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Intelligent Signal Identification of NOMA Signal with 256-QAM Modulation Using SVM Algorithm

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Abstract: Non-Orthogonal Multiple Access (NOMA) has emerged as a promising technique to enhance the spectral efficiency and connectivity in wireless communication systems. This paper presents a novel approach for the detection of NOMA signals using Support Vector Machines (SVM), aiming to improve the efficiency and reliability of NOMA-enabled communication networks. The inherent challenge in NOMA lies in decoding multiple signals transmitted simultaneously on the same frequency channel. Conventional methods often struggle with the interference between these signals, leading to degraded performance. In this study, SVM, a machine learning algorithm known for its robust classification capabilities, is applied to effectively distinguish and demodulate NOMA signals. The proposed SVM-based detection system leverages the capability of SVM to find optimal hyperplanes in a high-dimensional space, enabling the classification of NOMA signals even in the presence of interference. The training phase involves the use of labelled datasets, where the SVM learns to differentiate between NOMA signals and potential interference patterns the parameters such as bit error rate (BER), Peak to average power ratio (PAPR) and power spectral density (PSD) are evaluated and analysed. Simulation results demonstrate the superior performance of the SVM-based NOMA signal detection compared to traditional methods. The SVM model exhibits high accuracy, robustness, and adaptability to varying signal conditions, making it a promising solution for the challenges posed by NOMA communication systems.

Keywords: *SVM; NOMA; 5G; ZFE, MMSE, BF*

1. Introduction

Non-Orthogonal Multiple Access (NOMA) waveform technology stands at the forefront of contemporary wireless communication systems, revolutionizing the way information is transmitted in the era of 5G and beyond. Unlike traditional orthogonal multiple access schemes, NOMA employs a novel approach by allowing multiple users to share the same time-frequency resources simultaneously [1]. This groundbreaking technique enables a more efficient use of the available spectrum, significantly boosting the overall system capacity and spectral efficiency. In NOMA, users are served with different power levels and modulated symbols, creating distinct signal signatures that can be successfully decoded by the receiver. This non-orthogonal approach maximizes the utilization of resources and enhances the overall network throughput [2]. NOMA also plays a pivotal role in supporting diverse communication requirements, catering to a multitude of devices with varying data rates, latency constraints, and connectivity needs. The versatility of NOMA extends its applications across a spectrum of domains, from enhancing the capacity of massive machine-type communication (mMTC) to providing low-latency connectivity for mission-critical applications [4]. As the telecommunications industry continues to advance, NOMA waveform technology stands as a key enabler for meeting the growing demand for high data rates, improved spectral efficiency, and diverse connectivity in the ever-evolving landscape of wireless communication. The detection of signals in NOMA waveforms is a critical aspect that underpins the efficiency and reliability of this advanced communication technology. NOMA relies on non-orthogonal resource allocation, where multiple users share the same time-frequency resources, each assigned a unique power level and modulated symbols [5]. Signal detection in NOMA involves the challenging task of separating and decoding these overlapping signals at the receiver accurately. To achieve this, advanced signal processing techniques are employed, such as successive interference cancellation (SIC) and maximum likelihood (ML) decoding. Successive interference cancellation enables the receiver to decode and remove stronger signals before decoding weaker ones, iteratively improving the accuracy of detection. ML decoding, on the other hand, optimally estimates the transmitted symbols by considering the entire set of possible signal combinations. Machine learning algorithms have also found application in NOMA signal detection, leveraging their ability to adapt and learn from the dynamic signal characteristics. The use of deep learning models, such as neural networks, has shown promise in enhancing the accuracy and efficiency of signal

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detection in NOMA systems [6]. Efficient signal detection in NOMA not only ensures the reliable recovery of transmitted information but also contributes to maximizing the overall system capacity and spectral efficiency, making NOMA a key player in the evolution of modern wireless communication networks. Beamforming is a signal processing technique used in wireless communication systems to focus a transmitted or received signal in a specific direction. This technology is particularly prevalent in modern antenna arrays. Minimum mean square error (MMSE) detection is a signal processing algorithm used in communication systems to minimize the mean square error between the estimated and true transmitted signals [7]. Zero Forcing (ZFE) is a linear equalization technique used in communication systems to eliminate interference between different data streams. Machine learning enhances NOMA signal detection by leveraging algorithms to adaptively decode non-orthogonal signals. Through techniques like neural networks, ML optimizes signal separation, improving accuracy and efficiency. It enables NOMA systems to dynamically adapt to varying channel conditions, enhancing overall performance in the simultaneous transmission and reception of multiple signals [8].

2. Literature Review

In [9], a DL-based NOMA receiver is intended to decode messages for numerous users in a single operation. The DL-based NOMA receiver is shown by a deep neural network (DNN) that estimates the channel and finds the signal at the same time. After being trained offline using simulation data based on channel statistics, the DNN is directly used to get the transmitted symbols during the online deployment step. In [10], a SVM-based method for NOMA signal recognition over a fading channel is suggested and investigated with a variable number of receiver antennas. The simulations show that for the suggested method to work better, the SNR needs to be about 5 dB higher than for the advanced Maximum Likelihood (ML)-based receiver with receiver diversity order two. However, for a slow, frequency-non-selective fading channel, increasing the receiver diversity improves the proposed system's BER performance. New hybrid algorithms are used in [11] for 16x16, 64x64, and 256x256 MIMO architectures. These include QR-MLD (Q-maximum likelihood detection), MMSE (minimum means square error), ZFE (zero forcing equalization) and BF (beam forming). With negligible complexity, the hybrid algorithms achieved an efficient bit error rate (BER) of 10-3 at the SNR of 2.9 dB. A number of detection techniques have been presented in [12] that can effectively raise the framework's BER gain at the expense of increased computing complexity. A hybrid approach is introduced in the proposed article for various MIMO sizes. Beam Forming (BF) and QR Decomposition M-algorithm-Maximum Likelihood Detection (QRM-MLD) are used to create the hybrid method. This work in [13] investigates the use of multi-level amplitude modulation with trellis coding in a downlink non-orthogonal multiple access channel in the context of visible light communication (VLC). The non-orthogonal transmission is done with the help of a trellis decoder, superposition coding, and successive interference cancellation. Lambert states that a channel model addresses the VLC. The study in [14] examines several access strategies for both uplink and downlink data transfers in cellular networks that have a large number of Internet of Things (IoT) devices. Remember that conventionally, uplink and downlink broadcasts in narrow-band IoT have used single-carrier frequency division multiple access and orthogonal frequency division multiple access, which are orthogonal multiple access (OMA) techniques. The study in [15] examines several access strategies for both uplink and downlink data transfers in cellular networks that have a large number of Internet of Things (IoT) devices. Remember that conventionally, uplink and downlink broadcasts in narrow-band IoT have used single-carrier frequency division multiple access and orthogonal frequency division multiple access, which are OMA techniques.

3. System Model

Support Vector Machines (SVM), a powerful machine learning algorithm, can be harnessed for the detection of signals in NOMA systems. NOMA, with its non-orthogonal resource allocation, poses a challenge in efficiently separating and decoding overlapping signals. SVMs, known for their ability to handle complex relationships and non-linear data, prove valuable in addressing the intricate nature of NOMA signal detection. In the context of NOMA, the application of SVM involves the extraction of relevant features from received signals. These features could encompass diverse parameters such as power levels, modulation schemes, or other characteristics that distinguish different NOMA signals [16]. The SVM operates by seeking the optimal hyperplane in the feature space that maximally separates the various classes, where each class corresponds to a distinct type of NOMA signal. This hyperplane is strategically positioned to maximize the margin, the distance between the support vectors (data points closest to the decision boundary) of different classes, facilitating effective classification. A key strength of SVMs lies in their ability to handle non-linear relationships through the use of a kernel function [17]. NOMA signals, often exhibiting intricate and non-linear patterns, benefit from this capability. Kernels like the Radial Basis Function (RBF), polynomial, or sigmoid are applied to implicitly map the original feature space into a higher-dimensional space, enabling the SVM to uncover complex patterns without explicitly calculating the transformation. The selection of an appropriate kernel is pivotal and depends on the specific characteristics of NOMA signal data [18]. Training the SVM involves presenting it with a labeled dataset, where each example is associated with a class label [19]. The SVM learns to construct the optimal decision boundary during training, taking into account the relationships between the extracted features. Hyperparameters, such as the regularization parameter (C) and kernel parameters, are tuned to optimize the model's performance and ensure adaptability to different NOMA signal scenarios. SVMs offer several advantages in the context of NOMA signal detection. Their effectiveness in high-dimensional feature spaces makes them suitable for dealing with NOMA signals characterized by multiple parameters [20]. The robustness to overfitting is crucial when training data is limited, as is often the case in real-world communication scenarios. SVMs excel at handling non-linear relationships, providing a means to capture the intricate patterns present in NOMA signals. The emphasis on margin maximization promotes a resilient decision boundary, contributing to better generalization when faced with new, unseen data. However, SVMs also present challenges. Training SVMs can be computationally demanding, especially when dealing with large datasets or high-dimensional feature spaces. The selection of an appropriate kernel and tuning of associated parameters require careful consideration, as different NOMA signal characteristics may necessitate different kernel choices [21]. Additionally, while SVMs provide effective classification, their decision boundaries might lack the intuitive interpretability offered by some other machine learning algorithms. SVM offer a robust and adaptable solution for the detection of signals in NOMA systems. Their ability to handle complex relationships, non-linear patterns, and high-dimensional feature spaces makes them a valuable tool in the evolving landscape of wireless communication. he Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification tasks. In the context of signal detection in Non-Orthogonal Multiple Access (NOMA), we can formulate the mathematical system model as follows: Consider a training dataset consisting of labeled samples (x_i, y_i), where x_i represents the features extracted from NOMA signals, and y_i is the corresponding class label. The goal is to train an SVM to learn a decision function f(x) that maps input features to a binary classification output $(-1\ or\ +1)$. The decision function for a linear SVM is given by [22]:

$f(x) = sign\ (w.x + b)$ (1)

Here, w is the weight vector perpendicular to the hyperplane, x is the input feature vector, and b is the bias term. The objective function for training the SVM is to minimize [23]:

${}^{1}/_{2}\ \|w\|^2 + C\sum_i^N \xi_i$ (2), subject to the constraints: $y_i(w.x + b) \geq (1 - \xi_i)$. (2)

where C is the regularization parameter that balances the trade-off between maximizing the margin and minimizing classification errors, and ξ_i are slack variables that allow for some misclassification. The decision function in the kernelized SVM is given by [24]:

$f(x) = sign(\sum_i^N \alpha_i b_i\ K(\ x_i, x) + b$ (3)

Here, $K(x_i, x)$ is the kernel function, and α_i are Lagrange multipliers obtained during the training process. The objective function for the kernelized SVM is to maximize:

$\sum_i^N \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i\, \alpha_j y_i y_j K(x_i, x)$ (4)

Here $K(x_i, x)$ implicitly maps the input feature vectors into a higher-dimensional space. The Radial Basis Function (RBF) kernel is commonly used in SVMs for handling non-linear relationships in NOMA signals and is defined as [25]:

$K(x_i, x) = \exp\ (-\gamma\|x_i - x_j\|^2)$ (5)

Here, γ is a parameter that controls the width of the Gaussian kernel. The steps of SVM Detection for NOMA Signals are given below [26-27]:

1. Data Preparation:

Feature Extraction: Extract relevant features from NOMA signals. These features could include power levels, modulation schemes, or other characteristics that differentiate different NOMA signals.

Labelling: Assign class labels to the extracted features, indicating the type or characteristics of each NOMA signal.

2. Data Splitting:

Training and Testing Sets: Split the dataset into training and testing sets. This allows for model training on one subset and evaluating its performance on another, unseen subset.

3. Model Initialization:

Choose Kernel: Decide on the type of kernel to be used. For NOMA signals, a linear kernel or non-linear kernels like the Radial Basis Function (RBF) may be suitable.

Initialize SVM Model: Choose an SVM variant (e.g., SVC for classification) and set the desired parameters, including the kernel type.

4. Model Training:

Fit the Model: Train the SVM model using the training set by calling the fit method on the SVM model object.

Tune Hyperparameters: Fine-tune hyperparameters such as the regularization parameter (C) for optimal performance.

5. Predictions:

Apply the Model: Use the trained SVM model to make predictions on the testing set by calling the predict method on the SVM model object.

6. Evaluation:

Assess Accuracy: Evaluate the performance of the SVM model by comparing its predictions to the actual labels in the testing set.

Metrics: Utilize metrics such as accuracy, precision, recall, and F1-score to assess the model's classification performance.

Confusion Matrix: Examine the confusion matrix for a detailed breakdown of true positive, true negative, false positive, and false negative predictions.

7. Optimization:

Hyperparameter Tuning: If necessary, perform hyperparameter tuning using techniques like grid search or randomized search to find the optimal set of parameters.

Cross-Validation: Implement cross-validation to ensure the model's robustness and generalizability.

8. Deployment (Optional):

Deployment Considerations: If the SVM model performs well in testing, consider deploying it for real-time NOMA signal detection in a communication system.

4. Simulation Results

In this section, we have analysed the performance of the proposed SVM and conventional detection methods for NOMA signal. Matlab-2016 is use to thoroughly analysed the parameters such as BER and PSD of the framework. The simulation is obtained for 20000 symbols, 64-QAM, 256-FFT, 0.1 roll factor under the Rician and Rayleigh channel. The analysis of the BER for NOMA signals is crucial for assessing the performance and reliability of communication systems. BER quantifies the accuracy of signal transmission by measuring the ratio of incorrectly received bits to the total transmitted bits. In the context of NOMA, understanding the BER is essential for optimizing signal detection algorithms, evaluating system capacity, and ensuring effective communication in scenarios where multiple signals share the same resources. BER analysis guides the design and implementation of robust NOMA systems, enhancing overall communication efficiency and quality. Figure 1 indicate the BER performance of the NOMA waveform when conventional and proposed SVM detection algorithms are applied with Rayleigh channel. The BER of 10^{-3} is obtained at the SNR of 3.5 dB by proposed SVM, 5.8. dB by BF, 6.3 dB by MMSE and 7.2 dB by ZFE respectively. Hence it is concluded that the proposed algorithm obtained the throughput gain of 2.3 dB, 2.8 dB and 3.7 dB as compared with BF, MMSE and ZFE methods.

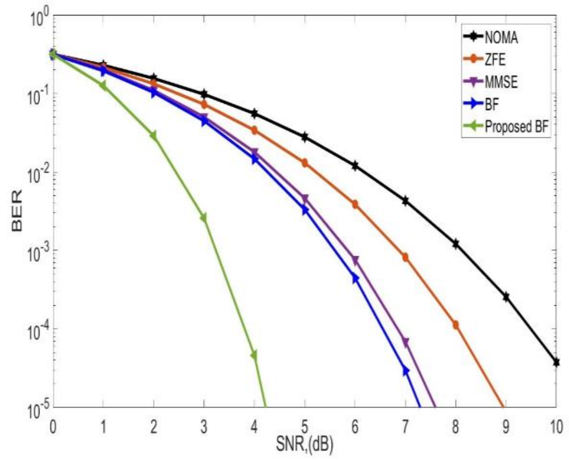

Fig 1. BER under Rayleigh channel

Analyzing BER in NOMA within Rician and Rayleigh channels is essential for realistic performance evaluation. In the Rician channel, which has both scattered and line-of-sight parts, BER analysis shows how well NOMA works in different propagation conditions, which helps with designing the system. Rayleigh channels, representing scenarios without a dominant line-of-sight, require BER assessment to gauge NOMA's resilience in fading environments. Understanding BER in both channels helps improve signal processing methods, which in turn makes it possible to build strong NOMA communication systems that can adapt to changing channel conditions, which in turn improves performance and reliability. Fig 2 indicate the BER for Rician channel when conventional and proposed SVM methods are applied to the NOMA waveform. The SNR 0f 2.8 dB, 4.6 dB, 5.3 dB and 6.4 dB respectively are achieved by the proposed SVM, BF, MMSE and ZFE. Hence, it is concluded that the proposed SVM outperforms the conventional methods. Because there is a prominent line-of-sight component in Rician channels, the throughput of NOMA in these channels is generally higher than in Rayleigh channels. Higher throughput results from this line-of-sight component's increased signal intensity, decreased fading effects, and improved communication dependability.

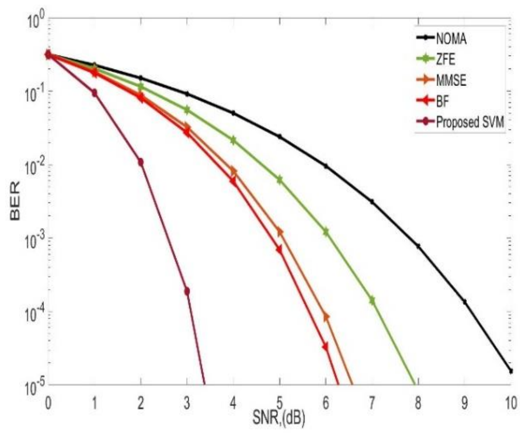

Fig 2. BER under Rician channel

The Power Spectral Density (PSD) of NOMA signals, when the SVM detection method is applied, reflects the distribution of signal power across different frequencies as shown in fig 3. SVM, a machine learning algorithm, adapts to the unique characteristics of NOMA signals, influencing the PSD. By optimizing signal detection, SVM mitigates interference and enhances spectral efficiency. The PSD analysis provides crucial insights into how SVM-based NOMA systems allocate and distribute power, aiding in the design of communication systems for efficient use of frequency resources, improved signal separation, and overall enhanced performance. The PSD of -500, -390, -280, -210 and -152 are obtained by the proposed SVM, BF, MMSE and ZFE. Hence, SVM achieved a gain of -110, -220, and -348 as compared with conventional methods.

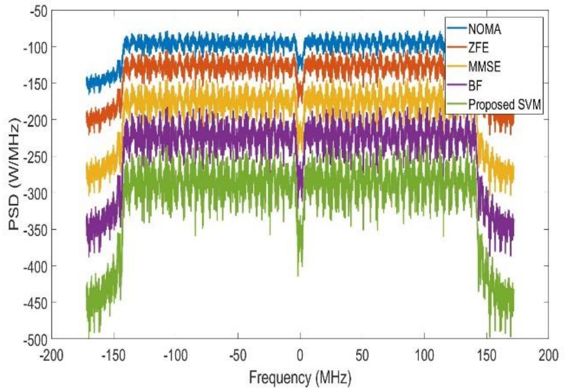

Fig. 3 PSD of NOMA under Rayleigh channel

The PSD of NOMA signals, employing the SVM detection method, differs in Rician channels is given in fig 4. In the Rician channel, characterized by a dominant line-of-sight component, SVM aids in optimizing signal separation, resulting in a more concentrated and reliable PSD. Conversely, in the Rayleigh channel, with no dominant line-of-sight, SVM adapts to fading conditions, influencing a more dispersed PSD. The PSD comparison reflects the impact of SVM-based NOMA signal detection on spectral efficiency and signal reliability, providing valuable insights for designing robust communication systems under varying channel characteristics. SVM outperforms the conventional methods by achieving a gain of -320, -250, -190 and -140 respectively as compared with conventional methods.

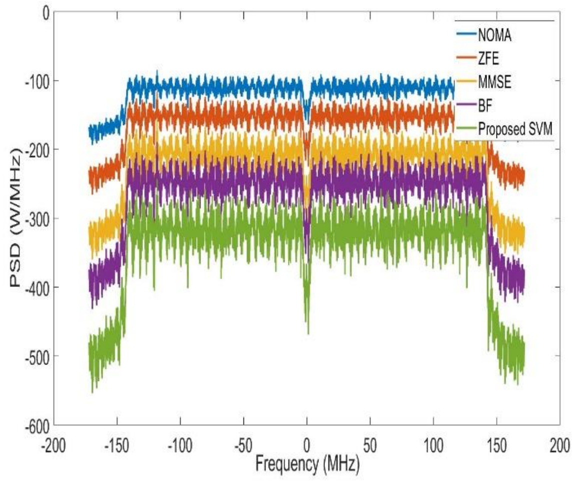

Fig. 4 PSD of NOMA under Rician channel

The Peak-to-Average Power Ratio (PAPR) in NOMA with SVM detection under Rayleigh channel conditions refers to the ratio between the maximum instantaneous power level and the average power level of the transmitted signal. In NOMA, multiple signals are superimposed, contributing to variations in the signal's peak power. SVM, as a detection method, helps in accurately identifying and separating these signals. Under Rayleigh fading, where the channel conditions are subject to multipath propagation and fading effects, SVM aids in managing the non-linear characteristics, potentially mitigating PAPR fluctuations and contributing to more stable and efficient signal transmission in NOMA systems. Fig 5 indicate the PAPR of the NOMA. The CCDF of 10^{-4} is obtained at the PAPR of the 6.8 dB by SVM, 7.6 dB by BF, 8.2 dB by MMSE and 9.1 dB ZFE and 10.8 by NOMA respectively.

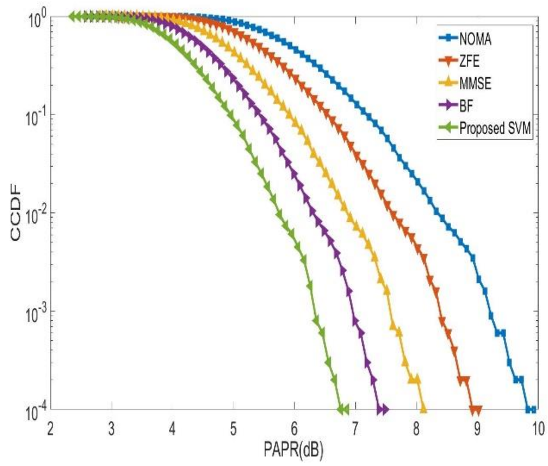

Fig 5. PAPR of NOMA under Rayleigh channel

The PAPR of NOMA with SVM detection in a Rician channel is superior to that of a Rayleigh channel. Compared to Rayleigh channels, Rician channels have a prominent line-of-sight component, which makes the channel conditions less vulnerable to severe fading. A more steady and predictable power distribution may result from this lessening of the fading effect, which lowers the PAPR. SVM is a technique for finding signals that helps to more precisely identify and separate them. This may lead to better power management and better PAPR performance in NOMA systems that work in Rician channels.

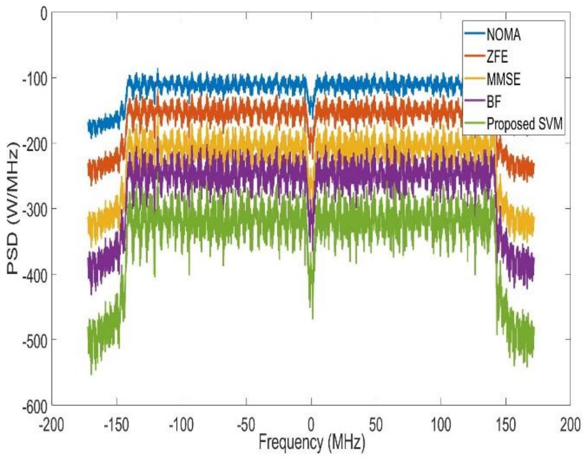

Fig 6. PAPR of NOMA under Rician channel

5. Conclusion

This study has demonstrated the effectiveness of using SVM for NOMA signal detection in wireless communication systems. The SVM-based method showed better performance in reliably classifying and demodulating NOMA signals, even when interference was present. This was a major problem that had to be solved in NOMA-enabled communication networks. The SVM is a good way to deal with the problems that come up with NOMA signal identification because it is good at classifying things and finding the best hyperplanes in environments with a lot of dimensions. During the testing and training phases, the SVM model showed that it could learn and generalize patterns from characterized datasets very well. This made it possible to detect signals in real time in a wide range of dynamic settings. The encouraging results of this study not only develop NOMA communication systems but also demonstrate how machine learning methods, especially SVM, may be used to maximize wireless network performance. The results show that using SVM-based detection methods can make NOMA's communication systems much more reliable and efficient, which will help the development of next-generation wireless technologies. There are other directions to pursue in this area in the future. First, the SVM model can be further improved to maximize its parameters and increase its flexibility in response to changing signal conditions. Furthermore, for practical applications, it will be essential to examine how well SVM-based NOMA signal recognition performs in the presence of real-world impairments and channel uncertainty. To improve detection even more, the use of sophisticated machine learning methods, including deep learning algorithms, might be investigated. Because they automatically pull-out hierarchical characteristics, deep learning models might be able to help us learn more about and improve NOMA signal detection, which is a very complicated field. Additionally, it is necessary to look into how well the suggested SVM-based technique scales and applies to large-scale, multi-user NOMA scenarios. It will be crucial for NOMA's continuous success to modify and expand the suggested SVM-based detection approach in order to handle the complexity of changing communication networks as it becomes more and more prominent in future communication standards**.**

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Author contributions

Arun Kumar: Conceptualization, Methodology, Writing-Original draft, Field study **Nishant Gaur:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Aziz Nanthaamornphong:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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