Bin-Based R: Resource-Efficient RF Modulation Classification Using Envelope Statistics

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***Abstract*—Lightweight and accurate RF modulation classification is critical for real-time processing on edge and embedded platforms. This paper presents a rule-based modulation classification framework that leverages bin-based R-values, a statistical measure derived from the ratio of variance to squared mean of segmented signal envelopes [1]. Each received signal is partitioned into fixed-length time bins, and the most informative R-values are selected to form a compact feature representation. Classification is performed using statistically defined decision thresholds, enabling training-free and low-latency operation.**

Two envelope extraction methods are evaluated: the Hilbert transform and the short-time Fourier transform (STFT). The proposed approach achieves high classification accuracy, with the Hilbert-based implementation yielding 98.4% (AM), 99.5% (DSB), and 98.9% (SSB), and the STFT-based implementation achieving 98.8%, 99.2%, and 98.4%, respectively. In addition to accuracy, computational efficiency is assessed in terms of memory usage, where the proposed framework achieves up to a $14\times$ reduction in storage for the Hilbert-based implementation and a $1.8\times$ reduction for the STFT-based implementation compared to prior approaches. These results demonstrate that the proposed R-value framework provides an effective and resource-efficient solution for modulation classification in IoT, software-defined radio, and edge AI systems.

***Index Terms*—Modulation Classification, Envelope Analysis, Hilbert Transform, STFT, R-value Features, RF Signal Processing**

I. Introduction

The rapid advancement of intelligent wireless communication systems, together with the growth of edge computing, has increased the demand for efficient and accurate automatic modulation classification (AMC). In resource-constrained environments such as embedded systems and Internet-of-Things (IoT) devices, traditional machine learning and deep learning approaches are often impractical due to their computational overhead, memory requirements, and latency [2], [3], [5]. Moreover, the need for rapid decision making in dynamic spectral environments, combined with limited availability of labeled data, further restricts the practical deployment of learning-based models [6]. As a result, recent research has explored lightweight and interpretable alternatives that maintain high classification accuracy while reducing resource consumption [2], [5]. Among these approaches, statistical features derived from signal envelopes have shown particular promise due to their simplicity, robustness under noise, and suitability for transparent decision-making [1], [2], [4].

In this work, we introduce a rule-based AMC framework that leverages binned R-values computed from segmented signal envelopes. The R-value, defined as the ratio of variance to the squared mean of the envelope within a segment, captures localized amplitude variability that is characteristic of certain modulation schemes. By selecting only the most informative R-values across time segments, the proposed method forms a compact feature representation that enables classification using fixed statistical thresholds. This training-free design avoids model optimization and iterative learning, making it well suited for low-power hardware platforms such as FPGAs and ASICs, where deterministic behavior and low latency are critical.

To balance classification accuracy and computational efficiency, we evaluate two envelope extraction methods: the Hilbert transform and the Short-Time Fourier Transform (STFT). While STFT provides improved robustness in non-stationary or noisy conditions, Hilbert-based envelope extraction achieves comparable accuracy with significantly lower computational and memory requirements, making it particularly attractive for embedded deployments. The proposed framework is evaluated on amplitude-based modulation schemes including amplitude modulation (AM), double-sideband (DSB), and single-sideband (SSB), for which envelope statistics provide strong discriminative capability. Extensions to additional modulation formats and adaptive thresholding strategies are identified as promising directions for future work.

The main contributions of this work are:

- A lightweight, bin-based R-value framework for envelope-driven modulation classification tailored to edge and embedded platforms.
- A top-k bin selection strategy that enables compact, noise-resilient, and training-free rule-based classification.
- An efficiency evaluation demonstrating up to a $14\times$ reduction in memory usage compared to prior envelope-based approaches.

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II. Related Work

Automatic modulation classification techniques are commonly categorized into likelihood-based, feature-based, and learning-based approaches. Likelihood-based methods are theoretically optimal under ideal assumptions but are computationally expensive and require accurate knowledge of channel parameters, which limits their practicality for real-time and embedded deployments. Feature-based approaches address this limitation by extracting handcrafted signal descriptors, including higher-order statistical measures, spectral characteristics, and cyclostationary features [1], [4]. While these methods offer improved efficiency and interpretability, they often rely on complex preprocessing pipelines and modulation-specific parameter tuning.

More recently, deep learning models such as convolutional neural networks, recurrent neural networks, and transformer-based architectures have been explored for modulation classification due to their ability to learn discriminative representations directly from raw I/Q samples or time–frequency representations [3]. Despite their strong performance, such models typically incur substantial computational and memory overhead, restricting their use on low-power or latency-sensitive platforms [3], [5]. As a result, several recent studies have shifted attention toward lightweight and hybrid strategies that combine statistical feature extraction with compact decision mechanisms to improve efficiency and transparency [1], [2], [7].

In contrast to learning-based approaches that require extensive training and data-dependent optimization, the proposed framework employs a rule-based classification strategy using statistical thresholds derived from R-values computed over segmented signal envelopes [2]. By leveraging envelope-based statistics and avoiding iterative model training, the approach achieves competitive accuracy with significantly reduced memory requirements, making it well suited for edge and IoT-oriented modulation classification scenarios [5], [7].

III. Proposed Methodology

This section describes the envelope-based feature extraction and rule-based classification framework proposed in this work. The method consists of three main stages: bin-based segmentation of the signal envelope, computation of statistical R-value features within each bin, and a lightweight threshold-based decision mechanism. By relying on compact bin-selected features and offline-computed statistical thresholds, the framework enables efficient and deterministic modulation classification without iterative model training. The following subsections detail the envelope extraction process, R-value computation, and bin-selection strategy.

A. Overview of the Envelope-Based Approach

For amplitude-based modulation schemes such as amplitude modulation (AM), double-sideband (DSB), and single-sideband (SSB), the primary discriminative information is largely encoded in the signal envelope rather than in phase or instantaneous frequency components [1]. The envelope captures temporal amplitude variations and provides an effective basis for low-complexity statistical analysis. Envelope-based features have therefore been explored in prior modulation classification studies as an interpretable alternative to full complex-signal processing [2].

Building on this concept, the proposed approach extracts the signal envelope and performs bin-level statistical analysis to characterize localized amplitude dynamics. Envelope extraction is carried out using either the Hilbert transform for efficient time-domain processing or the Short-Time Fourier Transform (STFT) to improve robustness under non-stationary conditions [3]. The resulting envelope is segmented into uniform time bins, and simple statistical measures are computed within each segment to capture modulation-dependent amplitude behavior. This envelope-driven, rule-based formulation enables modulation classification without requiring explicit in-phase and quadrature (I/Q) processing or iterative model training.

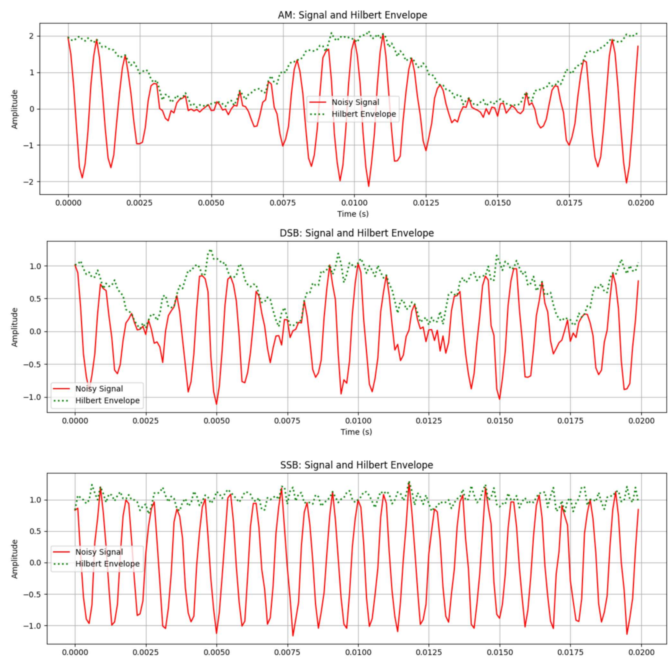

Fig. 1. Signal envelopes for AM, DSB, and SSB (top to bottom) demonstrating R value differences using Hilbert-based envelope extraction.

B. Envelope Extraction Methods

The envelope-based framework relies on established signal processing techniques to obtain an instantaneous amplitude representation of the received signal. In this work, two commonly used envelope extraction methods are considered: the Hilbert transform and the short-time Fourier transform (STFT). The Hilbert transform provides a computationally efficient time-domain envelope estimate, making it attractive for low-complexity and resource-constrained implementations. In contrast, STFT-based envelope extraction offers improved robustness in non-stationary or noisy conditions by incorporating localized time–frequency analysis.

Both envelope representations serve as inputs to the subsequent bin-based statistical R-value computation, enabling a consistent comparison of classification performance and resource efficiency across extraction methods. The use of these complementary techniques allows the proposed framework to balance accuracy, robustness, and implementation complexity depending on the target deployment scenario.

1) Envelope Extraction via Hilbert Transform: For a real-valued signal $s(t)$, the Hilbert transform constructs the corresponding analytic signal by suppressing negative frequency components. The analytic signal is defined as

$$s_a(t) = s(t) + j\,\mathcal{H}\{s(t)\}, \tag{1}$$

where $\mathcal{H}\{\cdot\}$ denotes the Hilbert transform operator. The signal envelope is obtained as the magnitude of the analytic signal,

$$A(t) = |s_a(t)| = \sqrt{s^2(t) + \mathcal{H}^2\{s(t)\}}. \tag{2}$$

The Hilbert-based envelope extraction operates entirely in the time domain and incurs low computational overhead, making it suitable for narrowband amplitude-modulated signals and real-time processing. However, its performance may degrade for wideband or rapidly time-varying signals where the narrowband assumption becomes less accurate.

2) Envelope Extraction via Short-Time Fourier Transform: To improve robustness under non-stationary or wideband signal conditions, an alternative envelope representation is derived using the short-time Fourier transform (STFT). The STFT of a signal $s(t)$ is given by

$$X(f,t) = \int_{-\infty}^{\infty} s(\tau)\, w(\tau - t)\, e^{-j2\pi f\tau}\, d\tau, \tag{3}$$

where $w(\cdot)$ is a finite-duration analysis window centered at time t. The magnitude of the STFT provides a localized time–frequency representation of the signal.

In this work, the envelope is approximated by aggregating spectral magnitudes across frequency at each time instant,

$$A(t) = \sum_f |X(f,t)|. \tag{4}$$

Compared to the Hilbert-based approach, STFT-based envelope extraction offers improved robustness to noise and time-varying spectral content at the expense of higher computational and memory requirements. This trade-off enables a direct comparison between time-domain efficiency and time–frequency robustness within the proposed bin-based R-value framework.

C. Bin Segmentation and Feature Extraction

To transform the continuous-time signal into a structured feature representation suitable for classification, a uniform binning strategy is applied to the extracted envelope. Each signal is divided into $N = 15$ non-overlapping time bins of equal duration, enabling localized analysis of amplitude fluctuations that are indicative of the underlying modulation scheme [1]. Computing statistical features at the bin level allows the method to capture temporal variations in the envelope that may be obscured by global metrics, particularly in the presence of noise or transient disturbances [2].

The choice of the number of bins N reflects a trade-off between temporal resolution and statistical stability. Increasing N improves localization of envelope dynamics but reduces the number of samples per bin, making the resulting statistics more sensitive to noise. Conversely, smaller values of N increase robustness but may smooth out short-duration amplitude variations that are important for discrimination. Empirically, $N = 15$ provided a stable balance between these effects, with larger values yielding marginal performance gains at increased sensitivity and computational cost.

Within each bin, a statistical descriptor known as the R-value is computed to capture the normalized variability of the envelope samples [2]. After R-values are computed across all bins, they are sorted in descending order, and the top-k values are retained, with k set to 7. This selection emphasizes envelope segments exhibiting the highest amplitude dispersion, which are more likely to contain discriminative modulation characteristics. Retaining only the most informative bins results in a compact, noise-resilient feature vector that preserves key temporal amplitude dynamics.

The choice of $k = 7$ reflects a balance between classification robustness and feature compactness. Empirical evaluation indicated that increasing k beyond this value provided diminishing accuracy improvements, while smaller values reduced resilience to noise and transient effects. By suppressing flat or low-energy regions that contribute limited discriminative information, the proposed bin-selection strategy enhances classification reliability and forms the basis for the subsequent rule-based decision mechanism, as illustrated in Fig. 2.

D. Definition and Role of R-Value

The R-value is a dimensionless statistical descriptor that quantifies envelope variability within a short segment of a received signal. It measures the relative strength of amplitude fluctuations by normalizing the envelope variance with respect to the squared envelope mean. The R-value is defined as

$$R = \frac{\mathrm{Var}(e)}{(\mathrm{Mean}(e))^2 + \varepsilon} \tag{5}$$

where e denotes the envelope samples within a segment and ε is a small constant introduced to ensure numerical stability.

This normalization renders the R-value largely insensitive to absolute amplitude scaling, which is advantageous in wireless environments where received signal strength may vary due to channel attenuation, receiver gain, or noise. As a result, the R-value primarily reflects modulation-induced envelope dynamics rather than raw signal power.

Modulation schemes exhibiting pronounced amplitude variations, such as amplitude modulation (AM) and double-sideband (DSB), tend to yield larger R-values, whereas single-sideband (SSB) signals produce lower values due to their comparatively stable envelopes. These modulation types are

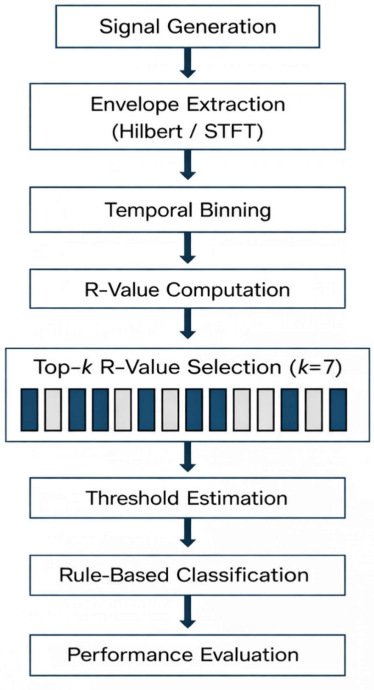

Fig. 2. Overview of the proposed bin-based R-value classification framework, illustrating top-k ($k = 7$) segment selection and statistical threshold-based decision making.

therefore well suited to envelope-driven statistical analysis. To capture time-varying behavior, R-values are computed over short, uniform time segments, enabling localized characterization of envelope fluctuations and improved robustness to noise and transient effects. While effective for amplitude-based modulations, the R-value alone is insufficient for modulation schemes with nearly constant envelopes, such as PSK, QAM, or OFDM, motivating future extensions that incorporate complementary phase, frequency, or cyclostationary-based features.

From a computational standpoint, the R-value relies only on first- and second-order statistical operations, making it well suited for low-complexity and hardware-efficient implementations. In this work, binned R-values form the basis of a rule-based classification framework that offers an interpretable and training-free alternative to data-intensive learning-based approaches.

E. Rule-Based Classification Framework

The proposed method adopts a rule-based classification framework that eliminates the need for model training or iterative optimization, unlike learning-based approaches that rely on large labeled datasets and computationally intensive retraining. After extracting R-value features, classification is performed by comparing the aggregated R-value against class-specific decision intervals defined as $\mu \pm \alpha\sigma$, where μ and σ denote the mean and standard deviation of R-values for each modulation class. The parameter α controls the trade-off between robustness and class separation; smaller values yield tighter thresholds that may be sensitive to noise, while larger values increase tolerance at the risk of overlap. In this study, $\alpha = 2.5$ was selected as a stable operating point, as performance saturated around this value. Because the R-value is a normalized statistic, the resulting thresholds generalize well across moderate variations in signal-to-noise ratio and carrier frequency and do not require recomputation for every operating condition. Although a large ensemble was used to obtain highly stable estimates, reliable thresholds can be derived with fewer samples in practice, making the framework transparent, low-complexity, and well suited for fixed-point hardware and real-time deployment on edge and embedded platforms.

IV. Experimental Setup

To evaluate the proposed rule-based modulation classification framework, a synthetic dataset was generated under controlled conditions, allowing precise control over modulation type, noise level, and signal duration. The study focuses on three amplitude-based modulation schemes-AM, DSB, and SSB-which are well suited for envelope-based R-value analysis.

Each signal employed a carrier frequency of 1 kHz and was sampled at 10 kHz. Modulation was performed using a 100 Hz cosine baseband signal. Additive white Gaussian noise was introduced, and the noise power was adjusted to achieve signal-to-noise ratio (SNR) levels ranging from -5 dB to 20 dB in order to assess robustness across varying noise conditions.

For each modulation class, 100,000 signal realizations were used exclusively for threshold estimation, while an independent set of 1,000 signals was reserved for performance evaluation. Each signal had a duration of 20 ms, corresponding to 200 samples per realization. Envelope extraction was performed using both the Hilbert transform and the short-time Fourier transform (STFT). The resulting envelopes were segmented into 15 uniform time bins, and the R-value was computed for each bin. To enhance robustness against noise and transient effects, the top seven R-values were aggregated and used for classification.

Thresholds for each modulation type were derived from the empirical R-value distributions using the mean and standard deviation statistics obtained from the threshold estimation set. The complete signal generation and implementation parameters are summarized in Table I.

V. Results and Analysis

This section presents an in-depth evaluation of the proposed R-value-based envelope classification framework using both the Hilbert transform and Short-Time Fourier Transform (STFT) domains. The results are structured to emphasize classification accuracy, threshold robustness, and computational efficiency - particularly for applications on resource-constrained platforms.

TABLE I
SIGNAL GENERATION AND IMPLEMENTATION PARAMETERS

Parameter	Value
Modulation types	AM, DSB, SSB
Carrier frequency	1 kHz
Message signal	100 Hz cosine
Sampling rate	10 kHz
Signal duration	20 ms (200 samples)
SNR range	−5 dB to 20 dB (AWGN)
Threshold estimation samples per class	100,000
Test samples per class	1,000
Envelope extraction methods	Hilbert transform, STFT
Number of time bins	15
Top R-values selected	7

A. Bin-Based R-Value Thresholds

To quantify the discriminative capability of the proposed R-value feature, statistical thresholds were established for three amplitude-based modulation types: AM, DSB, and SSB. For each class, R-values were computed from a representative ensemble of signal realizations and summarized using their empirical mean μ and standard deviation σ. Class-specific decision intervals were defined as $\mu \pm \alpha\sigma$, where α controls the trade-off between robustness and class separability. Smaller values of α yield tighter intervals that may be sensitive to noise, whereas larger values increase tolerance at the risk of class overlap. In this study, $\alpha = 2.5$ was selected as a stable operating point, as classification performance saturated around this value and further increases resulted in negligible gains while slightly increasing overlap.

Threshold estimation was performed independently for Hilbert- and STFT-based envelope extraction using a large ensemble of signal instances per modulation type. Because the R-value is a normalized statistic, the resulting decision intervals exhibit strong generalizability across moderate variations in signal-to-noise ratio and carrier frequency and do not require recomputation for every operating condition, provided that the modulation type and signal duration remain consistent. Although a large ensemble was used to obtain highly stable estimates, reliable thresholds can be derived with fewer samples in practice, with larger ensembles primarily improving statistical smoothness rather than classification accuracy. Once established, these thresholds enable rule-based classification of previously unseen signals, achieving high accuracy without model training or iterative optimization, with Hilbert- and STFT-derived R-values showing comparable performance.

B. Accuracy Across Modulation Types

To evaluate classification performance, R-values were computed from bin-based amplitude envelopes for each modulation type and classified using fixed decision boundaries derived from class-specific statistical thresholds. The decision rule assigns a signal to modulation class M_i if its aggregated R-value satisfies

$$R \in [\mu_i - \alpha\sigma_i,\ \mu_i + \alpha\sigma_i], \tag{6}$$

where μ_i and σ_i denote the empirical mean and standard deviation of the R-values for class M_i, respectively.

TABLE II
ACCURACY COMPARISON OF PREVIOUS METHODS AND THE PROPOSED BIN-BASED R-VALUE APPROACH. COLUMNS MARKED WITH (O) CORRESPOND TO THE PROPOSED METHOD.

Mod	Hilb [2]	STFT [2]	Chan [1]	Hilb (O)	STFT (O)
AM	98.60	98.80	90.5	98.4	98.8
DSB	97.30	99.10	94.0	99.5	99.2
SSB	97.90	99.00	80.0	98.9	98.4

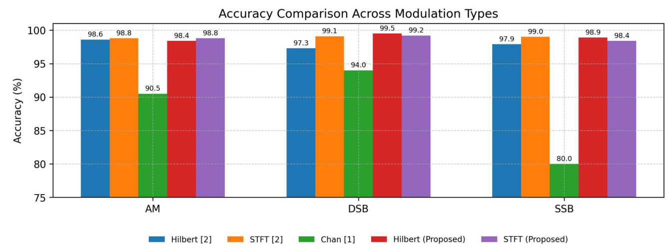

Fig. 3. Accuracy comparison across modulation types for previous methods and the proposed bin-based R-value approach. Accuracy values are annotated above each bar.

Reported accuracies represent average classification performance over the evaluated SNR range using independent test realizations that were not involved in threshold estimation. This evaluation protocol ensures an unbiased assessment of generalization performance under varying noise conditions.

Table II summarizes classification accuracy for AM, DSB, and SSB modulation types across previously reported methods and the proposed bin-based R-value approach. While earlier Hilbert- and STFT-based techniques exhibit strong performance, the proposed method achieves consistently high accuracy across all modulation classes using a simple statistical decision rule. Compared with Chan et al.'s approach, the proposed framework demonstrates substantial improvements, particularly for SSB signals, which exhibit limited envelope variability. Fig. 3 visually summarizes the accuracy trends reported in Table II.

Overall, these results confirm that bin-based R-value statistics provide sufficient discriminatory power for reliable modulation classification without reliance on learning-based models or complex optimization procedures.

C. Runtime and Memory Comparison

In addition to classification accuracy, computational efficiency is a critical consideration for practical deployment in embedded systems, software-defined radios (SDRs), and edge-AI platforms. To assess the computational cost of the proposed framework, the runtime and memory requirements of the Hilbert transform and STFT-based envelope extraction methods were evaluated and compared with previously reported results.

Table III summarizes the estimated runtime and memory footprint for both approaches under two operating conditions:

short signal batches consisting of 100 samples and large-scale processing involving 100,000 samples. The reported values were obtained by scaling empirical measurements from small-batch executions to larger sample sizes, providing insight into system-level feasibility and resource growth trends. While these estimates do not represent real-time optimized implementations, they offer a consistent basis for relative comparison across methods.

The results indicate that the Hilbert transform exhibits lower runtime overhead than the STFT-based approach, particularly as the number of processed samples increases. For large-scale processing involving 100,000 samples, the Hilbert-based implementation achieves approximately a 2× reduction in runtime compared to the STFT-based method (280 s versus 550 s), which can be attributed to its reliance on simpler time-domain operations, whereas STFT processing incurs additional computational cost due to windowing and repeated spectral analysis. A similar trend is observed in memory usage: at 100,000 samples, the Hilbert-based approach requires nearly 14× less memory than previously reported STFT implementations (15.1 MB versus 215 MB), while the proposed STFT-based variant itself achieves an approximately 1.8× reduction in memory compared to prior STFT methods (60.1 MB versus 110 MB). These improvements stem from the use of bin-based processing and lightweight statistical aggregation, which eliminate the need to store full-resolution time–frequency representations. As a result, the proposed bin-based R-value framework offers a reduced memory footprint, scalable runtime behavior, and a rule-based decision logic, making it well suited for resource-constrained and real-time signal classification environments.

TABLE III
RUNTIME AND MEMORY USAGE COMPARISON BETWEEN PRESENT AND PREVIOUS WORK

Metric	Hilbert Transform		STFT	
	Present	Previous [2]	Present	Previous [2]
Runtime (100 samples)	∼0.28 s	∼0.5 s	∼0.55 s	∼0.9 s
Runtime (100,000 samples)	∼280 s	∼35 s	∼550 s	∼85 s
Memory (100 samples)	∼15.1 KB	∼2.1 MB	∼60.1 KB	∼1.5 MB
Memory (100,000 samples)	∼15.1 MB	∼215 MB	∼60.1 MB	∼110 MB

VI. CONCLUSION

This paper presented a lightweight and interpretable R-value–based framework for modulation classification that achieves high accuracy with minimal computational and memory overhead. By leveraging simple envelope statistics and a rule-based decision strategy, the proposed method avoids the complexity and training requirements associated with learning-based approaches while maintaining reliable performance, achieving classification accuracies exceeding 98% for AM, DSB, and SSB modulation types. Experimental results further show that Hilbert-based envelope extraction provides particularly favorable efficiency, making the framework well suited for real-time and low-power deployment scenarios such as software-defined radios and FPGA-based signal processing platforms. While the current implementation focuses on amplitude-based modulations and software-level execution, future work will extend the framework to additional modulation formats, investigate parallel and hardware-accelerated implementations, and improve robustness through adaptive thresholding and hybrid rule–learning strategies. Overall, the results demonstrate that carefully designed statistical features combined with simple decision rules can offer an effective and practical alternative to more complex modulation classification pipelines.

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