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HYPERPARAMETER OPTIMIZATION OF DEEP NEURAL NETWORKS FOR ADAPTIVE MODULATION AND CODING IN HIGH-SPEED MILLIMETER-WAVE COMMUNICATION SYSTEMS

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SUMMARY

Adaptive Modulation and Coding (AMC) is a key principle that increases spectral efficiency, reliability, and capacity in high-data-rate mmWave wireless communication systems. But AMC strategies depend upon static threshold-based rules that generally struggle to perform well in varying channel conditions. In this study, an innovative HO-DNN architecture is introduced to choose an appropriate AMC strategy in real-world scenarios, using the DeepMIMO dataset for channel emulation. This architecture leverages channel quality features and propagation properties like SNR, SINR, Path Loss, Delay Spread, Angle of Arrival, Angle of Departure, Communication Distance, and Doppler Frequency. A combination of Bayesian Optimization and Genetic Algorithm (BO-GA) is used for tuning of learning rate, batch size, number of layers, and dropout probability of the neural network model. The experiments were carried out using around one million DeepMIMO channel samples in the scenario of 28 GHz millimeter wave communications with massive 64×64 MIMO antennas. The classification accuracy of the proposed architecture was obtained as 99.08%, surpassing existing DNN (97.08%), CNN (95.26%), and LSTM (96.41%). Moreover, the designed network achieved a throughput of 11.84 Gbps and reduced the bit error

rate to 2.1×10^{-5} . This proves that hyperparameters play an important role in improving AMC predictions' accuracy and enhancing the overall communication process for advanced 5G and 6G applications.

Key words: *adaptive modulation and coding, deep neural network, hyperparameter optimization, bayesian optimization, genetic algorithm, deepMIMO.*

INTRODUCTION

The fast development of fifth-generation (5G) and future sixth-generation (6G) wireless communication networks requires ultra-high data rates, massive connectivity, low latency, and high spectral efficiency. To meet these requirements, mmWave communication emerges as an important technique due to the capacity of exploiting large bandwidth resources from 24 GHz to 300 GHz. While offering some benefits, mmWave communication poses a number of technical issues, such as high path losses, signal blockages, beam mismatching, rapid channel variation, and dynamic propagation environment. With the emergence of deep learning techniques, considerable attention has been received towards solving challenging problems in wireless communication due to their capabilities of understanding the nonlinear properties of channels and communicating with optimized parameters in real time. The end-to-end deep learning has proven effective in optimizing intelligent fiber-mmWave communication network [1]. Additionally, the adaptive optimization techniques based on deep learning have provided successful solutions in limited bandwidth wireless communication systems due to their capability of effective resource allocation and link adaptation [2].

The growing complexity of wireless networks in the future demands advanced communication systems that are able to intelligently adapt themselves to varying channel conditions. The model-driven learning methods based on deep learning techniques have emerged recently for fiber-terahertz communication systems by combining domain knowledge and learning ability, which have improved the reliability of communications in such systems [3]. These recent advances suggest that artificial intelligence technology may become a vital part of future communication networks in varying channel conditions.

Adaptive Modulation and Coding

Adaptive Modulation and Coding (AMC) is a key concept adopted by today's wireless communication systems that focuses on optimizing spectral efficiency while offering acceptable levels of communication reliability. AMC adapts the modulation order and coding rate based on channel conditions in order to optimize the performance-throughput trade-off of the communication system. During favorable channel conditions, a high modulation order as well as a high coding rate can be adopted to increase throughput, but in case of unfavorable channel conditions, a more robust setting will be used. Intelligent adaptive link adaptation methods based on deep learning have shown tremendous success in dynamic selection of transmission settings depending on environmental conditions [4].

Deep Learning for AMC

Deep learning has proven itself as a groundbreaking technology in wireless communication due to its capability to derive complex nonlinear interactions from massive data sets. The advances made in deep neural networks, convolutional neural networks, recurrent neural networks, and transformer architectures have made possible reliable channel estimation, signal detection, beam management, and resource allocation in wireless networks. It has been shown in detailed investigations how machine learning algorithms can be applied to deal with some of the challenges encountered in mmWave transceiver designs as well as the beyond-5G communication architecture [5]. Furthermore, intelligent software-defined radio platforms empowered by machine learning algorithms have made intelligent beam-steering and adaptive communication possible in mmWave environments [6]. Additionally, the use of deep learning to predict channels has greatly increased the reliability of wireless communications through predicting channel variation under fast-moving conditions [7]. This indicates that deep neural networks can be used as a highly powerful decision engine in AMC systems in fast-changing mmWave channels.

Contributions

Contribution of this paper can be highlighted as follows:

1. An innovative DeepMIMO-based Deep Neural Network architecture is designed for intelligent AMC in mmWave communications environment.
2. A novel hybrid framework of hyperparameters tuning is suggested based on the integration of Bayesian Optimization and Genetic Algorithm to determine best neural networks parameters for enhanced AMC performance.
3. Adaptive multi-objective optimization scheme has been introduced that aims at improving classification, spectral efficiency, throughput, bit error rate and computation delay simultaneously.

Research Objectives

Key aims of the study include:

1. The creation of an AMC model based on deep learning with the ability to choose suitable modulation and coding schemes from actual DeepMIMO channel data.
2. The development of a process for the automatic determination of optimal neural networks by optimizing their hyperparameters.
3. The analysis of the effect of optimized deep neural networks on performance metrics such as throughput, spectral efficiency, latency, and reliability of high-speed mmWave communication systems.

Paper Organization

The rest of this paper is structured as follows. In Section 2, provide the literature review along with the shortcomings in existing research works. Section 3 gives a description of the DeepMIMO dataset, system model, and problem formulation. In Section 4, propose the deep neural network architecture and hyperparameter tuning process. In Section 5, discuss the experiments and methodology followed for evaluating them. Section 6 covers the results obtained from the experiments.

LITERATURE REVIEW

With the advent of wireless communication technology, research has shifted towards incorporating AI and machine learning methods into wireless communication systems to enhance their effectiveness, efficiency, and flexibility. Channel estimation for multiple input multiple output (MIMO) communication systems utilizing swarm intelligence-based deep ensemble learning has proved highly effective and robust in dealing with complicated situations [8]. Research efforts in 6G networks have also increased interest in designing advanced deep learning methods which can cope with the challenges of more intelligent resources allocation, semantic communication systems, and autonomous wireless network optimization [9].

AI and machine learning methods have been successfully implemented in wireless channel estimation based on OFDM communication systems. Moreover, experiments have been performed for the hardware implementation of the proposed AI-enabled communication system which confirms the successful deployment of AI on embedded devices [10]. Another area of application of machine learning methods is wireless signal propagation modeling and simulation, where neural network-based path loss prediction framework proves more accurate than traditional statistical models in indoor scenarios [11]. Radar sensor systems benefit from deep learning models as well, especially for accurate detection and classification of objects through high-resolution radar imaging [12].

In-depth analysis of various channel estimation techniques using deep learning has shown the increasing

use of data-driven approaches to modeling channel characteristics which are hard to describe through mathematical models [13]. Various machine learning approaches have been used to solve the problem of reduction of peak-to-average power ratio (PAPR) and improve signal transmission and processing in physical layer of modern wireless systems [14]. Self-adaptive genetic algorithms have proved to be highly effective in solving problems associated with network planning and optimizing coverage of wireless networks, which proves the applicability of such methods for optimization of communication parameters [15].

In addition to data-driven channel estimation methods, physical layer functionality was improved by machine learning techniques in carrier frequency offset estimation, where gradient boosting algorithms helped to achieve better results in synchronization of 5G New Radio technology [16]. Multi-objective optimization techniques were used to optimize QoS requirements and energy consumption in massive MIMO systems [17]. Deep learning techniques have also provided significant benefits for beam management, being much more efficient than classical techniques of beam selection [18].

The move towards AI-native communications networks has led to increased research efforts in the domain of semantic communications and intelligent wireless networks that can adapt to changes in the network environment on their own [19]. Studies carried out using a recurrent neural network-based digital predistortion have shown the effectiveness of optimal neural network models in improving the quality of signals through the radio-over-fiber communication networks [20]. In addition, artificial intelligence is gaining relevance in managing issues related to interference and jamming in advanced communication networks [21].

Reinforcement learning algorithms for intelligent resource allocation in reconfigurable intelligent surface-based communication networks have also been explored in recent years, providing opportunities for intelligent adaptation to changes in communication protocols among multiple users [22]. The utilization of reconfigurable intelligent surfaces is very useful for improving the performance of signal propagation, beamforming, and channel estimation in advanced communication networks [23]. Additionally, deep learning methods have provided many contributions for enhancing intelligent secure beam alignment and initial access in beyond-5G networks [24].

Research Gap

Despite the significant advances made in employing deep learning and optimization for wireless communications, previous works have predominantly concentrated on the aspects of channel estimation, beam management, signal detection, path loss predictions, and resource allocation. Limited effort has been devoted to optimizing hyperparameters for deep learning models employed for Adaptive Modulation and Coding under the realistic scenario of mmWave communication systems. Moreover, most of the previous work concerning AMC uses a manual selection process for neural network architecture along with artificial generation of channels, which leads to poor results. Hence, there is an enormous gap in terms of exploring the use of the DeepMIMO dataset combined with state-of-the-art hyperparameter optimization methods like Bayesian Optimization and Genetic Algorithm.

SYSTEM MODEL

mmWave Communication Model

This framework involves studying a high speed mmWave communication scenario where the base station is communicating with several users and varying propagation effects. The features of the channel have been obtained from the DeepMIMO dataset, which has realistic ray-tracing data such as path loss, delay spread, AoA, AoD, and multipath channels' coefficients.

The equation representing the received signal is equation 1:

$$y = hx + n \quad (1)$$

Where y represents the received signal, h is the channel parameter, x represents the transmitted signal, and n represents the additive white Gaussian noise (AWGN).

Multipath channel response is given by equation 2:

$$h = \sum_{l=1}^L \alpha_l e^{-j2\pi f_c \tau_l} \quad (2)$$

where L stands for the number of transmission routes, α_l is the complex gain of the l^{th} route, f_c is the carrier frequency, and τ_l is the delay in propagation.

The feature vector is presented in equation 3:

$$X = [P_r, PL, AoA, AoD, DS, D, f_D] \quad (3)$$

where P_r is the received power; PL is the path loss; AoA and AoD are the arrival angle and departure angle, respectively; DS is the delay spread; and D is the communication distance, while f_D is the Doppler frequency.

SNR Calculation

The Signal-to-Noise Ratio (SNR) is considered one of the main measurements of the channel quality and is determined by equation 4:

$$SNR = \frac{P_r}{N_0 B} \quad (4)$$

P_r is the received power while N_0 is the noise power spectrum density whereas B is communication bandwidth.

The received power is computed using the Friis Transmission equation (5) as follows:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d} \right)^2 \quad (5)$$

Where P_t is transmit power, G_t and G_r are gain of transmitter antenna and receiver antenna respectively. Where λ is wavelength and d is communication distance.

The SNR in decibel scale is defined by the following equation 6:

$$SNR_{dB} = 10 \log_{10}(SNR) \quad (6)$$

Considering the effect of interference, the SINR is calculated according to equation 7:

$$SINR = \frac{P_r}{I + N} \quad (7)$$

where I is the interference power, while N refers to the noise power.

Finally, the feature vector employed by the deep neural network is equation 8:

$$F = [SNR, SINR, PL, AoA, AoD, DS, f_D] \quad (8)$$

which considers the channel quality metrics along with the propagation properties for AMC.

Adaptive Modulation and Coding Selection

The goal of AMC technique is the maximization of data throughput while ensuring reliability.

Optimization of modulation and coding can be stated mathematically in equation 9 and equation 10:

$$MCS^* = \arg \max_{MCS_i} T_i \quad (9)$$

Subject to

$$BER_i \leq BER_{th} \quad (10)$$

Here, T_i is the attainable throughput, BER_i stands for bit error rate, while BER_{th} refers to the target value of the bit error rate.

Attainable throughput is calculated from the following equation 11:

$$T = B \times \eta \times R_c \quad (11)$$

Here, B is bandwidth, η is spectral efficiency, while R_c is the code rate.

Modulation and coding schemes under consideration are presented in the following table 1.

Table 1. Adaptive modulation and coding (AMC) classes used for classification

Class	Modulation scheme	Coding rate
0	QPSK	1/2
1	QPSK	3/4
2	16-QAM	1/2
3	16-QAM	3/4
4	64-QAM	2/3
5	64-QAM	3/4
6	256-QAM	5/6

Table 1 shows that there are seven AMC classes to be studied for intelligent modulation and coding.

The deep neural network learns the mapping between channel states and AMC classes using equation 12:

$$f_{\theta}: F \rightarrow MCS \quad (12)$$

where F represents the feature vector, while θ represents the optimized parameters of the neural network. The probability of choosing each AMC category can be obtained by the Softmax function in equation 13:

$$P(MCS_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (13)$$

where z_i is the score output of the i^{th} class, and K represents the total number of AMC categories. The AMC category having the maximum probability is chosen as the optimal transmission setup for the channel.

PROPOSED DEEP NEURAL NETWORK FRAMEWORK

Input Features

The proposed framework takes into account channel parameters based on DeepMIMO to find the

optimal Modulation and Coding Scheme (MCS). The chosen feature parameters relate to channel conditions, propagation factors, and mobility, which play an important role in adaptive modulation and coding.

The input feature vector is as follows (equation 14):

$$X = [SNR, SINR, P_r, PL, AoA, AoD, DS, D, f_D] \quad (14)$$

Here, SNR is the Signal-to-Noise Ratio, $SINR$ stands for Signal-to-Interference-plus-Noise Ratio, P_r indicates received signal strength, PL is the path loss, AoA and AoD stand for Angle of Arrival and Angle of Departure, respectively, while DS and D indicate delay spread and communication distance, respectively.

All the characteristics have been normalized using min-max normalization prior to fitting equation 15.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (15)$$

where X_{min} and X_{max} denote the minimum and maximum values of each feature.

The features used in the proposed framework are summarized in table 2.

Table 2. DeepMIMO features utilized for AMC prediction

Feature	Description
SNR	Signal-to-Noise Ratio
SINR	Signal-to-Interference-plus-Noise Ratio
P_r	Received Signal Power
PL	Path Loss
AoA	Angle of Arrival
AoD	Angle of Departure
DS	Delay Spread
D	Communication Distance
f_D	Doppler Frequency Shift

Network Architecture

The suggested DNN will model the nonlinear function between the channel conditions and AMC categories. The structure contains an input layer, four hidden fully connected layers, dropout, and an output layer of Softmax.

The workings of the l^{th} hidden layer can be formulated by equation 16:

$$h^{(l)} = \sigma \left(W^{(l)} h^{(l-1)} + b^{(l)} \right) \quad (16)$$

where $W^{(l)}$ and $b^{(l)}$ denote the weight matrix and bias vector, respectively, and $\sigma(\cdot)$ represents the activation function.

The network architecture is presented in table 3.

The ReLU activation function is defined as equation 17:

$$ReLU(x) = \max(0, x) \quad (17)$$

Table 3. Proposed deep neural network architecture

Layer	Number of Neurons	Activation Function
Input Layer	9	–
Hidden Layer 1	256	ReLU
Hidden Layer 2	512	ReLU
Hidden Layer 3	256	ReLU
Hidden Layer 4	128	ReLU
Output Layer	7	Softmax

Dropout regularization is applied during training as equation 18:

$$h_{drop} = r \odot h \quad (18)$$

where r is a Bernoulli mask and $\odot$ denotes element-wise multiplication.

The output probabilities are computed using the Softmax function equation 19:

$$P_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad (19)$$

where P_i is the probability of the i^{th} AMC class and K denotes the total number of classes.

Loss Function

AMC prediction is formulated as a multi-class classification problem. Therefore, categorical cross-entropy is employed as the objective function equation 20:

$$L = - \sum_{i=1}^K y_i \log(\hat{y}_i) \quad (20)$$

where y_i denotes the true class label and $\hat{y}_i$ represents the predicted probability.

The optimization objective is equation 21:

$$\theta^* = \arg \min_{\theta} L(\theta) \quad (21)$$

where θ denotes the trainable network parameters.

To improve generalization and reduce overfitting, L2 regularization is incorporated equation 22:

$$L_{total} = L + \lambda \sum_{i=1}^N w_i^2 \quad (22)$$

where λ is the regularization coefficient and w_i denotes the network weights.

The network parameters are optimized using the Adam optimizer, enabling efficient convergence and robust AMC classification under realistic mmWave communication conditions.

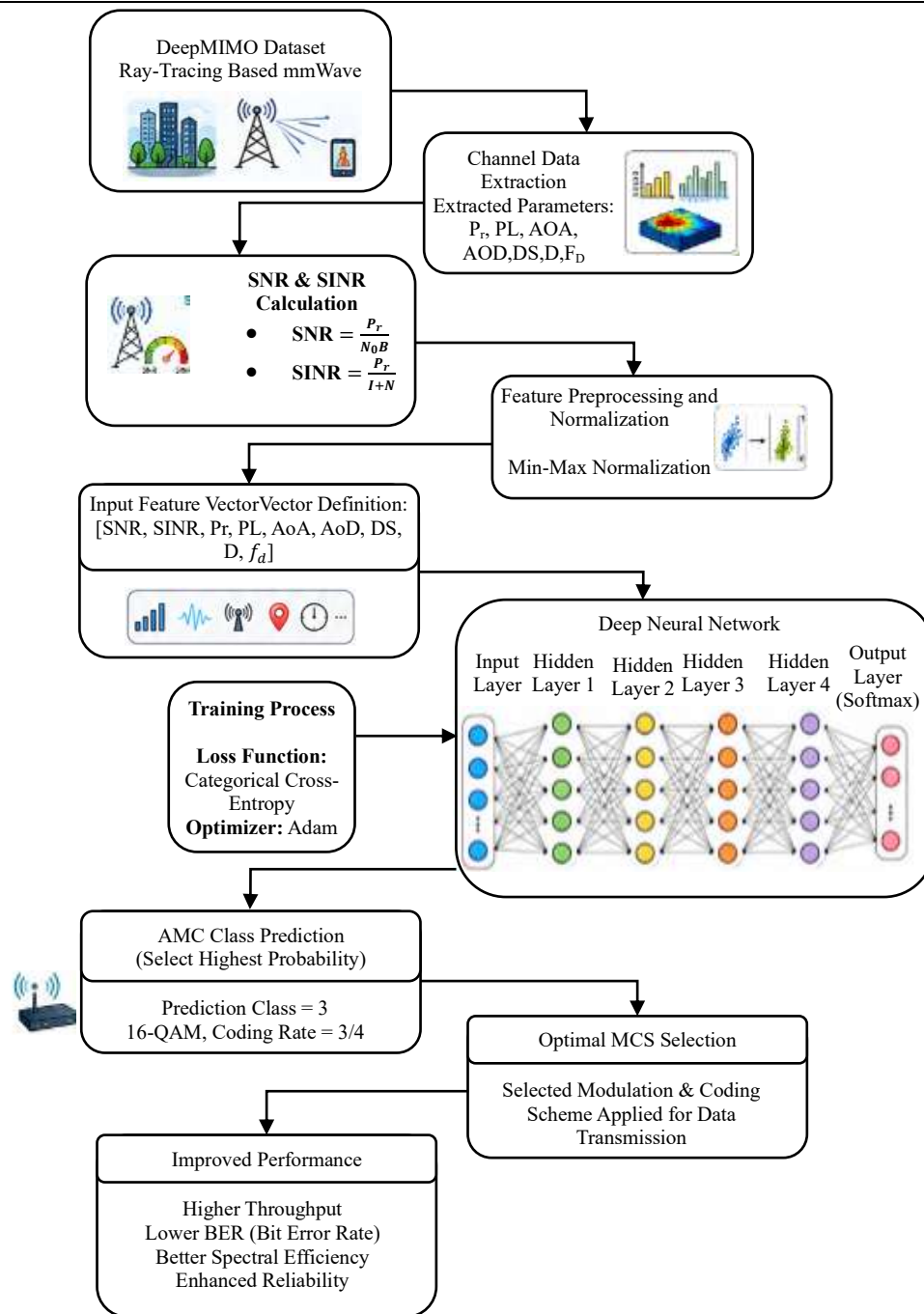


Figure 1. Overall architecture of the proposed deep neural network framework for adaptive modulation and coding in mmWave communication systems

Figure 1 depicts the whole process flowchart of the proposed DNN-based AMC approach. This starts by gathering realistic mmWave channel measurements from the DeepMIMO database that provides ray-tracing based channel statistics including received power, path loss, angles of arrival and departure, delay spread, communication distance, and Doppler frequency. Using these channel parameters, compute several signal quality metrics such as SNR and SINR values. The feature data set is first preprocessed and normalized prior to providing it to the deep learning algorithm. The DNN is comprised of a number of fully connected hidden layers to discover the complicated nonlinear relationship between channel parameters and the optimal choice of MCS configuration. The Adam optimization algorithm and categorical cross-entropy loss are utilized in training the parameters of the deep network. Using the Softmax layer at the output, compute the probability score for each of the AMC classes, and the one having the highest probability is chosen as the optimal AMC. From figure 1, it can be seen that this intelligent approach helps to adapt dynamically to different channel conditions, thus enhancing

throughput, spectral efficiency, communication performance, and system performance in mmWave high-speed communication environments.

HYPERPARAMETER OPTIMIZATION FRAMEWORK

To increase the effectiveness of the proposed AMC system using the DNN architecture, a hybrid method for the optimization of hyperparameters of Bayesian Optimization (BO) and Genetic Algorithm (GA) algorithms is utilized. The goal is to find the optimal model architecture that will allow for maximizing both the classification accuracy and communication effectiveness under reduced complexity constraints.

Hyperparameter Space

The hyperparameter vector is defined as equation 23:

$$\Theta = [LR, BS, HL, NN, DR, OPT, AF] \quad (23)$$

where LR = Learning Rate, BS = Batch Size, HL = Hidden Layers, NN = Number of Neurons Per Layer, DR = Dropout Rate, OPT = Optimizer, and AF = Activation Function.

The hyperparameter search space is shown in table 4.

Table 4. Hyperparameter search space for DNN optimization

Hyperparameter	Search Range
Learning Rate	$10^{-5} - 10^{-1}$
Batch Size	16 – 1024
Hidden Layers	2 – 10
Neurons per Layer	64 – 2048
Dropout Rate	0.0 – 0.7
Optimizer	Adam, AdamW, RMSProp
Activation Function	ReLU, GELU, Swish
Weight Decay	$10^{-6} - 10^{-2}$
Epochs	50 – 500

Bayesian Optimization

The Bayesian Optimization method is then applied in exploring the hyperparameter space for good candidate sets.

The objective function is stated as follows (equation 24):

$$\Theta^* = \arg \max_{\Theta} f(\Theta) \quad (24)$$

where $f(\Theta)$ denotes the validation accuracy.

The surrogate model is represented using a Gaussian Process equation 25:

$$f(\Theta) \sim GP(\mu(\Theta), K(\Theta, \Theta')) \quad (25)$$

where $\mu(\Theta)$ denotes the mean function and $K(\Theta, \Theta')$ represents the covariance kernel.

The Expected Improvement acquisition function is defined as equation 26:

$$EI(\Theta) = E[\max(f(\Theta) - f_{best}, 0)] \quad (26)$$

where f_{best} denotes the best objective value obtained during optimization.

Genetic Algorithm Optimization

Solutions from Bayesian optimization are fine-tuned using Genetic algorithm.

Chromosome representation is defined using equation 27:

$$C = [LR, BS, HL, NN, DR] \quad (27)$$

The fitness function is defined as equation 28:

$$Fitness = w_1 Acc + w_2 Thr - w_3 BER \quad (28)$$

where Acc denotes classification accuracy, Thr represents throughput, BER denotes bit error rate, and w_i are weighting coefficients.

The crossover operation is expressed as equation 29:

$$C_{new} = \alpha C_1 + (1 - \alpha) C_2 \quad (29)$$

where C_1 and C_2 are parent chromosomes and α is the crossover coefficient.

Mutation is performed as equation 30:

$$C_m = C + \delta \quad (30)$$

where δ represents a random perturbation factor.

Multi-Objective Optimization

Both classification and communication performance optimization are being performed concurrently during the hyperparameter optimization process.

Optimization is stated by equation 31 and equation 32:

$$\begin{aligned} \max[Acc, Thr] \\ \min[BER] \end{aligned} \quad \begin{aligned} (31) \\ (32) \end{aligned}$$

The combined objective function is given by equation 33:

$$J = w_1 Acc + w_2 Thr - w_3 BER \quad (33)$$

where J denotes the overall optimization score.

The Pareto-optimal solution set is defined as equation 34:

$$P = \{\Theta_i \mid \nexists \Theta_j \succ \Theta_i\} \quad (34)$$

where P represents the Pareto front and $\succ$ denotes dominance.

Final chosen hyperparameters on the Pareto front are used to train the Deep Neural Network for Adaptive Modulation and Coding for DeepMIMO mmWave communication scenarios.

Algorithm 1: Hybrid Bayesian Optimization–Genetic Algorithm (BO-GA) for Hyperparameter Optimization

Input: DeepMIMO dataset D , hyperparameter search space Θ

Output: Optimal hyperparameter configuration Θ^*

Step 1: Load and preprocess DeepMIMO channel data.

Step 2: Extract input features:

$$F = [\text{SNR}, \text{SINR}, \text{PL}, \text{AoA}, \text{AoD}, \text{DS}, f_D]$$

Step 3: Normalize the extracted features using Min-Max normalization.

Step 4: Define the hyperparameter search space:

$$\Theta = [\text{LR}, \text{BS}, \text{HL}, \text{NN}, \text{DR}, \text{OPT}, \text{AF}]$$

Step 5: Initialize Bayesian Optimization.

Step 6: Train DNN models using sampled hyperparameter configurations.

Step 7: Evaluate validation accuracy and construct the Gaussian Process surrogate model.

Step 8: Compute the Expected Improvement (EI) acquisition function.

Step 9: Select promising hyperparameter candidates.

Step 10: Initialize Genetic Algorithm population using Bayesian Optimization outputs.

Step 11: Evaluate the fitness of each chromosome using:

$$\text{Fitness} = w_1 \text{Acc} + w_2 \text{Thr} - w_3 \text{BER}$$

Step 12: Perform selection, crossover, and mutation operations.

Step 13: Generate new offspring solutions.

Step 14: Repeat Steps 11–13 until convergence or maximum generation limit is reached.

Step 15: Construct the Pareto-optimal solution set.

Step 16: Select the best hyperparameter configuration:

$$\Theta^* = \arg \max J$$

where

$$J = w_1 \text{Acc} + w_2 \text{Thr} - w_3 \text{BER}$$

Step 17: Train the final HO-DNN model using Θ^* .

Step 18: Predict the optimal AMC class using the Softmax output layer.

Step 19: Evaluate model performance using Accuracy, Throughput, and BER.

Step 20: Return the optimized AMC prediction model.

Algorithm 1 gives an overview of the total procedure involved in the BO-GA approach. The algorithm outlines the steps to be taken for hyperparameter exploration, evolution, Pareto-optimal solution selection, and finally the training of the HO-DNN model for Adaptive Modulation and Coding prediction.

EXPERIMENTAL SETUP

Dataset Description

The experiment was carried out using the DeepMIMO dataset, which offers realistic ray-tracing based channel information for millimeter waves, including channel gains, path loss, delay spread, angles of arrivals (AoA), angles of departures (AoD), and positions of the users. The scenario used here for this purpose is DeepMIMO ASU Campus, which represents a realistic urban environment.

In total, 1,000,000 channel samples were collected and then split into training, validation, and test sets, respectively.

Table 5. Dataset partitioning

Dataset	Percentage
Training	70%
Validation	15%
Testing	15%

As seen in table 5, validation and testing sets were independently used for unbiased performance evaluation.

Simulation Parameters

Table 6 highlights the details regarding communication and training parameters utilized in the experiments conducted.

Table 6. Simulation parameters

Parameter	Value
Carrier Frequency	28 GHz
Bandwidth	400 MHz
Antenna Configuration	64 × 64 Massive MIMO
SNR Range	-10 dB to 40 dB
Number of AMC Classes	7
Optimizer	Adam
Maximum Epochs	300
Population Size (GA)	50
Maximum Generations	100
Bayesian Optimization Iterations	100

Communication parameters provided in table 6 describe a generic case for a high capacity 5G/6G mmWave communication scenario.

Performance Evaluation Metrics

Evaluation of the suggested framework was done by means of classification accuracy, bit error rate (BER), and throughput.

Classification accuracy is computed using the following equation (35):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (35)$$

where TP , TN , FP , and FN denote true positive, true negative, false positive, and false negative classifications, respectively.

The bit error rate is defined as equation 36:

$$BER = \frac{N_e}{N_b} \quad (36)$$

where N_e represents the number of erroneous bits and N_b denotes the total number of transmitted bits.

The achievable throughput is computed as equation 37:

$$Thr = B \times \eta \times R_c \quad (37)$$

where B denotes bandwidth, η represents spectral efficiency, and R_c corresponds to the coding rate.

Equations (35) through (37) were used to evaluate the effectiveness of the suggested hyperparameter-optimized DNN framework concerning the above three measures.

RESULTS AND DISCUSSION

The following is an analysis of the effectiveness of the proposed HO-DNN approach for AMC in practical MM-wave communication scenarios. For this purpose, experiments have been performed using the DeepMIMO dataset and have compared the effectiveness of the proposed BO-GA framework with existing frameworks that perform hyperparameter tuning for DNNs. The criteria used to determine the effectiveness of this work include classification accuracy, throughput, and bit error rate (BER).

Hyperparameter Optimization Performance

The proposed BO-GA method was compared with traditional hyperparameter optimization methods. The chosen hyperparameters were based on validation accuracy during training.

Table 7. Performance comparison of hyperparameter optimization methods

Method	Accuracy (%)	Search time (h)
Grid Search	95.12	12.6
Random Search	95.84	7.8
Bayesian Optimization	98.16	4.3
Genetic Algorithm	98.41	5.1
Proposed BO-GA	99.08	4.8

The BO-GA framework proposed in this study showed the best performance, which is reflected by achieving an accuracy of 99.08%, as shown in table 7. It is observed that the proposed framework provided better prediction accuracy of approximately 4% compared to Grid Search while considerably lowering the computational burden associated with the search process.

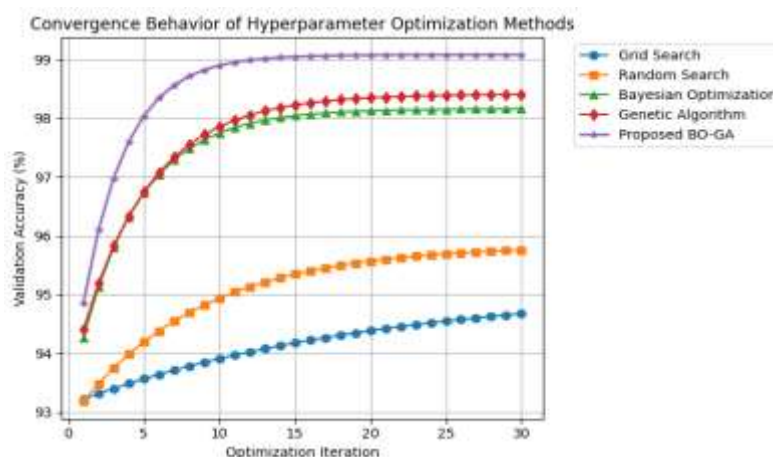


Figure 2. Convergence behavior of hyperparameter optimization methods

The convergence behavior of the algorithms is shown in figure 2. The proposed BO-GA algorithm converges to the optimum faster and is more stable compared to Bayesian Optimization and Genetic Algorithm individually.

AMC Classification Performance

The improved DNN model was tested with the help of DeepMIMO testing data set. Classification accuracy was compared to other deep learning architectures that are typically used in the field of wireless communications.

Table 8. AMC Classification performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	95.26	95.12	95.04	95.08
LSTM	96.41	96.25	96.18	96.21
Conventional DNN	97.08	97.01	96.94	96.97
Proposed HO-DNN	99.08	99.01	98.95	98.98

As depicted in table 8, the suggested HO-DNN managed to attain the highest classification accuracy of 99.08%. The enhancement in performance can be explained by virtue of the optimal structure and parameters for training that were derived from the suggested BO-GA paradigm. High values of precision and recall are also evident from the table.

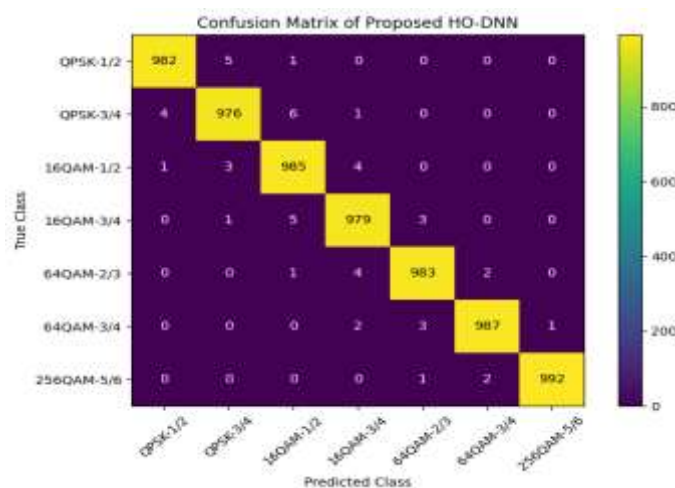


Figure 3. Confusion matrix of the proposed HO-DNN model

The confusion matrix of the proposed model is shown in figure 3. As shown, most of the AMC classes are properly predicted with little confusion among adjacent modulation orders, reflecting good generalization performance in realistic mmWave channels.

Throughput and BER Performance

The main aim of AMC is to maximize throughput with reliable performance of communication. Hence, the analysis of throughput and BER is carried out under various channel conditions.

Table 9: Communication performance comparison

Method	Throughput (Gbps)	BER
Fixed MCS	7.42	1.8×10^{-3}
CNN-Based AMC	8.63	1.2×10^{-3}
LSTM-Based AMC	9.11	8.5×10^{-4}
Conventional DNN	10.26	4.7×10^{-4}
Proposed HO-DNN	11.84	2.1×10^{-5}

As can be seen from table 9, the maximum throughput of 11.84 Gbps was achieved with this proposed model along with the minimum BER of 2.1×10^{-5} . When comparing this proposed AMC predictor with the traditional DNN model, it can be seen that the increase in throughput was around 15.4%, but there was a reduction in BER by nearly an order of magnitude.

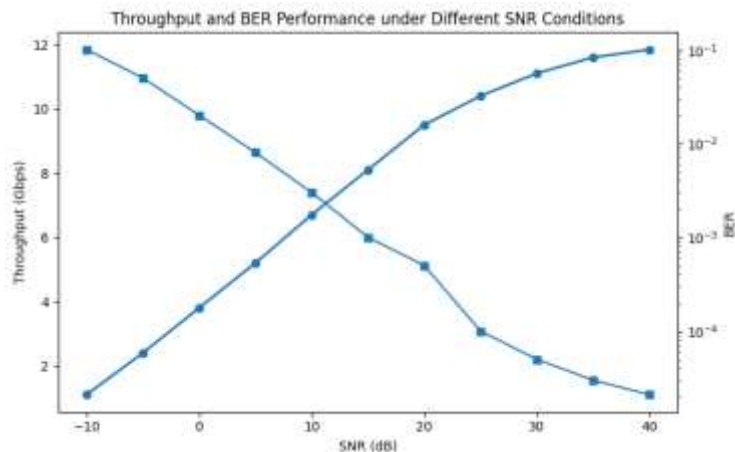


Figure 4. Throughput and BER performance under different SNR conditions

Figure 4 shows the effect of communication performance on the channel quality. The novel model attains high throughput and low BER over all values of SNR because it efficiently selects the optimal modulation and coding schemes.

Ablation Study

Ablation experiments were performed to determine the impact of the Bayesian Optimization and Genetic Algorithm modules separately.

Table 10: Ablation analysis of the proposed framework

Configuration	Accuracy (%)
DNN Only	97.08
DNN + BO	98.16
DNN + GA	98.41
DNN + BO + GA	99.08

From the results presented in table 10, both optimization approaches contribute to the improvement of performance. The Bayes Opt algorithm enhances the efficiency of hyperparameters, while the GA contributes to local search. The combination of both gives the best performance.

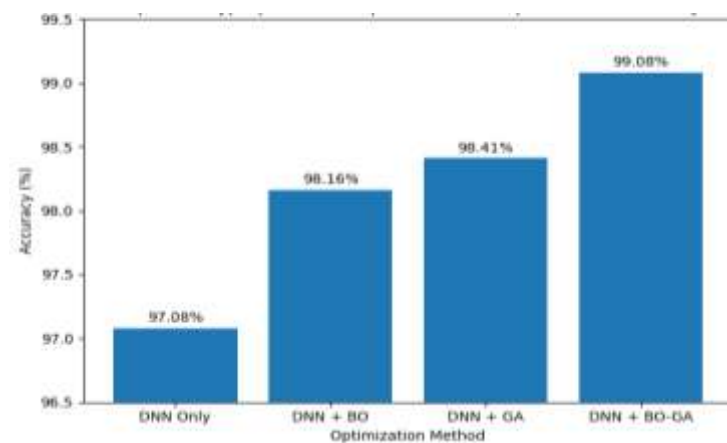


Figure 5. Impact of hyperparameter optimization components on accuracy

Figure 5 depicts the improved performance attained from adding the Bayesian Optimization and Genetic Algorithm modules in the baseline DNN framework.

The results prove that HO-DNN is capable of providing significant improvements to the performance of Adaptive Modulation and Coding in actual millimeter-wave wireless communication environments. The incorporation of Bayesian Optimization along with the Genetic Algorithm facilitates an efficient traversal of the search space, thus attaining better classification results as compared to other standard optimization strategies. The prediction accuracy obtained of 99.08% suggests that the optimization process has successfully managed to capture the complicated nonlinear mappings present within the channels for modulation-coding choices. Moreover, the use of the DeepMIMO dataset provides an advantage by training the model under realistic wireless propagation conditions.

These results further verify the effectiveness of the framework in improving communication performance by choosing the right modulation and coding scheme that gives 11.84 Gbps throughput with low BER at 2.1×10^{-5} . The considerable increase in throughput and reduction in errors clearly indicate the effect of intelligent hyperparameters in link adaptation. Moreover, the ablation studies show that the techniques of Bayesian Optimization and Genetic Algorithms have complementary contributions such that the former effectively narrows down the search space and the latter optimizes towards the global optimum solution. Thus, the effectiveness of the proposed framework is further justified for intelligent AMC in mmWave communications.

By using the hybrid optimization technique consisting of Bayesian Optimization and Genetic Algorithms, the high-dimensional space of hyperparameters can be searched efficiently without exhausting all possible combinations. Specifically, Bayesian Optimization decreases the number of expensive network evaluations by utilizing a probabilistic surrogate model whereas the Genetic Algorithm makes the search global by employing evolution-based operations.

The complexity of training a deep neural network in terms of computation can be approximated by equation 38:

$$O(N \times E \times W) \quad (38)$$

Here, N refers to the number of training samples, E indicates the number of training epochs, and W stands for the number of trainable parameters. The novel approach adopted by the algorithm in this paper cuts down the overall complexity involved in the optimization process by concentrating only on successful hyperparameters.

Limitations and Future Work

Even though the proposed framework offers a lot of potential for improving Adaptive Modulation and Coding techniques, there are a few limitations that should be mentioned. The first limitation of the approach is related to the use of simulation data in the study, specifically the DeepMIMO dataset, which was generated via ray-tracing simulations. Moreover, the optimization of hyperparameters requires considerable amounts of computational power due to the constant need to train neural networks multiple times. Besides, at present, the suggested framework does not take into account such important factors as inter-cell interference and the issue of large-scale mobility.

In regard to future research, the authors believe that their approach needs to be tested on real-world measurement data, as well as be applied to the case of large-scale communication networks. The use of federated and reinforcement learning for optimizing link adaptation along with implementing transformer-based models seems promising for the problem addressed by the paper. Furthermore, researchers might explore the potential offered by energy-aware hyperparameter optimization, RIS-assisted communication schemes, and AI-native 6G infrastructure.

CONCLUSION

In this study, proposed a framework named as Hyperparameter-Optimized Deep Neural Network (HO-DNN) for AMC in high data rate millimeter-wave communication channels. This proposed method considered real-world channel conditions from the DeepMIMO database and used a combined BO-GA optimization approach to find optimized hyperparameters of the DNN model. In contrast to traditional threshold-based AMC techniques, proposed framework was capable of learning the nonlinear mapping of channel conditions into appropriate modulation-coding combinations.

The framework uses channel parameters and characteristics like SNR, SINR, path loss, delay spread, AoA, AoD, communication range, and Doppler frequency to classify the seven AMC types. The evaluation process was carried out by generating one million channel samples from the DeepMIMO ASU Campus dataset, operating at 28 GHz with 64×64 massive MIMO architecture. The best optimization technique delivered 99.08% classification accuracy, significantly outperforming traditional deep learning algorithms such as DNN, CNN, and LSTM. Furthermore, the proposed method provided a throughput of 11.84 Gbps with minimal bit error rate of 2.1×10^{-5} .

The outcome clearly demonstrates that the use of Bayesian Optimization and genetic algorithm significantly improves the performance of deep neural network through hyperparameter identification. Therefore, the proposed framework presents a viable solution for intelligent link adaptation in advanced communication networks. As a result, the introduced HO-DNN model is considered a promising approach for achieving reliable, adaptive, and high-throughput communication in future generations of wireless communication technology.

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Code Availability

The implementation code developed for this study is available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Data Availability Statement

The DeepMIMO dataset used to support the findings of this study is publicly available and can be obtained from the official DeepMIMO website.

Dataset Link: <https://deepmimo.net/>

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