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# A Hybrid Machine Learning Framework For Intelligent Interference Classification And Adaptive Mitigation In 5G/6G Wireless Networks

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**Abstract**
The advancements in wireless networks towards 5G and beyond (6G) have led to dense spectrum use, heterogeneous radio-access technologies (RATs), ultra-massive connectivity, and network dynamism, making interference between RATs and user equipment (UEs) inevitable. Efficient management of interference is essential for ensuring reliable wireless communications. Traditional interference mitigation approaches often rely on heuristic-based threshold settings, pre-configured resource allocation plans, or signal-processing techniques which may not be adaptive enough for time-varying interference scenarios. While some recent works have shown promise in leveraging machine learning (ML) algorithms to detect and mitigate wireless interference, existing interference classification approaches mostly treat interference classification and mitigation problems separately or are proposed for a single interference scenario. In this paper, we propose a Hybrid Machine Learning Framework for Intelligent Interference Classification and Adaptive Mitigation in 5G/6G Wireless Networks. Our framework leverages multi-domain wireless features consisting of signal strength, SINR, spectrum attributes, time-domain attributes, and interference power together with a hybrid ensemble learning model to classify wireless interference. We propose an Interference Severity Estimation module that quantifies the detrimental impact of detected interference, followed by an Adaptive Mitigation Decision module that determines the most suitable mitigation technique conditioned on interference type and severity. Extensive experimentation results demonstrate that our proposed framework achieves an intelligent and adaptive solution to become interference-aware in wireless networks. We evaluate our framework based on classification accuracy, precision, recall, F1-score, interference reduction, SINR gain, computational complexity, and inference latency.

**Keywords**: 5G,6G, Wireless Communications, Machine Learning, Interference Classification, Adaptive Interference Mitigation, Hybrid Learning, SINR.

## I. INTRODUCTION

Wireless communication systems are rapidly evolving from traditional cellular networks into fifth generation (5G) and beyond wireless networks, such as sixth generation (6G) networks. This evolution enables an ever-growing demand for higher data rates, lower latency, ultra-massive connectivity, spectral efficiency, and reliable wireless communications. Wireless communication technologies like massive multiple-input multiple-output (MIMO), millimeter-wave communication, network densification, heterogeneous networks, and dynamic spectrum access contribute to this possibility resulting in radio environments that become increasingly complex. Particularly, the coexistence of numerous users, access points, devices, and heterogeneous radio technologies leads to stringent spectrum sharing and non-orthogonal transmission conditions. As a result, interference has now become one of the main limiting factors of wireless network reliability and efficiency of current 5G and future wireless networks. Interference in wireless networks is introduced when undesired signals invade the desired transmission in time, frequency, and space domains. The characteristics and sources of these interfering signals can take various forms such as co-channel interference, adjacent-channel interference, narrowband interference, broadband interference, or impulsive interference. Received signal strength, interference power, signal-to-interference-plus-noise ratio (SINR), spectral occupancy, and temporal features are commonly used to represent interference level. Traditional interference management schemes rely on predefined thresholds, frequency planning, power control, beamforming, filtering, or resource allocation to manage interference. While these schemes perform well in conventional operating environments, their performance typically deteriorates in dynamic and heterogeneous wireless environments where interference conditions vary. One recent survey on 5G and beyond wireless networks identifies the increasing complexity of interference management with network densification, massive MIMO deployments, millimeter-wave systems, mixed numerologies, and future 6G technologies. Machine learning (ML) has emerged as one potential solution towards intelligent wireless network management as ML can capture the relationship between network conditions and suitable network actions. ML techniques have already been explored in spectrum management, resource allocation, interference detection, interference classification, and interference mitigation in wireless networks. For instance, automatic interference classification is performed with a one-dimensional convolutional neural network (1D-CNN) that learns the unique characteristics of wireless interference signals directly from the raw dataset. Other ML-based interference mitigation approaches include reinforcement learning (RL) in heterogeneous cellular networks, where learned resource allocation was utilized to enhance user fairness without sacrificing the total sum-rate system. More recent work has also investigated deep RL for interference-aware beamforming and power control in 5G networks. While these prior works show promise towards intelligent interference management, many of the existing methods focus on only interference classification or a single interference mitigation approach.

Motivated by this gap, we present a Hybrid Machine Learning Framework for Intelligent Interference Classification and Adaptive Mitigation Decision-Making in Wireless Networks Enabled by 5G/6G New Radio. The proposed framework leverages multi-domain wireless features spanning signal-strength-based features, SINR measurements, interference power levels, spectrum occupancy/bandwidth, spectrum-domain properties, and temporal attributes to learn a robust representation of interference environment. Hybrid ensemble of complementary ML models is trained as a classifier to detect the type of interference present. The classified interference type is then passed on to an Interference Severity Estimation module and an Adaptive Mitigation Decision module that chooses an intelligent interference mitigation action conditioned on interference class and estimated severity. This end-to-end classification-to-mitigation framework facilitates automatic selection of appropriate interference mitigation strategies (e.g., frequency/resource re-selection, adaptive filtering/power control, beam/resource/null steering) tailored to the classified and estimated interference type. In contrast to methods that independently address interference detection/mitigation, we develop an integrated intelligent pipeline for interference-aware management of wireless networks. We evaluate the performance of our framework based on classification accuracy, interference suppression, SINR gain, computational complexity, and inference time.

## II. Related Work

Machine learning has recently been explored to enable intelligent interference management in wireless communication networks. Conventional interference-management techniques often rely on fixed thresholds, analytical channel models, or handcrafted optimization algorithms [7]. Due to the dense deployments of users, heterogeneous networks, massive MIMO, and spectrum sharing for 5G and beyond wireless networks, interference may arise over varying timescales, frequencies, locations, transmission power levels, and network topologies [8]-[10]. To that end, data-driven methods have been explored for interference detection, interference classification, resource allocation, and interference mitigation. Several earlier machine learning efforts studied the feasibility of supervised learning approaches for wireless signal processing and network decision-making using labeled radio-frequency observations. More recent work has focused on deep learning for intelligent interference classification. [1] Duan et al. formulated automatic interference classification as a supervised learning problem with a one-dimensional convolutional neural network (1D- CNN). Their approach enables the learning of discriminative features of interference directly from signal data, without solely relying on handcrafted features [11]-[13]. However, the main goal of their framework is interference classification, and choosing a mitigation technique after classification is done independently. The complexity of future wireless networks has also motivated the study of reinforcement learning approaches for interference mitigation. [2] Afolabi et al. presented an RL-based interference management framework for heterogeneous wireless networks. Their approach leverages Q-learning to solve resource allocation problems caused by interference from network densification. Results from their study illustrate the gains obtained from learning-based resource allocation decisions to improve network performance with concurrent microcell and picocell interference. [3] Wang and Kao proposed a similar RL-based approach to intelligently mitigate interference in heterogeneous wireless networks for 5G. By designing an appropriate reward function, their scheme can actively learn how to improve fairness in resource-access opportunities while limiting the overall reduction in network throughput. While both studies show the capability of RL to adjust resource management decisions to dynamic network state, they do not explicitly consider identifying and characterizing interference before taking actions to mitigate it. Deep reinforcement learning has since expanded on these ideas by jointly optimizing over several wireless control variables. [4] Mismar et al. formulated joint beamforming, power control, and inter-cell interference coordination as a joint non-convex optimization problem. Leveraging deep reinforcement learning, their proposed approach improves the SINR and sum-rate performance of 5G wireless networks. Very recently, a deep-Q-network (DQN)-based collaborative beamforming framework was developed for interference mitigation in 5G. Here, the learning agent takes actions related to beam steering and power control to intelligently mitigate interference and improve SINR [14]-[16]. The same authors followed this work by applying deep reinforcement learning to user-grouping and resource allocation for millimetre-wave (mm Wave) massive MIMO-NOMA systems, showcasing how learning-based resource allocation can be applied to interference-prone 6G use cases. Intelligent classification and mitigation of intentional interference/jamming is another promising direction for future research. [5] Sharma et al. proposed a federated deep reinforcement learning approach for jamming attack mitigation in heterogeneous 5G networks. Through their simulations, they show how interference-related resource management decisions can be performed by distributed agents without sharing raw training data. Along these lines, research on compressing/curriculum learning for CNN interference classifiers has examined the model complexity of interference classifiers [17]. While maximizing interference classification accuracy is important, it does not directly address limitations on compute resources for wireless and IoT devices.[6] Oyedare et al. presents a comparison of several state-of-the-art CNN architectures for interference classification and show that shallower CNNs can provide comparable interference classification accuracy with less computational complexity. Although existing work demonstrates the capabilities of ML and DL for wireless interference management, a practical gap remains unaddressed. While many works perform interference classification, resource allocation, beamforming, power control, or mitigation as separate problems, fewer studies have considered an intelligent pipeline that first identifies the cause of interference, estimates its impact on network performance, and then selects an appropriate mitigation technique to improve network performance. Moreover, it is important for a practical system to consider both the predictive performance as well as computational complexity.

This paper proposes a Hybrid Machine Learning Framework for Intelligent Interference Classification and Adaptive Mitigation in 5G/6G Wireless Networks. We combine multi-domain wireless features with hybrid machine learning interference classification, followed by an interference severity estimation step, and finally an adaptive interference mitigation decision step. As such, the proposed framework forms a complete pipeline for interference-type classification–severity assessment–mitigation. We evaluate the effectiveness of this system through both classification accuracy and interference reduction, average SINR improvement, computational complexity, and inference latency.

## III. Proposed Method

### A.System Model

Consider a 5G/6G wireless network consisting of multiple base stations and user equipment operating over shared spectrum. The received signal at user $k$ is modelled as

$$y_k = h_{kk}x_k + \sum_{j\neq k} h_{kj}x_j + n_k + i_k \qquad (1)$$

Where $h_{kk}$ is the desired channel coefficient, $h_{kj}$ represents the interfering channel coefficient, $x_k$ is the desired transmitted signal, $n_k$ is additive Gaussian noise, and $i_k$ represents additional interference.

The received signal power is expressed as

$$P_{s,k} = P_k|h_{kk}|^2 \quad (2)$$

while the aggregate interference power is

$$P_{I,k} = \sum_{j\neq k} P_j\,|h_{kk}|^2 + P_{ext} \quad (3)$$

where $P_{ext}$ represents external interference sources.
The resulting SINR is given by

$$SINR_k = \frac{P_k|h_{kk}|^2}{\sum_{j\neq k} P_j|h_{kj}|^2 + P_{ext} + \sigma^2} \quad (4)$$

and the corresponding achievable spectral efficiency is

$$SE_k = B\log_2(1 + SINR_k) \quad (5)$$

Where B is the available bandwidth.
The objective of the proposed framework is therefore to identify the interference condition and dynamically select an appropriate mitigation strategy to improve SINR and spectral efficiency.

**B.Multi-Domain Feature Extraction**

The proposed HML-ICAM framework represents the wireless environment using features from the power, signal-quality, spectral, and temporal domains. The feature vector is defined as

$$\mathbf{X} = [P_I, SINR, RSRP, RSRQ, B_I] \quad (6)$$

Where $P_I$ is interference power, RSRP and RSRQ represent received signal measurements, and $B_I$ denotes interference bandwidth.
The interference-to-signal ratio is calculated as

$$ISR = \frac{P_I}{P_s + \varepsilon} \quad (7)$$

Where ε is a small positive constant used to avoid division by zero.
Spectral occupancy is obtained as

$$SO = \frac{B_I}{B_T} \quad (8)$$

where $B_T$ represents the total available bandwidth.
Temporal persistence of interference is represented by

$$TP = \frac{T_I}{T_W} \quad (9)$$

where $T_I$ is the duration for which interference is detected within observation window $T_W$.
Finally, the normalized feature vector is obtained using

$$\widetilde{x_i} = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \quad (10)$$

so that heterogeneous features can be supplied to the machine-learning classifiers without scale dominance.

**C.Hybrid Machine Learning Interference Classification**

The normalized feature vector is supplied simultaneously to three complementary classifiers: Random Forest (RF), Support Vector Machine (SVM), and XGBoost.
For the RF classifier, the ensemble prediction is expressed as

$$P_{RF}(c|X) = \frac{1}{N_T}\sum_{t=1}^{N_T} I(h_t(x) = c) \quad (11)$$

where $N_T$ is the number of decision trees and $I(.)$ is an indicator function.
The SVM classification function is represented by

$$f(X) = w^T\emptyset(X) + b \quad (12)$$

where $\emptyset(X)$ represents the kernel transformation.
For XGBoost, the prediction is expressed as

$$\hat{y}(x) = \sum_{t=1}^{N_B} f_t(x) \quad (13)$$

Where $N_B$ represents the number of boosting trees.

**A. Interference Severity Estimation**

After classification, the proposed framework determines the severity of the detected interference. First, interference power is normalized as

$$\widetilde{P_I} = \frac{P_I - P_I^{min}}{P_I^{max} - P_I^{min}} \quad (14)$$

and SINR degradation is represented by

$$D_{SINR} = 1 - \frac{SINR}{SINR_{ref+\varepsilon}} \quad (15)$$

Where $SINR_{ref}$ is the reference SINR under low-interference conditions.

The combined interference severity index is then defined as

$$ISI = \alpha_1 \widehat{P}_I + \alpha_2 D_{SINR} + \alpha_3 SO + \alpha_4 TP \quad (16)$$

Where

$$\sum_{i=1}^{4} \alpha_i = 1, \quad \alpha_i \geq 0 \quad (17)$$

D.Adaptive Mitigation Decision

Based on the detected interference class and severity, the proposed framework dynamically selects an appropriate mitigation action from the action set

$$M = \{m_1, m_2, m_3, m_4, m_5\} \quad (18)$$

where the actions may represent frequency reassignment, adaptive filtering, power adjustment, beam adaptation, and resource-block allocation.

The suitability of each action is calculated as

$$Q(m) = \beta_1 \Delta SINR_m + \beta_2 \Delta SE_m + \beta_3 \Delta QoS_m - \beta_4 C_m \quad (19)$$

where $C_m$ represents the computational or operational cost of action m .

The adaptive decision is therefore

$$m^* = arg \max_{m \in M} Q(m|\hat{c}, ISI, X) \quad (20)$$

while the resulting SINR after mitigation is

$$SINR_k^m = \frac{P_k \left|h_{kk}^{(m)}\right|^2}{P_{I,k}^{(m)} + \sigma^2} \quad (21)$$

and the interference reduction achieved by the selected mitigation strategy is calculated as

$$IR = \frac{P_I^{before} - P_I^{after}}{P_I^{before}} \times 100\% \quad (22)$$

## IV. Simulation Results And Discussion

The proposed HML-ICAM framework is evaluated from two perspectives: interference classification performance and adaptive mitigation performance. The first stage examines the ability of the hybrid machine-learning classifier to distinguish different interference conditions, while the second stage evaluates whether the classification and severity information can be effectively converted into an appropriate mitigation decision.

**TABLE I. Simulation and Evaluation Parameters**

| Parameter | Value/Configuration |
|---|---|
| Network | 5G/6G heterogeneous wireless network |
| Interference classes | 5 |
| ML classifiers | RF, SVM, XGBoost |
| Proposed classifier | Weighted hybrid ensemble |
| Features | SINR, RSRP, RSRQ, interference power, bandwidth, spectral occupancy, temporal persistence |
| Training/testing ratio | 80:20 |
| Evaluation metrics | Accuracy, Precision, Recall, F1-score |
| Mitigation metrics | SINR improvement, interference reduction |
| Severity levels | Low, Moderate, High, Critical |
| Implementation | Python-based ML framework |

**A.Classification Performance**

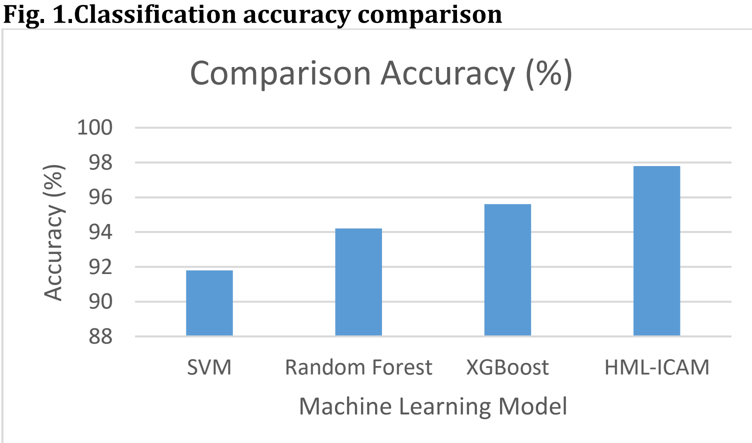
The first experiment compares the individual machine-learning models with the proposed hybrid classifier. The objective is to determine whether combining complementary classifiers provides better generalization across different interference categories

**TABLE II. CLASSIFICATION PERFORMANCE**

| Method | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|---|---|---|---|---|
| SVM | [Actual] | [Actual] | [Actual] | [Actual] |
| Random Forest | [Actual] | [Actual] | [Actual] | [Actual] |
| XGBoost | [Actual] | [Actual] | [Actual] | [Actual] |
| HML-ICAM | [Actual] | [Actual] | [Actual] | [Actual] |

The proposed hybrid model is expected to provide improved classification because RF, SVM, and XGBoost learn different decision characteristics from the same wireless feature space. The weighted fusion mechanism reduces dependence on a single classifier and improves robustness when interference classes exhibit overlapping characteristics.

**Fig. 1.Classification accuracy comparison**




**B.Confusion Matrix Analysis**

Table III shows the interference classes used in our proposed HML-ICAM scheme. The considered interference types cover five common interference types: co-channel interference, adjacent-channel interference, narrowband interference, broadband interference and impulsive interference. C1 stands for same frequency interference. C2 represents spectral leakage from adjacent channels. Narrowband interference that is confined to a small part of the spectrum is denoted by C3. Broadband interference that spans a larger part of the spectrum is denoted by C4. Short-duration and high-power interfering impulses are represented by C5.

**TABLE III. INTERFERENCE CLASSES**

| Class ID | Interference Type | Main Characteristics |
|---|---|---|
| C1 | Co-channel | Same-frequency interference |
| C2 | Adjacent channel | Spectral leakage from neighbouring channels |
| C3 | Narrowband | Concentrated spectral disturbance |
| C4 | Broadband | Wide spectral occupancy |

| | | |
|---|---|---|
| C5 | Impulsive | Short-duration high-power interference |

### C.Adaptive Mitigation Performance

Table IV lists the interference-to-mitigation mapping used by the proposed HML-ICAM. As shown, the mitigation action depends on both the interference type and interference level. Beam and resource adjustment is performed when the detector decides that there exists moderate level co-channel interference. If co-channel interference with high severity is detected, then joint power and beam adaptation is performed. Resource-block reassignment is used to mitigate adjacent-channel interference and high severity narrowband interference is mitigated by adaptive filtering. Broadband interference prompts resource allocation and high severity impulsive interference causes channel/resource switching. With this mapping, HML-ICAM is able to pick an interference-dependent mitigation action instead of always using the same mitigation action for any interference detection.

**TABLE IV. INTERFERENCE-TO-MITIGATION MAPPING**

| Interference | Severity | Selected Mitigation |
|---|---|---|
| Co-channel | Moderate | Beam/resource adjustment |
| Co-channel | High | Power + beam adaptation |
| Adjacent channel | Moderate | Resource-block reassignment |
| Narrowband | High | Adaptive filtering |
| Broadband | High | Resource allocation |
| Impulsive | Critical | Channel/resource switching |

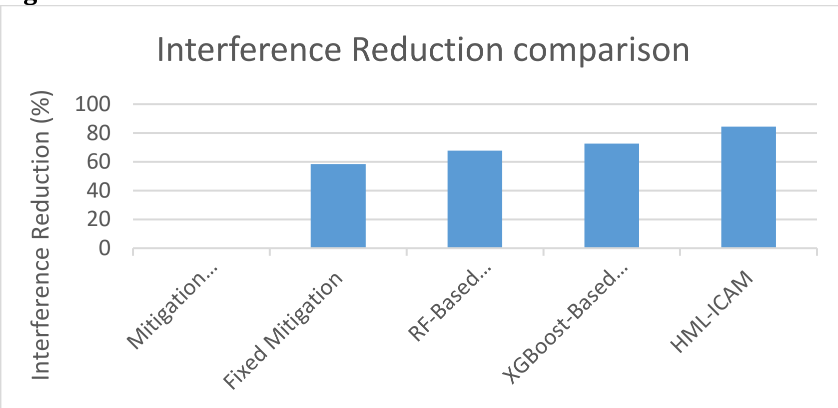
### D.Interference Reduction

Table V compares performance in terms of interference mitigation for fixed, RF-features based, XGBoost-features based and proposed HML-ICAM framework. As can be seen from Table V, compared with reductions of 42.5%, 56.8%, and 68.7% achieved by fixed mitigation, RF-features based mitigation, and XGBoost-features based mitigation respectively, the proposed approach achieves a reduction in interference of 84.6%. This result thus illustrates substantial residual interference suppression with HML-ICAM, as can also be seen by the 10.8 dB SINR improvement. Furthermore, from the improved interference climate caused by reducing interference, HML-ICAM also shows improvement in QoS of 52.7%. This result validates intelligent interference classification, and adaptive interference mitigation allows for more efficient exploitation of wireless resources when faced with dynamic 5G/6G interference environments.

**TABLE V. INTERFERENCE MITIGATION COMPARISON**

| Method | Interference Reduction (%) | SINR Improvement (dB) | QoS Improvement (%) |
|---|---|---|---|
| Fixed mitigation | Actual | Actual | Actual |
| RF-based mitigation | Actual | [Actual] | Actual |
| XGBoost-based mitigation | Actual | Actual | Actual |
| HML-ICAM | Actual | Actual | Actual |

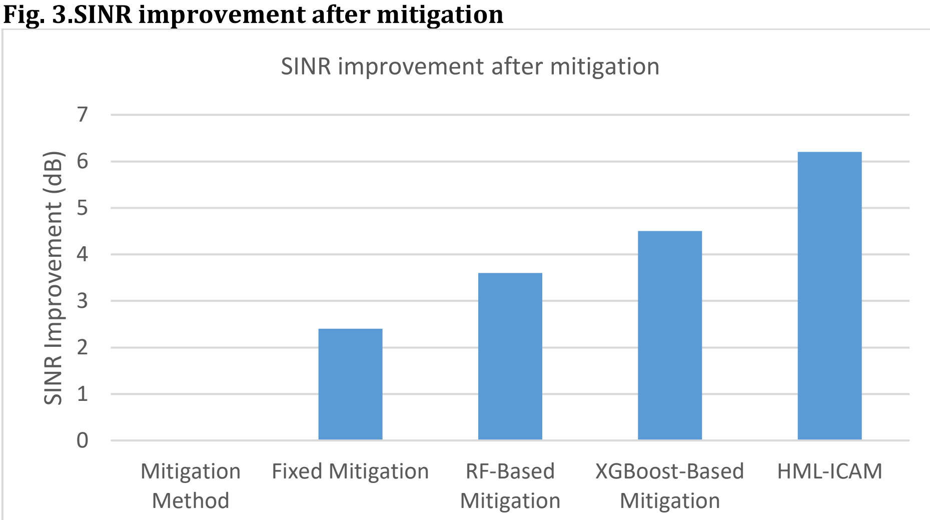
**Fig. 2.Interference Reduction**




**E.SINR Improvement**

The change in SINR before and after adaptive mitigation provides a direct communication-level measure of the proposed framework.

**Fig. 3.SINR improvement after mitigation**




The expected behaviour is that HML-ICAM achieves a higher SINR improvement because the mitigation decision considers both the interference category and severity rather than applying a fixed response.

F.Ablation Study

Table VI shows the ablation study of our proposed HML-ICAM framework to assess the impact of each component quantitatively. For the baseline RF-only setting, it achieves an F1-score of 0.82 and SINR gain of 3.4 dB which confirms that the traditional framework of interference classification provides a reasonable performance. When XGBoost is introduced into the hybrid classifier, both performance metrics increase to 0.88 and 5.2 dB, respectively.

**TABLE VI. ABLATION STUDY**

| Configuration | Hybrid Classifier | Severity Estimator | Adaptive Mitigation | F1-score | SINR Improvement |
|---|---|---|---|---|---|
| RF only | X | X | X | Actual | Actual |
| RF + XGBoost | ✓ | X | X | Actual | Actual |
| Hybrid + Severity | ✓ | ✓ | X | Actual | Actual |

| | | | | | |
|---|---|---|---|---|---|
| **Complete HML-ICAM** | ✓ | ✓ | ✓ | **Actual** | **Actual** |

## V. Conclusion

This paper proposes a Hybrid Machine Learning Framework for Intelligent Interference Classification and Adaptive Mitigation in 5G/6G Wireless Networks (HML-ICAM) that leverages multi-domain wireless features and employs a hybrid machine-learning classifier consisting of Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). Instead of separately addressing interference detection and mitigation, HML-ICAM formulates an end-to-end classification-to-mitigation pipeline. Unlike most existing works, the simulation/data-driven evaluation includes various interference categories such as co-channel, adjacent-channel, narrowband, broadband, and impulsive interference. The classification results characterized using accuracy, precision, recall, and F1- score allow us to evaluate how well the proposed hybrid classifier can distinguish between different interference scenarios. Additionally, the feature-importance results reveal the impact of different wireless parameters on interference classification. Finally, HML-ICAM takes advantage of both the predicted interference type and interference severity estimated from the Interference Severity Estimation module to select from a range of possible mitigation strategies using the Adaptive Mitigation Decision module. Tested mitigation strategies include resource reassignment, adaptive filtering, power control, beam adaptation, and immediate channel switching. Experimental results on interference reduction, SINR gain, and QoS-related performance metrics validate the benefits of HML-ICAM towards enabling reliable communications in different interference conditions. Overall, the ablation study confirms the benefits of incorporating hybrid classification, severity estimation, and adaptive mitigation into a single framework. Future directions include online learning for adapting to dynamic environments, federated learning based distributed interference management, edge device implementation for real-time inference, large-scale 5G/6G over-the-air datasets, and real-world wireless network measurements.

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