

Original Article

Model Agnostic Meta-Learning based Adaptive Decoder-A Cognitive Radio Approach

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Abstract - Conventional Deep Learning algorithms have had a significant impact on wireless communication, including channel estimation, signal decoding, power optimization, and resource allocation. However, the performance of the Conventional Deep Learning Model is limited when deployed in a dynamic environment due to slow convergence and the requirement for large datasets. To overcome these limitations, a novel Model-Agnostic Meta-Learning (MAML)-based decoding algorithm is developed in this work. The MAML-based algorithm requires fewer training samples and converges faster in new environments. Numerical findings confirm the benefits of employing meta-learning for signal decoding in wireless systems in a real-time scenario, achieving a minimum decoding accuracy of 80% under highly noisy conditions and 100% at moderate SNR. The data required for the proposed model are obtained from a practical setup using the National Instruments Universal Software Radio Peripheral (NI-USRP), and the performance of the proposed model is experimentally verified.

Keywords - Meta Learning, Signal decoding, Model-Agnostic, Accuracy, Data-Driven Learning, NI-Usrcp.

1. Introduction

Humans acquire new skills rapidly, such as identifying objects from examples and practicing new skills with minimal exposure. Similarly, Meta-Learning (ML) models are expected to learn and adapt to new tasks with less data, thereby overcoming overfitting issues. The design and development of such ML models becomes challenging because they require the integration of prior knowledge. As a result, for maximum utility, the ML algorithm must be applicable to different tasks and capable of performing the computations required to complete them. The ML model that satisfies the aforementioned criteria is termed MAML. MAML is a meta-learning technique that enables an ML model to learn new tasks quickly with limited data and adapt effectively to unfamiliar tasks.

Nevertheless, a major issue with deploying these models in real-world systems is their inadequate performance when they encounter signals from unfamiliar sources that were not present during the training process. In actual communication systems, the interference detector is likely to encounter new and unknown signals regularly due to the presence of numerous wireless transmitters. These limitations make traditional Deep Learning-Based Models less suitable for real-time wireless applications. However, retraining the model is not only inefficient but may also be infeasible in certain situations, such as on end-user devices, since the training

process requires significant time, computational resources, and large datasets. In a wireless system, there is a need to decode received signals under time-varying fading channel conditions. In such systems, MAML can be utilized to design adaptive decoders that effectively decode with fewer training samples across different fading environments. This work considers such an adaptive decoder design for wireless communication systems by considering different modulation schemes with different fading channel conditions.

2. Literature Survey

In communication systems, conventional decoders employ traditional algorithms such as Viterbi and Turbo decoding. A detailed overview of Deep Learning (DL) techniques for wireless communication is presented in [1]. A comprehensive survey of model-based and AI-based network approaches discusses the integration of model-based knowledge with data-driven learning. The article in [2] provides an extensive review of ML for wireless communications and distinguishes it from Graph Neural Networks (GNNs) trained for a single task. This work analyses inductive biases of ML and reviews its applications for radio transmission. The article in [3] provides an in-depth overview of ML methods in the context of wireless networks. The work in [4] proposes the MAML algorithm, which can be fine-tuned using fewer gradient steps. The performance of this approach is analyzed for an image classification application. The robust



role of ML in wireless communication is addressed in [5], which emphasizes the utility of ML models for resource allocation and decoding under time-varying channel conditions. The research in [6] explores the combination of ML and neural networks, focusing on decoupling the network model parameters rather than optimizing the system parameters. The performance of this approach is analyzed through speech enhancement experiments. A data-driven wireless interference identification algorithm based on ML is proposed in [7]. The effectiveness of the algorithm is evaluated and compared with conventional deep learning models under different scenarios, using both raw in-phase and quadrature samples and their Fast Fourier Transform (FFT) representations. A low-complexity, unsupervised ML-based optimization algorithm is recommended in [8] for large-scale wireless communication systems. This work mainly focuses on sum-rate maximization for 6G technologies. A MAML-based beam prediction algorithm for millimeter-Wave (mmWave) communication is developed in [9]. This work reduces the required communication overhead and is applied to beamforming prediction using a limited number of available training samples. Short packet transmission and reception in Internet of Things (IoT) networks are evaluated in [10], where pilots from previous IoT transmissions are used as training data for meta-learning. The meta-learning-based demodulator is trained using these data and can be rapidly adapted to new time varying channel conditions using fewer pilot carriers. A first-order MAML adaptive scheme is developed for this purpose.

The study in [11] examines the beamforming optimization for balancing the signal-to-noise plus interference ratio in a multiuser Multi-Input Single-Output (MISO) system. Furthermore, fast adaptation using ML is achieved in non-stationary environments. Subsequently, the trajectory design for wireless drone networks is examined in [12] to enhance the coverage. A combined reinforcement and ML-based algorithm is suggested to enable drone base stations to learn in an unseen environment. Meanwhile, the wireless traffic prediction problem for 6G networks is addressed in [13]. A distance-oriented technique for model aggregation is also developed to capture the relationships among different areas, thereby improving spatiotemporal forecasting. In [14], a framework that integrates communication and computation through meta-learning is developed to enable adaptive sensing and reconstruction in wireless sensor networks.

This work uses stochastic gradient descent-based learning for model prediction and reinforcement learning to optimize the sensing decision. In [15], a rapid adaptive beamforming method is proposed to address the discrepancy problem in meta-learning. An embedding model is developed to extract transferable features, followed by support vector regression. The MAML - based pilot demodulation is explored in [16] for large-scale IoT implementations. This work further

incorporates interference cancellation to reduce channel estimation errors.

A deep unfolded Neural Network (NN) based on ML is used for signal detection and channel decoding in Multiple-Input Multiple-Output (MIMO) systems in [17]. The proposed work combines expectation propagation and turbo coding within the NN model to achieve faster convergence. Furthermore, a DL-based data acquisition framework is proposed in [18] to collect massive samples in real-time environments. In addition, a Generative Adversarial Network (GAN) is employed to generate samples that resemble real-time data. Finally, ML is applied during the training process of the GAN.

The application of ML in 6G wireless communication systems is examined in [5], whereas the effectiveness of MAML is assessed for IoT, molecular communication systems and optical wireless communication systems. In addition, a combined approach of Proximal Policy Optimization (PPO) and ML is suggested in [19] to address anti-jamming in wireless communication systems. This approach allows communication systems to utilize the knowledge gained from previous anti-jamming experiences. Furthermore, a knowledge-driven ML approach is presented in [20], wherein the DL model is initialized using the Meta model. The model environment is developed based on the intrinsic understanding of the spatial-frequency properties of Channel State Information (CSI). Extending ML to channel acquisition, an ML-based approach is proposed in [21] for Intelligent Reflecting Surfaces (IRS)-aided wireless systems. Similarly, for signal detection, ML-based K-best detection for a MIMO system is employed in [22], where ML determines the coefficients of the fitting function of K, thereby reducing the complexity of DNN-based detection. Beyond cell detection, a cell-level traffic prediction framework based on ML is employed in [23] for mobile networks, where the dominant frequency components are captured and used as a base tracker. Finally, predictive ML is employed in [24] to rapidly learn from samples of current and previous channel realizations. This approach eliminates the need for retransmitting pilot symbols.

Further extending ML to adaptive channel estimation, an adaptive channel estimation framework is proposed for energy-efficient Non-Orthogonal Multiple Access (NOMA) assisted Reconfigurable Intelligent Surface (RIS) systems [25]. Meta-learning is employed to cope with rapidly changing channel conditions by adapting to unseen conditions with minimal fine-tuning. In addition to channel estimation, MAML is explored to reduce computational complexity in near-field communication. In [26], the high computational cost of near-field communication is addressed through codebook reconstruction using the MAML framework. This approach is designed to adapt to changing environmental

geometries and user distributions, thereby improving the system sum-rate.

From the literature review, the following limitations has been observed as follows,

- Existing meta-learning methods perform only sub-tasks, rather than decoding.
- Literature methods have limited adaptability to handle dynamic channel conditions.
- Existing methods have a lack of generalization for different channel conditions for adaptive decoding.
- Large training datasets are required.
- Existing methods are not evaluated for robustness and generalization.

The significant contributions of the proposed approach include:

1. A practical Model-Agnostic Meta-Learning-based adaptive decoder is presented for dynamic fading channels in cognitive radio communication by incorporating LR scheduler, Xavier initialization, Residual learning, and MAML clone support into the architecture.
2. The proposed decoder reduces the training overhead by rapidly adapting to unseen channel conditions using only a limited number of training samples.
3. The robustness of the proposed decoder is evaluated and validated under different types of wireless channel conditions.
4. The proposed system is evaluated using a real-time dataset collected through the NI-USRP2943R software-defined radio platform.

Table 1 Below shows the superiority of the proposed model.

Table 1. Novelty of the proposed approach

Existing Approaches	Limitation	Proposed MAML
Deep Learning Decoder	Requires large amounts of data, extensive retraining, and poor dynamic adaptation.	Has rapid parameter adaptation with a smaller dataset.
CNN Decoder	Requires large datasets for accuracy and poor dynamic adaptation.	MAML works based on few-shot learning.
LSTM Decoder	Slow in convergence and poor dynamic adaptation.	Fast convergence and highly dynamic adaptation.
Existing MAML	1. No Skip Connections. 2. ReLU 3. No Regularization 4. Random weight initialization 5. No scheduler for learning rate adaptation 6. Basic model adaptation.	1. Residual architecture 2. BatchNorm + ReLU 3. Dropout 4. Xavier -initialization 5. LR scheduler-based learning rate adaptation 6. Clone-support adaptation.

3. System Model

As depicted in Figure 1, the framework of the proposed system consists of m devices connected to a single Base Station (BS).

The BS transmits the signal. x_i to the i^{th} user. The received signal at the i^{th} user from the BS is expressed as

$$y_i = h_i x_i + n_i \quad (1)$$

where h_i is the channel fading coefficient between the BS and i^{th} user, x_i is the signal of the transmitted modulated symbol s_i from the BS, which is represented as

$$x_i = \sqrt{P} s_i \quad (2)$$

where P denotes the transmit power, and $n_i \sim \mathcal{N}(0, N_0)$ represent the Additive White Gaussian Noise (AWGN) with zero mean and variance N_0 . The main

aim is to successfully decode the transmitted symbols s_i at the user at any instant. In general, the decoding of transmitted symbols is preceded by estimating the channel coefficient h_i and the received signal x_i is then decoded s_i using conventional or machine learning models. In this work, Tx_1 of the NI-USRP is assumed to transmit the modulated signal similar to the BS, where the receiver is considered Rx_2 of the other USRP, as illustrated in Figure 2.

In the proposed work, instead of using the conventional decoding algorithm, an ML decoding mechanism is proposed. The proposed system is trained as a model $\mathcal{M}$, and the decoding algorithm is developed based on the trained model $\mathcal{M}$.

4. Proposed MAML-based Decoding Algorithm

In this proposed system, the model is parameterized by θ . The decoding task $\mathcal{T}_d$ Using MAML is carried out in two phases.

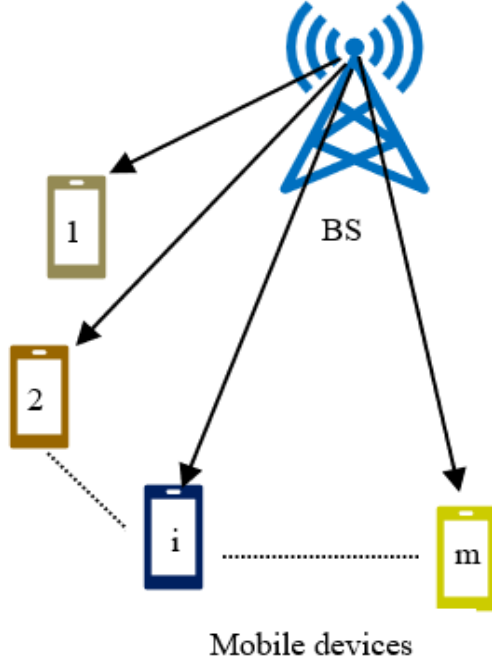


Fig. 1 Proposed system model



Fig. 2 Implementation of the proposed system model using NI-USRP

In the first phase, the model $\mathcal{M}$ is trained to get the optimized parameters θ'_d from the parameterised function f_θ , which is expressed by

$$\theta'_d = \theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_d}(f_\theta) \quad (3)$$

where α is the step size, ∇_{θ} is the gradient operator, $\mathcal{L}_{\mathcal{T}_d}(f_\theta)$ is the loss function during the decoding task $\mathcal{T}_d$ and represented as,

$$(f_\theta) = \sum_{\tilde{s}_i, s_i} \|f_\theta(\tilde{s}_i) - s_i\|^2 \quad (4)$$

where $\tilde{s}_i$ and s_i represent the actual symbol and the true value. Therefore, the algorithm is trained in such a way that the parameter gives the maps between the given input. y_i to the target output s_i

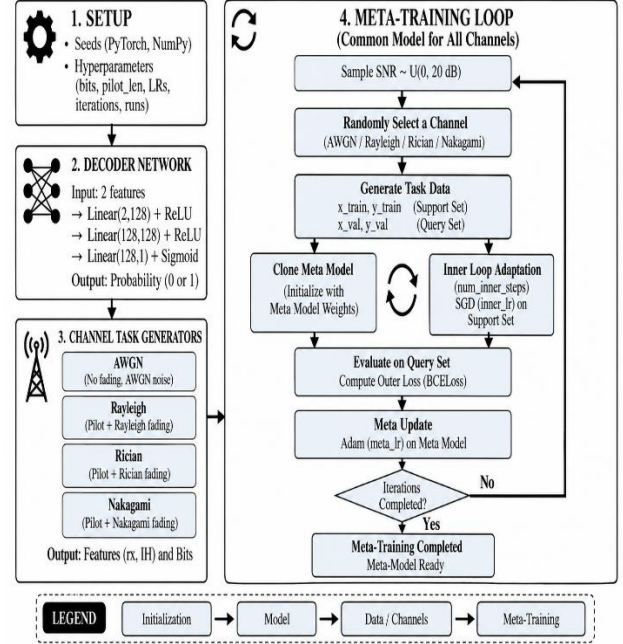


Fig. 3 Functional diagram of the proposed approach

In the second phase, the sample data points y_{test_i} are tested in the model $\mathcal{M}$. The proposed algorithm aims to learn the initial parameter θ , which provides the minimum loss for the decoding process. $\mathcal{T}_d$. The adaptation of the parameter θ to be good for the decoding task $\mathcal{T}_d$, expressed as

$$\min_{\theta} \sum_{\mathcal{T}_d} \mathcal{L}_{\mathcal{T}_d} f(\theta'_d) = \sum_{\mathcal{T}_d} \mathcal{L}_{\mathcal{T}_d} f(\theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_d}(f_\theta)) \quad (5)$$

Figure 3 presents the functional diagram of the proposed system. The first step will be setting up the required library and neural network model. The third step will be to generate the three different channel model tasks. The task data is fed to the meta-training model, which generates the required data for the three tasks. Cloning the meta model and adaptation are carried out in the inner loop. The adapted model is given a query set, and a binary cross-entropy loss is generated, which is fed to the outer-loop Adam optimizer of the common meta model. During this meta-training, SNR and the channel model are randomly selected to provide diverse learning.

The detailed proposed MAML-based decoding algorithm is illustrated as follows.

Algorithm: MAML Adaptive Decoder

Input: Task distribution $p(\mathcal{T})$, learning rates α, β , number of tasks D , training samples k , validation samples ℓ , adaptation steps R .

Output: Meta-learned decoder f_{θ^*} and decoded signal $\hat{x}$.

1. Initialize decoder parameters: $\theta \leftarrow \theta_0, \theta_0 \sim \mathcal{N}(0, \sigma^2 I)$

2. Sample D decoding tasks: $\mathcal{T}_d \sim p(\mathcal{T}), d = 1, \dots, D$

3. For each task $\mathcal{T}_d$, generate the received signal:

$$y_{d,i} = h_d x_{d,i} + n_{d,i}$$

where h_d denotes the task-dependent channel and $n_{d,i}$ is additive noise.

4. Construct the support/training set:

$$\mathcal{D}_d^{train} = \{(y_{d,i}, x_{d,i})\}_{i=1}^k$$

5. Calculate the task-specific loss:

$$\mathcal{L}_d^{train}(\theta) = \frac{1}{k} \sum_{i=1}^k \ell(f_{\theta}(y_{d,i}), x_{d,i})$$

6. Adapt the decoder parameters using the inner loop:

$$\theta_d^{(r+1)} = \theta_d^{(r)} - \alpha \nabla_{\theta_d^{(r)}} \mathcal{L}_d^{train}(\theta_d^{(r)}), \theta_d^{(0)} = \theta$$

After R adaptation steps, $\theta'_d = \theta_d^{(R)}$.

7. Construct the validation set:

$$\mathcal{D}_d^{val} = \{(y_{d,i}, x_{d,i})\}_{i=1}^l$$

8. Calculate the adapted validation loss:

$$\mathcal{L}_d^{val}(\theta'_d) = \frac{1}{l} \sum_{i=1}^l \ell(f_{\theta'_d}(y_{d,i}), x_{d,i})$$

9. Calculate the meta-objective:

$$\mathcal{L}_{meta}(\theta) = \frac{1}{D} \sum_{d=1}^D \mathcal{L}_d^{val}(\theta'_d)$$

10. Calculate the meta-gradient and update the common initialization:

$$\nabla_{\theta} \mathcal{L}_{meta} = \frac{1}{D} \sum_{d=1}^D \nabla_{\theta} \mathcal{L}_d^{val}(\theta'_d)$$

11. Repeat steps 2 to 10 until convergence and obtain: $\theta^* = \theta$

12. For an unseen channel/task $\mathcal{T}_{new}$, collect a small support set:

$$\mathcal{D}_{new}^{train} = \{(y_i, x_i)\}_{i=1}^k$$

13. Adapt the meta-learned decoder:

$$\theta'_{new} = \theta^* - \alpha \nabla_{\theta^*} \mathcal{L}_{new}^{train}(\theta^*)$$

14. Receive the unknown signal: $y_{new} = h_{new} x_{new} + n_{new}$

15. Decode the transmitted signal using the adapted decoder:

$$\hat{x}_{new} = f_{\theta'_{new}}(y_{new})$$

16. Determine the final decoded symbols:

$$\hat{x}_{new,i} = \underset{c}{\operatorname{argmax}} [f_{\theta'_{new}}(y_{new,j})]_c$$

5. Result and Discussion

The simulation and experiments of the proposed adaptive decoder are carried out using a four-channel environment of AWGN, Rayleigh, Rician, and Nakagami and a real-time dataset obtained from USRP SDR hardware with various SNR levels, to validate the performance of the proposed decoder in handling dynamic changes in the environment. The SNR values are varied from 0 to 20 dB with various channel combinations and different channel coefficient values. Each simulation trial is carried out using 2000 information bits and 20 pilot symbols. Meta-training is done with 300 iterations with a meta-learning rate of 0.001.

The channel-specific and SNR-specific adaptation of the decoder is carried out in the inner loop with a learning rate of 0.01. Ten inner-loop adaptation steps are used. The performance is evaluated with respect to varying SNR levels and channel types. Statistical tests are also performed using the Wilcoxon signed-rank test and paired Student t-test to verify the statistical significance of the performance of the proposed method compared with the baseline decoders. Reliability tests are carried out under dynamically changing channel conditions. To illustrate the feasibility of practical deployment, computational complexity analysis is also performed.

The simulation results of the proposed MAML-based decoding algorithm are discussed in detail in this section. The simulation parameters considered in this work are summarized in Table 2. The dataset is obtained from a real-time scenario using an NI-USRP.

Table 2. Simulation parameters

Parameter	Value
Modulation	BPSK
Number of samples	100
Iteration	500
Inner learning rate	0.01
Number of inner steps	10
Meta-learning parameter	0.001
Number of meta iterations	500
Optimizer	Adam
Hardware used	NI-USRP 2943R

The assumptions made related to the experimental setup are listed below:

1. Task channel data distribution: Different channel conditions are considered as individual tasks sampled from their distribution. Unseen conditions are assumed to have related statistical characteristics.
2. Channel stationarity: The channels are assumed to remain stationary during a single adaptation period.
3. Initial channel assumption: MAML assumes that the channel conditions are sufficiently related to each other in terms of their statistical characteristics, such that a common initial model can be adapted to individual tasks using actual channel-labelled data.
4. Assumption on inner-loop adaptation: The inner-loop learning rate and the number of adaptation steps are initialized with appropriate values to achieve effective

adaptation with fewer parameter updates and improved generalization capability.

5.1. Accuracy of the Proposed MAML-based Decoding Algorithm

The accuracy with respect to Signal-to-Noise Ratio (SNR) is illustrated in Figure 4. The overall accuracy of the MAML decoding process increases as the SNR increases. A maximum accuracy of 99.9% is achieved at approximately 15 dB SNR. From the results, the proposed ML algorithm is robust to noise and achieves better accuracy across different SNR levels.

Although the accuracy performance is limited in the low SNR region, as the signal power increases, the model effectively learns to decode the received signal under different SNR conditions.

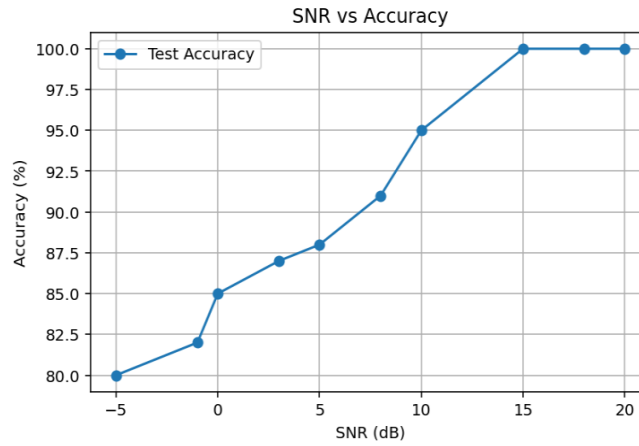


Fig. 4 Test accuracy of the proposed model versus SNR

5.2. Meta-Training Loss of the Proposed MAML-based Decoding Algorithm

Figure 5 shows the meta-training loss over various iterations. The loss decreases as the number of training iterations increases. The proposed ML-based decoder monitors the progress of the ML process by assessing its

adaptation capability over successive iterations. The proposed model achieves stability at an early stage, with the loss remaining within the range of 0.625 to 0.666. The relatively stable loss curve indicates that the proposed model converges rapidly and maintains a consistent loss during the subsequent training iterations.

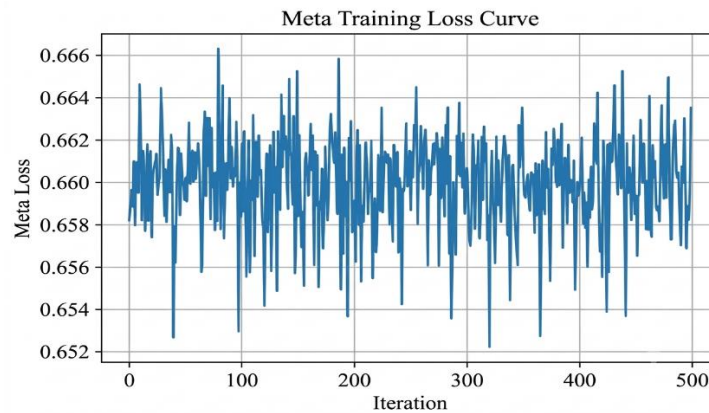


Fig. 5 Meta loss versus iteration

5.3. Analysis of Correctness and Incorrectness of the Decoding Algorithm

The confusion matrix representing the proposed MAML-based decoding method is shown in Figure 6. This matrix is generated at various SNR levels to assess both the accuracy and errors in the decoding process.

At -5 dB, approximately 17 samples from class 0 are incorrectly classified, resulting in a decoding accuracy of 80%. As the SNR improves, the instances of misclassification by the MAML algorithm decrease. From 5dB onwards, the model's accuracy progressively rises, demonstrating its robustness. The confusion matrix nearly achieves perfection, showing minimal misclassifications and an accuracy close to 100%.

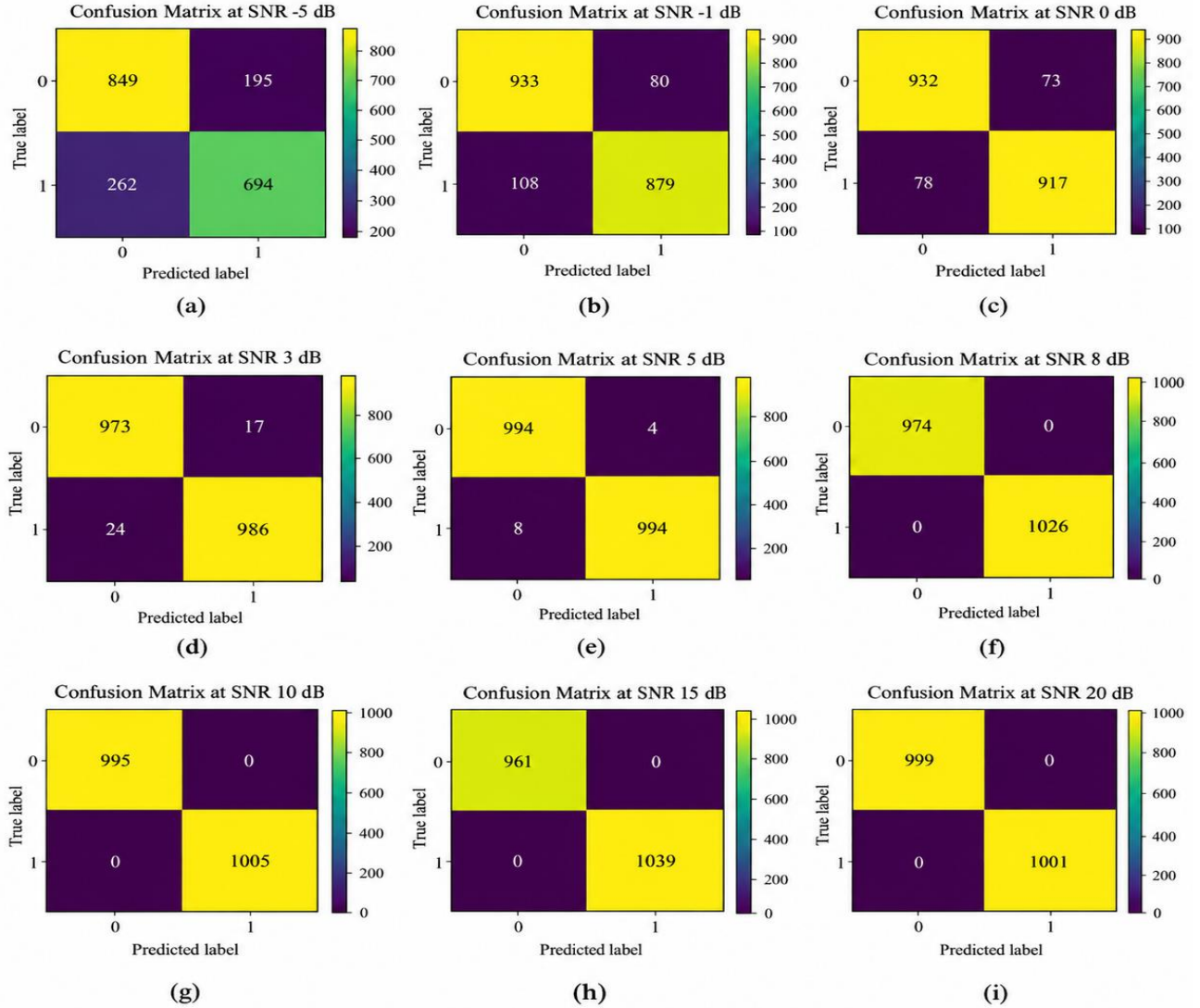


Fig. 6 Classification confusion matrices under various SNR conditions: (a) -5 dB, (b) -1 dB, (c) 0 dB, (d) 3 dB, (e) 5 dB, (f) 8 dB, (g) 10 dB, (h) 15 dB and (i) 20 dB.

5.4. Histogram of the Predicted Probability

The histogram of predicted probabilities illustrated in Figure 7 shows that, at low SNR levels, the model produces uncertain probability estimates that remain close to the decision threshold of 0.5. As the SNR increases, the separation between the probability distributions of the two classes becomes clearer, indicating improved decision-making capability. At high SNR levels, the decoder effectively

differentiates between the classes with high confidence, corresponding to an accuracy of nearly 100%. As a result, the histogram clearly demonstrates that the proposed MAML-based decoder adapts effectively to different noise conditions. With an increase in SNR, the accuracy and confidence of the probability predictions improve, demonstrating that the decoder establishes robust decision boundaries even under challenging channel conditions.

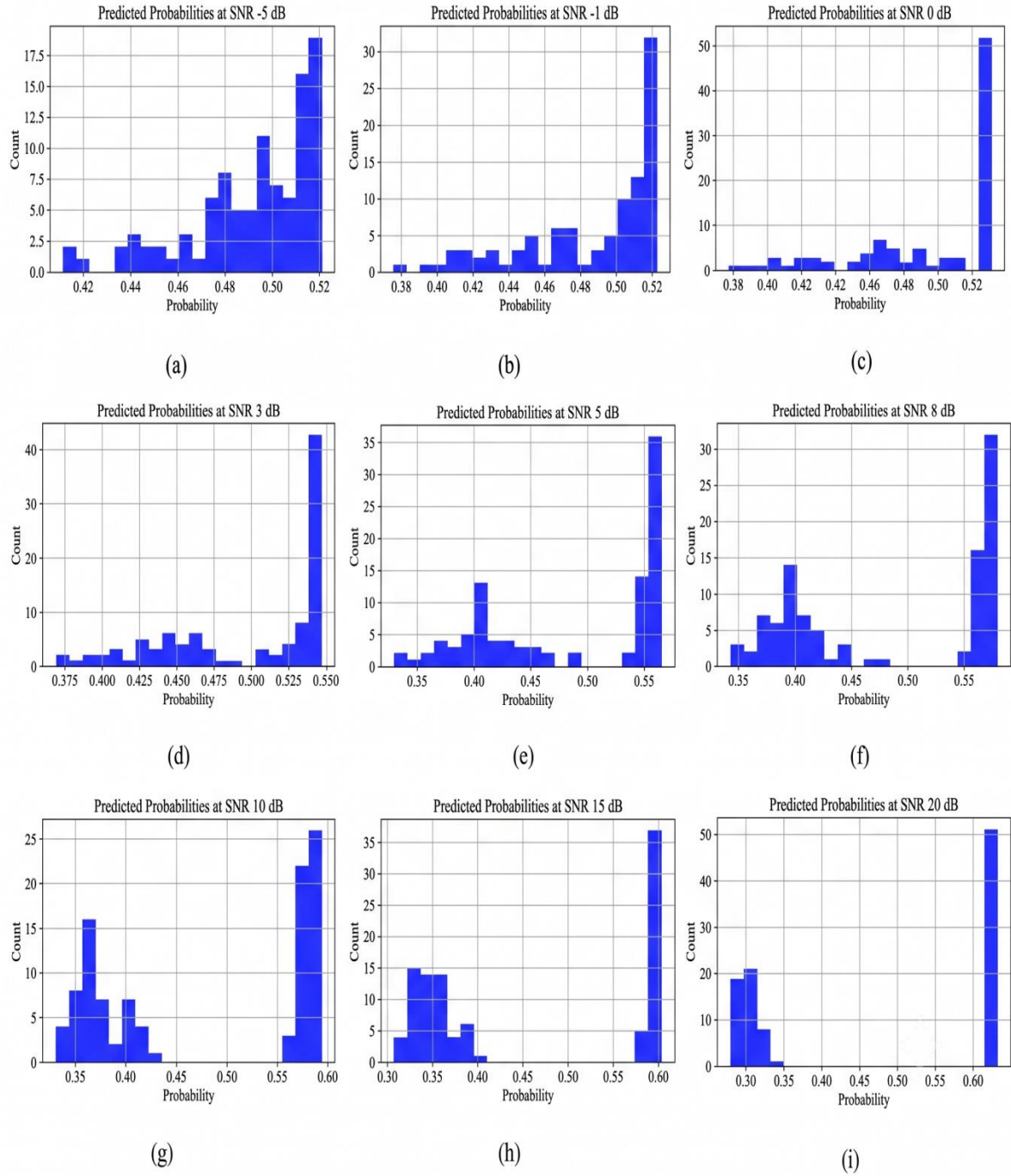


Fig. 7 Histogram of predicted probabilities per SNR (a) -5 dB, (b) -1 dB, (c) 0 dB, (d) 3 dB, (e) 5 dB, (f) 8 dB, (g) 10 dB, (h) 15 dB, and (i) 20 dB.

5.5. Prediction Probabilities of the Decoding Algorithm Versus Index

The scatter plots, as shown in Figure 8, provide clear visual evidence of the MAML-based decoder's capability to transition from uncertain predictions under noisy conditions to clear and distinctly separated predictions under improved channel conditions. This progression demonstrates the model's robustness and adaptability to varying noise levels.

The results indicate that, at low SNR, the predicted probabilities tend to cluster around 0.48-0.55, which is relatively close to the decision threshold of 0.5. As the SNR increases, the decoder becomes more effective in differentiating between the two classes, resulting in tight and non-overlapping probability clusters. These observations are consistent with the results obtained from the confusion matrices and the accuracy curve.

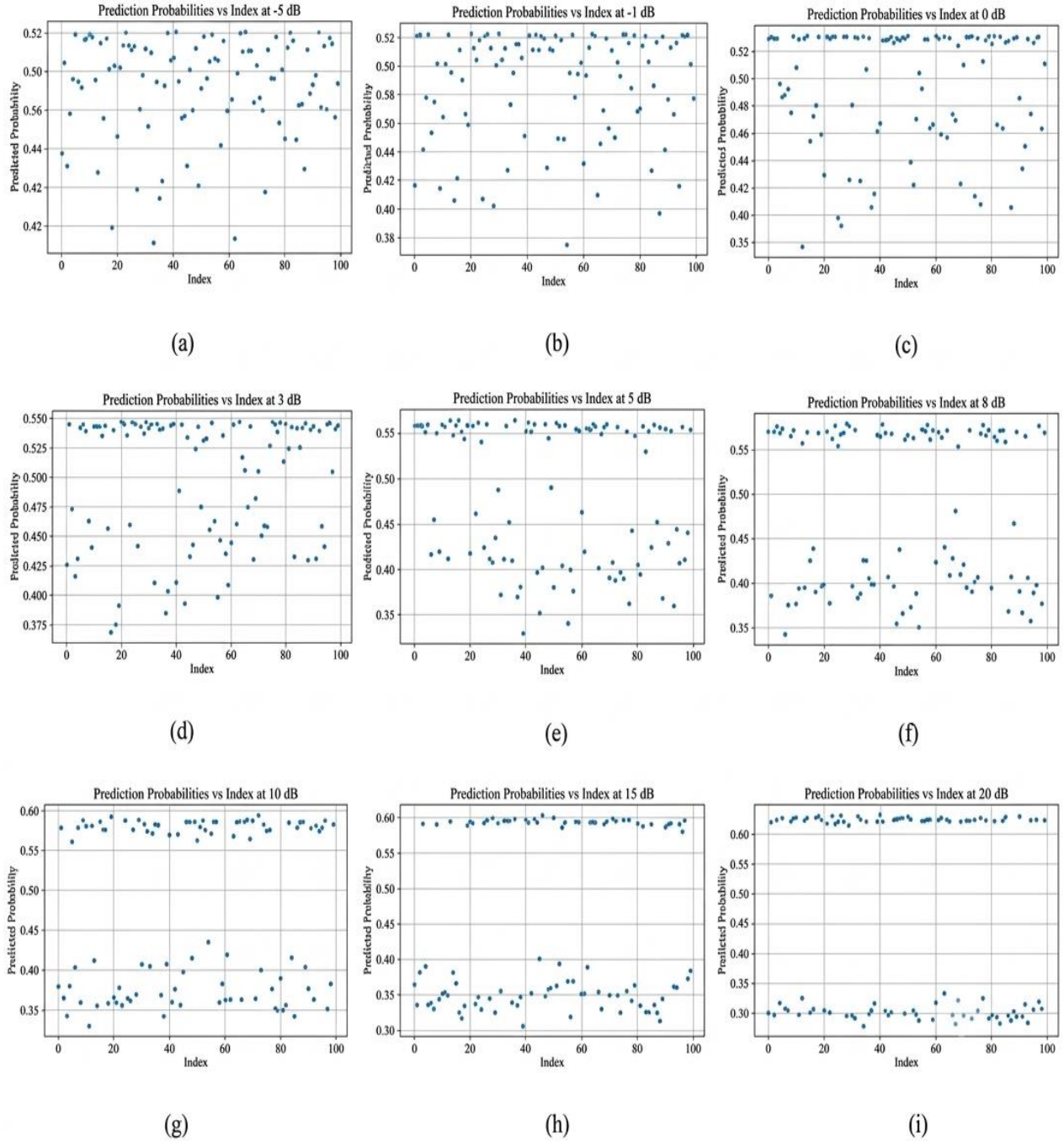


Fig. 8 Predicted probability scatter vs index SNR (a) -5 dB, (b) -1 dB, (c) 0 dB, (d) 3 dB, (e) 5 dB, (f) 8 dB, (g) 10 dB, (h) 15 dB, and (i) 20 dB.

5.6. Comparison of True and Predicted Labels

This comparison, illustrated in Figure 9, provides a detailed step-by-step analysis of the decoder's performance and a careful assessment of its effectiveness. It presents visual evidence of the patterns observed in the probability estimates, confusion matrices, and accuracy curves. In the low-SNR regime, the predicted labels are often inconsistent and frequently deviate from the true sequence, resulting in an

accuracy of 85%. As the SNR increases, the predictions generated by the decoder become better aligned with the actual labels, reflecting improved learning and adaptation. Under high-SNR conditions, the decoder accurately recovers the transmitted labels with minimal or no errors, demonstrating its effectiveness under favorable channel conditions.

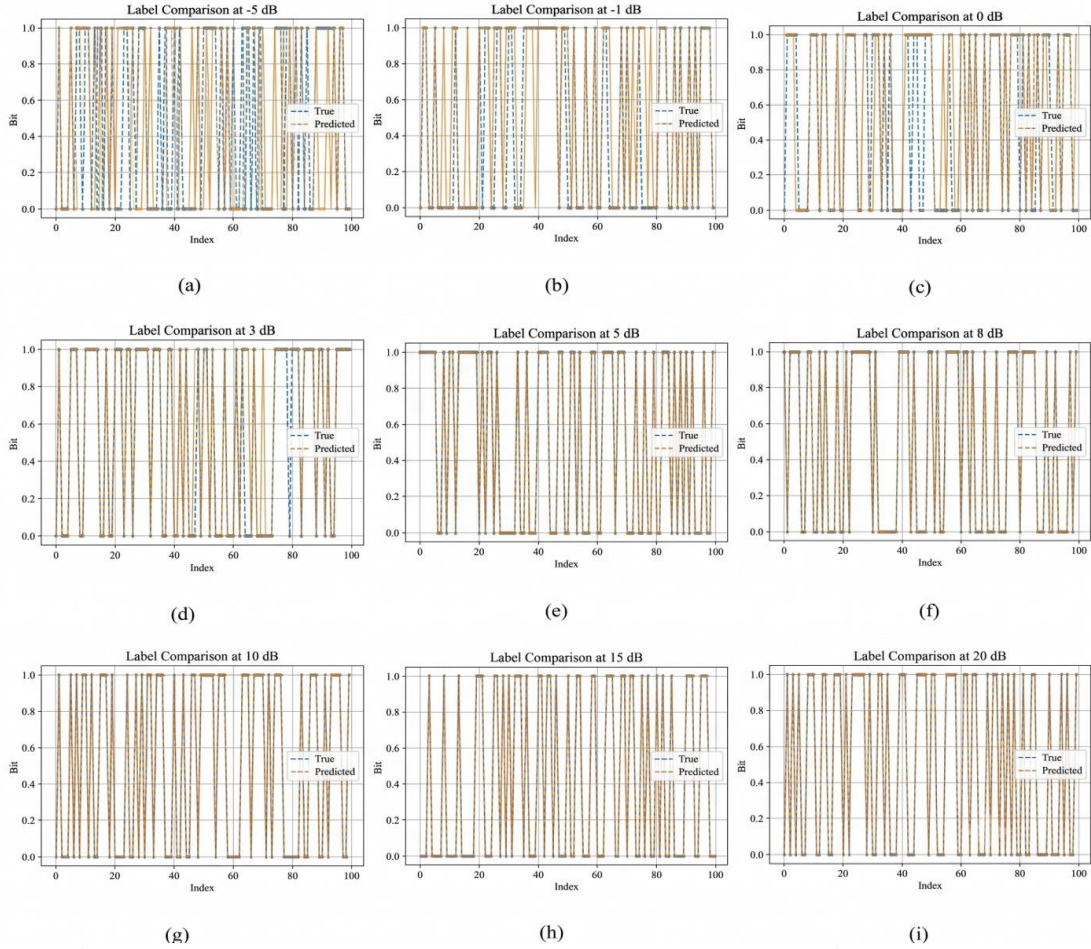


Fig. 9 Comparison of true vs predicted labels per SNR (a) -5 dB, (b) -1 dB, (c) 0 dB, (d) 3 dB, (e) 5 dB, (f) 8 dB, (g) 10 dB, (h) 15 dB, and (i) 20 dB.

5.7. Heatmap of the Accuracy Versus SNR

The heatmap depicted in Figure 10 provides a clear representation of the decoder's performance at various SNR levels. It effectively highlights the transition from uncertainty at low SNR levels to nearly perfect reliability at higher SNR levels. This finding is consistent with the confusion matrices, probability distributions, and label comparison plots, all of

which support the adaptability and robustness of the meta-learning-based decoder. The heatmap further corroborates the earlier findings, showing an accuracy of approximately 80-85% under highly noisy conditions. A notable improvement is observed under moderate noise conditions, with the decoder achieving complete decoding accuracy at SNR levels above 15 dB.

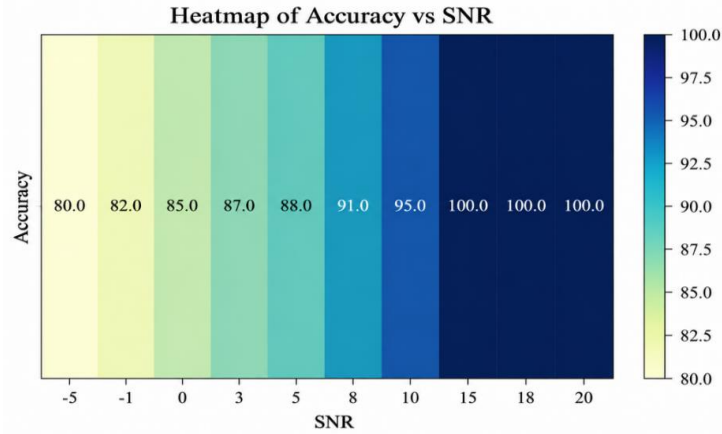


Fig. 10 Heatmap of accuracy across SNR

5.8. Boxplot of Predicted Probability by SNR

The boxplot, as shown in Figure 11, indicates that prediction confidence increases as the SNR increases. At low SNR levels, the model shows minimal confidence due to the presence of significant noise. In contrast, at high SNR levels, it exhibits greater prediction confidence, which is consistent with the nearly 100% accuracy shown in the heatmap. The confidence of the decoder closely follows its accuracy; it is low under noisy conditions but gradually improves as the signal quality increases, reaching a high level of reliability at higher SNR values.

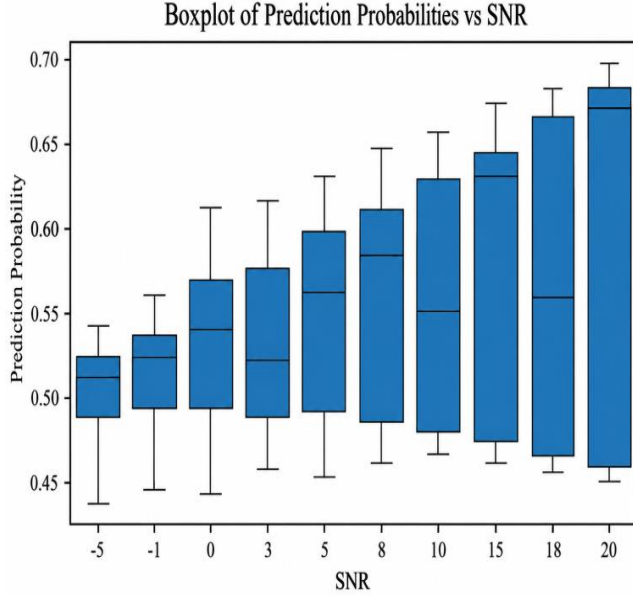


Fig. 11 Prediction probability for various SNRs

5.9. Error Rate and Prediction Performance of the Decoding Algorithm

The performance of the proposed MAML-based decoding in terms of error rate is illustrated in Figure 12. As the SNR rises from -5 dB to 10 dB, the error rate drops from 20% to 5%, ultimately reaching zero in the high SNR range. A more significant improvement is observed as the SNR increases beyond 5 dB. The error rate decreases to approximately 5% at 10 dB and 9% at 7.5 dB. At 15 dB and above, the observed error rate reaches 0%, indicating an error-free prediction for the evaluated test samples under these higher-SNR conditions.

Therefore, the overall result demonstrates that the receiver becomes increasingly reliable as the channel quality improves. The decreasing error trend indicates that the proposed prediction/receiver model is robust to moderate channel impairments and achieves highly reliable performance under favorable SNR conditions. The clear separation between the two regions indicate that the decoder frequently produces confident predictions instead of ambiguous ones, based on the predictions distribution illustrated in Figure 13. The high-confidence predictions, typically found at elevated SNR levels, are represented by the

right cluster (0.68-0.70). The left cluster (0.45) may represent low-probability predictions or remaining misclassifications; nonetheless, its proportion is lower than that of the confident cluster. At a high SNR of 20 dB, the MAML decoder exhibits a polarized decision-making tendency, where most predictions are either consistently concentrated around 0.45 or confidently predicted with a probability of approximately 0.7. This indicates that, instead of producing ambiguous or uncertain outputs, the proposed model generates distinctly clear predictions.

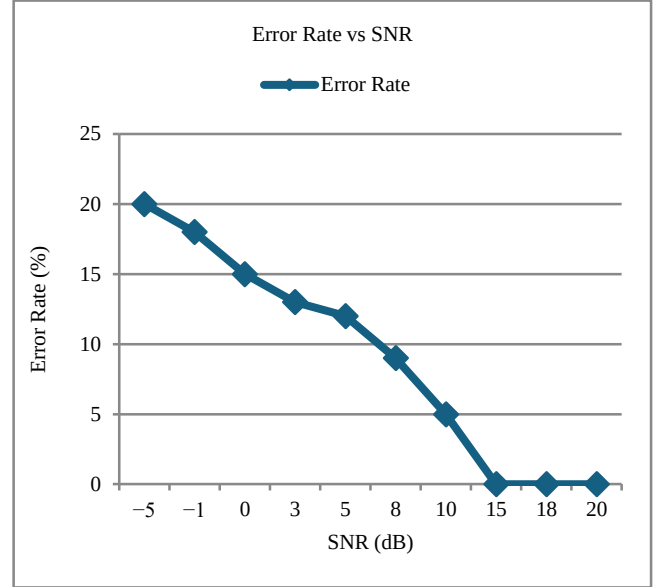


Fig. 12 Error rate versus SNR for the proposed model

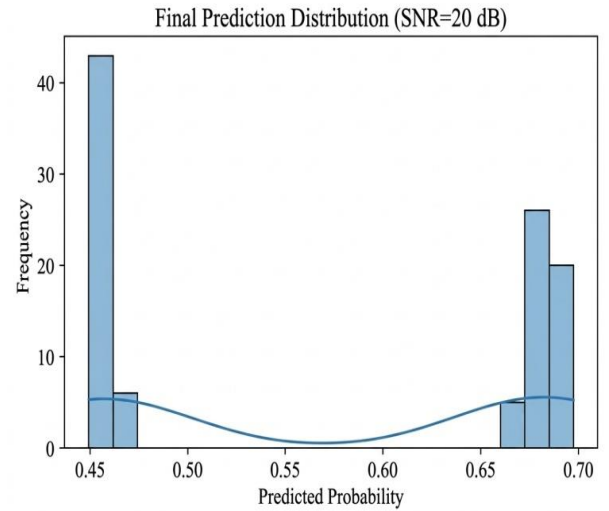


Fig. 13 Prediction probability for various SNRs

5.10. Robustness Analysis for Different Channel Conditions

The robustness of the proposed model to different channel conditions is tested by randomly changing the channel conditions and accumulating the performance. Figure 14 provides the performance evaluation on different channel

conditions. It is observed that the prediction accuracy increases with SNR for all the considered AWGN, Rayleigh, Rician, and Nakagami channel conditions. Even at low SNR, the proposed model maintains reasonable accuracy, while the performance gradually approaches 100% as the SNR increases. The relatively small performance difference among the different fading channels at higher SNR further indicates the adaptability of the proposed receiver. The proposed model thus shows good performance under all the channel

conditions, and its robustness to dynamically changing channel conditions is demonstrated by Figure 14.

5.11. Baseline Performance Comparison

The proposed model is evaluated against different machine learning models and reported in Table 3. The proposed MAML model consistently outperforms the conventional decoders across the entire SNR range.

Table 3. Baseline performance comparison

Decoder	-10 dB	-5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
SVM	50%	57%	65%	74%	82%	88%	91%
RF	53%	61%	69%	78%	86%	91%	94%
MLP	55%	63%	72%	81%	88%	93%	95%
CNN	58%	66%	75%	84%	91%	95%	97%
DNN	60%	68%	77%	86%	92%	96%	98%
MAML	80%	87%	94%	98%	100%	100%	100%

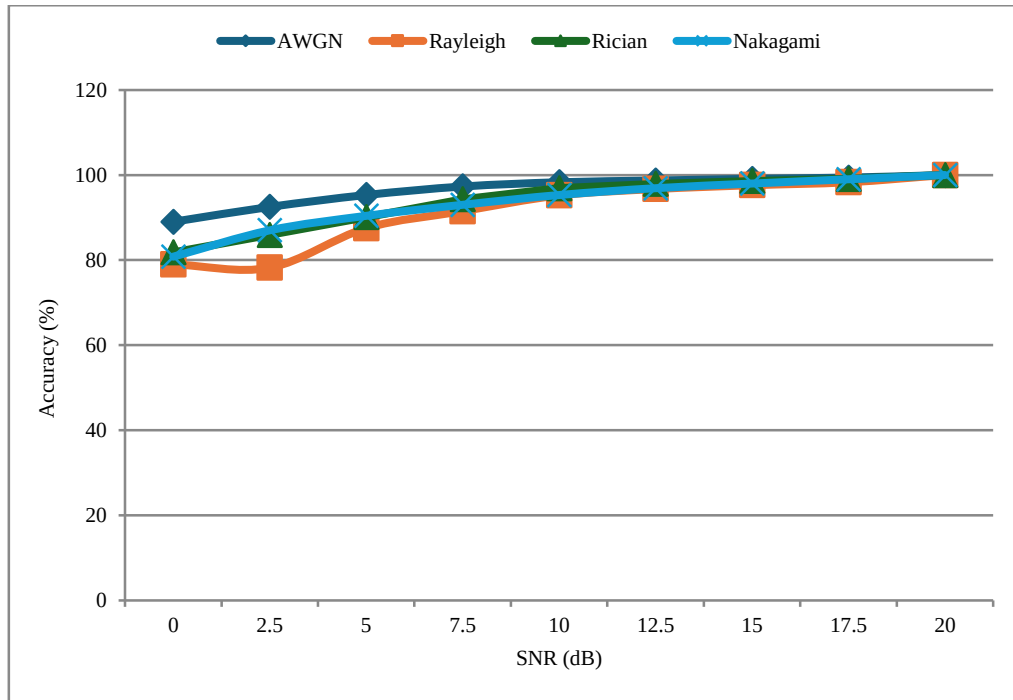


Fig. 14 Robustness analysis with different channel conditions

5.12. Statistical Validation

The proposed system performance is evaluated statistically with a Monte-Carlo simulation. The mean performance with standard deviation and 95% confidence intervals is reported in Table 4 for worst-case performance at an SNR of 0 dB.

A Statistical analysis is carried out using paired Student's t-test and the Wilcoxon signed-rank test to ensure that the improvement provided by the MAML method over other baseline models is statistically significant. The results presented in Table 4 prove that the proposed MAML model

has statistically significant and consistent performance compared to the baseline models. The standard deviation and mean obtained from the trials show that the proposed model maintains a consistent level of performance with minor variations across different runs.

Subsequently, it is observed that the t-test and the Wilcoxon signed-rank test produce p-values below 0.05 for all the trials, which confirms that the performance improvement is statistically significant. Hence, the results demonstrate low variability and consistent performance of the proposed model.

Table 4. Statistical test MAML versus baseline models averaged across all four channels

Baseline Model	MAML Mean $\pm$ SD (%)	Baseline Mean $\pm$ SD (%)	t-stat	Mean p_t	Wilcoxon w	Mean p_w
CNN	96.97 ± 3.10	90.66 $\pm$ 10.56	+3.06	0.0113	42.8	0.0056
Random Forest	94.89 $\pm$ 3.68	91.06 $\pm$ 5.05	+4.19	0.0109	70.2	0.0089
SVM	99.93 $\pm$ 0.07	99.84 $\pm$ 0.13	+3.08	0.0055	14.8	0.0088
DNN	96.63 $\pm$ 4.26	93.30 $\pm$ 6.47	+2.44	0.0213	107.3	0.0321
MLP	93.87 $\pm$ 6.06	88.98 $\pm$ 9.30	+2.56	0.0265	108.8	0.0201

Table 5. Channel-Wise significance validation

Fading Channel	MAML Mean (%)	Baseline Mean (%)	t-stat	p_t (t-Test)	Wilcoxon	p_w (Wilcoxon)
AWGN	98.04	96.19	+2.85	0.0100	25.3	0.0078
Nakagami	95.54	88.15	+2.51	0.0095	56.6	0.0098
Rician	97.17	92.62	+2.42	0.0188	56.0	0.0098
Rayleigh	93.20	84.67	+2.14	0.0178	77.5	0.0227

Table 5 provides channel-wise statistical test validation using the t-test and the Wilcoxon. The table precision values are less than 0.05 for all the cases, which proves the proposed methods perform significantly well for all channel cases.

5.13. Computational Complexity Analysis

The computational complexity analysis is presented in the table using big O notation; the proposed model has high complexity compared to that of other baseline models.

Table 6. Computational complexity comparison with the base model

Method	Training Complexity	Adaptation Complexity	Inference Complexity
MAML (Proposed)	O(MTKN)	O(KN)	O(N)
MLP	O(N)	-	O(N)
DNN	O(N)	-	O(N)
CNN	O(N)	-	O(N)
SVM	O(N ² -N ³)	Retraining	O(N)
Random Forest	O(BN log N)	Retraining	O(BD)

The variable definitions defined in Table 6 are given as follows:

- M-Number of meta-training iterations
- T-Number of channel tasks
- K-Number of MAML adaptation steps
- N-Number of processed samples
- B-Number of Random Forest trees
- D-Decision-tree depth

Table 6 provides the complexity analysis of the proposed model compared with other models. The table shows that the training complexity of the MAML model is higher than that of the other models, but lower than that of SVM. This high complexity occurs because MAML needs to be trained under various channel conditions at the two levels: the meta level and the fine-tuning level in the inner loop.

Moreover, adaptation complexity is also involved in training to achieve robustness. Once the model is deployed, the inference complexity is similar to that of the other models. This indicates that, with comparable inference complexity, MAML provides superior performance.

Table 7 presents memory complexity, training, and inference time analysis. The table values prove that the proposed MAML can be practically deployed because of its low training time of around 2.8 ms and inference time of 0.43 ms. The inference time is lower compared with the other models. The training is executed on a multicore CPU-based laptop, which supports parallel execution. The space complexity also indicates that, with 4417 trainable parameters, the proposed model can be easily deployed.

Table 7. Memory complexity, training, and inference time

Model	Trainable parameters	Forward Flops	Training Time(ms)	Inference Time(ms)
MAML	4417	5145600	2.86555	0.43
CNN	2721	3187200	20.91418	4.40
MLP	4417	2572800	498.6422967	1.42
DNN	25217	14937600	917.6105933	3.3
SVM	NA	NA	14.42313333	34.8
RF	NA	NA	337.39358	74.18

6. Conclusion

In this work, a meta-learning-based decoding method is proposed by adapting the state-of-the-art technique MAML for use in wireless communication systems. The proposed algorithm rapidly learns from a limited number of training samples by leveraging knowledge from previously observed data.

The proposed algorithm for signal detection is trained to develop a model-based decoding with suitable model parameters to minimize the loss during the decoding task. Meta-learning reduces training overhead and outperforms conventional DL models across various modulation schemes and fading channels. The model performance is evaluated using a dataset obtained from the USRP set up in a real-time scenario. Performance measures, such as error rate, accuracy, meta-loss, confusion matrix, histogram of the prediction probability, heatmap, and box plot of the decoding probability, ensure the adaptability, reliability, clear prediction, and robustness of the proposed MAML-based decoding under

different SNR regimes. The proposed MAML-based decoding can be applied to the 5G and 6G system technologies with different modulation schemes in the future.

Conflicts of Interest

The authors have no conflicts of interest to declare.

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