AI MODELS FOR TELECOMMUNICATION INTERFERENCES BETWEEN GSO AND NGSO SATELLITES: THE MODEL GENERALIZATION PROBLEM

David Andres Diaz Alvarez, Flor Ortiz
Suleima Briseno, Eva Lagunas, Symeon Chatzinotas,
Interdisciplinary Centre for Security, Reliability and Trust (SnT), L-1855 Luxembourg, Luxembourg, corresponding author: david.diaz.001@student.uni.lu

1. Abstract

Over the past decade, the deployment of multiple satellite telecommunication constellations in Low Earth Orbit (LEO) has posed a significant challenge to Geostationary Orbit (GSO) systems. As more satellites are launched, telecommunications interference has increased, primarily because both GSO and Non-Geostationary Orbit (NGSO) satellites operate within the same frequency bands. This interference may degrade GSO satellite services, impacting their overall quality. To maintain reliable service delivery, it is crucial to develop methodologies and solutions for detecting and managing telecommunication interference. The present study focuses on the generalization of an AI model developed by the Signal Processing and Communications (SIGCOM) research group at the University of Luxembourg for interference detection in satellite communications.[1][2] It examines the current state of the model and explores strategies to enhance its applicability across diverse scenarios. The model performance is evaluated with different interfered signals changing from the initial conditions of frequency and Signal to Noise Ratio (SNR) to different modulations which lead to multiple scenarios. The study demonstrated that the model works better detecting the interference in the frequency domain than in the time domain. Also, the changes of SNR have a greater impact in the behavior of the model in the time domain. In general, the model struggles with the detection of no-interference in the signal, confusing it with the interference. The study demonstrated that the model could generalize in frequency and can be trained with all the different scenarios to enhance its applicability.

2. Introduction

In recent years, the rapid expansion of Low Earth Orbit (LEO) satellite constellations has intensified concerns about interference with traditional Geostationary Orbit (GSO) systems. [1] Since both NGSO (non-geostationary) and GSO satellites frequently share the same frequency allocations, the risk of signal overlap has escalated, potentially undermining the quality and reliability of GSO services.[2] To ensure the continuous delivery of essential satellite communications, it has become imperative to develop effective detection and management techniques tailored to such interference.

In previous years some new methods for interference detection in satellite telecommunications have gone beyond classical spectrum analysis toward machine learning and adaptive algorithms as the use of AI in satellite communications has increased.[3] PSD or filter-based methods are traditional methods that can detect interference but generally fail in low SNR conditions, advanced jamming signals, or heavy computations in real-time systems [4]. Machine learning solutions, such as Long Short-Term Memory (LSTM) networks for spectrum prediction [5], autoencoders for anomaly detection with Machine Learning and hybrid approaches combining statistical methods with CNN-based shift estimation [6][7], allows us to generalize in some level across unseen interference patterns which can lead to a certain level of generalization. Still, the ability to generalize is still a specific topic that is being study at the University of Luxembourg and it will be presented in this work.

This work studies the generalization of an AI model developed by the Signal Processing and Communications (SIGCOM) research group at the University of Luxembourg designed to detect interference detection in satellite communications.[8][9] Originally, the model was trained under specific frequency and signal-to-noise configurations. The model was trained with simulation model done in Matlab to recreate and generate the interference. This simulation is based on monitoring the Bit Error Rate (BER) and Quality of Service (QoS) of the signal received from GSO satellites. When interference occurs between GSO and NGSO signals, the quality of the GSO signal deteriorates, and the Signal-to-Noise Ratio (SNR) decreases. These variations are captured by the simulation model and are used to recreate interference events.

The generalization of AI models has been studied in the past by different authors. For models based on neural networks the generalization can be studied based on the behavior of the model at different levels.[10] For this purpose, Rholf [11] planted the ways a model can generalize going from the behavior of the model in a new sample to a completely different and new scenario or scope. This can be seen in figure 1 where the model can generalize going from left to right. For this study, the generalization will be studied from a new sample to a new domain.

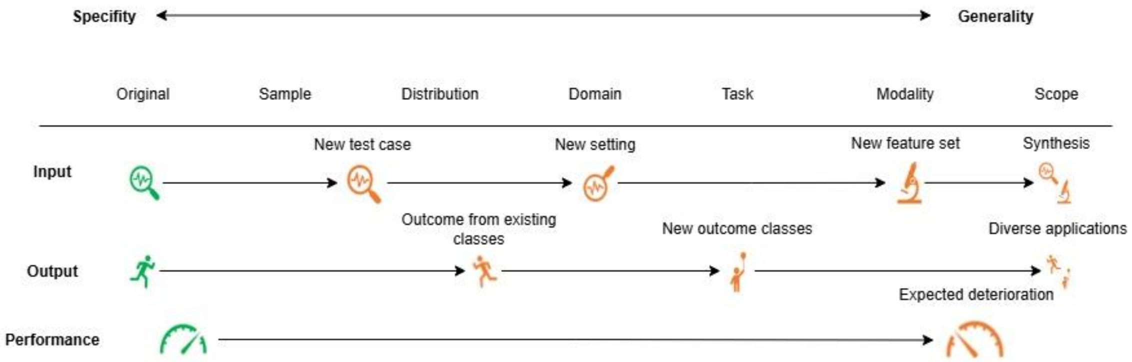

Figure 1 Types of Generalization adapted from [11]

3. Methodology

For this study the methodology used is presented as diagram in the in figure 2 where it followed three stages. First the model is trained with new data set in both time and frequency domain, then the model is tested in new signals varying some parameters and then the performance of the model under these conditions is compared. In previous studies, the model went through the fine-tuning process to have a good performance under the baseline scenario that will be explained after.

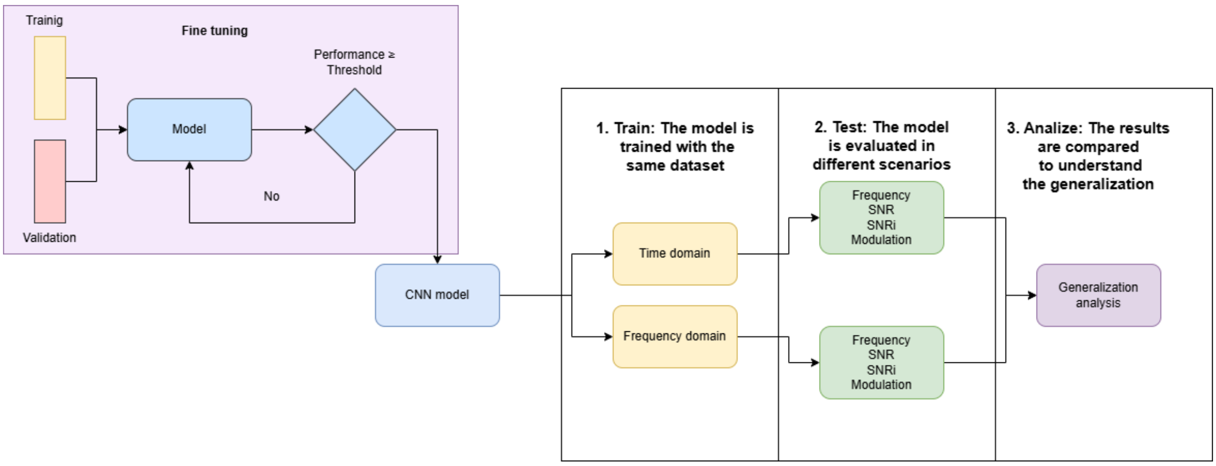

Figure 2 Diagram of the methodology to study the generalization

3.1 Model training and baseline scenario

The model used for this analysis was developed by the Sigcom research group, based on the parameters listed in Table 1. It was trained in both the frequency and time domains, using a frequency band centered at 29 GHz, where interference was artificially introduced. The interference was modeled as if a GSO satellite telecommunication link were being interfered with by an NGSO satellite. The signal was modulated using the Binary Phase Shift Keying (BPSK) modulation.

Parameters	Frequency (GHz)	SNR (dB)	SNRi (dB)	Modulation
	29	16	6	BPSK

Table 1 Baseline parameters

The signal bandwidth of 500 MHz was divided into five sub-bands of 100 MHz each, where interference could potentially occur. As a result, the model was trained to classify six different scenarios: class 0 representing no interference, and classes 1 through 5 representing interference in sub-bands 1 through 5, respectively. Figure 3 illustrates the sub-band divisions and the locations where interference could be artificially introduced.

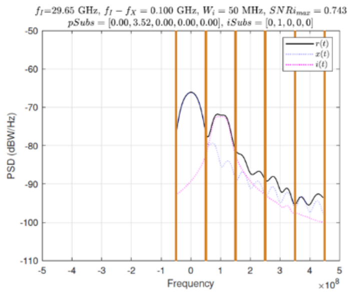

Figure 3 Division of the bandwidth where the interference is introduced taken from [12]

The model architecture consists of a 2D convolutional (Conv2D) layer with 100 filters and a kernel size of (1,1). This layer performs convolution operations on the input data to extract relevant features. The output of this layer is a tensor of shape (1, 100, 100), where 100 × 100 represents the feature map size and 1 corresponds to the number of filters (see Figure 4 and [6] for more details).

The input dataset consisted of matrices of size 12,000 × 100 for the frequency domain and 12,000 × 1,000 for the time domain. Each sample in the dataset represents a signal that may or may not be interfered with. The first 2,000 samples correspond to non-interfered signals (labeled as class 0)., while the next 2,000 contain interference in the first subband (labeled as class 1). This pattern continues until the final 2,000 samples, which contain interference in subband 5 and are labeled as class 5. For frequency training, we used a reduced Fourier transform. The training signals corresponded to the baseline scenario, in which the model achieved an accuracy of 96% in the frequency domain and 100% in the time domain. These results served as a reference for comparison with other scenarios, allowing us to evaluate the model's ability to generalize across different domains.

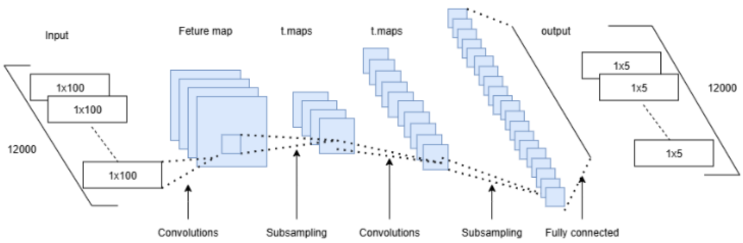

Figure 4 Architecture of the model adapted from [6]

3.2 Generation of different scenarios

To evaluate the model's generalization capabilities, different signals were generated by varying the parameters from the baseline scenario in the interference generation process. As Rohlf [11] established in his paper, the generalization of a model can be assessed by presenting it with new data from previously unseen scenarios. In this study, two levels of generalization were tested:

a. Distributions shift: The modulation of the signal keeps being the same but parameters like Signal-to-Noise Ratio (SNR), Interference Signal-to-Noise Ratio (SNRi) and Frequency were varied. This approach tested the model with data from a new distribution while remaining within the same domain.
b. Domain shift: The modulation of the signal was changed to test the model in new domain scenario. This can imply that the model could be used in cases completely different from the baseline scenario.

Before doing the analysis, the model already went through the process of fine tuning to ensure that in the baseline conditions a good performance was achieved. The model was assessed at different frequencies from the C-band to Q-band where interference was introduced (Table 2)

Band	C	X	X	X	Ku	K	Ka	Ka
Fecuency (GHz)	5	8	11	12	13	20	27	28

Table 2 Band and frequency of the different scenarios

3.3 Evaluation of the model under challenging conditions

After training, all tests were conducted over the new signals. Some parameters such as the desired Signal-to-Noise Ratio (SNR) and the Interference Signal-to-Noise Ratio (SNRi) were modified to evaluate the model under more challenging conditions. As the SNR decreased, interference detection became more difficult due to lower signal power and increased noise.

Additionally, the signal modulation was varied from BPSK to QPSK, 8PSK, 16APSK and 32APSK to assess the model's ability to detect interference under these conditions. The following table presents the number of scenarios in which the model was tested. Since the model was trained and tested in both time and frequency domains, the total number of scenarios amounted to 68.

Parameters	Frequency	SNR	SNRi	Modulation	Total
Number of scenarios	9	10	10	5	34

Table 3 Number of different scenarios tested in each parameter

To evaluate the model's performance across different scenarios, three metrics were chosen: overall accuracy reflects global classification performance, loss indicates optimization efficiency, and per-class accuracy used to assess the model's behavior in detecting interference within each sub-band. These performance metrics were recorded to compare results and determine the model's ability to generalize.

4. Tests and results

a. **Test # 1:** As stated before, the change of frequency was introduced in the generation of interference signal. As figure 5 shows, the test was conducted both in the Time and Frequency domain where the model was trained. It can be seen in the figures; the model performed well in other frequencies. For the frequency domain, the minimum accuracy was 96 % and between classes 80 % for class 1. In other hand, in the time domain, the model performed almost a 100 % of accuracy in all the frequencies and all the classes presenting desired behavior for these scenarios.

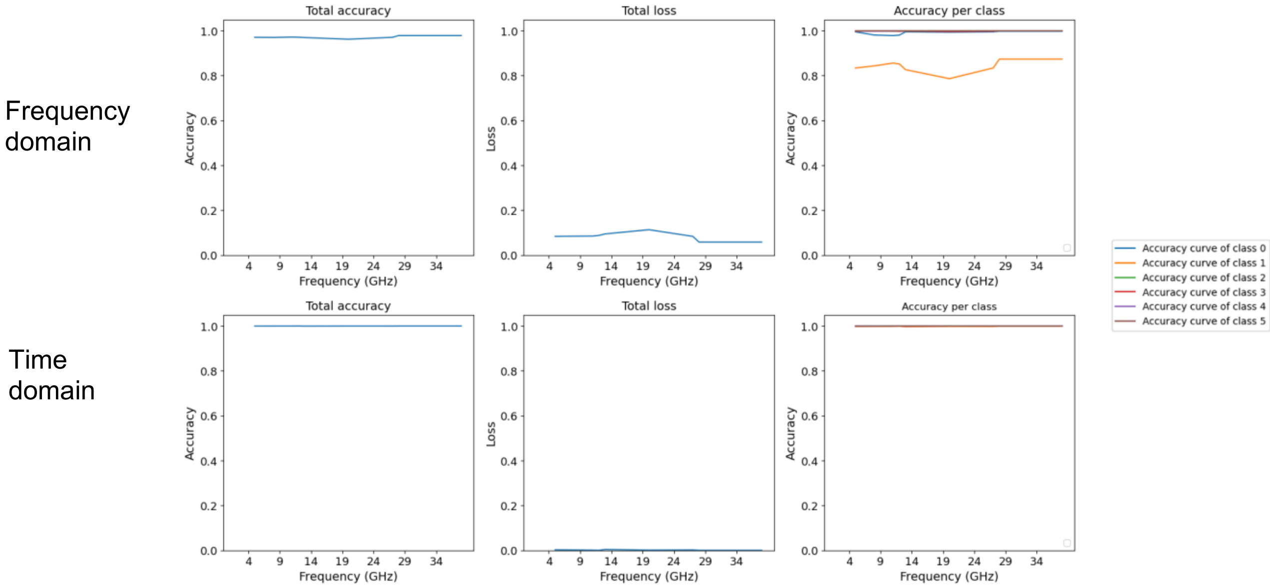

Figure 5 performance of the model when changing the central frequency of the signal

b. **Tests # 2:** After evaluating the model in the frequency domain, its performance was further tested under varying noise conditions by adjusting the SNR and SNRi parameters. Both parameters were varied from –6 dB to 12 dB in the frequency and time domains. Figure 6 illustrates the model's behavior in the frequency domain under different noise levels. As expected, the overall accuracy decreases as noise increases. Specifically, when the SNR drops below 2 dB, the total accuracy tends to fall below 80%. Furthermore, from 6 dB and below, the accuracy for class 0 (no interference) and class 1 (interference in sub-band 1) also drops below 80%, indicating that the model struggles to correctly classify interference-free signals.

   A similar trend is observed when varying the SNRi: the total accuracy decreases significantly below 0 dB. In the SNRi plots, the purple line represents the threshold below which the interference becomes negligible and does not significantly impact the signal quality.

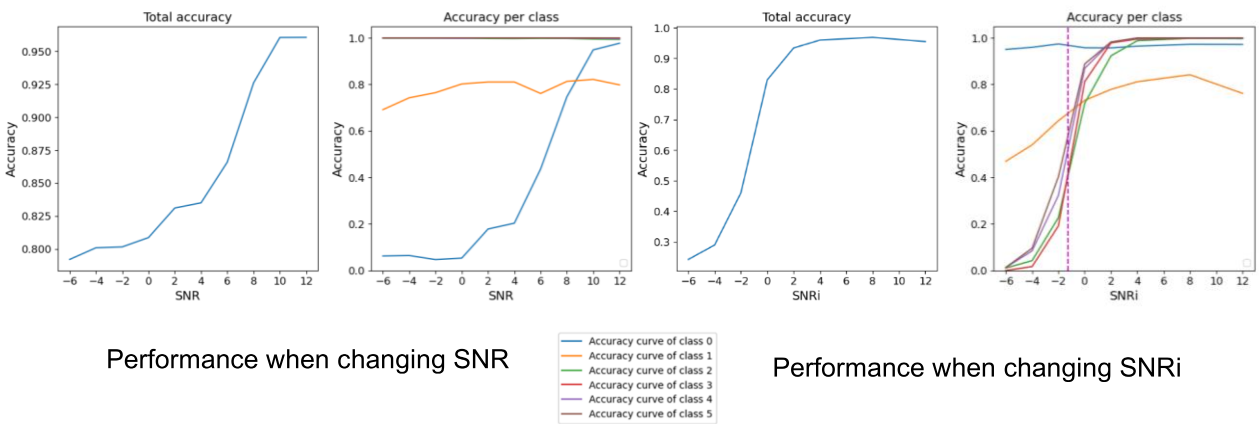

Figure 6 Tests done changing the SNR and SNRi in the frequency domain

c. **Tests # 3:** The previous test was also performed in the time domain. In this case, the accuracy exhibited a sharp decline, as illustrated in Figure 7. Specifically, when the SNR was reduced, the accuracy fell below 80% at 10 dB for SNR and 4 dB for SNRi. These results suggest that reductions in SNR and SNRi significantly hinder the model's ability to reliably detect interference.

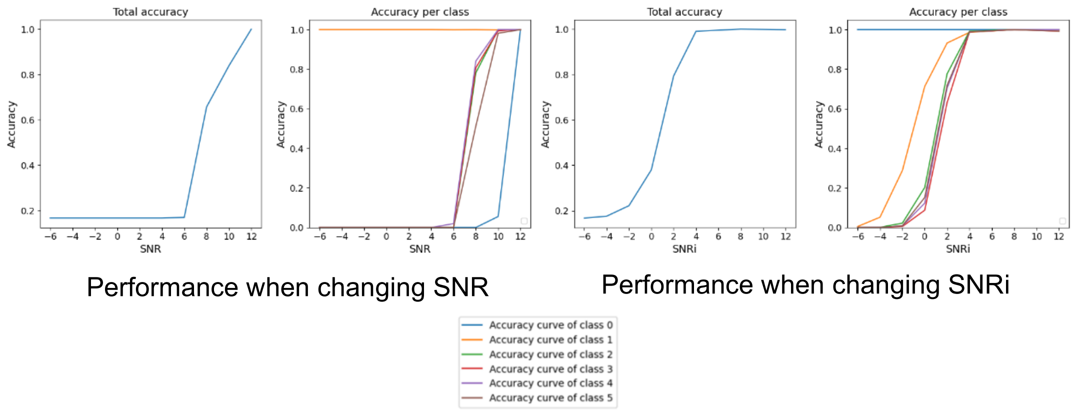

Figure 7 Tests done changing the SNR and SNRi in the time domain

d. Test #4: The model was evaluated in different modulations keeping the baseline scenario of frequency and SNRi. The only change was the SNR as higher constellation will require a higher SNR to keep the signal well-modulated. The modulation tested was BPSK, QPSK, 8PSK, 16PSK and 32PSK. These modulations were tested in the frequency domain and in the time domain (Figure 8). As can be seen for the frequency domain the general accuracy of the model in the different modulations was about 80%. In the other hand, the accuracy of the class 0, no interference, was around 0 % in the different modulation which indicates that the model couldn't detect the signals without interference. More drastic behavior can be seen in the time domain when even the total accuracy of the test in the different modulation was lower. This indicates that the model cannot detect the interferences in the time domain with an accuracy lower than 20%.

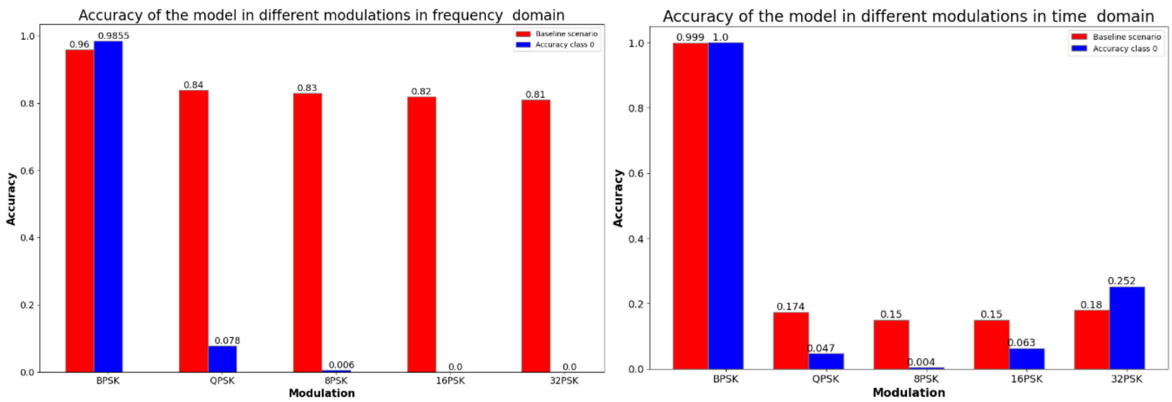

Figure 8 Model tested in different modulations

The model exhibited strong performance in the frequency domain, as shown in Figure 9, when tested under variations in SNR, SNRi, and frequency. Even when the modulation scheme was changed, the model was able to detect interference in the different sub-bands. However, its inability to accurately identify class 0 (no interference) indicates potential issues with generalization, particularly in scenarios where no interference is present.

In the time domain, the model performed relatively well when the frequency was varied, but its performance degraded under changes in SNR and SNRi, where it showed reduced accuracy. Additionally, the model performed poorly when the modulation of the signal was changed in the time domain, as illustrated in figure 9. This highlights the model's limited ability to generalize under time-domain conditions, especially when signal characteristics deviate from those seen during training.

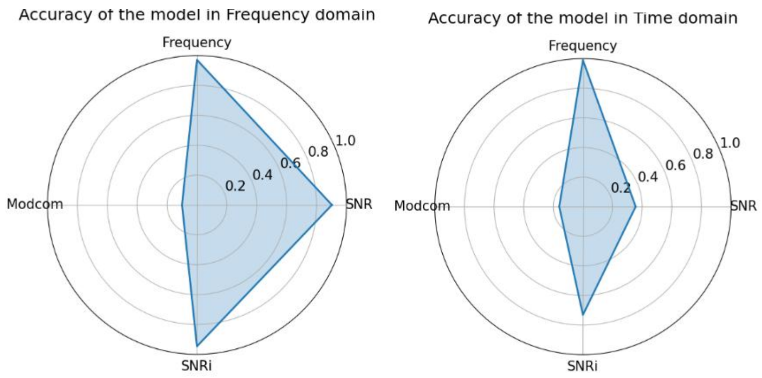

Figure 9 Resume of the performance of the model in frequency and time domain

Finally, the model was tested in a combination of changes in the SNR and SNRi parameters for the baseline modulation BPSK keeping the frequency the same in 29 GHz. This combination is shown in figure 10 and the general accuracy of the model goes as low as 85% in the hardest conditions with SNR and SNRi of 2 dB. In general, keeping the same frequency and modulation of the baseline scenario, the model shows an adequate performance (around 90 %) when changing these two parameters. This test was not made in the time domain as the model had bad performance, accuracy below 70 %, when changing the SNR and SNRi as shown in previous test (figure 9).

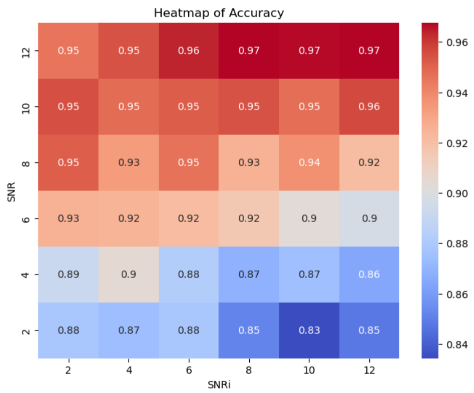

Figure 10 Accuracy of the test done in the baseline scenario mixing the SNR and SNRi values

5. Conclusions

The model was evaluated across a total of 104 scenarios: 70 in the frequency domain and 34 in the time domain. In these experiments, the model demonstrated superior performance in the frequency domain compared to the time domain. This suggests that the model generalizes more effectively in the frequency domain, as variations in SNR, SNRi, and frequency did not significantly impact its performance. Therefore, in this domain, the model achieved a level of generalization that allows it to perform reliably across different distributions.

However, with respect to modulation, although the model generally exhibited good accuracy in the frequency domain, it failed to detect scenarios without interference. This limitation indicates that the model is not suitable for generalizing to other modulation types, constituting a failure in generalization at the domain level.

In the time domain, the model was more sensitive to noise, and interference detection proved more challenging. While it performed well under baseline conditions and when the frequency of the signal was modified, it failed to detect interference when the SNR or SNRi changed. Consequently, the model did not generalize effectively at the distribution level and cannot be reliably applied to scenarios beyond those specifically tested. Similar behavior was observed for other modulation types, where the model's accuracy dropped to approximately 20%, further indicating a lack of domain-level generalization

In conclusion, the model shows strong generalization capabilities in the frequency domain but fails to do so in the time domain. Its generalization can potentially be improved by training it with data tailored to the specific scenarios in which it will be applied. As demonstrated in this study, the model is capable of delivering good results with relatively small training datasets when applied to satellite telecommunication interference detection. Nevertheless, since real-world signals are typically received in the time domain, this limitation may affect the practical applicability of the model. For future work, given the clear patterns in the model's performance shortcomings, retraining it using the complete set of available datasets may enhance its accuracy across different domains and modulation schemes.

This study aims to illustrate how the generalization problem can be addressed in practice and aspires to serve as a reference for future research in this area.

6. Acknowledgements

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7. References

[1]A.C.BoleyandM.Byers, "Satellite mega-constellations create risks in Low Earth Orbit, the atmosphere and on Earth,"ScientificRep.,vol. 11,no.1,May2021.
[2]B. Al Homssi et al., "Next Generation MegaSatellite Networks for Access Equality: Opportunities, Challenges, and Performance,"inIEEE Communications Magazine,vol.60,no.4,pp.18-24,April2022
[3]Fourati, F., & Alouini, M. S. (2021). Artificial intelligence for satellite communication: A review. Intelligent and Converged Networks, 2(3), 213-243.
[4]Cui, K., Yang, L., Guan, T., Wang, Y., & Liu, L. (2025). Efficient Interference Detection for Satellite Communications Based on Non-Uniform Adaptive Segmentation. Electronics, 14(9), 1792.
[5]Pellaco, L., Singh, N., & Jaldén, J. (2019, October). Spectrum prediction and interference detection for satellite communications. In Advances in Communications Satellite Systems. Proceedings of the 37th International Communications Satellite Systems Conference (ICSSC-2019) (pp. 1-18). IET.
[6]de Senneville, A., Ogbe, D., & Towfic, Z. (2025). Machine Learning for Interference Detection and Mitigation on Space Telecom Software-Defined Radio Signals.
[7]Saifaldawla, Almoatssimbillah, et al. "GenAI-based models for NGSO satellites interference detection." IEEE Transactions on Machine Learning in Communications and Networking (2024).
[8]Daoud, Saed, et al. "CNN-Based on-board interference detection in satellite systems: An analysis of dataset impact on performance." 2023 IEEE International Conference on Acoustics, Speech, and Signal Processing Workshops (ICASSPW). IEEE, 2023.
[9]Saifaldawla, A., Ortiz-Gomez, F. G., Lagunas, E., Daoud, S., & Chatzinotas, S. (2023, September). NGSO-To-GSO satellite interference detection based on autoencoder. In 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC) (pp. 1-7). IEEE.
[10]Akrout, Mohamed, et al. "Domain generalization in machine learning models for wireless communications: Concepts, state-of-the-art, and open issues." IEEE Communications Surveys & Tutorials 25.4 (2023): 3014-3037.
[11]Rohlfs, C. (2025). Generalization in neural networks: A broad survey. Neurocomputing, 611, 128701.
[12]Geoffrey Eappen, et al., "Neuromorphic Models for Energy-Efficient Onboard Interference Detection in Satellite Systems", IEEE Transactions on Aerospace and Electronic Systems, 2025.