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Research article

Implementation of the deep learning method for signal detection in massive-MIMO-NOMA systems

Arun Kumar [a], Nishant Gaur [b], Manoj Gupta [c], Aziz Nanthaamornphong [d,*]

[a] Department of Electronics and Communication Engineering, New Horizon College of Engineering, Bengaluru, India
[b] Department of Physics, JECRC University, India
[c] School of Computer Science and Engineering (SCOPE), VIT-AP University, Amravati, (Andhra Pradesh), India
[d] College of Computing, Prince of Songkla University, Phuket Campus, Thailand

A R T I C L E I N F O

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A B S T R A C T

The deep learning method (DLM) is one way to fix issues in optical nonorthogonal multiple access (O-NOMA) systems that are caused by signals that overlap and interfere with each other. NOMA increases the optical framework's spectrum efficiency, allowing several users to share the same time-frequency resources. However, NOMA-DLM-based detection's complicated interference patterns and variable channel conditions are challenging for conventional detection methods to manage. By utilizing deep neural networks' advantages, these methods are able to overcome these challenges and improve detection performance. An overview of the main features and advantages of DLM detection in massive multiple input and output (M-MIMO) O-NOMA systems is given in this article. It describes the essential elements, such as the training procedure and the network design. In order to process the sent symbols or decode data streams, DLM networks are built to process the incoming signal, power allocation coefficients, and extra information. Gradient descent optimization is used to update the network parameters iteratively while training the network, and a diverse and representative dataset is created. Additionally, the challenges of detecting deep learning in O-NOMA systems are examined. It recognizes that in order to get the best results, significant computational resources, a large amount of training data, and careful model design are required. It looks at and compares the 16×16, 32×32, and 64×64 M-MIMO-NOMA models in terms of bit error rate (BER), complexity, and power spectral density (PSD). The suggested DLM algorithms have been demonstrated to perform better than traditional methods by achieving an excellent BER of 10-3 at 4.1 dB and PSD (−2500) performance with low complexity.

1. Introduction

The advanced wireless communication technique, recognized as M-MIMO, uses several antennas at the base station to simultaneously serve numerous consumers. Signal detection is essential for correctly recovering broadcast signals from the received signals in M-MIMO systems. To extract the necessary information, this procedure requires calculating the channel state information (CSI) and conducting data detection [1]. Optical NOMA (O-NOMA), a technology for optical communication systems, expands the usage of NOMA in wireless communication systems. In NOMA, multiple users share the same frequency and time resources; however, their data are encoded differently. O-NOMA offers advantages in optical networks by multiplexing signals with different power levels, increasing

* Corresponding author.
E-mail address: aziz.n@phuket.psu.ac.th (A. Nanthaamornphong).

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spectral efficiency, and simultaneously supporting more users. This leads to an enhanced capacity, improved energy efficiency, and reduced latency in optical communication systems. The technology known as O-NOMA is used in advanced radio systems to increase the network capacity and spectrum efficiency. In NOMA, several users use various power levels and superposition coding to share the same time and frequency resources [2]. A new technique in optical communication networks, called O-NOMA, enables numerous users to share resources and increase bandwidth utilization and capacity. However, because of the interference caused by concurrent transmissions, it might be difficult to recognize and decode signals from various users in an O-NOMA system. In O- NOMA, signal detection entails separating and decoding sent signals from various users [3]. Despite the interference brought on by other users who share identical resources, the objective is to recover individual user signals properly. Effective and trustworthy signal-identification techniques are essential for O-NOMA systems to provide high-performance communication. In an O-NOMA system, signal detection entails the separation and decoding of signals sent by various users. An enormous array of antennas, sometimes numbered in hundreds or even thousands, is installed on the base station in M-MIMO systems. These antennas have many advantages including better spectral efficiency, more reliable links, and better interference control. The main idea of M-MIMO is to serve numerous customers simultaneously on an identical resource using spatial methods [4]. Channel state information (CSI) and data detection are the two primary processes in M-MIMO signal-detection. To determine the CSI between the base station and each user in the M-MIMO structure, channel estimation is essential, as the users obtain known pilot symbols from the base station, which are often orthogonal sequences. The base station can estimate the channel response for each user by receiving these pilot symbols from the users and sending them back to it. The base station then performs data detection to extract the sent symbols or data from the received signals after estimating the CSI. Despite the presence of noise, interference, and multipath fading, the objective is to reliably recognize symbols delivered by each user. M-MIMO systems employ a variety of data-detection methods, including linear and iterative detectors [5]. Simple computations using linear algebra provide the basis for linear-detection systems. To estimate the transmitted symbols, they use channel information [6,7]. The zero-forcing (ZF) and minimal mean square error (MMSE) detectors are two common linear detectors. While the MMSE detector reduces the mean square error between the detected symbols and the actual sent symbols, the ZF detector eliminates interference from other users [8]. By eliminating interference from other users, iterative detection techniques, including successive interference cancellation (SIC) and approximate message passing (AMP) detectors, iteratively identify sent symbols. These iterative techniques enhance detection performance by using combined information from many antennas [9]. System constraints, computational complexity, and performance tradeoffs are only a few examples of variables that influence the method of choice for data detection. M-MIMO systems are also investigating advanced detection methods, such as DL-based detectors, that consider channel uncertainties and nonlinearities. Signal identification in M-MIMO systems is difficult; nevertheless, for several reasons, the same pilots broadcast by many users may interfere with one another in M-MIMO systems, resulting in pilot contamination. Pilot contamination can reduce the accuracy of channel estimates, which can affect data detection performance [10]. To address this problem, strategies such as pilot decontamination and adaptive pilot allocation have been used. M-MIMO systems frequently function in situations involving interference restrictions. Signal identification in O-NOMA systems is a challenging process because of interference from other users who share the same resources, it is crucial to mention. Researchers are continually investigating and developing novel detection algorithms and techniques [11].

1.1. Motivation

Although O-NOMA systems offer advantages in terms of spectral efficiency and capacity, signal detection in O-NOMA faces several challenges. Some of the key problems encountered in signal detection in O-NOMA systems include [12].

1. Interference: Several users share the same resources in O-NOMA. Therefore, the interference is a significant problem. Because the signals from several users interact with one another, it is challenging to effectively isolate and identify signals from individual users.
2. Power Allocation: For effective signal detection in O-NOMA, users must be given an appropriate amount of power to be utilized. However, finding the best power allocation approach that maximizes system performance while considering interference levels can be a challenging challenge.
3. Channel Estimation: Accurate estimation of the channel conditions is essential for successful signal detection in O-NOMA. However, channel estimation becomes challenging owing to the presence of interference and the need to simultaneously estimate multiple user channels.
4. User Grouping: In O-NOMA, users are grouped into clusters to exploit the power differences between them. However, determining the optimal user grouping strategy that minimizes interference and maximizes system performance is a nontrivial problem.
5. Computational Complexity: Signal detection algorithms in O-NOMA often involve complex mathematical operations such as matrix inversions and optimization procedures. These processes can be computationally strenuous only when there are a lot of users or high data rates, which makes real-time implementation difficult.
6. Multiuser Diversity: Users with varying channel conditions and power levels coexist in O-NOMA. Exploiting multiuser diversity to improve signal detection performance requires efficient algorithms that adapt to varying channel conditions and user configurations.

Addressing these challenges requires the development of advanced signal-detection techniques and algorithms tailored to the characteristics of O-NOMA systems. Researchers are actively investigating and proposing solutions such as advanced interference cancellation schemes, optimized power allocation algorithms, robust channel estimation techniques, intelligent user grouping strategies, and low-complexity detection algorithms. These efforts aimed to improve the performance and reliability of signal detection in

O-NOMA systems, paving the way for their practical deployment in future optical communication networks. Table 1 indicates the acronyms used in the proposed method.

2. Related work

To solve the difficulties of poor signal recognition produced by multiple interference causes in large-scale MIMO technology, Sadat et al. [13] proposed a DL algorithm to detect the signal. The conventional MIMO system receiver receives Deep Neural Network (DNN) detection after the MIMO system model first gathers the data bits, codewords, and channel status information given by transmitters. Finally, the proposed method was empirically tested using the TensorFlow DL framework. The BER and mean square error, when the signal-to-noise ratio is 10 dB, are both less than 0.005 and 0.1, according to the experimental results. To solve the problems of subpar signal recognition caused by numerous forms of interference in the MIMO environment, this study recommends a signal identification method based on the DLM. However, the PSD and complexity of the system are not analyzed and discussed. Using channel estimation as the detector [14], provided a cooperative MIMO channel approximation and signal recognition. The channel estimate is enhanced by the found data and incorporates detection errors, while also accounting for channel statistics. The model-driven DL-based MIMO detector outperforms earlier DLM detectors and exhibits improved resistance to innumerable disparities according to numerical results. In addition, it performs far better than the corresponding traditional iterative detector. The complexity and scalability challenges in modeling the dynamic and diverse nature of MIMO channels and systems with deep learning are concerns of the proposed work. He et al. [15] presented a DLM centred detection framework. The use of signal detectors based on fully connected deep neural networks (FCDNN) and convolutional neural networks (CNN) has also been demonstrated. Diverse aspects of co-channel interference, such as signal types, changeable SNR and SIR, level of interference, and neural network layers, have been studied and compared. In simulated experiments, CNN and FCDNN outperformed ZFE in a fading environment, but FCDNN outperformed CNN in the presence of a low SIR. The proposed methods suffer from overfitting when dealing with limited data, which requires extensive data augmentation or regularization techniques to effectively mitigate this issue. The Block Gauss-Seidel network decreases the complexity of the concurrent execution of the standard Gauss-Seidel iterative technique and is a model-driven deep learning detector network. By breaking up a huge matrix inversion into smaller ones, complexity can be minimized. It is suggested to improve the BGS-Net in order to reduce the SER of the BGS-Net when used with the MAUE system. The results of the simulation demonstrate that, in comparison to existing model-driven methodologies, BGS-Net has a lower level of complexity and equal detection performance [16]. The proposed method in MIMO systems may exhibit slow convergence, particularly in high-dimensional scenarios, leading to increased computational time and potentially limiting its practicality in real-time communication applications. In Ref. [17], MAOR-based iterative detection was proposed. Furthermore, it was noticed that the Chebyshev acceleration, when using error analysis, has a rather simple structure. The performance experiments showed that under comparable channel conditions, the resulting Chebyshev-accelerated MAOR outperformed traditional detectors, providing near-MMSE performance. The proposed algorithm suffers from increased computational complexity, making it less suitable for real-time applications or resource-constrained devices owing to its demanding processing requirements. The throughput and intricacy of the suggested technique are equal to those of the current methods in Ref. [18] based on the BER and number of convolutions. The results demonstrated that the recommended approach significantly lowers the computational complexity while providing the required performance with a constrained number of repeats. At QAM, 20 dB SNR, 80–120 antenna arrangement, and $n = 2$, the recommended detector outperformed the GS detector by 99.82 %. The recommended detector performs 99.89 % better for 32QAM, 25 dB SNR, 120–180 antenna formation, and $n = 5$. At 64QAM, 28 dB SNR, 80–120 antenna arrangement, and $n = 3$, the recommended detector performed 99.93 % better. The proposed algorithm for signal detection in

Table 1
Acronym used in proposed work.

Acronym
O-NOMA: Optical Non-Orthogonal Multiple Access
PSD: Power Spectral Density
SIC: Successive Interference Cancellation
M-MIMO: Massive-Multiple Inputs and Multiple Outputs
BER: Bit Error Rate
CSI: Channel State Information
ZFE: Zero-Forcing Equalizer
MMSE: Minimal Mean Square Error
DNN: Deep Neural Network
FCDNN: Fully Connected Deep Neural Network
CNN: Convolution Neural Networks
MAUE: Multiple-Antenna User Equipment
SER: Symbol Error Ratio
QAM: Quadrature Amplitude Modulation
AMP: Approximate Message Passing
DLM: Deep Learning Method
DL: Deep Learning
PAPR: Peak-to-Average Power Ratio
MLD: Maximum Likelihood Detection
MIMO: Multiple Input and Multiple Output

M-MIMO uplinks, while promising for improving spectral efficiency, can suffer from high computational complexity, cost, and limited adaptability, potentially hindering its practical implementation in real-world M-MIMO systems. Gebeyehu et al. [19] used a hybrid detection method, which is based on matrix inversion, to examine matrices of various sizes, including 16×16, 64×64, and 256×256. The growth in MIMO may have an impact on the BER. The recommended method outperformed conventional algorithms when compared to hybrid algorithms that used classic Rayleigh and Rician channel detection techniques. It should also be seen that the projected QRM-MLD-BF provided a perfect BER with a trivial intricacy. The proposed hybrid detection method for 5G signals has several limitations. This requires complex hardware and increased power consumption, making it less energy-efficient. In addition, its performance may degrade in highly dynamic or noisy environments. Moreover, hybrid methods can be challenging to optimize, leading to potential implementation difficulties in 5G systems. The AMP algorithm works well in terms of BER and is less difficult than the MMSE and MDP algorithms [20]. However, the PAPR is one of these. The simulation results indicate that the 64×64 MIMO has a greater PAPR than the 32×32 MIMO. To reduce the PAPR, it is also suggested to use the proper PAPR algorithms in the transmitting part of the 5G radio, which might further complicate the schemes. However, the AMP algorithm for 5G signals is limited. It can struggle with non-Gaussian interference or noise, thereby impacting its robustness in realistic environments. Additionally, AMP may require accurate knowledge of channel statistics, which can be challenging to obtain, thereby hindering its practicality in dynamic and rapidly changing 5G networks. The authors suggested a nonorthogonal multiuser precoding method to obtain the lowest possible rates for all users in a group. This ensures that everyone obtains a fair share of the aggregated beams. A max-min problem was proposed as a solution to this difficulty, and artificial intelligence (AI) was used to address this challenging challenge. A data-driven, unsupervised DNN was trained to map the instant channel coefficients to the precoders after the problem was first transformed into an equivalent penalized minimization problem. Performance analyses show that the proposed system can significantly increase the maximum–minimum data rate when compared to the standard scheme [21]. This study examines how systems are dynamic and interdependent, as well as how well wireless resources are used. The wireless resource efficiency of the system was assessed using game theory, and an evaluation model for efficiency was built. Additionally, a simulation was used to confirm the effectiveness of the first study [22]. Guan et al. [23] investigated likelihood-based and feature-based techniques for NOMA signature categorization. First, a likelihood-based approach is suggested, and it is demonstrated that despite high computing complexity, it is best in the asymptotic limit of the observations. Although feature-based categorization algorithms are simple, it is difficult to create efficient features manually. As far as we are aware, based on the material that is currently in circulation, the following are the proposed article's contributions.

- In this study, we compared the effectiveness of cutting-edge deep learning techniques and established detection methods for O-NOMA waveforms in the Rician channel.
- Different metrics, including the BER and PSD, are calculated and applied to traditional detection systems. The main goal of the developed technique is to decrease the propagation complexity and latency with little loss in the BER performance.
- The complexity is also increasing as a result of the standard PAPR procedures, which have been considerably improved in the present work.

3. Proposed system model

A cutting-edge technique called O-NOMA enables effective use of the optical spectrum in radio networks. Owing to their potential to upsurge the dimensions and effectiveness of optical networks, they have drawn a lot of attention recently [24]. The implementation of the proposed algorithm for signal detection in M-MIMO-NOMA structures offers several advantages. This can significantly reduce computational complexity, enabling real-time processing even in large-scale MIMO environments. Deep learning models can adapt to complex and dynamic channel conditions, thereby enhancing their robustness and performance. Moreover, they handle nonlinearities and interference, making them suitable for the challenging interference-limited scenarios of M-MIMO-NOMA, ultimately improving the spectral efficiency, user experience, and overall efficiency of the communication system. A block of the O-NOMA system in detail is shown in Fig. 1.

The structure of an O-NOMA system consists of several key components that work together to achieve the efficient transmission and reception of data [25]. These components include the transmitter, the optical channel, and the receiver. On the transmitter side, the data to be transmitted are first processed and encoded using various modulation techniques. The encoded data were then divided into multiple streams, each associated with a specific power level. The simultaneous transmission of several signals at various power levels within the same spectrum resources is made possible by power allocation, which is an essential component of NOMA. Normally, power

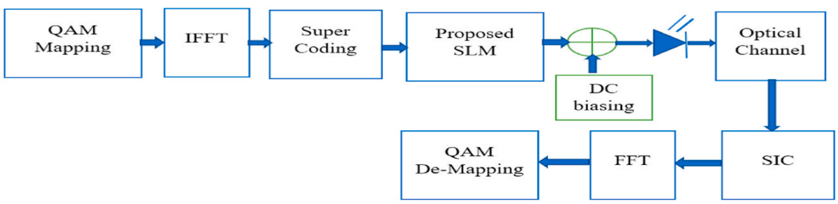

Fig. 1. O-NOMA structure.

division is performed on the channel surroundings and users' expected levels of quality of service. The data streams were merged using a superposition approach after they were produced and given power. Multiple signals can be delivered concurrently over the same frequency range owing to this superposition. A modulator, such as an intensity modulation/direct detection (IM/DD) modulator, transforms the combined signal from electrical to optical, making it acceptable for transmission via the optical channel. The optical channel is the means by which an optical signal is directed from the transmitter to the receiver. Optical fibers, optical amplifiers, and other optical components can all be included in this channel. As the optical signal travels through the channel, attenuation and distortion may occur, which can reduce the signal quality. To lessen these impacts, it is crucial to consider the channel characteristics and use proper signal processing techniques, including equalization and dispersion correction. The optical signal was initially transformed back to an electrical signal at the receiver side using a photodetector. The unique data streams supplied by individual user were then removed from the electrical signal through further processing. Owing to the simultaneous transmission of several signals in NOMA, the receiver must use sophisticated signal separation techniques, such as SIC, to decode various data streams. Using SIC, the receiver can identify and decode the signals of users who are more powerfully powered before removing them from the received signal to recover the weaker signals. This process is repeated until all of the data streams are correctly decoded. The original data can be recovered using further signal processing and decoding techniques after the data streams have been decoded. Depending on the particular modulation scheme employed at the transmitter, these methods may include equalization, demodulation, and error-correcting coding [26]. The data can then be further processed and sent to appropriate users or apps once they have been properly retrieved. The block diagram of an O-NOMA system shows how several data streams with varied power levels are integrated and sent concurrently via an optical channel [27]. Advanced signal-processing techniques are used by the receiver to extract and decode various data streams, allowing for effective and high-capacity transmission. The performance of optical networks can be increased using O-NOMA, enabling greater data rates, better spectrum efficiency, and better use of network resources. Its incorporation into upcoming optical communication systems has the potential to completely alter how data are sent and received, paving the way for the creation of more sophisticated and effective communication networks [28].

3.1. Mathematical model of M-MIMO system

M-MIMO represents the relationship between the transmitted and received signals, considering the channel conditions, noise, and interference [29].

Let K represent users or terminals in the system. Each user i, where $i = 1, 2, ..., K,$ transmits symbol $s(i)$ from a constellation set $S(i)$ with cardinality $M(i)$. The transmitted signal from user i is shown in Eq. (1) [30]:

$$x(i) = \sqrt{P(i)} \times s(i) \tag{1}$$

where $P(i)$ is the transmit power assigned to user i, and $\sqrt{P(i)}$ scales symbol $s(i)$ to achieve the desired transmit power level. The total transmitted signal vector from all users is given by Eq. (2) [31]:

$$x = [x(1), x(2), ..., x(K)]^{\mathsf{T}} \tag{2}$$

A matrix depicting the propagation from each user's antenna to the base station antennas was used to simulate the channel in a large MIMO system. Let H be an $M\,X\,N$ channel matrix, where M is the total number of user antennas and N is the number of base station antennas. The received signal from the BS is given by Eq. (3) [32]:

$$y = H \times x + n, \tag{3}$$

where y is the acknowledged signal at the base station, n is the noise vector with a covariance matrix $\sigma^2 I$, and I is the identity matrix. Using y and H, data detection in M-MIMO aims to estimate the broadcast symbols $s(i)$ for each user, i. To increase the probability or decrease the detection error, an optimization issue must be solved. The challenge of data detection can be expressed in Eq. (4) [33]:

$$\widehat{s} = argmax\ \Pi(i)\ P(y|s(i), H), \tag{4}$$

where ŝ is the estimated symbol vector, and $P(y|s(i), H)$ represents the conditional probability of the received signal y given the transmitted symbol $s(i)$ and channel matrix H. Accurate CSI is vital for accurate detection in M-MIMO frameworks. The channel estimation process involves transmitting known pilot symbols from the base station to users, and the users send back their received pilot symbols. Given that L is the number of pilot symbols and N is f user antennas, let C be a pilot matrix of size $L \times N$. The estimated channel matrix Ŝ can be obtained using techniques such as least-squares estimation or maximum likelihood estimation is shown in Eq. (5) [34]:

$$\hat{S} = H \times \widehat{C}^{\mathsf{T}} \times (\widehat{C} \times \widehat{C}^{\mathsf{T}} + \sigma^2 I)^{-1}, \tag{5}$$

Where $\widehat{C}$ is the received pilot matrix. The estimated channel matrix Ŝ is then used for data detection. This mathematical system model provides a foundation for analyzing and optimizing the gain of M-MIMO systems. It captures the relationships between the transmitted and received signals, considers the channel characteristics, and highlights the data-detection and channel-estimation processes. The specific details of the channel model, detection algorithms, and channel estimation techniques may vary depending on the system design and specific assumptions made [35].

3.2. Proposed DL detection model

DL-based detection for O-NOMA is a cutting-edge method that makes use of the capacity of deep neural networks to increase the efficiency of detection in NOMA systems. NOMA boosts the spectral effectiveness of optical communication frameworks by enabling numerous users to allocate equal resources [36]. However, the detection process in NOMA can be challenging because of interference caused by overlapping signals. The detection process in O-NOMA involves separating and decoding the individual data streams transmitted by different users. Traditionally, this task has been addressed using conventional detection algorithms such as maximum likelihood (ML) detection or SIC. However, these algorithms may suffer from complexity and performance degradation when dealing with a large number of users or highly overlapping signals. Deep learning offers a promising alternative by utilizing artificial neural networks to learn the detection process directly from data [37]. Fig. 2 displays a schematic illustration of the DLM.

DLM networks are composed of multiple layers of interconnected neurons that can extricate complex structures and patterns from input data. By training the network on a large dataset of labeled examples, it can learn to make accurate predictions and perform the detection task efficiently. In the context of O-NOMA, DL-based detection can be implemented by designing a deep neural network architecture specifically tailored for the detection problem [38]. The input to the network typically consists of the received signal, which may be represented as a complex-valued vector, and additional information such as the power allocation coefficients or channel conditions. The network then processes this input and produces an estimate of the transmitted symbols or decoded data stream. Training a deep neural network for O-NOMA detection involves two main steps: data generation and network training. In the data-generation step, a large dataset of labeled training examples was created. This dataset should cover a wide range of channel conditions, power allocations, and interference scenarios, to enable the network to learn robust and generalizable detection models. labeled examples are generated by simulating the transmission and reception processes of the O-NOMA system, incorporating various channel models and interference scenarios. Once the dataset was prepared, a network training step was initiated. The deep neural network was initialized with random weights, and the training examples were fed into the network iteratively. During each iteration, the network processes the input and produces an output that is compared with the ground-truth labels. A loss function, such as the mean square error or cross-entropy loss, is used to estimate the difference among the expected output and the real result [39]. The network weights are then adjusted through backpropagation and gradient descent optimization to diminish the forfeiture and improve detection performance. After the training process was completed, the deep neural network was ready for deployment in real-world scenarios. It can be used to detect transmitted symbols or decode the data streams of an O-NOMA system, thereby providing reliable and efficient detection performance. The DL-based approach has the advantage of being able to control the complicated interference patterns and adapt to different channel settings, making it suitable for practical NOMA systems with varying operating conditions. An excellent method to get over the problems of interference and overlapping signals in NOMA systems is to use DL-based detection for O-NOMA. Using deep neural network technology, this approach can provide accurate and efficient detection, enabling a higher spectral efficiency and improved performance in optical communication systems. It is anticipated that additional study and development in this field will improve the proficiencies of DL-based detection and contribute to the future evolution of O-NOMA technology [40]. The algorithm for the proposed DL technique is presented in Table 2.

3.3. Mathematical model of DL algorithm

The network architecture and training procedure are mathematically represented in the mathematical model of the DLM detection scheme for O-NOMA. The proposed algorithm combines several convolutional layers with fully linked layers. In this study, the DLM structure was modified to accommodate signals with a smaller input (2×128). Because the pooling function can obscure the input data owing to its small size and impact on the veracity of the data, it is not used. We used 1×6 as the kernel size of the convolution window because it is appropriate for the input (2×128). Convolutional layer insertion was followed by the application of dense layers with a 50 % dropout rate. Here is a mathematical representation of the functions of a DL-based detection system [41].

3.3.1. Network architecture

Let X be the input representing the received signal and power allocation coefficients. A DL network can be represented as a series of layers, denoted as $f(i), where\ i = 1, 2, \ldots, L$. Each layer applies a transformation to the input and produces an output. The output of the ith layer, for instance, may be represented by Eq. (6) [42]:

$$H(i) = f(i)\left(H_{\{i-1\}}\right), where\ H(0) = X \tag{6}$$

The final output of the network, representing the predicted symbols or decoded data streams, is indicated in Eq. (7) [43]:

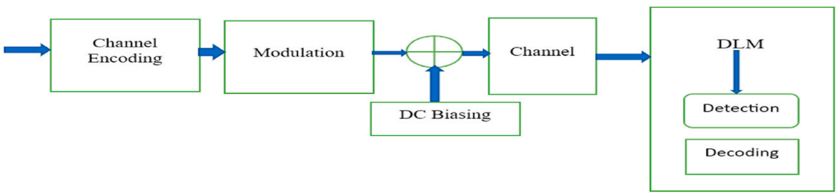

Fig. 2. Schematic of DLM procedures.

Table 2
Deep learning algorithm.

Data Preparation
Generate a large dataset of labeled training examples by simulating the transmission and reception process of the O-NOMA system.
The received signal, power allocation coefficients, and any further details, like channel conditions, should be included in every case.
Ensure that the dataset covers a wide range of channel conditions, power allocations, and interference scenarios.
Network Architecture Design
Design a deep neural network architecture appropriate for the O-NOMA detection problem.
Decide the number of layers, types of layers (e.g., convolutional, recurrent, fully connected), and activation functions based on the problem's complexity and input characteristics.
Consider incorporating techniques like residual connections or attention mechanisms if they prove beneficial.
Network Training
Initialize the deep neural network with random weights.
Divide the dataset into training and validation sets for typical evaluation.
Set hyperparameters such as learning rate, batch size, and number of training epochs.
Use a suitable optimizer and a loss function for training.
Iterate through the training set and perform forward propagation to obtain predictions.
Calculate the loss between the predictions and the ground truth labels.
Perform backpropagation to update the network weights using gradient descent optimization.
Repeat the training process until convergence or for a specified number of epochs.
Use the validation set to assess the model's performance and adjust the hyperparameters as needed.
Model Deployment
When training is finished, the deep neural network is prepared for deployment.
In practical situations, use the network to find sent symbols or decode data streams.
Give the network input in the form of the received signal, power allocation factors, and supplementary data.
Use the network to process the input and output the anticipated symbols or decoded data streams.
Use any necessary decision rules or post-processing procedures to get the final detection findings.
Evaluation and Improvement
Use metrics like BER to assess the efficacy of the DLM detection scheme.
Examine the system's effectiveness in different settings and evaluate it against traditional detection techniques.
Hyperparameter Tuning
Experiment with different hyperparameters (e.g., learning rate, batch size, model architecture) to optimize the model's performance.
Deployment
Once satisfied with the model's performance, deploy it to a real-time or near-real-time processing environment.
Continuously monitor and update the model to adapt to changing signal conditions.
Post-processing
Implement post-processing techniques to improve the model's accuracy, such as filtering out false positives or false negatives.
Security and Robustness
Consider security measures to protect against signal spoofing or interference.

$$Y = H(L) \tag{7}$$

3.3.2. *Training process*

Let $D = \{(X(1), Y(1)), (X(2), Y(2))), ..., (X(N), Y(N))\}$ be the dataset consisting of N labeled training examples.

The goal is to determine the optimal set of network parameters, denoted as θ, that minimizes the discrepancy between the predicted output Y and the ground truth labels $Y(GT)$.

Define a loss *function* $L(Y, Y(GT)$ that quantifies the dissimilarity between Y and (GT).

The training process involves minimizing the average loss over the training examples as given by Eq. (8) [44]:

$$J(\theta) = \frac{1}{N}\sum L\bigg(Y, Y(GT) \tag{8}$$

The network parameters θ are updated iteratively using gradient descent optimization is represented by Eq. (9) [45]:

$$\theta \ < (- \ \theta \ - \ \alpha \ * \nabla J(\theta)), \tag{9}$$

where α is the learning rate, and $\nabla J(\theta)$ is the slope of the loss function with respect to θ.

3.3.3. *Inference*

Given a new input $X(new)$, the DL-based detection system can perform inference to obtain the predicted output $Y(prediction)$.

This can be done by passing the input through the network layers defined by Eqs.(10)–(12) [46,47]:

$$H(0) = X(new), \tag{10}$$

$$H(i) = f(i)\left(H_{\{i-1\}}\right) \, for \, i = 1, 2, ..., L, \tag{11}$$

$$Y(prediction = H(L)) \tag{12}$$

The core of DLM detection for O-NOMA was captured using this mathematical model. However, the particular network design, activation functions, and loss function formulation determine the precise mathematical equations for the network layers and the loss function. It is important to select appropriate mathematical models for each component based on the characteristics of the problem and desired performance objectives [48]. Fig. 3 illustrates the deep neural network topology. To improve the potential for complicated patterns to converge, deep neural networks add more hidden layers than artificial neural networks do. Each network layer was chained together by using the output of the previous layer as the input of the one that came before it. One method of building deep neural networks is using fully connected neural networks, which are also known as fundamental deep neural network topologies. Each neuron in a layer is connected to all other neurons in the layer that comes after it, which is composed of multiple thick layers. However, when the network size increases, overfitting may occur because there are too many parameters. To avoid overfitting, a dropout layer may be added to the network to remove random neurons. In contrast, convolutional neural networks, which have been extensively used in the field of computer vision, are constructed using fully connected neural networks to extract features. A convolutional layer was added to convolve the inputs. Convolution reduces the output size and the number of parameters that require training. As a result, it offers a way to simplify things while also increasing the training effectiveness.

3.4. Complexity in DLM

DL-based detection methods for O-NOMA offer several advantages over conventional detection methods, but they also have their own complexities. The complexities associated with DL detection compared with conventional detection methods are as follows [49].

1. **Training Complexity**: DL models require a significant amount of labeled training data to learn the detection task effectively. Creating a diverse and representative dataset for training is a complex and time-consuming process. The dataset must cover various channel conditions, power allocations, and interference scenarios to ensure robustness and generalizability. Additionally, training deep neural networks involves iterating through the dataset multiple times, which requires substantial computational resources and time.
2. **Model Complexity:** Deep neural networks consist of multiple layers and numerous parameters. Designing an optimal network architecture that includes the number of layers, types of layers, and connectivity patterns is a complex task. Choosing appropriate activation functions, regularization techniques, and optimization algorithms requires careful consideration, and often involves extensive experimentation. Model complexity increases with the size and depth of the network, which can lead to higher computational requirements and training times.
3. **Computational Complexity**: DL models are computationally intensive, particularly in the training phase. Training deep neural networks involves performing forward and backward propagation on large-scale datasets, which require significant processing power. This complexity is further amplified when working with high-dimensional data such as complex-valued signals in O- NOMA. Training DL models may require access to specialized hardware, such as graphics processing units (GPUs) or dedicated accelerators, to handle computational demands.
4. **Generalization Complexity**: DL models have the ability to learn complex patterns and generalize well to unseen data. However, achieving good generalization requires careful regularization and hyperparameter tuning. Determining the optimal network architecture, regularization techniques, and hyperparameter settings can be challenging and may require extensive trial-and-error or advanced optimization methods. Effective mitigation measures are needed to address the common worry in DL of overfitting, which occurs when a model performs well on training data but badly on new data.
5. **Interpretability Complexity**: DL models are often referred to as black boxes because of their complex nature. Understanding how a model arrives at its predictions or decisions can be challenging. Interpreting learned representations and decision-making

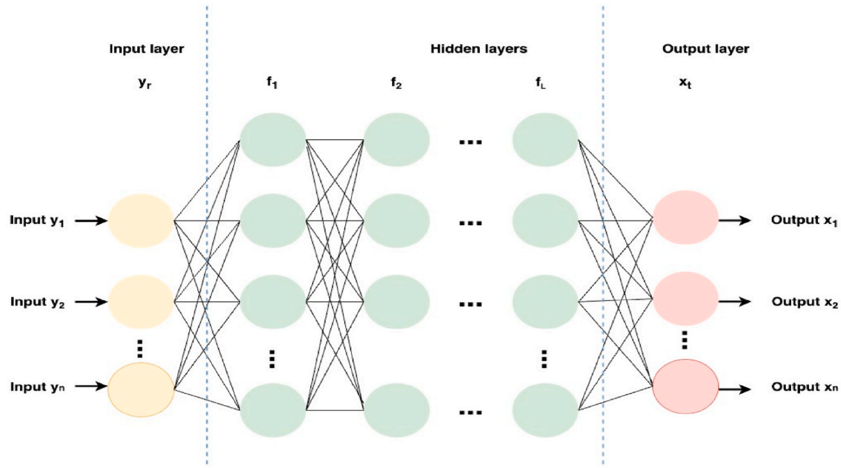

Fig. 3. Structure of Neural network.

processes of deep neural networks is an ongoing research area. On the other hand, conventional detection methods often have more straightforward interpretations, allowing for a better understanding of the underlying algorithms and decision rules.

It is important to note that while DL-based detection methods introduce complexities, they also offer significant advantages in handling complex interference patterns and adapting to varying channel conditions. These complexities can be mitigated through careful network design, efficient training strategies, and leveraging advancements in hardware and software. As the field of DL continues to advance, efforts are being made to address these complexities and to make DL more accessible and efficient for various applications, including O-NOMA detection.

3.5. User cluster strategy

A user group or user cluster strategy for signal detection in 5G waveforms using DL is a sophisticated approach for efficiently managing the complex and dynamic wireless communication environment of 5G networks. In this strategy, users are grouped or clustered based on various parameters such as modulation schemes, signal-to-noise ratios, mobility patterns, and traffic demands. These user groups help to create a more structured representation of diverse user bases in 5G networks. DL methods such as neural networks are then applied to these user clusters to improve signal detection and resource allocation. The DL model learns to recognize the patterns and characteristics specific to each user group. This allows for more accurate and efficient detection of signals within each cluster, thereby enhancing network performance. Furthermore, by understanding the unique requirements and behaviors of different user clusters, network resources can be allocated more effectively. For example, users with high data demands may receive higher priority or more bandwidth, whereas low-power, low-data-rate Internet of Thing devices can be managed differently. Overall, this user group or cluster strategy leverages DL to enhance the intelligence and adaptability of 5G networks, ultimately leading to improved network performance, user experience, and efficient resource utilization in the era of 5G communications.

4. Simulation results

For the M-MIMO structures, DL and conventional algorithms were simulated using MATLAB 2014. The main goal of the proposed study was to investigate the performance of DL algorithms for 16 × 16, 32 × 32, and 64 × 64 M-MIMO topologies. For our investigation, we chose the Caribbean channel and 256-QAM transmission method. The subcarriers were chosen to be 128, the FFT size was 128, the iteration performance was 40, the coding rate was 1/16, and the constraint length was 8. The structure of the proposed DLM is listed in Table 3.

When compared to the reference O-NOMA signal at the SNR of 8.8 dB, the (16 × 16 MIMO) BER performance for Fig. 4 is accomplished at an SNR of 5.5 dB by the DLM, 7 dB by AMP, 7.6 dB by ZFE, and 8.4 dB by MMSE. Thus, it can be said that the new DLM approach outperformed the standard methods by 2.5, 2.1, and 3.1 dB in terms of SNR gain (see Fig. 5).

In order to evaluate the DLM's expected performance even more completely, the DLM was used to detect the signal in a simulated 32 × 32 MIMO configuration. Fig. 5's BER curve illustrates how effective the DLM is in comparison to traditional detection systems. It is also mentioned that the 32 × 32 MIMO structure outperformed the 16 × 16 MIMO structure in terms of performance. DLM achieved a 2.5 dB boost in 64 × 64, which is equivalent to AMP's (16 × 16). Additionally, compared to 64 × 64 MIMO, it is found that 32 × 32 architectures have a higher level of complexity.

Fig. 6 shows the BER of the 64 × 64 MIMO structure using the DL method. For DLM, AMP, ZF, and MMSE, a BER of 10^{-3} was reached for SNRs of 3.2, 4.8, 5.6, and 6 dB, respectively, as equated with the O-NOMA signal (8.2 dB). As can be observed, the suggested DLP produced gains of 1.6, 2.4, and 2.8 dB in comparison with using the aforementioned detection technique. Owing to the absence of matrix inversion, the suggested low complexity of the DLM is evident. Further, it is realized that the DLM is 64 × 64 gained 1.6 dB (64 × 64 DLM) and 2.3 dB (16 × 16 DLM. Therefore, it can be observed that the suggested DLM outperforms the detection algorithms used by AMP, ZF, and MMSE.

The PSD of the 16 × 16 O-NOMA waveform represents the distribution of the signal power across different frequency components, as shown in Fig. 7. In DL applications, analyzing this PSD helps neural networks understand the spectral characteristics of the NOMA signal, aiding in tasks such as channel estimation, interference management, and modulation recognition. This spectral information is crucial for optimizing MIMO-NOMA communication systems, enabling efficient data transmission, and enhancing the overall system performance. The original signal has a PSD value of −425, which is further improved by applying detection algorithms such as MMSE

Table 3
DLM structure.

Layer	Parameters	Activation
Input size	2 × 128	
Dropout	50 %	
Dense layer	256 neurons	Re-LU
Dropout	50 %	
Dense layer	256 neurons	Re-LU
Conv layer	1 × 6 filter	Re-LU
Conv layer	1 × 6 filter	Re-LU
Dense layer	256 neurons	Re-LU

Table 4
Complexity.

S. No	Detection methods	Complexity
1	MMSE	$2L(Mm + 2l - 1)$
2	ZFE	$2L(Mm + 2l)$
3	AMP	$2LMm$
4	Proposed Method	LM

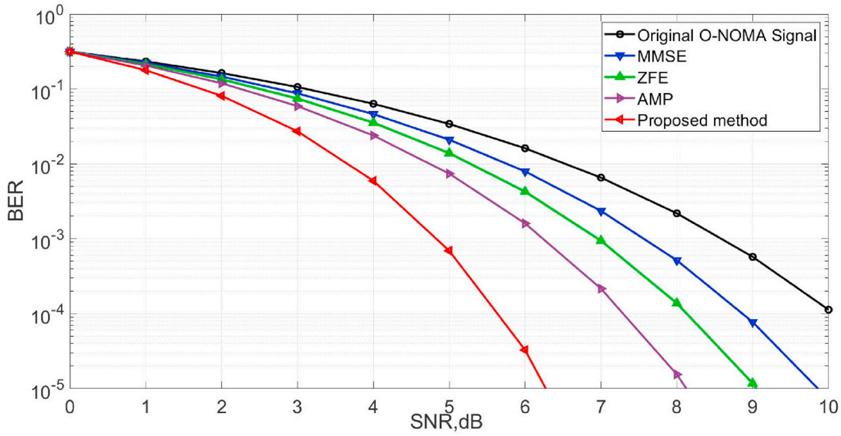

Fig. 4. 16 × 16 BER analysis.

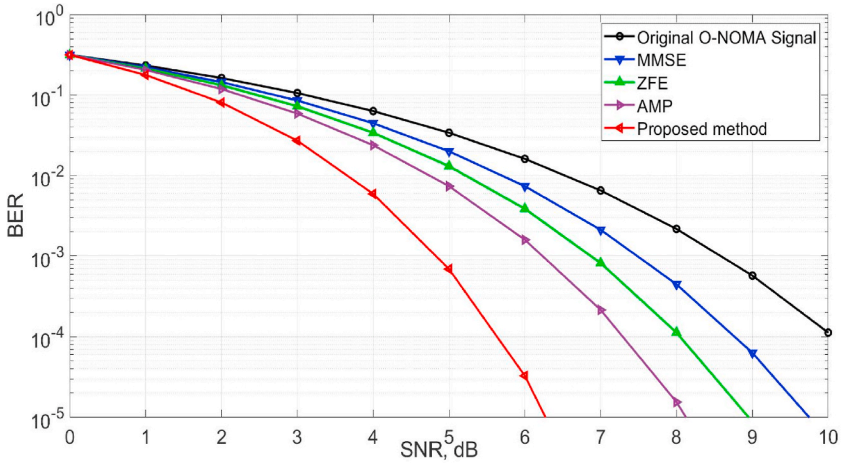

Fig. 5. 32 × 32 BER analysis.

(−530), ZFE (−690), AMP (−720), and the proposed method (−495). Hence, it is concluded that the proposed method obtains a gain of −570 as compared with the original signal. Hence, the out-of-band signal is suppressed by utilizing detection algorithms.

Fig. 8 shows the PSD analysis for the 64 × 64 NOMA structure. The original signal has a PSD value of −680, which is further improved by applying detection algorithms such as MMSE (−720), ZFE (−880), AMP (−930), and the proposed method (−1110). Hence, it is concluded that the proposed method obtains a gain of −570 as compared with the original signal. Hence, the out-of-band signal is suppressed by utilizing detection algorithms.

We examined the performance of the PSD for the O-NOMA signal, DLM, AMP, ZFE, and MMSE, as shown in Fig. 9. The bandwidth leakage of the O-NOMA signal was − −1200, whereas that of the DLM was − −2500, AMP was − −2200, ZFE was 1900, and MMSE was 1600. Consequently, DLM achieves effective spectrum access compared to traditional techniques.

1. Table 4 and Fig. 10 both show the complexity levels of the detection techniques. The number of summations and convolutions is necessary to obtain the best detection, which is referred to as the complexity. The intricacies of the designed MLD were 19761, and the criteria for adding 16 × 16 systems for MMSE [13], ZFE [13], and AMP [26] were 33372, 28276, and 22624, respectively. For

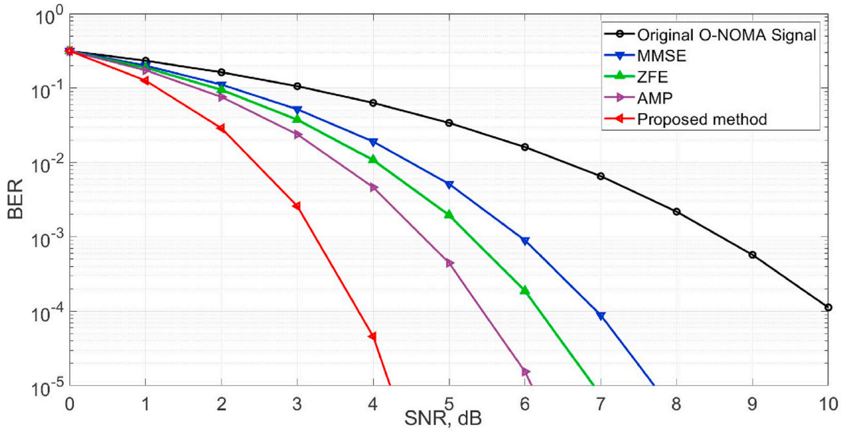

Fig. 6. 64 × 64 BER analysis.

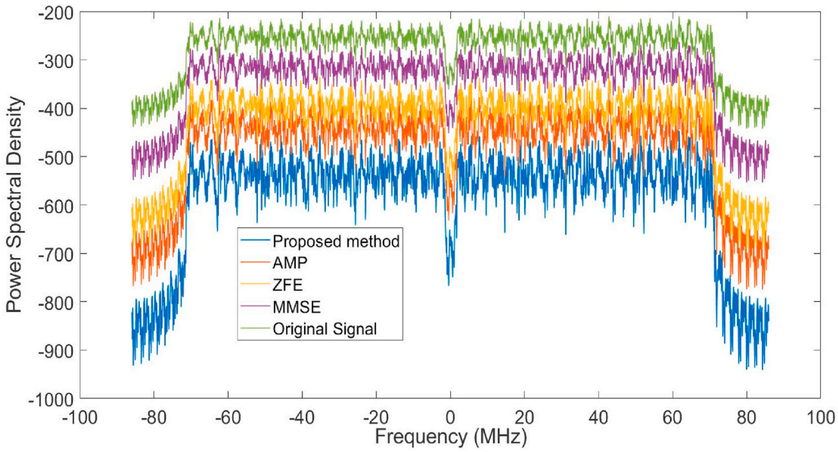

Fig. 7. PSD analysis for 16 × 16.

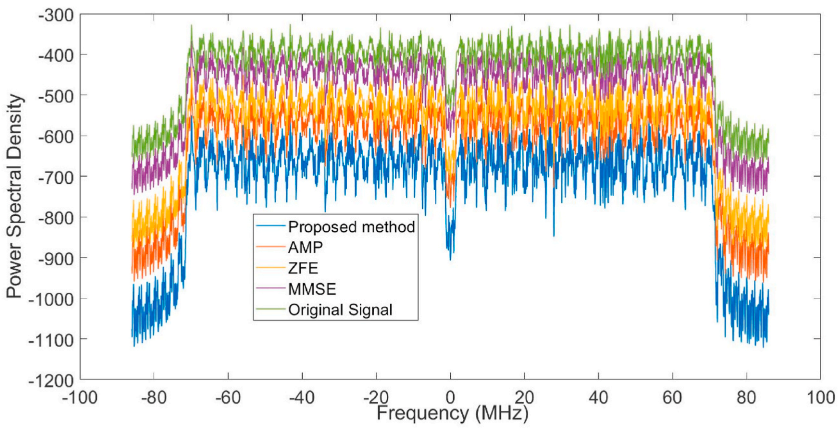

Fig. 8. PSD analysis for 64 × 64.

32 × 32, the necessary increases were 61128, 52213, and 59347, respectively, and the recommended MLD was 51786. The MMSE [13], ZFE [13], and AMP [26] requirements for 64 × 64 are 86543, 73425, and 69743, respectively, whereas the suggested MLD is 61543 [39].

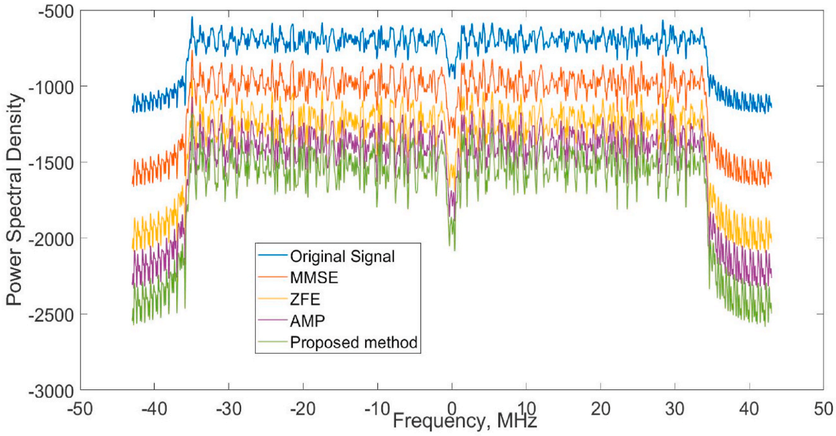

Fig. 9. PSD analysis of 256 × 256.

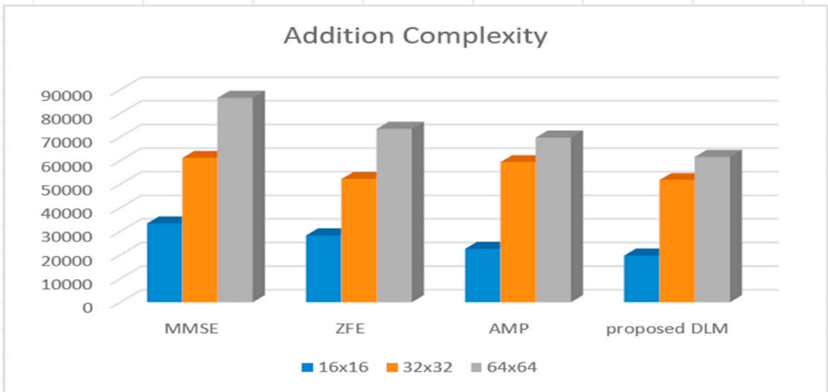

Fig. 10. Complexity.

5. Conclusion

In this article, we examine the performance of DLM signal detection in M-MIMO systems, which has shown significant potential for improving the BER and PSD efficiency with minimum complexity. The proposed DLM effectively detects signals in M-MIMO systems while considering factors such as BER, PSD, and complexity. It is seen that the DLM obtained a substantial BER gain of 1.6, 2.4, and 2.8 dB for 64 × 64 and 1.5 dB, 2.1 dB, and 2.9 dB for 16 × 16 M-MIMO systems. Furthermore, it significantly reduced the spectrum leakage to −2500 as compared to the original O-NOMA (−1200). However, it is noted that the high-order modulation schemes contain high computational intricacies due to the utilization of large numbers of antennas. Overall, combining DL methods with M-MIMO signal detection offers a potential way to improve the efficacy and throughput of 6G radios. Future wireless networks may benefit even more from improved signal recognition algorithms, which could result from continued research and development in this field. The DL method for signal detection in M-MIMO-NOMA systems has some notable limitations. First, the enormous computational complexity required for training deep neural networks can be a significant drawback, particularly in real-time communication scenarios. The large-scale nature of M-MIMO-NOMA systems requires substantial computational resources, which may not be feasible in resource-constrained devices or in situations where low-latency communication is essential. Second, DL methods often rely on extensively labeled datasets for training, which may not always be readily available, especially in emerging communication scenarios such as M-MIMO-NOMA. Acquiring labeled data for various channel conditions and user scenarios can be time consuming and costly. Additionally, DL models may lack interpretability, making it challenging to understand the decision-making process, troubleshoot issues, or adapt effectively to changing network conditions. In conclusion, while DL holds promise for signal detection in M-MIMO-NOMA systems, addressing these limitations is crucial. Future research should focus on reducing computational complexity, developing efficient training techniques, and enhancing model interpretability to make DL a more practical and effective solution for this challenging communication paradigm.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Arun Kumar: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Nishant Gaur:** Writing – review & editing, Investigation, Conceptualization. **Manoj Gupta:** Writing – review & editing, Validation, Methodology, Formal analysis, Data curation. **Aziz Nanthaamornphong:** Writing – review & editing, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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