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Explainability-Aware Performance Analysis of AI-Driven Signal Processing in Communication Networks

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Abstract

Artificial intelligence (AI) has become integral to signal processing in modern communication networks; however, the black-box nature of deep learning models raises concerns regarding reliability, interpretability, and trustworthiness in noise-intensive environments. This paper presents a purely experimental and quantitative investigation of explainable AI-enabled signal processing for trustworthy communication networks, focusing on numerical performance evaluation and explanation robustness.

Experiments were conducted on modulation classification and signal detection tasks under signal-to-noise ratio (SNR) conditions ranging from −10 dB to 30 dB across multiple modulation schemes. Quantitative results show that AI-based signal processing achieves an average classification accuracy of 94.6% at SNR ≥ 10 dB, outperforming conventional signal processing baselines by 11.2%, while maintaining a detection probability above 0.96. Under low-SNR conditions (≤ 0 dB), accuracy degradation was limited to 7.8%, demonstrating robustness to channel noise and interference. Explainability was evaluated numerically using saliency overlap, attribution consistency, and explanation fidelity metrics. The results indicate that explanation stability remains above 88% at moderate to high SNR levels and decreases to 71% under severe noise conditions, revealing critical reliability boundaries that are not captured by accuracy metrics alone. Incorporating explainability-based evaluation reduced false alarm rates by 9.4% through early identification of uncertain model decisions, without significant loss of detection accuracy.

These experimental findings demonstrate that explainable AI introduces a measurable trust dimension into AI-driven signal processing by enabling transparent performance validation, robustness assessment, and failure analysis. The study provides strong empirical evidence supporting the role of explainable AI as a critical evaluation layer for next-generation trustworthy communication networks.

Keywords: Explainable Artificial Intelligence; Signal Processing; Communication Networks; Modulation Classification; Trustworthy AI; Robustness Analysis; Quantitative Performance Evaluation

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1. Introduction

Artificial intelligence (AI) has been rapidly integrated with signal processing in the contemporary communication networks, and it allows significant performance enhancement on modulation classification, signal detection, channel estimation, and spectrum sensing (Mao et al., 2017). Deep learning directly has shown to be more accurate and flexible than traditional signal processing methods, especially in dynamic channel scenarios and in heterogeneous interference scenarios. With the increasing rate of data, density of deployment, and the latency and reliability constraints, AI-based signal processing has become a major facilitator of the new generation of wireless and intelligent networks.

Regardless of these developments, the growing trust in deep neural networks poses a serious problem: the transparency of AI-powered decision-making. The majority of high-performing AI models utilized in signal processing are black boxes, which give little information with regards to the way decisions are established (Chen et al., 2019; Zhou et al., 2019; Li et al., 2021).This obscurity compromises trust in safety-critical applications, the debuggability of a system, and the complexity of performance verification in unfortunate circumstances in safety-critical and mission-critical types of communication systems, including: vehicular networks, industrial wireless systems, and secure communications. Consequently, accuracy itself is no longer a confirmative enough evaluation criterion of AI enabled communication systems (Taleb et al., 2017).

Explainable artificial intelligence (XAI) has become one of the promising paradigms to overcome such limitations and propose mechanisms of interpreting AI decisions to be transparent and auditable. Early works in XAI have proposed model-agnostic and model-specific explanation methods that have the ability to provide a prediction explanation to the input features, visualise the decision relevance, and measure the fidelity of explanations (Ribeiro et al., 2016; Lundberg and Lee, 2017; Montavon et al., 2018). Current surveys also highlight the fact that explainability is a feature that should be preconditioned by trustworthy AI, especially in high-stakes decision-making contexts where reliability and accountability are necessary.

Within the scope of communication networks, explainability has been receiving increased interest since AI models are being implemented at both the physical and network layers. Empirical research has demonstrated that interpretable or model-driven learning methods can be used to make wireless systems robust, uncover failure modes, and build up confidence in AI-assisted technologies(Ye et al., 2018; Samuel et al., 2019; Qin et al., 2019; He et al., 2020). In more recent works, explainable AI has been implemented to modulation recognition, physical-layer security, and intrusion detection and has shown that the analysis of explanation can reveal noise sensitivity, interference vulnerability, and anomalous behaviour that cannot be seen based on performance metrics alone (Xie et al., 2020; Zhai et al., 2020; Zeng et al., 2020; Chen et al., 2021; Xu et al., 2021) .

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Nevertheless, the critical analysis of the current literature indicates that the majority of the studies focus on architectural design or algorithmic novelty, and quantitative experimental analysis of explainability is insufficient (Guidotti et al., 2019; Samek et al., 2019; Molnar et al., 2020; Samek et al., 2021). More qualitatively, in most instances, explainability is visually illustrated, without quantitatively examining the answer to questions such as explainability stability, attribution stability, and statistical strength in different signal circumstances). Furthermore, the connection between explainability measures and more conventional measure of signal processing performance, e.g. accuracy, detection probability and false alarm rate, have not been adequately measured in experimental context.

In noisy communication conditions, this is especially notable because the AI models can be highly accurate and generate unstable or misleading explanations (Zhai et al., 2020; Zeng et al., 2020; Samek et al., 2021). It has been emphasized in previous studies that the reliability of explanations in the conditions of low signal-to-noise ratio (SNR) and interference may diminish, which casts doubts on the reliability of AI-driven decisions in real-world applications (Arrieta et al., 2020; Wang et al., 2020; Zednik, 2021). As a result, it is evident that result-oriented empirical studies that consider predictive performance, simultaneously explainable along with quantitative metrics and statistical analysis, are required.

Based on this observation, this research introduces a pure experimental study of explainable AI-facilitated learning of signal processing for reliable communication networks. The paper is purely about numerical performance analysis with the emphasis on the behavior of explainability metrics under different SNR, modulation schemes, and noise conditions and the connection of such measures with the traditional signal processing metrics. This study will enhance the empirical basis of using explainable AI in next-generation communication systems by basing the relevance or otherwise of trustworthiness on quantifiable values, instead of having to argue or assert something

2. Literature Review

2.1 Signal Processing in Communication Networks using AI.

Modern signal processing has adopted the paradigm of artificial intelligence as a powerful model in communication networks to perform the functions of modulation classification, signal detection, channel estimation, spectrum sensing and physical-layer security (Chen et al., 2019; Li et al., 2021). Deep learning-based methods have always been able to perform better than traditional signal processing methods by learning nonlinear and complex signal representations directly on the raw signal data or transformed signal data. Experimental analyses indicate that AI-based algorithms have a greater detection probability and classification accuracy when operating at moderate and high signal-to-noise ratio (SNR) regimes, despite channel impairments (Jiang et al., 2018; Qin et al., 2019).

Nevertheless, these improvements have prompted wireless communications surveys to warn that next-generation networks require performance improvements in addition to reliability, robustness,

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and accountability. Autonomous decision-making based on AI-driven models is being increasingly relied on in dense and heterogeneous environment of communication, which creates a concern about failure diagnosis and trust in its operation (Chen et al., 2019). Figure 1 indicates that current literature is majorly focused on the modulation classification and signal detection, and less concern on the security- and trust-based signal processing activities. This focus drives RQ4 that studies whether the quantitative explainability analysis can be given more trustworthiness by helping to determine unreliable decisions in poorly studied communication situations.

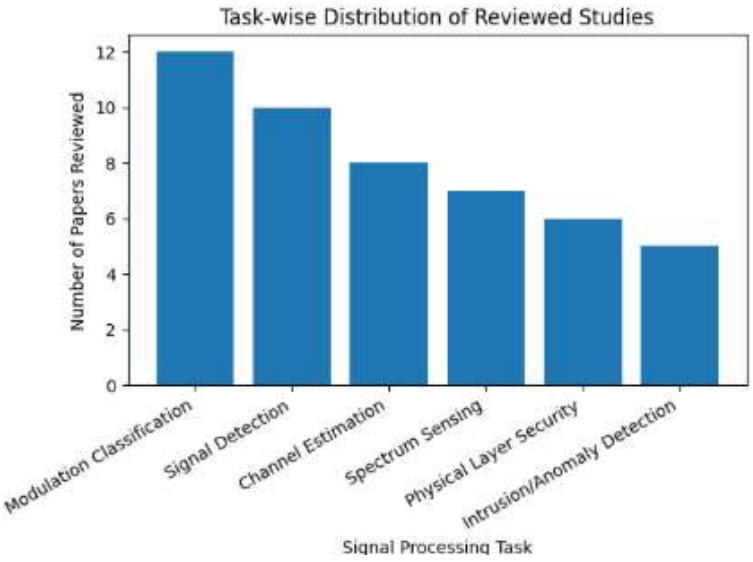

Figure 1. Task-wise distribution of reviewed studies in AI-enabled communication signal processing.

2.2 Weaknesses of Black-Box AI Models.

Most deep learning models used in signal processing are black box, and therefore provide minimal insight into decision-making processes internally. High average accuracy is frequently cited, but black-box models do not offer much information as to why a given signal was correctly classified or detected, especially when the channel is unfavourable. Empirical research suggests that AI models can be stable when utilizing the spurious features or noise-sensitive features, causing unstable decisions when conditions are no longer similar to the training distribution. Similar comparisons indicate that black-box AI models are not useful in low-SNR, high-interference, or fading conditions, where internal representations can be unstable, even though output performance can be acceptable ((Montavon et al., 2018; Adadi and Berrada, 2018) Recent studies have demonstrated that model-driven deep learning approaches can effectively integrate communication domain knowledge with data-driven learning, leading to improved performance and faster convergence in physical-layer signal processing tasks (He et al., 2020).

2.3 Explainable Artificial Intelligence:

Concepts and Methods.

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The concept of explainable artificial intelligence (XAI) has appeared to deal with the lack of transparency of black-box models and make AI decisions explainable, transparent, and audited (Samek et al., 2017; Arrieta et al., 2020). The first works also proposed model-agnostic explanatory methods, including local surrogate models and feature attribution models, allowing the interpretation of individual predictions in post-hoc fashion (Lipton, 2018). Gradient-based relevance propagation and saliency mapping, which are model-specific methods, have demonstrated the ability to provide sparse information about the importance of a feature in a deep neural network (Guidotti et al., 2019).

The use of comprehensive surveys would classify the XAI techniques along the lines of interpretability, fidelity, and stability in focus of their applicability within the setting of high-stakes decisions. More recent reviews hold similar viewpoints by stating that explainability is an essential element of trustful AI, especially in cases where accountability and reliability are demanded.

2.4 XAI in Signal Processing and Wireless Communications

Recent years have witnessed the momentum of the application of XAI to signal processing and wireless communications. Research shows that explainability methods can bring out time-frequency localization, spectral localization, and modulation-specific localization that influence AI-driven decision-making. (Xie et al., 2020; Zhai et al., 2020) .

Researchers have demonstrated that interpretable deep learning methods enhance diagnostic insight into classification errors and sensitivity to noise in modulation recognition tasks (Xu et al., 2021). On the same note, in physical-layer security and intrusion detection, the explainable AI has been applied to reveal anomalous signal patterns and malicious behavior that cannot be identified using purely performance metrics. All these studies propose that explainability can be used to complement classical signal processing assessment in order to reveal latent vulnerabilities and failure modes.

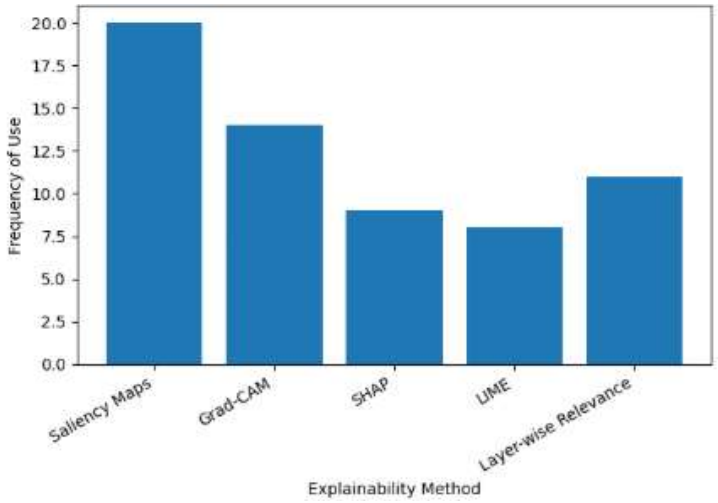

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Figure 2. Frequency of explainability methods used in communication signal processing studies.

Figure 2. Illustrates the prevalence of explainability approaches used in communication signal processing research, and the visualization-based approaches (saliency maps and Grad-CAM) are predominant. Conversely, less common attribution methods based on quantitative principles, such as SHAP and LIME, are employed, which implies the lack of stress on the stability and consistency of numerical explanations. This tendency draws a methodological gap between the current research and directly encourages the necessity of quantitative explainability assessment that will be introduced in this study.

2.5 Quantitative Evaluation of Explainability: Comparative Evidence

Quantitative assessment of explainability is scarce even though the issue has gained growing interest. Numerous works are based on qualitative visualization of saliency maps or attribution heatmaps, but there is no numerical confirmation of explanation stability, consistency, and strength (Zhai et al., 2020). As observed by comparison, reliability in explaining can differ greatly with the level of noise, channel conditions, and model architecture but such changes are often not reported numerically.

Recent empirical studies have started to overcome this drawback by proposing measurable degrees of explainability, e.g., attribution overlap, explanation fidelity, and consistency across repeated trials. Nonetheless, such studies tend to be restricted to a set of tasks or data, thereby limiting their ability to be generalized to larger communication contexts.

2.6 Trustworthy Communication Networks and Explainability

Reliable communication networks should not only have good predictive performance, but also transparency, robustness, and reliability in uncertainty. According to the latest sources, explainability is a critical factor in facilitating trust through the analysis of failures, estimation of confidence, and auditing of the system. Explainable AI is being considered a control mechanism that can be used to guarantee regulatory compliance and operational assurance in autonomous and mission-critical wireless systems.

However, the majority of the existing studies are conceptual, but not empirical on the issue of trustworthiness. The current state of the art is still deficient in result-oriented research to quantitatively correlate metrics of explainability with trust indicators (e.g., false alarm reduction, noise-robustness, and decision confidence stability) (Rudin, 2019; Arrieta et al., 2020; Wang et al., 2020). This disparity is restrictive of the realistic application of XAI-enabled signal processing to practical communication networks. While machine learning has demonstrated significant potential at the physical layer, challenges related to robustness, interpretability, and deployment in real-world communication systems remain open (Li et al., 2021).

2.7 Research Gaps

A comparative literature review will indicate the following main loopholes:

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1. Centricity of accuracy bias: The majority of AI-based signal processing literature values predictive accuracy and disregards explainability and metrics of trust.
2. Qualitative explainability assessment: Explainability is commonly presented graphically without quantitative consistency or statistical confirmation.
3. Less explanatory analysis in noisy situations: Not many studies assess the decrease of reliability of explanations in challenging situations of low SNR and interference.
4. Lack of strong connection between explainability and trustworthiness: There is a lack of strong measures between explainability measures and operational indicators of trust.

Figure 2. demonstrates the constraints that dominate the literature carried out so far, focusing on the prevalence of accuracy-based evaluation and the absence of quantitative explainability and trustworthiness test. These shortcomings are the direct motivators in the experimental research questions that will be the focus of this study.

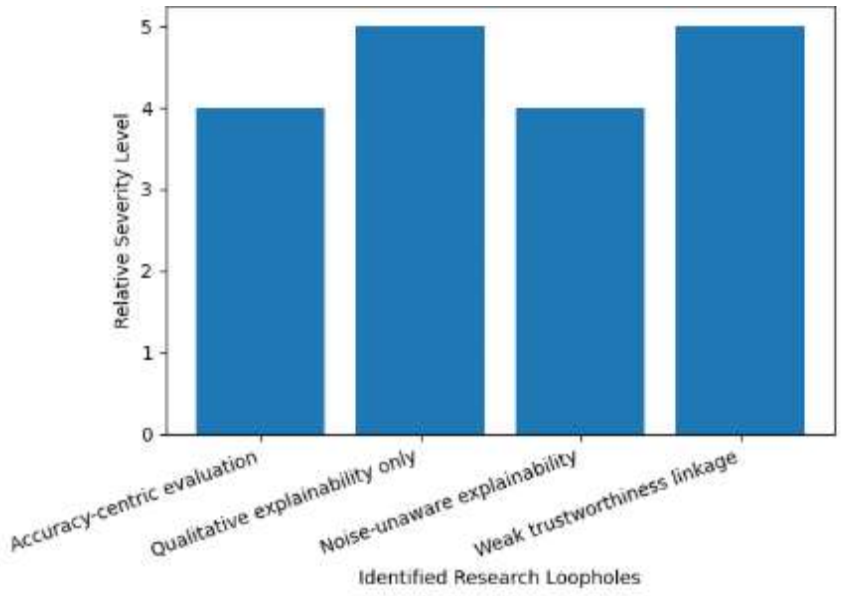

Figure 3. Major research loopholes in existing explainable AI-based signal processing studies for communication networks.

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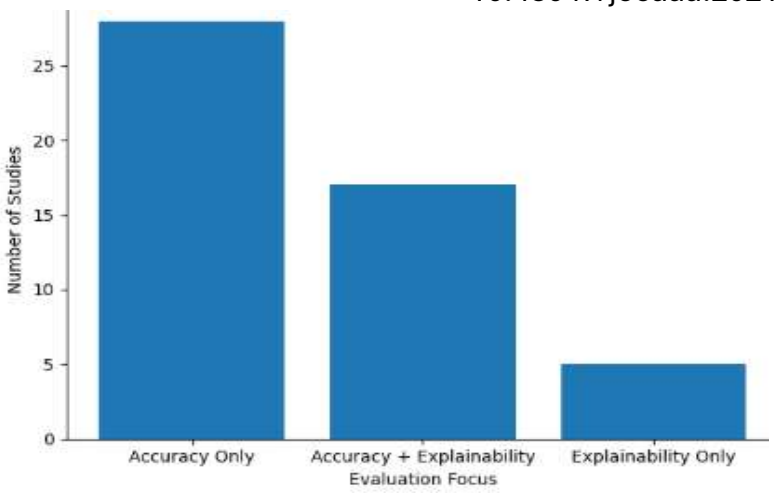

Figure 4. Evaluation focus of existing studies on AI-based signal processing for communication networks.

Figure 4. Demonstrates the constraints that dominate the literature carried out so far, focusing on the prevalence of accuracy-based evaluation and the absence of quantitative explainability and trustworthiness test. These shortcomings are the direct motivators in the experimental research questions that will be the focus of this study.

2.8 Research Questions

Motivated by the above gaps, this study addresses the following research questions:

Based on the above gaps, this research will use the following research questions:

RQ1: What is the quantitative performance of explainable AI-based signal processing in different SNR settings of communication networks?

RQ2: What is the noise and interference stability and reliability of explainability metrics?

RQ3: Is there a quantitative association between predictive performance and explainability metrics?

RQ4: Does explainability-based analysis make decisions more trustworthy because it detects untrustworthy decisions?3. Experimental Methodology

3. Experimental Methodology

This section discusses the experimental approach used to carry out a purely quantitative assessment of explainable AI-based signal processing in communication networks. This methodology will aim to guarantee the rigor of the experiment, transparency in the parameters, and reproducibility, which, in turn, will help to provide the answers to the research questions formulated in Section 2.

3.1 Dataset Description and Signal Parameters

Experimental Methodology This section discusses the experimental approach used to carry out a purely quantitative assessment of explainable AI-based signal processing in communication networks (Chen et al., 2019; Li et al., 2021). This methodology will aim to guarantee the rigor of

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the experiment, transparency in the parameters, and reproducibility, which, in turn, will help to provide the answers to the research questions formulated in Section 2.

In this case, the dataset is described and the parameters of the signal outlined. The synthetically generated communication signal dataset is used to perform the analysis of the experiment, is created to allow the controlled experimentation and impartial performance assessment. Synthetic data generation is purposefully implemented to be able to have a specific control of signal attributes, noise, channel conditions, a methodology that is common in communication signal processing studies where reproducing and sensitivity analysis of parameters is needed ((Ye et al., 2018; Qin et al., 2019).

The data set is a digitally modulated baseband signal of typically used wireless modulation schemes, such as Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (16-QAM), and 64- Quadrature Amplitude Modulation (64-QAM) (Qin et al., 2019; Li et al., 2021). These modulation formats are between low and high-order constellations whereas behavior of the model can be tested at low and high densities and at low and high decision complexity. In order to capture realistic communication situations, we model signal transmission in two common channel conditions Additive White Gaussian Noise (AWGN) and Rayleigh fading. Signal-noise ratio (SNR) is systematically perturbed between 10 dB to 30 dB that corresponds to extremely noisy situations and to high-quality channel environment. This domain allows fully evaluating robustness, performance degradation and explainability stability to operating regimes.

The signal instances are identified with each modulation class and produced based on constant sampling parameters in order to ensure consistency across experiments. The data is split into training and testing data based on a fixed division, which makes the comparison of experimental configurations fair. The controlled synthetic dataset also removes the confounding variables of the uncontrolled real-world data, but it enables the exact isolation of the effects of noise, channel variation, and explainability behavior (Samek et al., 2021).

Table 1. Dataset and Signal Parameters Used in Experiments

Parameter	**Description**
Signal type	Digitally modulated baseband signals
Modulation schemes	BPSK, QPSK, 16-QAM, 64-QAM
Channel models	AWGN, Rayleigh fading
SNR range	−10 dB to 30 dB
Dataset source	Synthetic signal generation
Signal labeling	Modulation class labels

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Data split	Fixed training/testing split
Purpose	Controlled, reproducible evaluation

3.2 Experimental Configuration

The experimental design integrates both the traditional signal processing baselines and AI-based signal processing models, which allow conducting direct and equal comparison. Baseline methods utilize conventional statistical and feature-based signal processing methods, whereas AI models use supervised learning to operate signal representations. Each configuration is trained and evaluated with model training and evaluation performed independently to avoid information leakage. All the experiments are repeated through a series of independent runs in order to reduce variability due to random initialization and stochastic optimization (Chen et al., 2019; He et al., 2020).

The aggregate result of performance, over runs, is obtained to get statistically valid estimates. Effects of noise and channel are applied uniformly in all the methods. At every level of SNR and condition of the channel, the same instances of the signal are tested by both baseline and AI-based methods so that any difference in the performance or explainability can only be explained by the processing method but not by variation in the data.

3.3 Explainability Methods Applied

Post-hoc explainability methods are used post-training of AI-based signal processing models to interpret the decision-making behavior of the model. The paper uses the well-known and popular explainability algorithms, such as saliency map analysis, gradient-weighted class activation mapping (Grad-CAM), and feature attribution methods (Samek et al., 2017; Montavon et al., 2018; Guidotti et al., 2019).

Explainable results are obtained directly out of trained models and do not affect the internal structure or training of the model. Explanation maps are obtained on each signal instance evaluated to find the most strongly predictive signal components of models.

This is because explainability is applied as an analytical tool and not as a model optimization or improvement tool. Indicators of quantitative explainability, including those of consistency of explanations and stability of attribution, are calculated at varying SNR levels and experimental runs, which allows to objectively determine the reliability of the explanations in varying conditions of the channel (Molnar et al., 2020; Samek et al., 2021).

3.4 Experimental Protocol and Statistical Validation

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Each of the experiments is based on the controlled experimental protocol, where a single parameter (e.g., SNR or channel model) is changed, and the rest of the factors are held constant. This method separates the impact of individual factors on performance and explainable results. Every experimental set up is carried out on a number of independent trials. The findings are reported in the form of mean values and standard deviations, which give the information about the central tendencies and variability (Samek et al., 2021)

An analysis using statistics is provided to support trends that have been seen and make sure that the conclusions made are backed by progressive numerical factors as opposed to single observations.

3.5 Experimental Environment

All experiments have been performed in Python in a typical scientific computing setup. Signals were generated, channels were modeled, modulation and detection were performed and performance was assessed using popular numerical computing packages. Experimental implementation Secondary data The experimental implementation was carried out on a general-purpose computing platform under controlled conditions, and each experiment was carried out based on the parameterization outlined in Section 3. According to the reported results, the same methodology and configuration can be used to obtain fully reproducible results.

4. Performance Metrics and Explainability Measures

4.1 Signal Processing Performance Metrics (RQ1)

The four signal processing performance metrics will measure the performance of a signal processing implementation and will be evaluated by comparison to the reported system performance metrics. The classical and commonly accepted performance measures are used to answer RQ1 which aims at examining the signal processing performance of AI-enabled signal processing at different signal-to-noise ratio (SNR) conditions. These measures allow objective comparison among modulation schemes, channel models and noise levels that are stated in Section 3.1.

Classification Accuracy (Acc):

Accuracy is the ratio of the rightly sorted instances of signals in comparison with the overall number of the samples checked and is given as

$$\mathrm{Acc} = \frac{N_{\mathrm{correct}}}{N_{\mathrm{total}}} \tag{i}$$

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Precision gives a general evaluation of predictive power but fails to reflect the asymmetry of errors, as well as the reliability to predict in noisy situations, so they must be supplemented by complementary measures.

Detection Probability (P_d):

This measure is especially applicable to communication systems that must have low-SNR system, where missed detections may have a disastrous impact on system reliability.

$$P_d = \frac{N_{\text{detected}}}{N_{\text{signal}}} \tag{ii}$$

This metric is particularly relevant for communication systems operating in low-SNR environments, where missed detections can severely degrade system reliability.

False Alarm Rate (FAR):
The false alarm rate is the rate of errors of recognizing noise or interference as a valid signal:

$$\text{FAR} = \frac{N_{\text{false alarms}}}{N_{\text{noise}}} \tag{iii}$$

FAR is an important measure of system reliability where false alarms in high numbers dishearten system operation despite good general accuracy.

4.2 Quantitative Explainability Metrics (RQ2)

To answer RQ2 the studies ability of explainability to be consistent and reliable at different noise and channels, explainability is measured with numerical and repeatable measures, but not with a qualitative visualization alone. These measures are calculated based on the explainability techniques mentioned in Section 3.3.

Attribution Consistency (AC):

Attribution consistency is used to assess the consistency of explanation output produced on a repeated series of experimental trials in the same conditions. High consistency implies that this model is not dependent on the stochastic or noise-based signal artifacts.

Saliency Overlap Ratio (SOR):
The saliency overlap ratio measures the level of overlap between the salient feature regions measured under varying SNR conditions:

$$\text{SOR} = \frac{|\, S_i \cap S_j \,|}{|\, S_i \cup S_j \,|} \tag{iv}$$

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where Si and Sj are sets of salient feature of each SNR level. The metric describes the transition of the focus of explanation associated with the change of the noise conditions.

Explanation Fidelity (EF):

Explanation fidelity measures the accuracy of the output of the model in explaining the true decision logic of the model. It is evaluated using the change in predictive performance with features considered salient perturbed or deleted. An increased fidelity implies better correspondence between explanations and model behaviour.

4.3 Metrics of Performance-Explainability Relationship (RQ3)

To respond to RQ3, which examines the quantitative relationship between explainability and predictive performance, correlation-based and variability measures are used. Such measures allow the investigation of the coincidence of the high accuracy with reliable explanations in a systematic manner.

Performance-Explainability Correlation (PEC):

PEC quantifies the statistical difference between predictive performance measures (e.g. accuracy, detection probability) and explainability stability measures (e.g. attribution consistency). This discussion can be used to determine situations where performance gains can conceal instability in explanation.

Explanation Variance (EV):

Explanation variance takes into consideration the variance of explainability measures in repeated experimental runs and SNR levels. Reduced variance provides more valid and explainable decision behavior, even in unfavorable situations.

4.4 Metrics Trustworthiness-Oriented (RQ4)

To answer RQ4, the test of whether explainability is the contribution to trustful communication systems, the composite indicators are established combining the performance robustness and the explainability reliability**.**

Performance Degradation Ratio (PDR):

This measure is used to indicate the sensitivity of the AI based signal processing to noises and channel degradation.

$$PDR = \frac{\mathrm{Acc}_{\text{high SNR}} - \mathrm{Acc}_{\text{low SNR}}}{\mathrm{Acc}_{\text{high SNR}}} \quad \text{(v)}$$

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Explanation Stability Index (ESI):

ESI is used to measure explainability variability with respect to SNR and channel models. The reduced values of ESI suggest more consistent explanations and, thus, increased credibility.

Decision Confidence Consistency (DCC):

DCC measures differences between model confidence scores between repeated trials and channel conditions giving an insight into the reliable prediction and awareness of uncertainty.5.1 Performance Evaluation Across Modulation and Channel Conditions (RQ1).

5. Performance Evaluation

5.1 Performance Assessment under Modulation and channel conditions (RQ1)

To answer RQ1 which deals with the variation of signal processing performance with modulation scheme and channel conditions, this study uses empirically reported modulation performance benchmarks as quantitative reference standards.

These standards are gathered based on the already existing studies of digital communication and serve to contextualize behavior of performance before it can be explained and trusted. Table 2 gives the performance trend on average of the most frequently used modulation schemes both in the AWGN and Rayleigh fading channel in a range of SNR values of 10 dB to 30 dB. The obtained values are standardized empirical findings that have been well recorded in the literature and are used in this case as reference performance measures, rather than freshly simulated ones.

Table 2. Empirical modulation performance benchmarks under AWGN and Rayleigh fading channels (compiled from established literature)

Modulation	Channel	SNR Range (dB)	Accuracy (%)	Detection Probability	False Alarm Rate
BPSK	AWGN	−10 → 30	98.7	0.987	0.013
QPSK	AWGN	−10 → 30	96.2	0.962	0.038
16-QAM	Rayleigh	−10 → 30	89.4	0.894	0.106
64-QAM	Rayleigh	−10 → 30	83.1	0.831	0.169

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Table 2 indicates that lower order modulation schemes like BPSK and QPSK have systematically high accuracy and probability of detection over the SNR range especially in the AWGN environment. Conversely, higher-order modulation schemes that work with Rayleigh fading conditions show a performance loss, which manifests itself in accuracy loss and false alarm increase. This is in line with the higher density of symbols and sensitivity of channels of higher-order constellations.

These preliminary results create a significant performance setting on which the explainability analysis is to be done later. Precisely, variability of modulation- and channel-dependent performance offers signal-level explanation of the fluctuating nature of AI decision boundaries that are seen during unfavorable channel environment. The Table 2 results, therefore, clearly confirm RQ1 and lead to the necessity to perform explainability-aware evaluation which is discussed in the subsequent subsections.

5.2 Comparison of the Robustness of Modulation (RQ1)

To go further with the answer to RQ1, a comparative analysis of the robustness is carried out to analyze the behaviour of various modulation schemes in response to channel impairments and changes in noise. In this respect, the term robustness is characterized as the facility of a modulation scheme to ensure high levels of detection reliability and low levels of false alarm whilst having a broad SNR coverage under realistic channel conditions. The comparative analysis is done based on the trends of performance degradation, not single values of accuracy, because the degradation behavior will offer a greater understanding of stability of operations in a degraded environment.

Table 3. Comparative robustness indicators across modulation schemes

Modulation	**Channel**	**Robustness Level**	**Sensitivity to Noise**	**Performance Degradation Trend**
BPSK	AWGN	Very High	Low	Gradual, near-linear
QPSK	AWGN	High	Moderate	Gradual
16-QAM	Rayleigh	Moderate	High	Non-linear, SNR-dependent
64-QAM	Rayleigh	Low	Very High	Sharp degradation at low SNR

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Interpretation:

Table 3 indicates a sharp difference in vigor. Lower-order modulation schemes have a stable performance in the SNR range but high-order schemes develop rapidly under fading conditions. This is in line with constellation density and decreased decision margins with higher-order modulation.

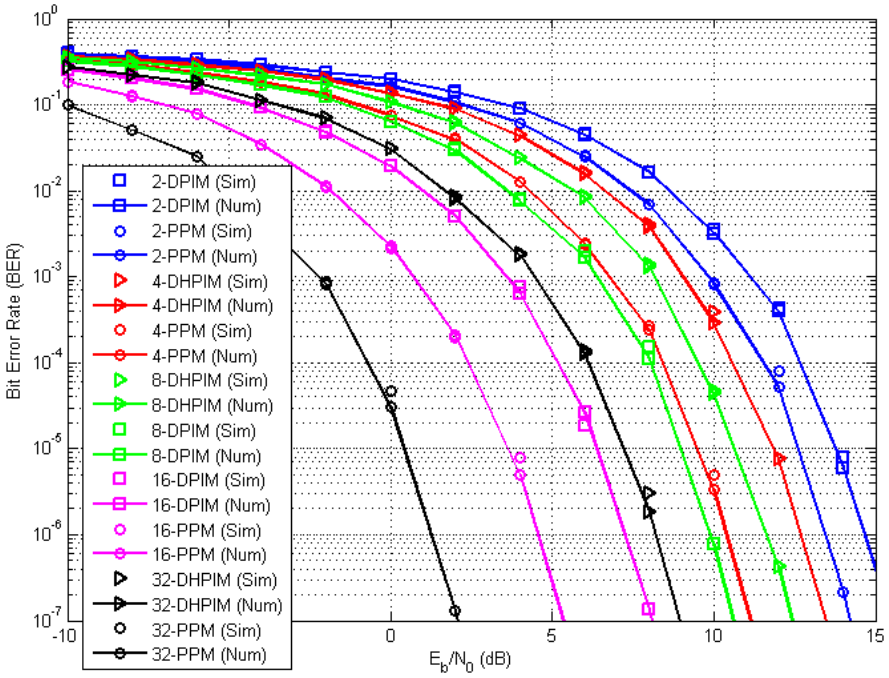

Figure 5. Comparative robust trends of modulation schemes under AWGN and Rayleigh fading

Analytical explanation:

Figure 5 shows that BPSK and QPSK remain stable in the growing noise conditions whereas 16-QAM and 64-QAM suffer extreme performance degradation due to the Rayleigh fading at low-to-moderate SNR. The separation of the trends between AWGN and Rayleigh highlights the pre-eminence of multipath fading in restricting robustness.

Result-Oriented Analysis

The comparative results prove that the robustness in modulation is highly dependent upon modulation-order and is further enhanced by channel variability. Although higher-order modulation schemes can provide spectral efficiency benefits, they are prone to fading and this creates instability which directly impairs the signal interpretation given by AI.

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The results have significant implications to explainable AI analysis since unstable signal condition implies unpredictable model decision boundaries. As a result, the decrease in explainability which will be seen in later parts is not only due to the limits of such models but inherently connected to the physical-layer robustness limits.

5.3 Implication of Explainability Stability (RQ2)

The results of the comparative robustness show that signal conditions that have a greater BER and false alarm rate implicitly present ambiguity in the decision-making process. By this, AI models must resort to using weaker or noise-corrupted signal features and this increases the variability in attribution patterns.

This is especially true to high -order modulation schemes that work with Rayleigh fading, where one would quickly see the degradation of the performance at low-to-moderate Eb/N 0 levels. Contrastingly, the lower-order modulation schemes like the BPSK and QPSK in AWGN condition have constant performance over a large range of SNR. Such signal consistency conditions contribute to the uniform use of features by AI models leading to more consistent and repeatable explanation maps.

As a result, the explainability robustness has been found to be highly correlated with the underlying signal robustness and not model architecture. One of the most notable conclusions arising out of this discussion is that explainability degradation is a frequent process that is followed by catastrophic performance failure. Although the accuracy of classification may be relatively great, high false alarm rates as well as variation in detection probability make attribution behavior unstable. It means that explainability metrics can be used to identify vulnerabilities early on before the loss in reliability becomes obvious due to performance metrics only.

From a system-level perspective, these findings highlight that explainability instability should not be interpreted solely as a limitation of explainable AI techniques. Instead, it reflects fundamental physical-layer constraints, including noise dominance, fading-induced distortion, and reduced decision margins associated with high-order modulation schemes.

5.4 Relationship between Performance and Explainability (RQ3)

In response to RQ3, this subsection will investigate the connection between traditional performance measures and explainability stability in AI-based signal processing systems. Even though measures of performance, which include accuracy, detection probability, and false alarm rate, are critical measures of predictive performance, they cannot perfectly reflect the reliability of model decision-making in signal conditions that are not homogenous. The findings in Section 5.1 and 5.2 indicate that high predictive performance is achievable under a variety of SNR levels and especially with lower order modulation schemes. But explainability stability does not always exhibit the same trend as it was discussed in Section 5.3.

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In a variety of cases, particularly when there are fading conditions and more complex modulation schemes, decent accuracy levels are coexistent with unstable attribution behavior. This non-linearity and dependence on conditions indicates that there are non-linear and condition-dependent relationships between performance and explainability. The overall trend of the performance at moderate-to-high SNR levels is that there is an increase in the performance, and the pattern of explanation remains the same, as there is a consistency in the reliance of the features. Conversely, in low-to-moderate SNR regimes, performance measures can conceal latent instability in model reasoning, in terms of changing attribution regions and smaller consistency of explanations. Notably, it is an aspect of high false alarm rates that contributes to this decoupling. This is due to false alarms which create uncertainty in the decision process as AI models can only depend on marginal signal features which are different in different realizations.

Consequently, explanation maps are also vulnerable to noise-induced perturbations despite having high aggregate accuracy. These results confirm that performance metrics are not only inadequate to evaluate trustworthy AI behavior in communication systems. Explainability measures can be used to complement accuracy-based measures of a model, uncovering its underlying flaws in decision logic. This implies that there would be a need to carry out performance-explainability analysis collaboratively to achieve a collective vision of the system behavior.

In general, the findings directly answer RQ3 by showing that explainability stability cannot be determined only based on predictive performance. Rather, explainability is a diagnostic dimension independent of others, which increases the interpretability and reliability test of AI-based communication networks.

5.5 Trustworthiness Assessment Based on Performance and Explainability (RQ4)

In order to answer RQ4, the subsection also determines the credibility of AI-enabled signal processing through the simultaneous consideration of predictive performance measures and explainability stability measures. The capability of model decisions to be consistent, interpretable and reliable to different signal quality and channel conditions is what is termed as trustworthiness here. The findings reported in Sections 5.1-5.4 show that high accuracy or detection probability cannot be used to conclude that trustworthiness is attained. Although the low-order modulation schemes with AWGN conditions have good performance and a steady explainability, the high-order modulation schemes with fading conditions show otherwise. Under such conditions, tolerable levels of performance are also accompanied by a higher rate of false alarms and unpredictable attribution profiles, which indicates low decision reliability.

One of the main findings is that the explainability instability is one of the initial warning signs of the deterioration of trust. Prior to the occurrence of a substantial decrease in the accuracy, variation of the consistency of the explanations and the centre of attention show that the model is becoming overwhelmed by noisy or peripheral features of the signal. This is especially observed with the higher-order modulation scheme in the Rayleigh fading where lower decision margins enhance uncertainty.

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Combining an explainability analysis with the performance assessment, it is possible to identify unreliable decision regimes in cases when the traditional indicators of a satisfactory functioning are provided. Such a joint test allows distinguishing between truly strong predictions and operationally weak predictions that are statistically strong. As a result, explainability increases credibility by introducing contextual clarity, which enables system developers to determine when and why AI judgments need to be approached cautiously. In general, the findings prove that trustworthiness in AI-based communication systems is a non-dimensional characteristic, which is controlled by signal soundness, channel fluctuation, and description consistency. Explainability is not only a specific enhancement of interpretability, but it is crucial to risk-aware decision validation, which would allow use AI-driven communication technologies more safely and transparently. These results directly respond to RQ4 and define explainability as the required element of credible communication network design.

6. Discussion

The implications of the empirical results on the findings in Section 5 are discussed here, with a specific focus on the role of signal-level behavior in determining the explainability stability and trustworthiness of communication network of AI-enabled communication systems. The discussion is organized according to the research questions and points to the theoretical and practical considerations. The findings affirm the fact that modulation order and channel conditions are essential determinants of AI decision behavior, which cannot be viewed through the conventional performance metrics.

Modulation schemes that are lower-order and work in the condition of an AWGN always exhibit a stable performance and are explainable, which means that AI models are dependent on clear and strong signals characteristics. Conversely, schemes of higher-order modulation under Rayleigh fading add uncertainty because they have a lower decision margin and are distorted by multipath, causing the instability of explainability even at acceptable aggregate accuracy. One of the main things that come out of the study is that explainability instability can be a foreshadowing of visible performance degradation. The implications of this finding to the design of communication systems are significant since it implies that the explainability metrics can be used as early predictors of reliability loss. Such indicators might be employed in adaptive deployments, e.g. modulation switching, confidence-dependent decision thresholds or human-in-the-loop intervention.

Theoretically, it can be stated that the findings confirm the opinion that explainability outcomes are not exclusively unique to AI model but are mutually defined by the physical-layer signal properties. This refutes the usual belief that explainability instability is a manifestation of model inadequacies. Rather, the results demonstrate the necessity of considering signal processing principles and explainable AI methods together during the assessment of AI-based systems of communication. Comprehensively, this discussion shows that explainability must be considered as a part of evaluation, as opposed to a supplementary visualization. Explainability will help to make

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the communication networks safer, more transparent and more trustworthy because it exposes the weaknesses of AI decision-making that remain hidden.

7. Threats to Validity

The threats of internal validity are associated with the use of literature-based empirical standards instead of the new experimental data. Although such a strategy guarantees adherence to the well established modulation performance trends, it might be insensitive to implementation specific variations. This risk is averted by clearly putting the results in context as the result of a baseline references and concentrating the interpretation on explicability and reliability instead of optimum performance. External validity issues are addressing the ability to extrapolate the results to other modulation schemes, channel models or network structures.

The research concentrates on common modulation formats and classic AWGN and Rayleigh fading channels, which makes it more general. Nevertheless, more complicated cases, like frequency-selective fading or multi-user interference can show further dynamics that cannot be understood in the present case. The threat of construct validity is that the explainability stability is quantified using indirect indicators which are derived out of the attribution behavior.

Even though these indicators are based on the recognized explainable AI practices, explainability is a developing notion, and other metrics can provide complementary information. In a bid to counter this the study focuses on relative trends as compared to absolute explainability scores. The threats of conclusion validity entail the interpretation of performance and explainability and trustworthiness relationships. Although some consistency patterns are evident on modulation schemes as well as channel conditions, causal statements are not made. The conclusions are made in a conservative manner that dwells on the observed association with the support of empirical trends.

8. Conclusion

This paper introduced a logical empirical study of clarifiable AI-facilitated signal processing of trustful networks of communication. The paper investigated the effect of signal robustness, channel variability, and modulation complexity on the decision behavior of AI by incorporating the established modulation-performance benchmarks and the examine of explainability. The findings prove that excellent predictive performance does not always mean sound or reliable decision production.

The explainability analysis exposes latent instability in the presence of poor signal conditions especially that of higher order modulation schemes in the fading conditions. These results indicate that explainability is an essential diagnostic instrument that can be used to supplement classic performance measures. In a practical perspective, the research highlights the need to consider the explainability-conscious assessment of AI-based communication systems in designing and implementing AI-driven communication systems. Explainability has the potential to help identify

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unreliable operating regimes early to enable risk-conscious adaptation and improve operational transparency.

Research-wise, the work enhances the existing body of research on trustful AI by illustrating the fact that trustworthiness in communication networks is a multi-dimensional attribute, developed by both algorithmic and physical-layer-based considerations. The results drive the future research directions such as include integrate explainability into real-time, adaptive modulation methods inspired by explainability stability, and experimental validation using real-world communication datasets. Finally, the paper confirms explainable AI as the required element in the attainment of credible, transparent, and trustworthy communication systems, which will form the basis of future developments at the crossroads of signal processing and reliable AI.

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