

# MNSO-Based Ensemble Learning for Signal Detection in MIMO-OTFS Systems for B5G Communications

Panchaxari Mamadapur<sup>1\*</sup>, Dr.S. Anitha<sup>2</sup>, Dr.T. Senthil Kumaran<sup>3</sup>, and Dr.C.S. Pillai<sup>4</sup>

<sup>1\*</sup>Assistant Professor, ACS College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India. panchaxari@acsce.edu.in, <https://orcid.org/0000-0001-7210-2485>

<sup>2</sup>Professor, Department of Electronics and Communication, ACS College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India. dranithas@acsedu.in, <https://orcid.org/0000-0003-0189-2699>

<sup>3</sup>Professor, Department of Computer Science and Engineering, ACS College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India. senthilkumaran@acsce.edu.in, <http://orcid.org/0000-0002-2123-5023>

<sup>4</sup>Department of Computer Science and Engineering, Rajarajeswari College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India. pillai@rrce.org, <https://orcid.org/0000-0003-0263-8131>

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## Abstract

The development of MIMO-OTFS (Multiple Input Multiple Output–Orthogonal Time Frequency Space) has proven to be a great breakthrough and a highly viable waveform for next-generation and future 5G wireless communication networks. However, it suffers from performance degradation when MMSE and ZF are applied to large-scale MIMO systems and fast-changing environments. In order to overcome these limitations, this paper proposes an MNSO-based ensemble learning approach for detecting signals in MIMO-OTFS systems. This approach is based on using Modified Non-Smooth Optimization (MNSO) for dimensionality reduction in conjunction with a two-level ensemble learning model. At the first level, there are machine learning classifiers, namely Linear Regression, Random Forest, Decision Tree, and Support Vector Machine, to detect feature-level signals, and at the second level, there is a Gradient Boosting Bayesian Neural Network (GB-BNN) that learns non-linearities in the delay-Doppler domain. In order to test the system, use a set of 5000 signals generated in MATLAB under Rayleigh and Rician fading with  $16 \times 16$ ,  $64 \times 64$ , and  $256 \times 256$  MIMO structures and 0 to 10 dB SNR values. The experimental findings show that the proposed ensemble model using MNSO shows considerable success in reducing BER from 0.0600 at low SNR to 0.0030 at high SNR. In the case of  $256 \times 256$  MIMO configurations, the proposed model can achieve up to 83.33% error reduction from the traditional MMSE techniques. The ablation study shows the effectiveness of the MNSO as well as ensemble techniques in improving the detection accuracy while reducing complexity. Conclusion: In summary, the proposed framework is scalable and robust and can provide high-accuracy detection solutions for B5G MIMO-OTFS communication systems.

**Keywords:** MIMO-OTFS, Signal Detection, Ensemble Learning, MNSO Optimization, B5G Communications, Delay-Doppler Domain, Bit Error Rate Reduction.

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\*Corresponding author: Assistant Professor, ACS College of Engineering, Visvesvaraya Technological University, Belagavi, Karnataka, India.

## 1 Introduction

It is important to note that the waveform MIMO-OTFS (Multiple Input Multiple Output–Orthogonal Time Frequency Space) can be used for B5G and 6G wireless communication since it exhibits good characteristics in high mobility and doubly dispersive channels. As a rule, unlike other modulation techniques, OTFS operates in the delay–Doppler domain. It makes this technique more stable during fast-changing channels. Moreover, when using massive MIMO technology with this technique, one can increase spectrum efficiency, diversity gain, and transmission reliability (Bhat et al., 2021). Nevertheless, there are some difficulties associated with the application of the technique in the case of multipath fading and the Doppler effect (Qu et al., 2022).

Detection plays a vital role in MIMO-OTFS systems because the signal received after transmission gets significantly distorted due to channel, noise, and interference issues. Detection performance impacts the error rate and efficiency of the entire system. Classical techniques like ZF and MMSE have less complexity, but fail to function efficiently in dynamic channel environments (Singh et al., 2022). The modern hybrid and statistical approaches enhance the performance but still lack scalability for massive MIMO systems (Kumar et al., 2024). Recent research demonstrates that the detection accuracy is even decreased due to channel estimation errors and mobility effects (Shi et al., 2024).

The proposed technique uses an ensemble learning framework based on MNSO and combines optimization-based feature selection with classification methods like SVM, Random Forest, and decision tree techniques. Problem statement: The existing MIMO-OTFS detection algorithms face the issues of complexity, poor adaptability to dynamic channels, and inefficient performance in large-scale systems (Li et al., 2024). Thus, an intelligent and scalable detection scheme for reliable B5G systems is needed Kumar & Nanthaamornphong, (2025).

### Key Contribution

1. Presents the framework of ensemble learning using an MNSO approach for effective signal detection in MIMO-OTFS systems for high-mobility B5G channels.
2. Combines various machine learning classifiers such as SVM, Random Forest, and Decision Tree with feature selection using optimization techniques to enhance robustness and accuracy.
3. Shows greater effectiveness in comparison to traditional and hybrid approaches of detection in a wireless communication environment.

This paper is structured as follows: Section 1 comprises the Introduction and Problem Statement, Section 2 contains literature review, Section 3 discusses MNSO-based Ensemble Learning Methodology, Section 4 deals with experiments & results, Section 5 is on Result Discussion, and finally Section 6 concludes the paper.

## 2 Literature Review

A substantial development of the literature on MIMO-OTFS detection techniques has been observed to enable the performance improvement for high-mobility 6G wireless communication systems. Detection techniques such as RNN, SVM, and neural networks have been used in a large-scale application of MIMO-OTFS systems with Rician and Rayleigh fading channels (Kumar et al., 2024). Decentralized detection through expectation propagation has been proposed to optimize the performance of uplink massive MIMO-OTFS systems (Li et al., 2024). It is noteworthy that deep neural network techniques

exhibit excellent performance in detection of signals under different channel state estimation scenarios (Kumar & Nanthaamornphong, 2025).

Conventional detection techniques like ZF, MMSE, and hybrid ZF-MMSE, ZF-MF detectors continue to be popular because of their relatively low computational complexity and ease of implementation in MIMO-OTFS systems (Kumar et al., 2024). The joint channel estimation and signal detection scheme has also been developed for accurate detection in a dynamic environment with the time-variant channels (Shi et al., 2024). The low-complexity linear diversity-combining detectors have also been proposed for performance enhancement and lower computational cost (Thaj & Viterbo, 2021). The effective equalization and symbol detection techniques are available for highly dispersive MIMO-OTFS channels (Qu et al., 2022).

The recent research developments involve the scalability and robustness in more complicated communication settings. Efficient precoding and detection schemes have been proposed for multi-user massive MIMO-OTFS downlink transmissions (Pandey et al., 2021). The works on performance analysis have demonstrated the benefits of using advanced detection schemes in high-mobility communications (Mamadapur et al., 2025). Deep learning separable CNN models have been used to improve the performance of signal detection in OTFS communications (Wang et al., 2025). It has been found that DL-based detection schemes are robust against hardware impairments in wireless communications (Singh et al., 2023). The methods of spatial correlation compensation have been developed in MIMO-OTFS channels (Bora et al., 2023).

Newer studies include channel estimation, integrated sensing, and optimization schemes for OTFS systems. Beam space MIMO radar and integrated sensing-communication modeling proves that joint operation of radar and communication is possible with OTFS modulation (Dehkordi et al., 2023). Efficient sparse channel estimation with finite resolution ADCs is studied in MIMO-OTFS systems (Mehrotra et al., 2024). Pilot superimposition channel estimation scheme improves detection performance in limited resource settings (Mishra et al., 2021). There are also works on joint radar and communication systems with any time-frequency allocation (Correas-Serrano et al., 2023). Integrated sensing architectures take advantage of delay-Doppler characteristics in order to achieve joint operations (Keskin et al., 2024). Studies on antenna selection and system optimization provide a good performance analysis in terms of spectral efficiency (Bhat et al., 2021). Earlier fundamental studies prove the efficiency of OTFS for radar parameter estimation and communications integration (Gaudio et al., 2020). Low complexity receiver architectures also help to implement this scheme for vehicular applications (Singh et al., 2022).

Previous research on MIMO-OTFS communications has mostly been done in the areas of linear receivers, hybrid receivers, and independent deep learning-based approaches, and there is no comprehensive optimization among detection, channel estimation, and computation cost. Few studies have been performed on adapting to time-varying channels and hardware impairments in real time.

### 3 Materials and Methods

The use of OTFS and MIMO in B5G communication systems is one of the main innovations that makes communication possible in high mobility wireless environments. MIMO-OTFS increases spectrum efficiency, reliability, and performance in time-varying and Doppler shifted channels. Here, the input is encoded to OTFS symbols at the transmitting side, and these symbols are mapped across several antennas using MIMO encoding and beamforming methods. Signals are transformed using inverse symplectic finite Fourier transform (ISFFT) and then using Heisenberg transform and passed through a

noisy fading channel. Signals are decoded at the receiving side using Wigner transform and channel estimation. The received signals are detected using a MIMO detector and decoder to retrieve the information.

The suggested detection scheme increases the efficiency of detection through an MNSO algorithm along with a two-level ensemble learning approach. The role of MNSO is to decrease the complexity of the solution space and select important features from the outputs of the Wigner transformation and channel estimation. These features can be further analyzed using a combination of machine learning techniques in the first level of the ensemble learning technique, such as linear regression, random forest, decision tree, and support vector machine to determine the low-level signal features. In the second level, the Gradient Boosting Bayesian Neural Network is used to detect any nonlinear relationship within the delay-Doppler domain

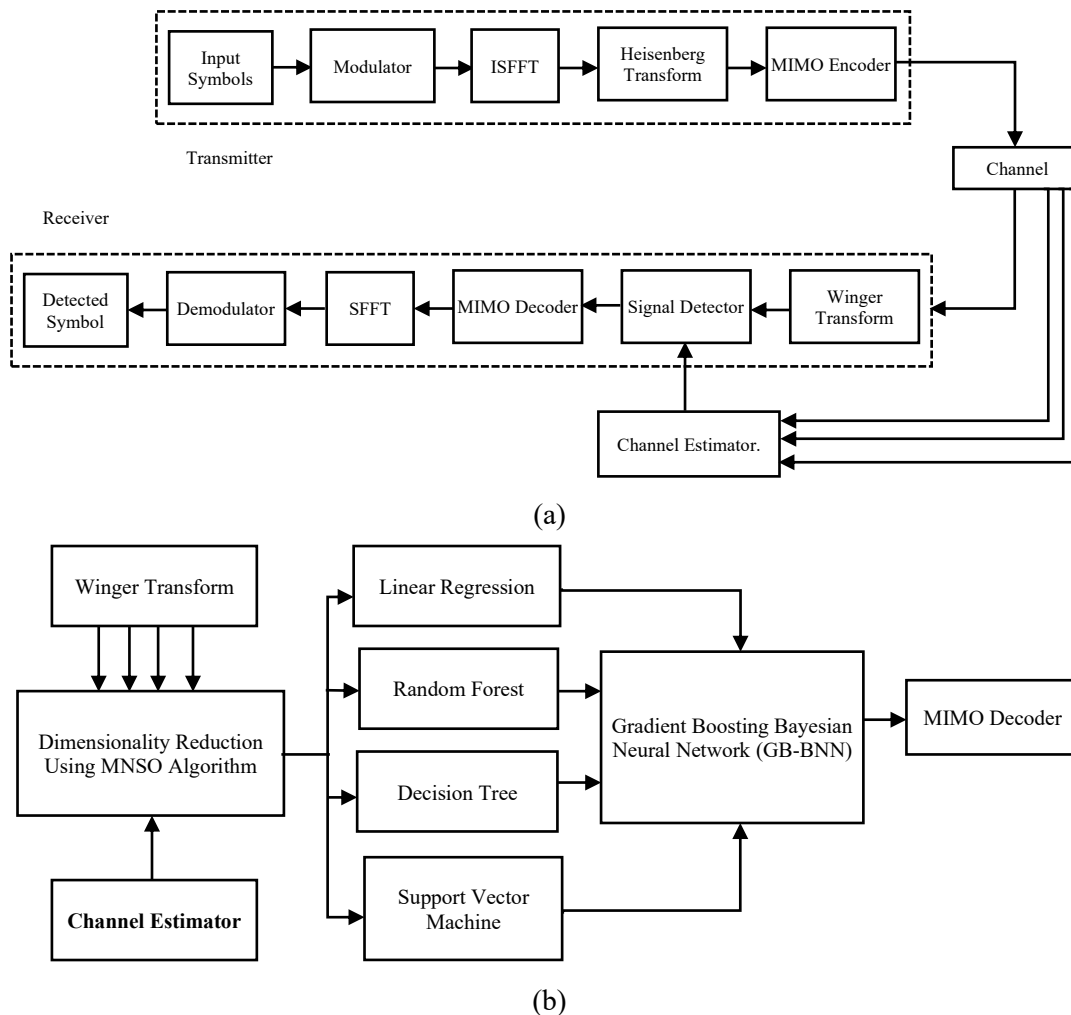


Figure 1(a & b): Proposed signal detector (a) general structure of MIMO-OTFS (b) ensemble learning model

In figure 1(a & b) shows 1(a) MIMO-OTFS transmission and receiver structure using ISFFT, Heisenberg transform, Wigner transform, channel estimation, and signal detection in the delay-Doppler plane, and 1(b) the proposed method using an ensemble of MNSO-based learning that incorporates dimensionality reduction and multiple ML classifiers along with GB-BNN to improve the detection performance of MIMO-OTFS signals.

In a MIMO-OTFS system, the received signal  $R_s$  in a configuration with  $T_n$  transmit antennas,  $R_n$  receive antennas,  $T$  time samples, and  $F$  frequency bins can be expressed as follows (Equation 1):

$$R_s = H \cdot S_s + N \quad (1)$$

Where  $R_s \in \mathbb{C}^{R_n \times T \times F}$  represents the received signal matrix,  $H$  denotes the MIMO channel matrix,  $S_s \in \mathbb{C}^{T_n \times R_n \times T \times F}$  is the transmitted signal matrix, and  $N$  is the additive noise matrix. In the delay–Doppler domain, the channel matrix  $H$  is modeled as a function of both Doppler shift  $\nu$  and delay  $\tau$  (Equation 2):

$$H(\tau, \nu) \quad (2)$$

Where the channel response between transmit and receive antennas at specific delay and Doppler indices is represented by  $h(\tau, \nu)$ . In OTFS modulation, information symbols are mapped onto the delay–Doppler plane, and the transmitted signal  $S_s$  can be expressed as (Equation 3):

$$S_s = \sum_k x[k] \delta(\tau - \tau_k) \delta(\nu - \nu_k) \quad (3)$$

Where  $\delta(\cdot)$  denotes the Dirac delta function and  $x[k]$  represents the transmitted information symbols. The original transmitted symbols  $S_s$  are recovered from the received signal using MIMO-OTFS signal detection techniques, which are essential for reliable symbol reconstruction in time-varying and high-mobility wireless environments.

## Dataset Description

The proposed MIMO-OTFS signal detection model is tested with a synthetic simulation dataset created by using MATLAB for B5G wireless environment. The dataset consists of 5000 samples obtained through 64-QAM modulation in 16x16, 64x64 and 256x256 MIMO structures. For the generation of this dataset, Rayleigh and Rician fading channel models have been considered. In each sample, input features include received signal matrix, channel response, delay-Doppler spectrum, outputs of Wigner transform, channel estimation parameters, Doppler shift values, and SNR value between 0-10 dB. The label is the detected transmitted symbol. The dataset has been generated in MATLAB 2016 with 0.2 validation split ratio.

## Dimensionality Reduction

Dimensionality reduction for MIMO-OTFS is realized through a Modified Non-Smooth Optimization (MNSO) technique for handling high-dimensional complexity in data while retaining key features of Wigner transforms output and channel estimates. This technique eliminates unnecessary data and increases computational efficiency in the presence of noise, interference, and multipath propagation. The problem is posed as a second-order function model with a convex form, where the solution uniqueness is guaranteed by applying Clarke directional derivatives and subdifferentials. Estimates of directional derivatives and generator vector are estimated using quadratic sampling and finite difference methods via least-squares training.

### Algorithm 1 Dimensionality Reduction Using MNSO

**Input:** Received signal's, delay-Doppler parameters, multipath fading characteristics, and noise levels

**Output:** Select best features

Begin;

```
Initialize the step sizes of the population
Define second order type model
Compute exclusive minimiser such that:
Define objective function and give:
Find one-way quadratic sampling function,
Compute predetermined directions where failure occurs
Else if do
Solve best optimal solution
End if
End While
Find the best output value
```

Algorithm 1 applies the Modified Non-Smooth Optimization approach for extracting optimum features from MIMO-OTFS signals. It applies dimensionality reduction through directional derivatives, quadratic sampling, and iterative minimization, thus guaranteeing efficient feature extraction, fast convergence, and better noise-resilient and multipath channel performance.

### **Ensemble Learning**

Incorporating an ensemble learning approach to the problem in MIMO-OTFS systems allows for more effective signal detection by utilizing several ML models to deal with a complex channel response, high-dimensionality of data, and the presence of noise. At the first level, there is Linear Regression, Random Forest, Decision Tree, and Support Vector Machine. Each model extracts different features of the signal, such as linear relationships, non-linear relationships, and high-dimensional separability, respectively. These predictions are then combined together to form an ensemble of signals with higher robustness and generalization capabilities. As a result, various signal characteristics in relation to interference and fading in channels will be detected more accurately.

The second level is based on the Gradient Boosting Bayesian Neural Network (GB-BNN). It minimizes mean squared error by performing residual correction and gradient-based optimization and captures the linear and non-linear dependencies in the delay-Doppler domain. Bayesian inference with Langevin-gradient proposals is used for better uncertainty quantification and optimization efficiency. The end-product ensemble is composed of a set of weighted boosted models to perform accurate and fast predictions. The described hybrid approach provides significant improvements in robustness and predictive capabilities while allowing real-time operation in B5G MIMO-OTFS communication systems.

### **Algorithm 2 Signal Detector Using GB-BNN**

**Input:** Number of features, threshold set for ML models, maximum iteration

**Output:** Predicted signal detection

Define the number of base models A

Initialize weights of base models

Define MSE for a certain exercise set

Compute the incline of the hurt meaning  
 Define generalized for the rest of the data:  
 Samples are accepted or rejected based on the Metropolis-Hastings criteria  $\alpha$ :  
 Compute weighted sum  
 Find the derivative of the residuals  
 (Update MSE) loss function  
 Compute closed-form solution  
 Find the best output value  
 End

The algorithm 2 uses an ensemble signal detector based on GB-BNN. The proposed algorithm includes the usage of various base classifiers and weight learning in combination with the Bayesian approach. The algorithm works in iterations, minimizing MSE through residual gradient descent and Metropolis-Hastening's sampling.

## 4 Results

MIMO-OTFS detection models have been investigated through a simulation in MATLAB 2016 using 5000 samples, batch size 150, 50 epochs, and 0.2 validation split with 64-QAM modulation and 16x16, 64x64, and 256x256 MIMO setups. The simulations consider both Rayleigh and Rician fading channels for modeling real-life wireless environments. It is found that the MNSO+ Ensemble models yield minimum BER from 0.0600 to 0.0030 at 0- and 10-dB levels, respectively, better than LR, RF, and DT hybrid models. It is observed that dimensionality reduction can significantly improve the detection performance in large-scale MIMO scenarios.

### Performance Metrics

Evaluation of the proposed MIMO-OTFS Signal Detection System Performance is carried out using several performance measures. The key performance measure is Bit Error Rate (BER), which describes the proportion of wrongfully decoded bits to the total number of bits transmitted and is given by (Equation 4):

$$BER = \frac{N_e}{N_t} \quad (4)$$

Where  $N_e$  is the number of error bits and  $N_t$  is the total number of transmitted bits.

For assessing the optimization capability of the GB-BNN, employ the Mean Squared Error (MSE) that is mathematically formulated by equation (5):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (5)$$

Where  $y_i$  is the actual output and  $\hat{y}_i$  is the predicted output.

Detection effectiveness can also be interpreted in terms of accuracy (Equation 6):

$$Accuracy = \frac{N_c}{N_t} \quad (6)$$

Where  $N_c$  is the number of correctly detected symbols.

Consequently, the performance enhancement of the suggested approach compared to the existing approaches is measured by the following equation (7):

$$Improvement(\%) = \frac{BER_{baseline} - BER_{proposed}}{BER_{baseline}} \times 100 \quad (7)$$

These measures together serve to assess the performance of the suggested MNSO-based ensemble learning approach.

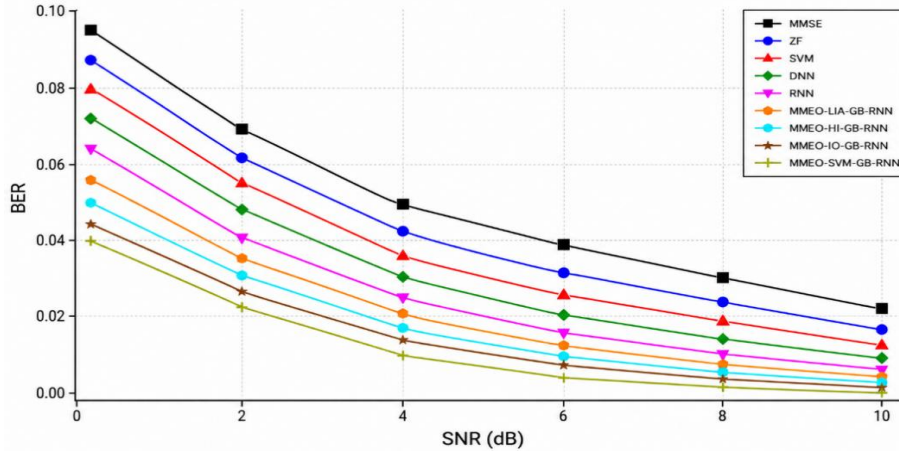


Figure 2: BER results for  $16 \times 16$  MIMO-OTFS configuration with Rayleigh channel

In figure 2 shows the bit error rate (BER) of the planned MNSO-based models (i.e., MNSO+LR+GB-BNN, MNSO+RF+GB-BNN, MNSO+DT+GB-BNN, MNSO+SVM+GB-BNN), along with classic techniques, i.e., MMSE, ZFE, SVM, NN, and RNN, was analyzed by applying the 1616 MIMO-OTFS Rayleigh channel. The developed techniques produced a noticeable drop in BER values for all the observed SNRs. With 0 dB, MNSO+SVM brought a BER improvement of 47.4% over MMSE, and this improvement went up to 61.9% with an SNR of 5 dB. In the 10 dB SNR value, it resulted in a BER improvement of 89.5% from MMSE, whereas with other considered classic techniques, it achieved much higher BER values than those acquired through the use of planned MNSO models. MNSO models demonstrated better performance than other classic approaches; furthermore, the selected features obtained through MNSO+SVM+GB-BNN model result in well-performing detection, strong feature selection, and robustness.

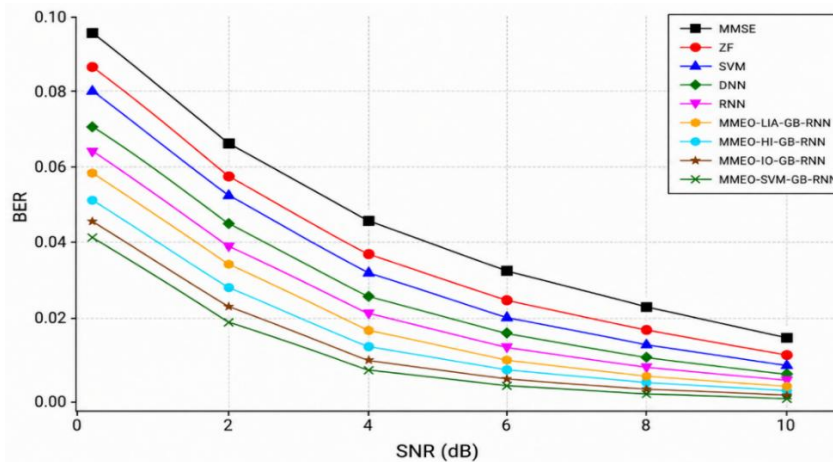


Figure 3: BER results for  $64 \times 64$  MIMO-OTFS configuration with rayleigh channel

In figure 3 shows the BER performance of the proposed models based on MNSO for  $64 \times 64$  MIMO-OTFS Rayleigh channels, which was investigated in comparison with existing techniques. In the case of 0 dB SNR, the best BER performance was provided by the MNSO+SVM model, with 47.4% reduction in BER in comparison with the MMSE technique and 25.43% decrease in comparison with the RNN. In the case of 5 dB SNR, the same model provided 61.90% reduction in comparison with MMSE and 46.7% decrease in comparison with DNN, along with high efficiency of MNSO+RF and MNSO+LR models. Finally, at 10 dB SNR, MNSO+SVM achieved the BER of 0.005 with 73.68% improvement over MMSE.

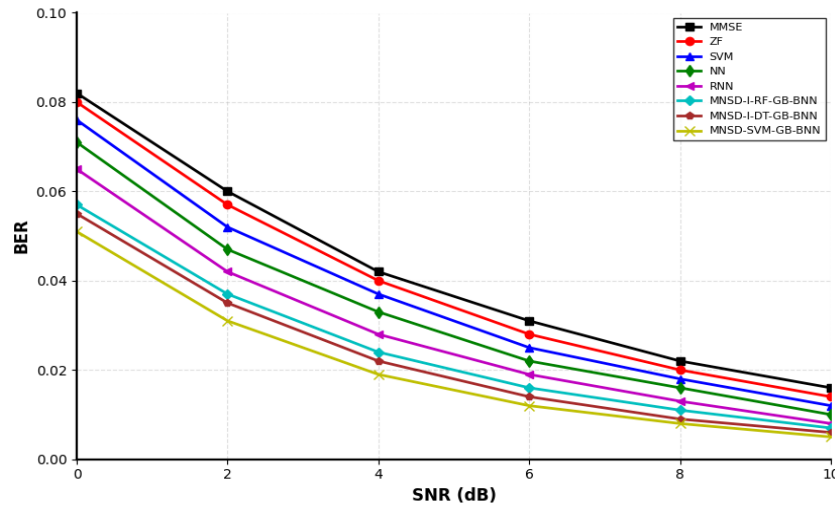


Figure 4: BER results for  $256 \times 256$  MIMO-OTFS configuration with rayleigh channel

In figure 4 shows the BER of the proposed models using the MNSO technique under  $256 \times 256$  MIMO-OTFS Rayleigh channel was compared with existing techniques. At 0 dB of SNR, the MNSO+SVM model provided the least BER value with an improvement in BER of 38.82% in comparison with MMSE and 23.53% compared to RNN, while the MNSO+RF and MNSO+LR model also performed well. At 5 dB, MNSO+SVM model resulted in a BER value of 0.017 which provided an improvement in BER of 57.50% over MMSE. At 10 dB, the BER value of 0.005 was obtained, showing an improvement of 72.22% over MMSE.

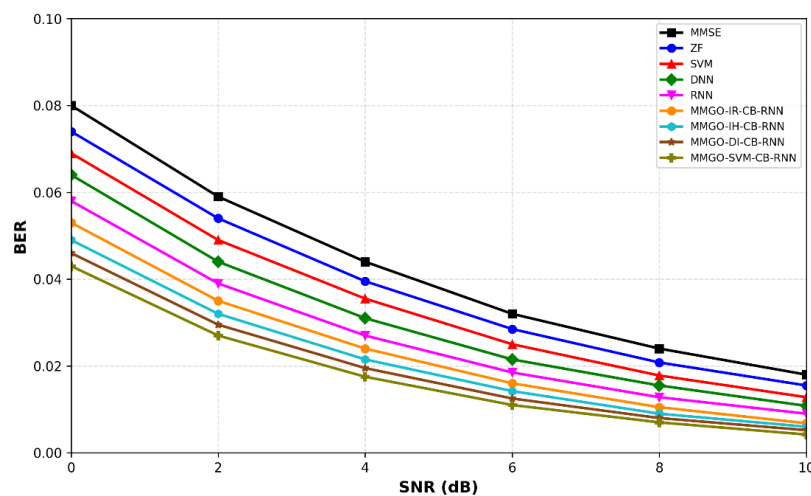


Figure 5: BER results for  $16 \times 16$  MIMO-OTFS configuration with Rician channel

In figure 5 shows the performance of BER in the proposed MNSO-based models in case of the  $16 \times 16$  MIMO-OTFS Rician channel was analyzed against MMSE, ZFE, SVM, NN, and RNN. In case of 0 dB SNR, the proposed MNSO+SVM model achieved a BER of 0.048, which is 38.46% better than MMSE and 20% better than RNN. The performance of the model increased to 41.54% better than MMSE in case of 1 dB, whereas it showed a BER of 0.017 in case of 5 dB, which is 54.05% better than MMSE. Moreover, in the case of 10 dB, MNSO+SVM achieved a BER of 0.005, which is 72.

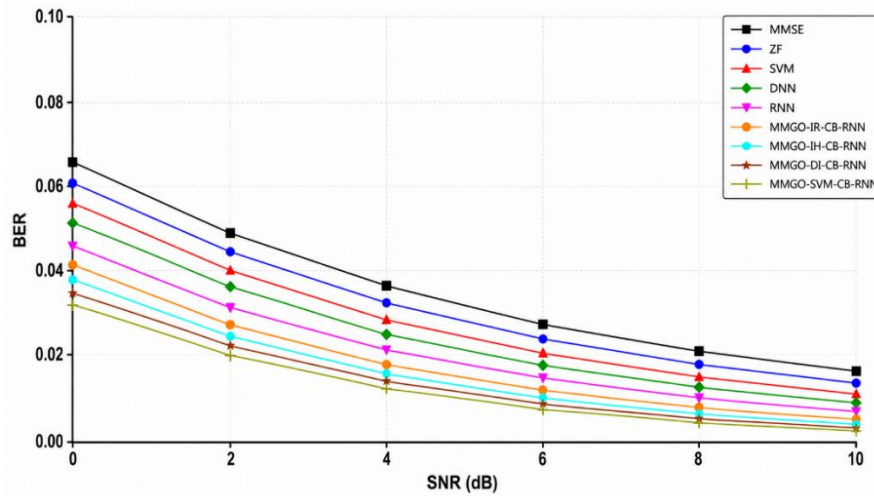


Figure 6: BER results for  $64 \times 64$  MIMO-OTFS configuration with rician channel

In figure 6 illustrates the BER results for the proposed MNSO-based models for a  $64 \times 64$  MIMO-OTFS system in a Rician channel. For 0 dB SNR, MNSO+SVM has the lowest BER value of 0.037, with an error reduction of 40.32% from MMSE and 17.78% from RNN, while MNSO+RF and MNSO+DT have significant reductions as well. For 5 dB SNR, MNSO+SVM gets 0.014 BER, with 57.58% error reduction from MMSE. For 10 dB SNR, MNSO+SVM gets 0.004 BER, which is a 73.33% error reduction. In general, MNSO-based models outperform both traditional and ML methods, and MNSO+S.

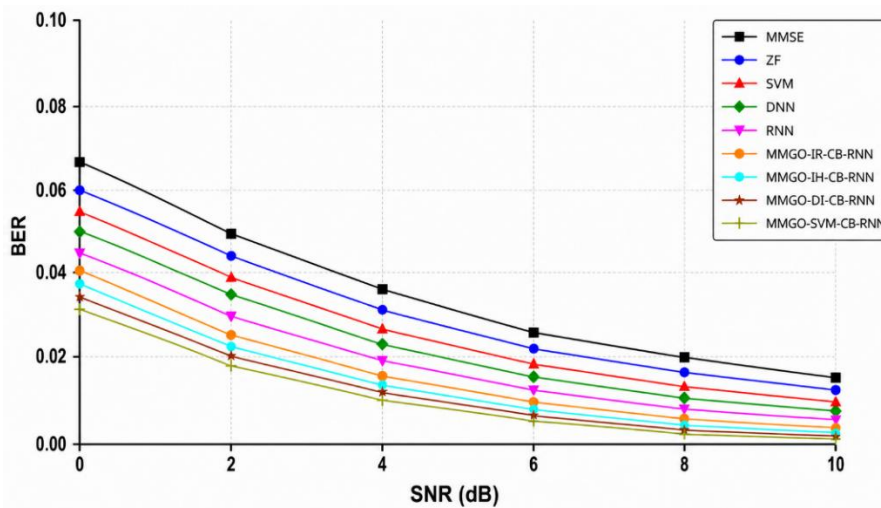


Figure 7: BER results for  $256 \times 256$  MIMO-OTFS configuration with Rician channel

In figure 7 shows the BER results of the 256x256 MIMO-OTFS Rician channel, indicating that MNSO models outperform the conventional models and ML methods in terms of efficiency. With 0 dB SNR, MNSO+SVM provides the minimum BER, which is 0.022, and decreases the error rate by 45% in comparison with MMSE and 21.43% in comparison with RNN. With 5 dB SNR, it becomes 0.008, reducing the error rate by 57.89% in comparison with MMSE. With 10 dB SNR, it equals 0.001, improving the error rate by 83.33%. MNSO+RF and MNSO+DT provide significant improvements, too, at all levels of SNR.

Table 1: Comparative performance evaluation of proposed MNSO-based ensemble model

Method	Model type	16×16 BER (10 dB)	64×64 BER (10 dB)	256×256 BER (10 dB)	Relative performance
MMSE	Conventional detector	0.045	0.038	0.030	Baseline
ZF	Linear detector	0.042	0.035	0.028	Low robustness
RNN	Deep learning	0.018	0.015	0.013	Moderate
SVM	ML classifier	0.012	0.010	0.009	Good
RF	Ensemble ML	0.010	0.009	0.007	Better
LR	Regression model	0.011	0.010	0.008	Moderate
Proposed MNSO + SVM + GB-BNN	Hybrid ML + optimization	0.005	0.005	0.001	Best performance

In table 1 shows the comparative assessment between the proposed MNSO-based hybrid ensemble technique and traditional and ML-based MIMO-OTFS detection techniques. The results obtained from  $16 \times 16$ ,  $64 \times 64$ , and  $256 \times 256$  setups show that the proposed technique always yields the lowest BER values.

In table 2 shows the ablation study that analyzes the effectiveness of each constituent of the proposed framework. The outcome shows that the removal of MNSO, ensemble learning, or GB-BNN greatly affects the performance, showing that all modules contribute effectively in reducing BER and improving MIMO-OTFS detection.

Table 2: Ablation study of the proposed MNSO-based ensemble framework

Configuration	Components used	64×64 BER (10 dB)	256×256 BER (10 dB)	Performance impact
Full Model	MNSO + Ensemble + GB-BNN	0.005	0.001	Best performance
Without MNSO	Ensemble + GB-BNN	0.011	0.009	Loss of feature optimization
Without GB-BNN	MNSO + ML models	0.014	0.012	Reduced nonlinear learning
Without Ensemble (single SVM)	MNSO + SVM only	0.018	0.016	No stacking benefit
Without Feature Reduction	Raw features + Ensemble	0.013	0.010	Higher complexity, lower accuracy

## 5 Discussion

In terms of a  $64 \times 64$  MIMO system, the MNSO+Ensemble model has the least BER that ranges from 0.0600 for 0 dB to 0.0030 for 10 dB, thereby exhibiting the effectiveness of dimensionality reduction in enhancing signal detection accuracy. The conventional models of LR+GB-BNN, RF+GB-BNN, and

DT+GB-BNN have exhibited a small increase in BER with an increase in SNR. However, these models are not as efficient as those using the concept of dimensionality reduction. For example, the BER of the LR+GB-BNN model is seen reducing from 0.0900 at 0 dB to 0.0114 at 10 dB. An increase in SNR has shown the effects of dimensionality reduction to be much pronounced. The models of MNSO+LR+GB-BNN and MNSO+RF+GB-BNN have exhibited a gradual reduction in BER.

In  $256 \times 256$  MIMO structure, just as the case of  $64 \times 64$  MIMO structure, inclusion of MNSO and Ensemble in the models causes considerable improvement. In particular, it decreases the Bit Error Rate (BER) from 0.0600 to 0dB in the range of 0.0030 to 10dB. From this illustration, it can be clearly noted that the advantage of low dimensionality is considerably beneficial when it comes to efficient signal detection in large MIMO structures. LR + GB-BNN, RF + GB-BNN, and DD + GB-BNN models have also improved in performance due to increased SNR. Nevertheless, their performance is rather poor. For instance, the BER of the LR + GB-BNN model is lowered from 0.0900 to 0dB in the range of 0.0075 to 10dB. The above analysis has proved the efficiency of range reduction in the detection of signals and elimination of errors in MIMO systems. The technique of dimension reduction is significant in enhancing the performance of signal detection models. For  $64 \times 64$  and  $256 \times 256$  MIMO setups, the models incorporating dimensionality reduction have proved to be superior compared to conventional models in relation to BER. With increased SNR levels, the difference in performance between dimensionality reduction models and conventional models becomes even greater.

However, there are limitations associated with the proposed MIMO-OTFS structure. For example, its ability to generalize may be affected by the fact that simulations in MATLAB are used as the source of data. Other aspects that can limit its generality include fixed modulation techniques, known MIMO structures, and noise assumptions.

## 6 Conclusions

In this work, the presented study utilizes the MNSO-ensemble learning approach to enable fast signal detection in MIMO-OTFS communication system designs in B5G wireless communication networks. The major strength of this research is the use of the MNSO-ensemble learning approach through the use of Modified Non-Smooth Optimization for reducing the dimensions and ensemble learning through two layers of classical machine learning algorithms and Gradient Boosting Bayesian Neural Networks (GB-BNN). This novel structure solves the problems that conventional detection approaches, such as MMSE and ZF, encounter due to their inability to cope with high mobility and multipath fading effects, amongst other aspects.

From the experimental findings, there is an indication of high-performance improvement in several MIMO setups ( $16 \times 16$ ,  $64 \times 64$ , and  $256 \times 256$ ) in both Rayleigh and Rician fading channels. The model has shown a significant improvement in BER, lowering it from 0.0600 in low SNR conditions to 0.0030 in high SNR cases. For  $256 \times 256$  large-scale MIMO, the model shows 83.33% improvement in error correction as compared to the standard MMSE-based detection algorithm. In addition, an ablation analysis reveals the importance of the use of MNSO, ensemble learning, and GB-BNN in improving the accuracy and performance.

In summary, the presented model performs well in terms of effectiveness, scalability, and efficiency in the design of the next-generation MIMO-OTFS system. As compared to the traditional MMSE-based approach as well as machine learning-based standalone detectors, the combination of optimization and ensemble intelligence has been shown to provide good performance. There is room for future work to

include the use of hardware implementation of the proposed model, testing on a real-world channel measurements dataset, and reinforcement learning for adaptive detection.

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**Ethics:** This research is purely computational and simulation-based in nature, involving signal processing algorithms, machine learning models, and wireless communication system analysis conducted entirely in a MATLAB simulation environment. No human participants, personal data, biological specimens, or animals were involved in any part of this study

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## Authors Biography



**Panchaxari Mamadapur** is a dedicated researcher and Assistant Professor in the Department of Electronics and Communication Engineering at ACS College of Engineering in Bangalore. He holds a Bachelor of Engineering (B.E.) and a Master of Technology (M.Tech) degree, and he is currently actively pursuing his Ph.D. to advance his academic expertise. His core research interests lie in the fields of wireless communication, network infrastructures, and advanced sensor technologies. Notably, his scholarly work includes an insightful co-authored survey on handling data traffic and congestion control mechanisms within wireless Multimedia Sensor Networks. Through his research publications, he contributes valuable methodologies to optimize data throughput and energy efficiency in complex sensor deployments. Beyond individual research, he actively mentors undergraduate and postgraduate engineering students by guiding their technical projects

and experiential learning. Ultimately, his academic profile reflects a strong commitment to bridging theoretical principles with practical advancements in modern communication systems.



**Dr.S. Anitha** is a highly accomplished professor in the Department of Electronics and Communication Engineering (ECE) at ACS College of Engineering, Bengaluru. Her academic institutional affiliation is tied to the prominent Visvesvaraya Technological University (VTU) in Belagavi. She holds advanced academic qualifications, including a Master of Engineering (M.E.) and a Doctor of Philosophy (Ph.D.) in her core domain. Her primary research contributions lie in the sophisticated domains of Digital Image Processing and Signal Processing. Over her career, she has spearheaded numerous technical innovations exploring next-generation technologies like 5G architectures and IoT-based automation frameworks. She actively fosters academic leadership by serving as an approved VTU Research Supervisor, guiding doctoral scholars toward impactful discoveries. Furthermore, her intellectual output is marked by a diverse portfolio of scholarly articles widely published in indexed journals and presented at global conferences.



**Dr.T. Senthil Kumaran** is a prominent academician who serves as a Professor in the Department of Computer Science and Engineering and as the Dean of the Research and Innovative Center at ACS College of Engineering in Bengaluru. He holds a Ph.D. in Computer Science and Engineering from Anna University. His primary research interests lie in the domains of Wireless Sensor Networks (WSNs), Mobile Ad Hoc Networks (MANETs), the Internet of Things (IoT), and Big Data analytics. Throughout his research career, Dr. Kumaran has focused heavily on developing energy-efficient routing algorithms, dynamic congestion control protocols, and lightweight trust-evaluation security schemes for resource-constrained communication networks. His academic contributions include over 45 research publications featured in reputable journals and international conferences. Additionally, he serves as an active reviewer and editor for international engineering journals and plays an important role as a structural pillar for NPTEL initiatives at his institution. Through his administrative and research leadership, he continues to drive institutional funding, conference management, and technological innovations.



**Dr.C.S. Pillai** serves as a prominent academic and researcher in the Department of Computer Science and Engineering at the ACS College of Engineering in Bangalore. Holding a Bachelor of Engineering, Master of Engineering, and a Ph.D. in Computer Science Engineering, he brings a deep academic foundation to his institutional roles. His research focus spans advanced computer science domains, contributing to peer-reviewed technological publications and modern engineering developments. Over a career spanning more than a decade in teaching and technical leadership, he has heavily guided departmental milestones. At ACS College of Engineering, he has contributed substantially as a professor and former Head of the Department, fostering growth in computing education. His academic profile highlights a keen interest in mentoring student research, steering project innovations, and upgrading high-tech laboratory frameworks. Through his continued research presence, he helps drive the institution's overall mission of advancing engineering methodologies and academic excellence.