TECHNICAL UNIVERSITY OF CLUJ-NAPOCA

ACTA TECHNICA NAPOCENSIS

Series: Applied Mathematics, Mechanics, and Engineering
Vol. 69, Issue Special III, July, 2026

SPECTROGRAM BASED INTERFERENCE DETECTION USING SOFTWARE DEFINED RADIO

Annamaria SÂRBU, Antonio HOCIUNG

Abstract: *Software defined radio (SDR) platforms enable flexible and cost-effective radio frequency (RF) monitoring, supporting detection and classification of interference across diverse wireless environments. In this work, a SDR-based interference detection and classification framework is presented, focusing on two widely used frequency bands: the FM band (88–110 MHz) and the 2.4 GHz ISM band. A novel over-the-air dataset of labeled spectrograms was collected using low-cost SDR hardware and GNU Radio, emulating idle spectrum and three representative interference types: burst noise, continuous wave, and chirp signals. A convolutional neural network (CNN) was designed and evaluated under multiple configurations, investigating the impact of different optimization solvers and activation functions on classification performance. Experimental results demonstrate very high accuracy for interference detection (binary classification) in both frequency bands, exceeding 98% on the test datasets. For multi-class interference type classification, the model achieves up to 98% accuracy in the FM band, while reduced performance is observed in the 2.4 GHz band due to time–frequency resolution limitations inherent to spectrogram-based representations for higher signal bandwidths. The results highlight the effectiveness of deep learning for SDR-based interference monitoring, while also emphasizing the trade-offs between computational efficiency and discriminative capability when using spectrogram representations in wideband wireless systems.*

Keywords: *Software Defined Radio (SDR), RF interference, convolutional neural networks (CNN), spectrogram analysis*

1. INTRODUCTION

Recent progress in signal processing and deep learning (DL) has significantly improved the performance of automated classification systems across a wide range of applications. Convolutional Neural Networks (CNNs) have proven highly effective when applied to image-based representations of signals, such as spectrograms. This approach enables machine learning models to identify subtle but discriminative features embedded within complex signal structures.

The aim of this paper is to design and evaluate a CNN-based interference detection and classification framework based on spectrogram representations of signal data. The methodological workflow begins with the collection and labeling of signal data under controlled conditions to ensure reliability and consistency. The acquired signals are then transformed into spectrogram images using the Fast Fourier Transform (FFT), enabling the extraction of time–frequency characteristics. These spectrograms serve as inputs to a CNN model, which is trained and validated to perform the classification task.

2. STATE-OF-THE ART

Software defined radio (SDR) platforms became a key element for modern electromagnetic monitoring systems, offering agility and cost-effectiveness [1]. These systems are increasingly vital for monitoring, detecting and classifying radio frequency (RF) emissions across diverse wireless environments. SDR-based systems were reported to monitor wide frequency bands in real time, with demonstrated capabilities such as 10 MHz and 20 MHz

bandwidths for Long Term Evolution (LTE) and 4th generation (4G) signals, and even ultra-wideband monitoring up to 300 MHz per channel using advanced USRP hardware [2-4]. In addition, low-cost SDR platforms (e.g., ADALM-PLUTO, RTL-SDR dongles, Hack RF platforms) enable RF monitoring at a fraction of the cost of traditional spectrum analyzers, supporting both stationery and mobile deployments [5,6]. SDR-based systems are portable and scalable, integrating compact sensors that can be deployed in networks for large-scale, distributed monitoring, including outdoor and mobile scenarios [7,8].

With their recent advances these systems support sophisticated detection and classification, including frequency hopping, interference detection, and source localization, using real-time signal processing and machine learning [9-13].

To identify RF interference events, SDR-based systems utilize real-time spectrum analysis, adaptive thresholding and advanced signal processing. Reported methods include dynamic threshold calculation for alarm systems [7], amplitude probability distribution analysis [9], and robust threshold selection for real-time detection [14]. These approaches enable accurate detection even in complex or noisy environments, supporting both continuous monitoring and event-triggered alerts.

SDR-based interference detection is applied in Global Navigation Satellite System (GNSS) protection [15,16], satellite communications [17,18], cognitive radio [19,20] and spectrum monitoring [21]. Open-source tools (GNU Radio, USRP) and commercial SDR hardware enable rapid prototyping and deployment across research, defense, and commercial sectors.

Beyond detection, SDR systems can classify interference types using machine learning (e.g., decision tree classifiers for modulation recognition [15]) and localize sources via direction finding and angle-of-arrival estimation [15]. Some platforms, like Kraken SDR, offer compact, phase-coherent arrays for precise localization in Global Navigation Satellite System (GNSS) bands [15]. Mitigation strategies include adaptive beamforming [22] to spatially filter interference, and real-time signal cancellation [14,23].

The recent up rise of Artificial Intelligence (AI) has shifted research efforts towards the use of DL algorithms for interference detection. Compared to traditional signal processing or machine learning (ML) models, DL approaches such as CNNs and recurrent neural networks (RNNs) can automatically extract hierarchical features from data, enabling improved generalization across diverse interference scenarios. For example, composite CNN models can achieve high correct classification rates with low false positives [24], and DL-based frameworks in radar systems report true positive rates above 99% even in low Signal to Interference Ratio (SINR) conditions [25]. DL models, including transfer learning approaches, maintain high detection accuracy across different datasets and real-world conditions, outperforming conventional algorithms in both simulated and real environments [26-28]. These methods have shown superior performance in tasks like modulation classification [29], spectrum anomaly detection, and interference type identification.

However, a key challenge remains the availability of representative datasets. Deep learning algorithms typically require large, labeled datasets to achieve robust performance. In the wireless domain, real-world interference examples are scarce, highly variable across frequency bands, and often difficult to capture due to regulatory and operational constraints. Synthetic datasets generated via simulation can help, but they may not fully reflect the complexity of practical environments. This lack of standardized, openly accessible datasets limits the reproducibility of results and hinders the deployment of DL-based interference detection systems in operational settings.

Authors found several interference detection databases in open public literature. The Electromagnetic Interference (EMI) Dataset [30] provides nine classes of EMI and normal signals, each consisting of 4000-time steps in mV, making it well-suited for supervised classification. It captures diverse fault conditions such as arcing, corona, partial discharge, and noise, preserving temporal and amplitude characteristics. Its application is limited to electrical equipment condition monitoring signals affected by electromagnetic

interference (EMI). Another available dataset is [31] that can be used for interference detection in high-frequency over-the-horizon (OTH) radar by providing both simulated and real range-Doppler image databases. Authors of [32] report results on interference analysis in four wireless networks: Bluetooth, Wi-Fi, Zigbee, and GPS. Other studies report the use of machine learning on GNSS data [33,34], GPS [35] or geostationary orbit satellite systems [36].

Most of the literature and available databases focused on EMI in electrical equipment, radar-specific interference detection, or GNSS and satellite communication systems, leaving general-purpose wireless bands such as FM and Wi-Fi largely unexplored. Existing resources often emphasize simulated or domain-specific datasets, which, while valuable, do not fully represent interference patterns encountered in everyday wireless environments.

To address this gap, the present work focuses on collecting over-the-air SDR-based transmitted and received spectrograms in the FM and Wi-Fi frequency bands, explicitly emulating three types of interference scenarios. Following, the paper presents the testing of various solvers and activation functions on a dedicated CNN architecture, enabling a systematic evaluation of how network design choices impact interference detection performance in a realistic wireless environment. This approach provides both a novel dataset and a preliminary framework for advancing machine learning-based RFI detection in widely used wireless systems.

3. DATA COLLECTION AND PREPROCESSING

Hack RF SDR platforms combined with GNU Radio flowcharts [37] were used to generate and record spectrogram images. Hack RF is a low-cost transmit/receive SDR device operating from 1 MHz to 6 GHz, capable of streaming I/Q samples up to 20 MS/s at a resolution of 8 bits. GNU Radio is an open-source signal-processing toolkit (with the graphical user-friendly interface GNU Radio Companion) that enables the development of flowgraphs from modular blocks (filters, modulators/demodulators, FFTs, decimators, encoders, sinks/sources) and visualization blocks (spectrogram/FFT sinks). Together, they enable rapid prototyping of RF chains by capturing wideband I/Q with HackRF, processing signals in GNU Radio, and generating spectrograms or other outputs for analysis.

The experimental setup used for interference generation; signal recording and processing is presented in fig. 1.

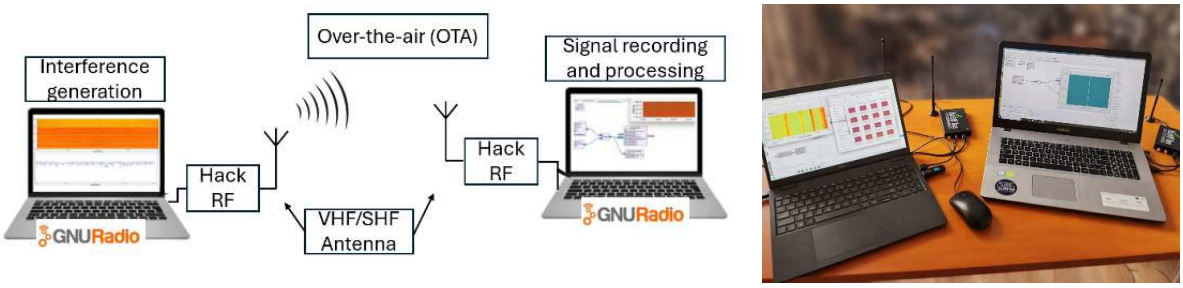


Fig. 1. Experimental setup for data collection

All measurements were performed indoors in a research laboratory, between May and July 2025 in the city of Sibiu. Two distinct laptops, running GNU Radio Companion together with two corresponding Hack RF devices were used. The RF channel of the SDR device was connected to an omnidirectional VHF/UHF antenna (model Aaronia Omnilog 7600) depending on the operating frequency band, and the interfering signal was captured over-the-air (OTA) by a distinct measurement platform. To obtain different SINRs and emulate realistic wireless environment the interference signal power and emission location was randomly varied during the measurements. Spectrogram images were collected in two datasets: one corresponding to the FM frequency band (88-110 MHz) and the second for the 2.4 GHz ISM band (2.4 GHz – 2.48 GHz). Three types of interferences were considered: burst noise,

continuous wave and chirp signal. A fourth class comprising idle spectrograms was also collected.

Fig. 2 presents the GNU radio flowchart for burst noise interference generation in the FM band and its corresponding spectrogram. For this case the burst noise appearance was obtained by multiplying a square wave signal with a noise source and then feeding the signal to the SDR (Hack RF) for emission.

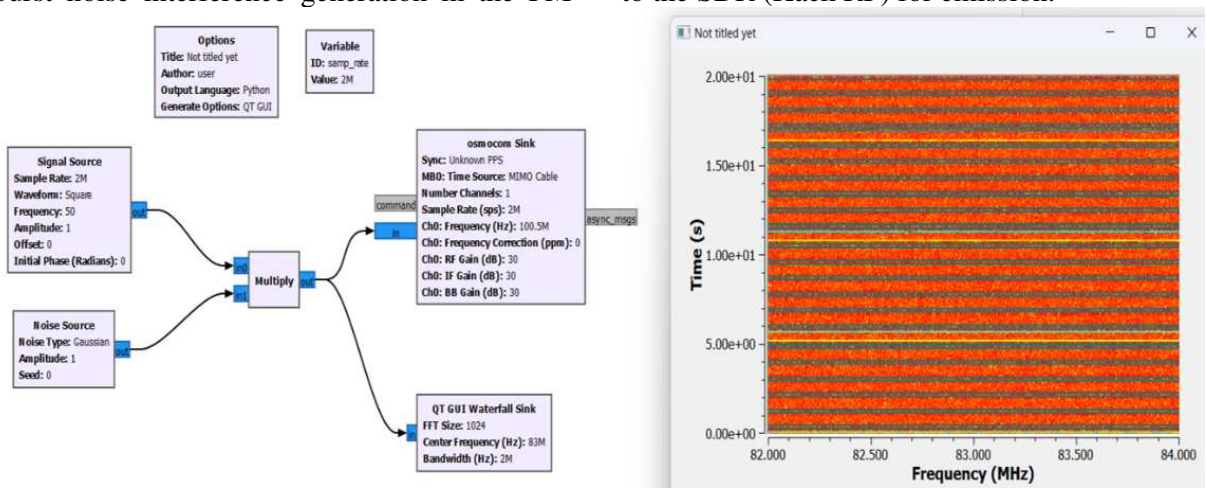


Fig. 2. GNU Radio flowchart for burst signal interference type generation

Similar flowcharts were used for continuous chirp (varying frequency signal) types of interference. The description of the signal classes collected is depicted in Table 1.

Table 1

Types of interference generated and their characteristics

Class/ interference type	Desription	SDR generation (GNU Radio)
Idle spectrum	No intentionally transmitted signal, with background noise and ambient signals present.	No emitted signal
Burst noise	Short periods of intense activity	Burst signal + Gate / Control Block
Continuous wave (CW)	Constant line in the spectrogram on fixed frequency	Sine Wave Source + Throttle
Chirp signal	Diagonal line on the spectrogram ascending or descending	Signal Source + Varying Frequency

Automatic spectrogram acquisition and saving was also implemented in GNU Radio on the designated signal recording and processing station, using the flowchart presented in fig.3.

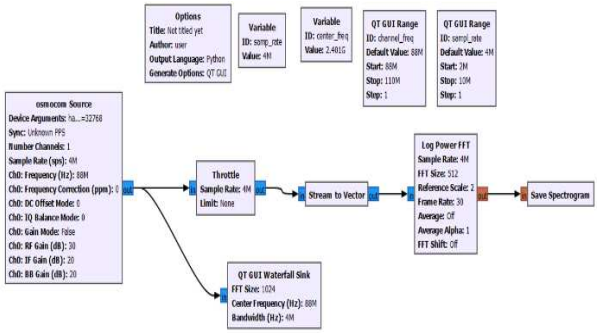


Fig. 3. GNU Radio flowchart for signal acquisition and spectrogram saving

Signal reception is performed by the Osmocom Source block, configured for this example with a center frequency of 88 MHz (FM band) and a variable sampling rate (2-10 MHz). These parameters can be dynamically modified by the QT GUI Range blocks, providing flexibility during application runtime. The received signal is split into two branches: the first goes to the QT GUI Waterfall Sink, where the spectrogram (graphical display of signal energy as a function of frequency and time) is displayed; the second branch passes through a processing chain: throttle - stream to vector - log power FFT, preparing the FFT data for saving. The final block, save spectrogram, is a

customized Python embedded block that collects the FFT data, adds it to a buffer, and every 10 seconds automatically saves a heatmap image representing the accumulated signal spectrogram.

The generated images were automatically saved in a predefined directory on the local system, using a standardized naming convention (spectrogram_00001.png, etc.), as shown in fig. 4. This method provided complete control over the capture process, eliminating the need for manual intervention and ensuring consistency in format, resolution, and frequency of saves. After each save, the buffer used to store the FFT lines was reset, allowing efficient and continuous signal processing.

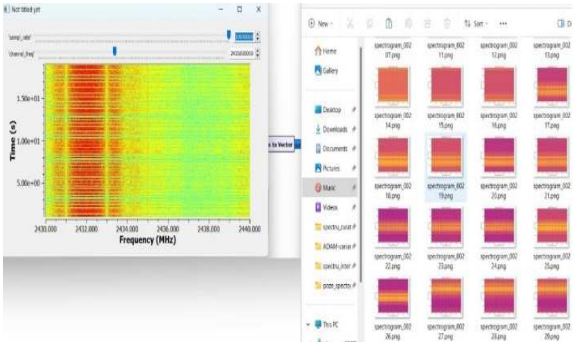


Fig. 4. OTA measured spectrogram and its corresponding directory

Each image was manually labeled based on the type of signal active during its capture and saved in a directory corresponding to the category to which it belongs. The data was organized into subfolders dedicated to each interference class to facilitate the model training and testing process. The image resolution was standardized at 224×224 pixels using a dedicated Python script.

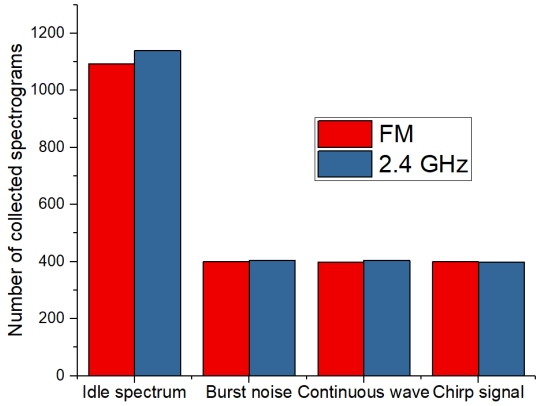


Fig. 5. Datasets histogram

Fig. 5 presents the distribution of the spectrogram classes in the two data sets (FM and 2.4 GHz). An uneven distribution between the idle spectrogram class and the interference types of classes is observed. The higher number of idle spectrograms compared to interference classes reflects the main objective of first detecting the presence or absence of interference before classifying its type. This distribution is therefore beneficial, as it ensures the datasets emphasize normal conditions while still including representative samples of different interference types for accurate classification once interference is detected.

The datasets were randomly divided into three subsets: 70% for training, 20% for validation, and 10% for testing and used accordingly in the deep learning network described in the following section.

4. DEEP LEARNING NETWORK DESIGN

In this paper, MATLAB was used to design and train a supervised CNN to classify the presence/absence of interference as well as the interference type. The proposed network is a three-layer CNN composed of convolution layers, followed by batch normalization layers, rectified linear unit layers (RELU) and maximum pooling layers. The network's general architecture is illustrated in fig. 6.

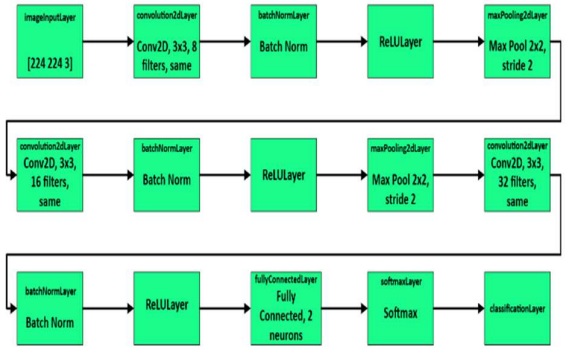


Fig. 6. Network architecture

The image input layer receives input images of size 224×224×3, being responsible for automatically normalizing pixel values before further processing. Each convolutional layer applies a set of filters (3×3 kernels) to the image or previous feature maps, extracting relevant

local visual patterns. The number of filters increases progressively 8 - 16 - 32, which allows the network to learn increasingly complex representations. Batch normalization layers normalize the activations from the previous convolutional layer. Its role is to stabilize and accelerate the training process by reducing sudden variations between data batches. In the initial design the ReLU activation function was used but the impact of other activation functions (Elu, LeakyReLu, Swish and Sigmoid) on the network classification performance was also investigated. The maxPooling 2D layer applies spatial reduction by selecting the maximum value in a 2×2 window. This step reduces the dimensionality of the data, preserves dominant features, and gives the network robustness to local translations. The fully connected layer connects all values from the last feature maps to the two/four final classes. The SoftMax layer transforms the output activations into probability values, one for each class, to facilitate a clear decision while the classification layer compares the softmax output with the actual labels, calculating the error that will be used to update the weights during training.

Two experimental scenarios were investigated: a. detection of the presence/absence of interference (2 classification classes) and b. detection of the interference type (when present) – 4 classification classes.

The main training options set for the designed network are presented in table 2.

Table 2

CNN training options

Solver	ADAM/ RMSprop/ SGDM
Initial Learn Rate	0.0001
Learn Rate Schedule	none
Max Epochs	10
Shuffle	Every epoch
Mini Batch Size	16
Validation Frequency	5
Output Network	Best validation loss

Three types of solvers were investigated to determine the best choice in terms of desired output (classification accuracy) according to table 2. ADAM (Adaptive Moment Estimation) uses adaptive learning rates with momentum for fast convergence. Root Mean Square Propagation (RMSprop) scales the learning rate by a moving average of squared gradients. Stochastic Gradient Descent with Momentum (SGDM) accelerates convergence by accumulating a velocity term from past gradients.

5. RESULTS AND DISCUSSION

The first scenario investigated is based on a binary classification (presence/absence of interference). First, the ADAM solver was used to train the CNN network according to the parameters specified in the previous section. FM dataset was first used to investigate the impact of the type of activation function on the classification accuracy. The results obtained are presented in table 3.

Table 3

Binary classification accuracy for various activation functions for the FM dataset and ADAM solver

Activation function	Accuracy (%)		
	Training	Validation	Test
ELU	99.8	97.8	96.9
Leaky ReLU	98.4	96.7	94.3
Sigmoid	98.1	96.9	97.3
Swish	100	98	97.2
ReLU	99.9	98.4	98.2

Although all tested functions provided very good results, it is noteworthy that Swish and ReLU had the most consistent and highest performance, both on the validation dataset and on the test dataset. Swish achieved perfect accuracy in training and very good performance in testing (97.82%), suggesting that the network learned efficiently without overfitting. Similarly, ReLU demonstrated excellent generalization ability, with the highest accuracy in testing (98.25%). The ELU and Sigmoid functions had balanced results, while LeakyReLU showed a slight decrease in testing. Based on these results ReLU activation function was selected, as it demonstrates best compromise between accuracy and stability.

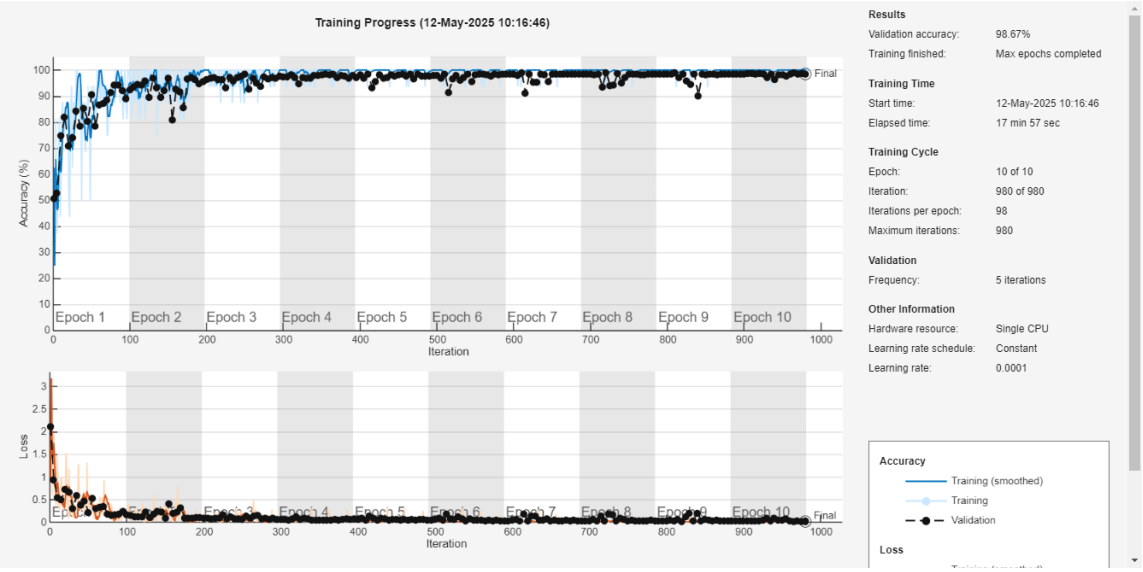


Fig. 7. Accuracy and loss evolution (ADAM) – 2.4 GHz dataset, binary classification

The accuracy and loss evolution during training using the ADAM solver and ReLU activation function for the 2.4 GHz dataset is depicted in fig. 7.

While training on the 2.4 GHz dataset, as shown in fig. 7, using the ADAM optimizer, the model demonstrated fast and efficient learning. The accuracy curves increase steadily from the first epoch, and the values stabilize quickly, with no signs of instability or large oscillations. The validation accuracy reaches almost 98.9%, and the loss remains low and constant throughout training. The combination of ReLU and ADAM seems to provide fast convergence and a good balance between accuracy and generalization ability, even in a dense and variable radio environment such as the 2.4 GHz ISM band. Similar results were obtained for the FM dataset.

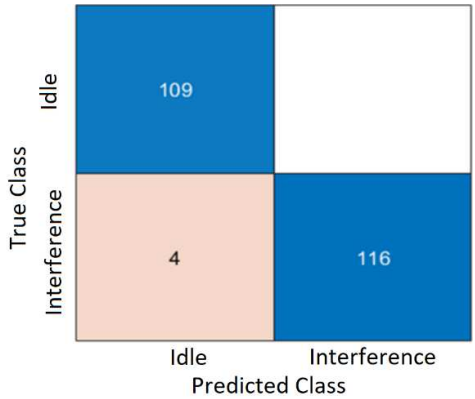


Fig. 8. Confusion matrix for FM test datasets (binary classification)

Fig. 8 presents the confusion matrix for the test data for FM dataset, reflecting the performance of the CNN model trained with the ADAM optimizer. Out of a total of 229 images in the FM test dataset, only 4 images with interference were incorrectly classified as idle. This indicates a very high correct classification rate with minimal false negative error, which is essential in scenarios where rapid interference identification is a priority.

Table 4 presents the obtained accuracy for both FM and 2.4 GHz datasets using 3 different solver types.

Table 4

Binary classification accuracy for various solver types

Solver	Dataset	Accuracy (%)		
		Training	Validation	Test
ADAM	FM	100	98.47	98.25
	2.4 GHz	100	98.67	99.56
SGDM	FM	99.81	98.91	98.25
	2.4 GHz	99.62	99.56	99.46
RMSprop	FM	99.88	98.47	98.69
	2.4 GHz	99.94	99.11	99.72

As observed, all three optimization algorithms tested proved to be effective in detecting interference in both frequency bands. ADAM stands out for its speed and consistent performance, RMSprop offers good adaptability

in variable conditions, and SGDM brings stability to the learning process. RMSProp achieves the highest test accuracy (99.72%) in both frequency bands, indicating very good model generalization in this scenario. However, it should be noted that different network configurations, datasets, or fine-tuning strategies could alter this outcome, in which case solvers like ADAM or SGDM might prove more advantageous due to their stability and consistent convergence.

In the second scenario the network was trained to differentiate between four classes of spectrograms, also highlighting the interference type (burst noise/chirp/CW) if present.

Fig. 9 presents the confusion matrix obtained for the test dataset, with the network trained on the FM train dataset with the ADAM solver. One can observe that the obtain accuracy remains high (98%) in this case as well. The confusion matrix indicates that most samples are correctly classified, with only a small number of misclassifications across the considered classes (orange cell values). This result confirms the strong generalization capability of the proposed model when evaluated on unseen data for this scenario as well.

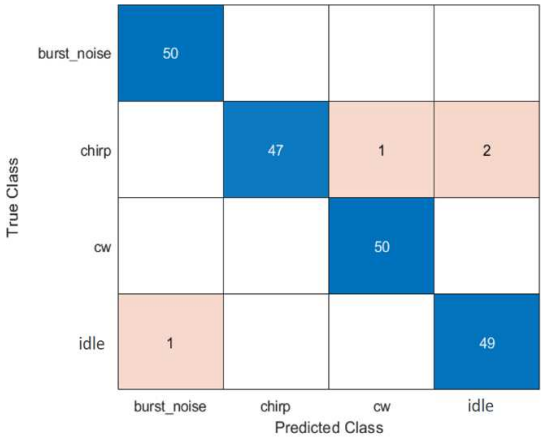


Fig. 9. Confusion matrix for FM test dataset (ADAM solver)

Following, the same algorithm was applied on the 2.4 GHz dataset. Fig. 10 presents the confusion matrix obtained for the test dataset using the classification obtained from training the network on the 2.4 GHz train dataset with the SGDM solver.

For this case, one can observe the reduced classification accuracy obtained (78.75%). The confusion matrix indicates that most misclassifications occur between chirp and CW interference types. This was explained by the following: although both FM and 2.4 GHz spectrograms were computed using the same FFT size (512), the higher sampling rate in the 2.4 GHz band (10 MHz as compared to 4 MHz) results in larger frequency bin spacing and thus reduced frequency resolution. Under these conditions, chirp signals with low sweep rates may appear quasi-stationary within individual time frames, producing spectrogram patterns similar to CW interference.

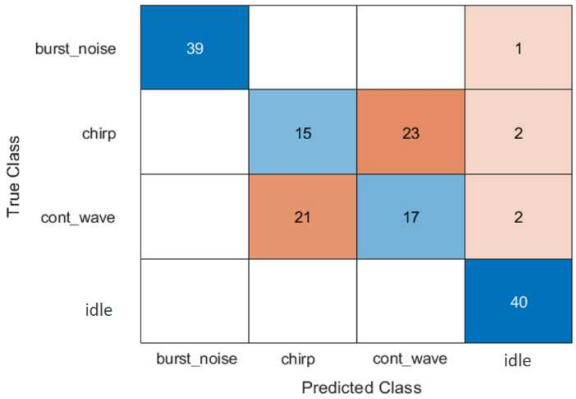


Fig. 10. Confusion matrix for 2.4 GHz test dataset (SGDM solver)

The same limitation was also observed for the other solvers (ADAM, RMSProp), resulting in lower overall train/test acuracies as presented in table 5.

Table 5

Classification accuracy for various solver types

Solver	Dataset	Accuracy (%)		
		Training	Validation	Test
ADAM	FM	100	99.50	98.00
	2.4 GHz	85.51	73.91	68.12
SGDM	FM	99.93	96.75	97.50
	2.4 GHz	84.09	73.29	78.75
RMSprop	FM	99.64	96.25	97.00
	2.4 GHz	87.02	73.60	75.00

The observed performance degradation was attributed to the limitations of spectrogram-based data representations. By compressing the original time-domain signals into lower-

dimensional time–frequency images, certain discriminative characteristics are inevitably smoothed or averaged out. In the 2.4 GHz band, where signals are sampled at higher rates, this effect becomes more pronounced and leads to less distinctive feature patterns for interference types with similar spectral behavior. As a result, the network exhibits reduced separability between chirp and CW classes, which is consistently reflected in the lower classification accuracies observed across all solver configurations.

6. CONCLUSION

This paper presents an SDR-based framework for over-the-air interference detection and classification in two widely used wireless frequency bands: FM (88–110 MHz) and the 2.4 GHz ISM band. A novel dataset of real-world spectrograms was collected using low-cost SDR hardware and GNU Radio, covering idle signals and three representative interference types: burst noise, continuous wave, and chirp signals. A compact CNN architecture was designed and systematically evaluated using different solvers and activation functions to assess its performance under realistic operating conditions.

The experimental results demonstrated that the proposed approach achieves excellent performance for binary interference detection in both frequency bands, with test accuracies exceeding 98% across all investigated solvers. This confirms the suitability of spectrogram-based CNN models for reliable interference presence detection in practical SDR monitoring systems. For multi-class interference type classification, high accuracy was achieved in the FM band (up to 98%), indicating strong generalization and clear separability of interference patterns at lower sampling rates.

In contrast, classification performance in the 2.4 GHz band was noticeably lower, particularly due to confusion between chirp and continuous wave interference. This limitation was shown to originate from reduced frequency resolution caused by higher sampling rates combined with fixed FFT dimensions, as well as from the inherent information loss introduced by spectrogram-based dimensionality reduction. These effects lead to overlapping time–frequency features for interference types with similar spectral behavior, consistently affecting all tested optimization solvers.

Overall, the study highlights both the effectiveness and the limitations of spectrogram-based deep learning approaches for interference classification. While they provide a computationally efficient and robust solution for interference detection, careful selection of time–frequency representation parameters is required, especially for high-bandwidth signals. Future work will focus on optimizing spectrogram resolution, exploring alternative signal representations (e.g., raw I/Q or multi-resolution features), and expanding the dataset to include additional interference types and real-world scenarios, with the goal of improving classification robustness in dense wireless environments.

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Detecția interferențelor bazată pe spectrograme utilizând platforme radio definite software

Rezumat: Platformele radio definite software (SDR) oferă soluții flexibile și eficiente din punct de vedere al costurilor pentru monitorizarea spectrului de radiofrecvență (RF), permițând detecția și clasificarea interferențelor în timp real, în medii wireless diverse. În această lucrare este prezentat un cadru de detecție și clasificare a interferențelor bazat pe SDR, concentrat pe două benzi de frecvență larg utilizate: banda FM (88–110 MHz) și banda ISM de 2,4 GHz. A fost creat un set de date original de spectrograme etichetate, obținut prin transmisii radio (over-the-air) folosind echipamente SDR cu cost redus și platforma GNU Radio, care include atât semnale culese din spectrul necorupt, cât și trei tipuri reprezentative de interferențe: zgomot de tip burst, semnal de undă continuă și semnale de tip chirp. A fost proiectată și evaluată o rețea neuronală convoluțională (CNN) în mai multe configurații, analizând impactul diferiților algoritmi de optimizare și al funcțiilor de activare asupra performanței de clasificare. Rezultatele experimentale demonstrează o acuratețe excelentă (depășind 98%) pentru detecția interferențelor (clasificare binară) în ambele benzi de frecvență. Pentru clasificarea multi-clasă a tipurilor de interferență, modelul atinge o acuratețe de până la 98% în banda FM, în timp ce în banda de 2,4 GHz se observă o scădere a performanței, cauzată de limitările de rezoluție timp–frecvență specifice reprezentărilor bazate pe spectrograme la rate mari de eșantionare. Rezultatele evidențiază eficiența metodelor de învățare profundă pentru monitorizarea interferențelor utilizând SDR, subliniind totodată compromisurile dintre eficiența computațională și capacitatea de discriminare în sistemele wireless de bandă largă.

Annamaria SÂRBU, Associate Professor, "Nicolae Bălcescu" Land Forces Academy of Sibiu, Department of telecommunications, IT and Cybersecurity, Faculty of Military Management, sarbu.annamaria@armyacademy.ro, +40 269 432 990, 3-5 Revolutiei Street, Sibiu, Romania.

Antonio HOCIUNG, Master student, "Nicolae Bălcescu" Land Forces Academy of Sibiu, Faculty of Military Management, hociung_antonio@yahoo.com, +40 269 432 990, 3-5 Revolutiei Street, Sibiu, Romania.