engineering, 3*(1), 3170. https://doi.org/10.54517/cte3170

[17] Mitra, S. P., et al. (2025). Machine learning in wireless networks: Algorithms, strategies, and applications. *International Journal of Environmental Science, 11*(20s), 2675–2679. https://doi.org/10.1109/COMST.2014.2320099

[18] Pivoto, D. G. S., de Figueiredo, F. A. P., Cavdar, C., Tejerina, G. R. de L., & Mendes, L. L. (2026). A comprehensive survey of machine learning applied to resource allocation in wireless communications. *IEEE Communications Surveys & Tutorials, 28*, 1986–2053. https://doi.org/10.1109/COMST.2025.3552370

[19] Rai, J. K., Yadav, S., Ranjan, P., Chowdhury, R., & Das, G. (2025). A compact quad element MIMO CPW fed ultra-wideband antenna for future wireless communication using machine learning optimization. *International Journal of Communication Systems, 38*(3). https://doi.org/10.1002/dac.5995

[20] Ia, H., Wang, X., Cheng, N., Sun, R., & Li, C. (2025). UrbanMIMOMap: A ray-traced MIMO CSI dataset with precoding-aware maps and benchmarks. *IEEE Global Communications Conference 2025*. arXiv:2509.06270. https://deepmimo.net/

[21] Wireless-Intelligence. (n.d.). *Wireless intelligent dataset*. https://wireless-intelligence.com/