Scientific Journal of the Ternopil National Technical University
2026, vol. 121, no. 1, pp. 119–129,
ISSN: 2522-4433 Print, ISSN: 2522-4441 Online
https://doi.org/10.33108/visnyk_tntu2026.01.119

Submitted: 2025-09-13 | Revised: 2026-02-19 | Accepted: 2026-03-24

Recognition of Low-Probability-of-Intercept Radar Signals Based on a Hybrid CNN-MLP Model

Ivan Peleshchak [1]*, **Vasyl Lytvyn** [2], **Mykhailo Mykytyn** [3], **Roman Peleshchak** [4]

[1] Lviv Polytechnic National University, Lviv, Ukraine, ivan.r.peleshchak@lpnu.ua

[2] Lviv Polytechnic National University, Lviv, Ukraine, vasyl.v.lytvyn@lpnu.ua

[3] Lviv Polytechnic National University, Lviv, Ukraine, mykhailo.mykytyn.msaad.2024@lpnu.ua

[4] Lviv Polytechnic National University, Lviv, Ukraine, roman.m.peleshchak@lpnu.ua

* Corresponding author: ivan.r.peleshchak@lpnu.ua

Abstract: *This paper proposes an intelligent recognition system for low-probability-of-intercept (LPI) radar signals based on a hybrid neural network model that combines a complex-valued convolutional neural network (Complex 1D-CNN) for processing in-phase and quadrature (IQ) components with a multilayer perceptron (MLP) for extracting parametric signal features. Unlike conventional approaches that rely on time-frequency transforms such as the short-time Fourier transform (STFT) and Choi–Williams distribution (CWD), the proposed model operates directly on complex-valued data while preserving the phase structure of the signal. To improve robustness under noisy conditions, a Hankel Cross-Attention mechanism and SNR-aware loss weighting are employed. Experiments conducted on the RadChar Baseline dataset (5 classes) achieved an accuracy of 90.0% and a macro F1-score of 0.90, outperforming single-branch CNN models and demonstrating stable performance at SNR levels down to -12 dB. The obtained results confirm the effectiveness of the proposed integrated approach for LPI radar signal recognition in noisy environments.*

Keywords: *LPI signals, complex CNN, Hankel Cross-Attention, hybrid CNN+MLP model, RadChar, radar signal recognition.*

1. INTRODUCTION

Low-probability-of-intercept (LPI) radar systems are widely used in modern communication and reconnaissance applications due to their ability to minimize signal detectability. The high time-frequency variability and complex modulation schemes of such signals make their recognition one of the most challenging tasks in the field of electronic intelligence. Traditional approaches based on handcrafted time-frequency feature extraction, including the Wigner–Ville Distribution (WVD), Choi–Williams Distribution (CWD), and Pseudo-Wigner Distribution (PWD) [1–3], demonstrate limited accuracy in noisy environments and require substantial computational resources.

The emergence of deep learning has created new opportunities for automatic feature extraction without preliminary signal transformations [4, 5]. However, most existing CNN-based models operate on real-valued inputs and do not account for the complex-valued nature of radar data, which leads to the loss of phase information [3, 6]. In addition, models relying on time-frequency signal representations are computationally expensive and scale poorly to large datasets.

The problem of recognizing low-probability-of-intercept (LPI) signals remains highly relevant because of the growing need to ensure radar stealth performance in complex interference environments. In [6], the concept of LPI radar systems was formulated, showing that conventional detection techniques are ineffective for extracting signals under low signal-to-noise ratio (SNR) conditions. Later, study [3] employed time-frequency distributions for signal recognition based on WVD and its modifications. Although these methods improved visualization of signal energy characteristics, they required high computational cost and suffered from phase information degradation under severe noise conditions.

Further progress was achieved through the use of convolutional neural networks (CNNs). The authors of [7] demonstrated the effectiveness of CNNs for LPI signal classification without handcrafted feature extraction, whereas [8] proposed automatic CNN architecture optimization using the TPOT framework. In [9], a deep CNN approach with transfer learning was developed, improving generalization when training data were limited. The authors of [10] introduced a dual-channel CNN with feature fusion of I and Q components, achieving high classification accuracy; however, the method remained restricted to real-valued processing without full complex-domain representation.

Other studies focused on alternative learning paradigms and signal processing strategies. In [11], semi-supervised learning combined with a support vector machine (SVM) was investigated for effective use of partially labeled data. The authors of [12] proposed a hybrid autoencoder-CNN model that provided improved noise robustness and reduced information loss during signal reconstruction. Meanwhile, [13] employed graph-based structures to model signal topology and relationships among signal components, thereby improving interpretability and classification accuracy.

In [14], a hybrid CNN-MLP model was developed for IQ signals represented in polar coordinates, preserving phase information and improving generalization for low-SNR signal classification. The architecture most closely related to the model proposed in this paper is the Multi-Channel 1D-CNN introduced in [15], which employs parallel convolutional branches for multichannel IQ signal analysis.

Thus, previous studies have demonstrated the effectiveness of CNN-based models for LPI signal recognition, but predominantly in the real-valued domain, without complex-valued representation and without explicit consideration of the signal-to-noise ratio. In this paper, a hybrid complex-valued CNN-MLP model is proposed that combines complex convolutional encoding, amplitude-domain feature processing, and SNR-aware fusion, thereby extending and generalizing the approaches presented in [9, 10, 14, 15].

To overcome these limitations, this paper proposes a hybrid CNN-MLP model that combines:

1. A complex-valued convolutional branch for analyzing the phase characteristics of IQ signals;
2. An amplitude-processing branch for modeling the signal energy structure;
3. An MLP branch for integrating parametric features;
4. An SNR-aware feature fusion mechanism and Hankel Cross-Attention module to improve classification accuracy under low-SNR conditions.

The proposed approach eliminates the need for time-frequency transforms, reduces computational cost, and provides high classification accuracy even in severe noise environments. Experimental results on the RadChar dataset demonstrate the superiority of the proposed model in terms of accuracy, robustness, and generalization capability compared with existing solutions such as ResNet-152-SVM and DC-CNN [9].

The aim of this study is to improve the classification accuracy of LPI radar signals in noisy environments through the development of a hybrid CNN-MLP model [14, 15] with complex-valued convolutions and adaptive feature fusion.

2. METHODS

RadChar (Radar Characteristics Dataset) is an open synthetic corpus of radar signals developed for research in the field of automatic recognition of low-probability-of-intercept (LPI) signals. The dataset includes from 50 thousand to more than 2 million IQ samples belonging to several modulation types.

In this study, the RadChar Baseline subset was used, containing 1,000,000 signals from five major LPI modulation classes: Coherent Pulse Train (CPT), Barker Code, Polyphase Barker, Frank Code, and Linear Frequency Modulation (LFM). Each signal is represented by 512 samples of the complex-valued In-phase (I) and Quadrature (Q) components:

$$x[n] = I[n] + jQ[n] \quad (1)$$

Additionally, the following signal generation parameters are provided for each record:

- number of pulses;
- pulse width (PW);
- initial delay;
- pulse repetition interval (PRI);
- signal-to-noise ratio (SNR), varying from -20 dB to +20 dB with a step of 1 dB.

Such parametric coverage makes it possible to model a wide range of realistic radar operating scenarios and to evaluate model robustness under changing observation conditions. The radar IQ signals in RadChar are generated programmatically using mathematical modulation models, ensuring precise parameter control and full experimental reproducibility [16].

Mathematical model. The proposed model is based on a hybrid architecture that combines a complex-valued one-dimensional convolutional neural network (Complex 1D-CNN) for processing sequences of the In-phase I and Quadrature Q signal components together with the amplitude $|s|$, and a multilayer perceptron (MLP) for analyzing additional parametric features. Let the input signal be defined as in (1). Its amplitude is given by:

$$A[n] = |x[n]| = \sqrt{(I[n]^2 + Q[n]^2)} \quad (2)$$

Table 1. Main Types of LPI Signals in the RadChar Dataset.

Signal	Modulation Type	Description
0	Coherent Pulse Train (CPT)	A coherent pulse sequence with a constant phase relationship between pulses. It ensures high coherence and signal stability due to a fixed phase connection.
1	Barker Code	A binary sequence of length 7, 11, or 13 that minimizes the sidelobe level in the correlation function, thereby improving target detection quality.
2	Polyphase Barker	An extended version of the Barker code with multiple phase states. It is used to improve resolution and reduce mutual interference between signals.
3	Frank code	Frank polyphase coding (M=4…8), which provides a uniform energy distribution in the spectrum and improves noise robustness.
4	linearFM (LFM)	A linear frequency-modulated signal in which the frequency changes proportionally with time; it is widely used in radar systems to increase target detection range and improve resolution.

Thus, the input to the model consists of three channels, (I, Q, A), which preserves both the phase and energy structure of the signal [1, 2]. The complex-valued convolution operation for kernel $w = w_r + jw_i$ is defined as follows:

$$(W*x)[n] = (w_r * I - w_i * Q)[n] + j(w_r * Q + w_i * I)[n], \tag{3}$$

where σ denotes convolution in the time domain [14]. For the real-valued amplitude channel (2), a parallel convolution with the same parameters is applied, and its output is concatenated with the outputs of the complex-valued branch. After each convolutional layer, complex batch normalization is applied.

$$\begin{bmatrix} \hat{I} \\ \widehat{Q} \end{bmatrix} = \Gamma \Sigma^{-\frac{1}{2}} \left(\begin{bmatrix} I \\ Q \end{bmatrix} - \mu \right) + \beta, \tag{4}$$

where Σ is the covariance matrix between channels I, while $[Q, \Gamma, \beta]$ are learnable scale and shift parameters, respectively. Next, the activation function *modReLU* is applied, which regulates the amplitude without distorting the phase [10]:

$$modReLU(z) = RELU(|z| + b)\frac{z}{|z| + \varepsilon}. \tag{5}$$

The output feature maps are aggregated using global average pooling over their magnitudes, forming the vector h_{CNN}, which represents the temporal-phase structure of the signal. In the parallel branch, the multilayer perceptron (MLP) processes the normalized parameter vector $z = [pulses, PW, delay, PRI, SNR]$ through a sequence of linear layers and ReLU activation functions, forming the vector h_{MLP}. Both branches are combined by late fusion into a shared latent space $h = [h_CNN; h_MLP]$, after which the resulting representation is passed to the classification layer with the Softmax function. The model is trained by minimizing the weighted cross-entropy loss function:

$$l = -\frac{1}{N}\sum_{i=1}^{N} \omega(s_i) \sum_{k=1}^{K} q_{ik} log\hat{p}_{ik}, \tag{6}$$

where q_{ik} denotes the soft labels obtained using label smoothing. The weighting coefficient that increases the contribution of low-SNR samples [1, 2] is defined as:

$$\omega(s_i) = 1 + \lambda\left(1 - \tilde{s}_i\right)^{\gamma} \tag{7}$$

Training is performed using the AdamW optimizer with OneCycleLR scheduling, gradient norm clipping, EMA-based weight smoothing, and early stopping. Thus, the model simultaneously analyzes the phase (I, Q), amplitude $(|s|)$, and parametric (PW, PRI, SNR) characteristics of the signal, providing a comprehensive representation of LPI signals and improving classification accuracy even at low signal-to-noise ratios [10, 14].

In addition, for signals with periodic or quasi-cyclic structure, segmentation into partial intervals is applied, which makes it possible to more accurately represent phase transitions and amplitude modulations. The approach to extracting deterministic cyclic components is consistent with the method presented in [17].

Architecture. The proposed model has a hybrid structure that combines the advantages of complex-valued convolutional neural networks (Complex-CNNs) for IQ signal processing and multilayer perceptrons (MLPs) for the analysis of parametric signal features. The main purpose of this design is to ensure robust recognition of radar modulations under low signal-to-noise ratio (SNR) conditions by using both spectral-temporal and statistical information. The model consists of three main branches: a complex IQ branch, an amplitude branch, and a parametric MLP branch, which are integrated through component-wise projection and feature concatenation [14, 15]. image.

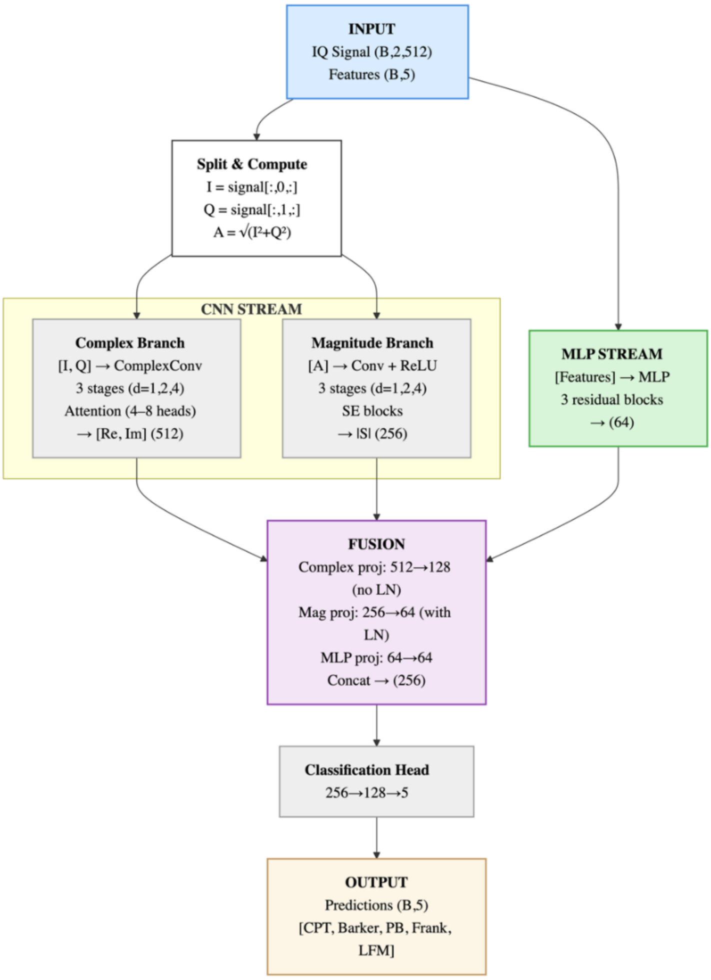

Figure 1. Architecture of the hybrid CNN-MLP model with three branches – Complex-IQ, Amplitude, and MLP – and the SNR-aware fusion mechanism.

The first branch takes the complex signal components as input – the real part $I(t)$ and the imaginary part $Q(t)$ – represented as a two-channel tensor (B, 2, L), where B is the batch size and L=512 is the signal length. The input data are passed through a sequence of complex-valued convolutional blocks, ComplexResDilBlock, each of which performs convolution in the complex domain:

$$W * x = (W_r * I - W_i * Q) + j(W_r * Q + W_i * I), \tag{8}$$

where W_r and W_i are the real and imaginary parts of the complex convolution kernel of size $(N,\ 1,\ K)$ where N is the number of filters (output feature maps) and K is the kernel length. These kernels are applied independently to the I and Q components along the temporal axis of the input two-channel tensor of size $(B,\ 2,\ L)$ where B is the batch size, $L = 512$ is the signal length, and I and Q denote the real (In-phase) and imaginary (Quadrature) components of the input sequence, respectively.

After each layer, complex batch normalization (ComplexBatchNorm) and the ModReLU activation function are applied, ensuring stable training and proper scaling of the amplitude-phase components [10, 11]. The output of this branch is aggregated using Global Average Pooling (GAP), forming the complex-valued feature vector f_{IQ}.

The second branch processes the signal amplitude:

$$|s(t)| = \sqrt{(I^2 + Q^2)} \tag{9}$$

It is implemented as a sequence of three convolutional blocks of the Conv–BN–ReLU–Pooling–Dropout type. This subsystem models the energy structure of the signal, which is less sensitive to phase distortions, and forms a compact vector of amplitude features. In the low-SNR range, it improves recognition stability by compensating for the loss of phase information in the complex-valued branch [6].

The third branch receives a set of numerical signal parameters, such as the number of pulses, pulse width (PW), pulse repetition interval (PRI), delay, and SNR [14]. These features are passed to an MLP with two to three hidden layers using ReLU nonlinearity and Dropout, which forms the parametric feature vector f_{param}.

All three feature vectors, $f_{IQ}, f_{param}, f_{amp}$, are combined in the hybrid fusion layer. Unlike simple concatenation, this layer takes the noise level into account by weighting the contribution of each branch using the coefficient $\lambda(SNR)$:

$$f_{fusion} = \lambda(SNR) \cdot [f_{IQ} || f_{amp}] + (1 - \lambda(SNR)) \cdot f_{param}, \tag{10}$$

where $||$ denotes the concatenation operation. This fusion implements adaptive coordination between statistical and spectral features depending on signal quality. At low SNR values, the network increases the weight of amplitude-parametric features, whereas at high SNR values, it gives greater weight to the complex-valued components [1, 2].

After the fusion layer, the combined feature vector is passed to the final fully connected classifier with Softmax activation. The output of the model is a probability vector for N types of LPI signals, such as CPT, Barker, Polyphase Barker, Frank, LFM. Thus, the proposed model combines deep complex-valued convolutional representation, amplitude-energy analysis, and parametric modeling, ensuring high noise robustness and classification accuracy over a wide range of SNR values.

Compared with conventional CNN or ResNet-based structures, the hybrid approach reduces the loss of phase information, adapts the model behavior to the noise level, and improves generalization for weak signals.

The experiments were conducted in the Google Colab environment using an NVIDIA L4 graphics accelerator with 24 GB of VRAM based on the Ada Lovelace architecture. The model was trained in Python 3.12.12 using PyTorch 2.8.0 with CUDA 12.6 and cuDNN 9.1.0. The use of mixed precision, namely bfloat16 and TF32, together with torch.compile(mode="reduce-overhead"), provided an approximately 3-4-fold acceleration of training compared with the baseline FP32 mode.

3. RESEARCH RESULTS AND DISCUSSION

At this stage, an experimental evaluation of the proposed Hybrid CNN-MLP model was conducted on the test subset of the RadChar Baseline dataset [16], which contains 200,000 signals belonging to five types of LPI modulations. The model was trained for 30 epochs using the AdamW optimizer, SNR-aware loss weighting, and the EMA mechanism.

To quantitatively evaluate performance, standard classification metrics – Precision, Recall, F1-score, and Accuracy – were used, as presented in the classification report (Fig. 2). To analyze misclassifications between classes, a confusion matrix (Fig. 3) was constructed, showing the proportions of correctly and incorrectly classified signals for each type.

The obtained results demonstrate that the model provides high and well-balanced accuracy across all classes, while the greatest difficulties are observed for Polyphase Barker (PB) signals due to the loss of phase patterns at low SNR levels.

Classification Report:

	precision	recall	f1-score	support
CPT	0.96	0.97	0.96	39924
Barker	0.96	0.92	0.94	39868
PB	0.87	0.84	0.85	40213
Frank	0.83	0.91	0.87	40097
LFM	0.90	0.88	0.89	39898
accuracy			0.90	200000
macro avg	0.90	0.90	0.90	200000
weighted avg	0.90	0.90	0.90	200000

Figure 2. Classification Report for Five Types of LPI Signals on the RadChar Test Set.

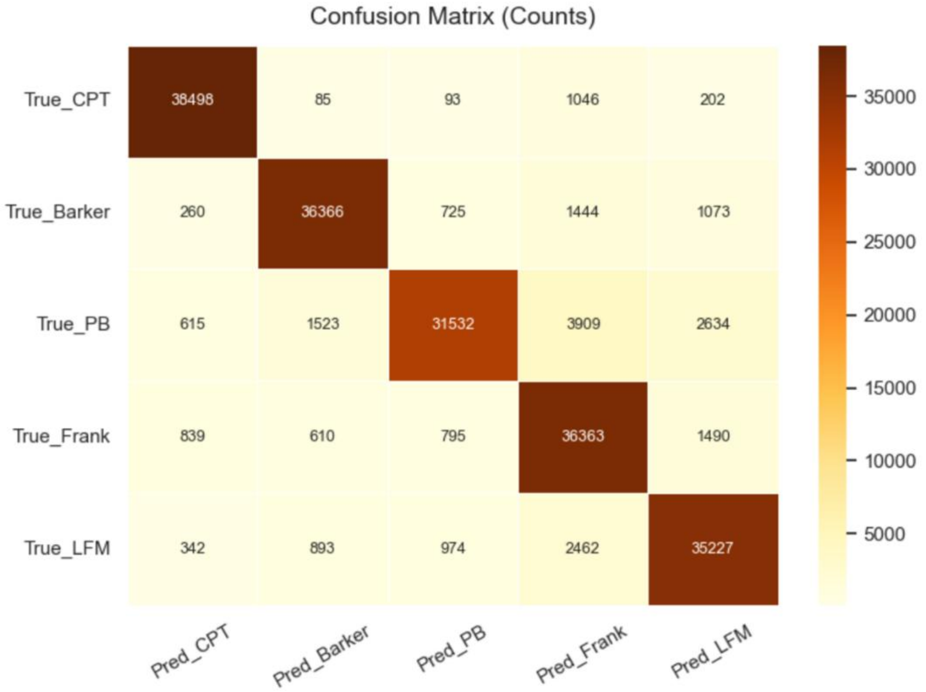

Figure 3. Confusion Matrix for the Five RadChar Classes.

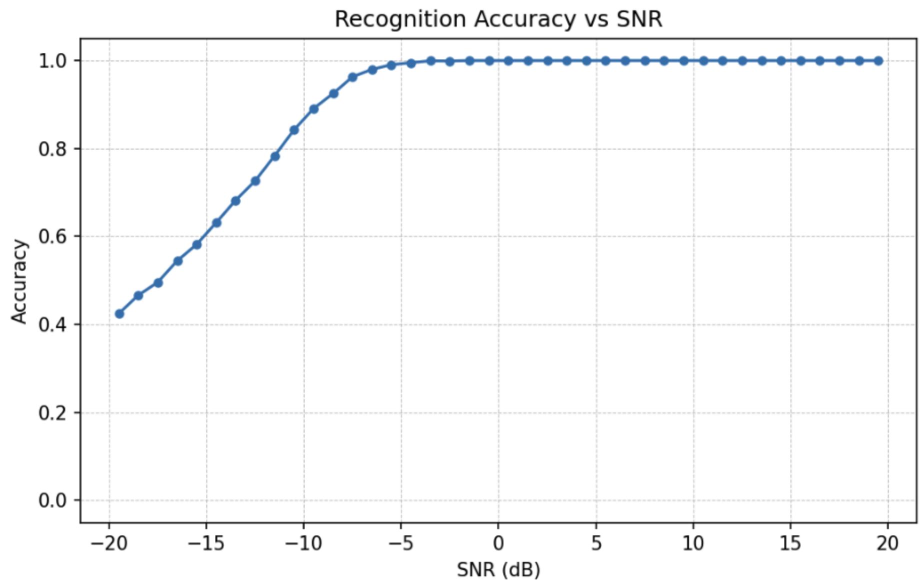

Figure 4. Dependence of Recognition Accuracy on SNR Level.

The proposed Hybrid CNN-MLP model with complex-valued convolutions and the Hankel Cross-Attention mechanism demonstrated a classification accuracy of 90.0% on the test set containing 200,000 signals.

The average macro and weighted F1-scores were both 0.90, indicating balanced performance across all classes. This confirms the stable generalization capability of the model even under challenging noisy conditions.

Among the five signal types – CPT, Barker, PB, Frank, and LFM – the best results were obtained for CPT (F1=0.96) and Barker (F1=0.94).

Frank and LFM signals achieved F1=0.87 and F1=0.89, respectively, whereas Polyphase Barker (PB) showed slightly lower performance (F1=0.85) due to the loss of phase patterns at low SNR levels. This confirms the effectiveness of complex-valued convolutional layers in representing both amplitude and phase components of the signal.

Analysis of the results over the SNR range from -20 dB to -11 dB showed that the model maintains considerable robustness to noise. In particular, CPT signals preserve more than 90% accuracy already at -15 dB and achieve complete recognition at -12 dB. In contrast, PB signals demonstrate a significant performance degradation, with accuracy decreasing to 10-28% in the range from -20 dB to -15 dB, which is caused by the loss of phase structure in the noisy environment.

The robustness of the model at low SNR levels is provided by two key mechanisms:

1. SNR-aware loss weighting in the CrossEntropyLoss function (λ=2.0), which increases the contribution of weak signals to the gradient;
2. The Hankel Cross-Attention module, which filters structural dependencies in temporal windows of 48 samples, increasing sensitivity to periodic components.

Figure 4 shows the change in classification accuracy depending on the signal-to-noise ratio (SNR). It can be observed that at SNR$\approx$-20 dB, the accuracy is about 42%, whereas at SNR$\geq$-12 dB, it exceeds 70%. A further increase in SNR leads to almost complete classification (Accuracy$\approx$1.0), which indicates the high robustness of the model under noisy conditions.

For comparison, in [15], the Multi-Channel 1D-CNN model shows a noticeably lower curve: its accuracy decreases to approximately 30–35% at SNR=-20 dB and increases only to approximately 65% at SNR=-10 dB. This confirms the advantage of the proposed Hybrid CNN-MLP model, which preserves phase coherence and amplitude information even under severe noise conditions.

Unlike two-dimensional approaches that require preliminary computation of time-frequency images and complex data processing, the proposed model operates directly on the IQ signal in the polar coordinate representation. This makes it possible to:

- reduce computational complexity;
- improve identification accuracy in the phase domain;
- ensure high performance in real-time processing.

To evaluate the effectiveness of the proposed model, a comparison was conducted with the recently proposed Multi-Channel 1D-CNN model [15], which uses parallel convolutional branches for IQ signal analysis, was included in the comparison. Its average accuracy on the same data was approximately 87%, which is lower than the result achieved by the proposed hybrid CNN-MLP model, namely 90%.

The obtained improvement is due to the use of SNR-aware normalization and MLP fusion, which allow the network to adapt to low SNR values and better generalize information across signal classes. Thus, the proposed hybrid model demonstrates an advantage over existing CNN-oriented approaches, especially under low signal-to-noise ratio conditions, in the SNR range from -20 dB to -10 dB, confirming its high effectiveness in realistic radar scenarios.

4. CONCLUSIONS

The proposed Hybrid CNN-MLP model demonstrated high efficiency in the classification of low-probability-of-intercept (LPI) radar signals under noisy conditions. By combining complex-valued convolutional processing of IQ components, amplitude-based signal representation, and an MLP branch for parametric features, the model provides a comprehensive representation of both phase and energy characteristics of radar signals. Experimental evaluation on the RadChar Baseline dataset showed that the proposed model achieved an overall classification accuracy of 90.0% and macro and weighted F1-scores of 0.90, confirming its balanced performance across the five considered LPI modulation classes.

The use of complex-valued convolutional layers, the Hankel Cross-Attention mechanism, and SNR-aware loss weighting improved the recognition of weak signals and increased robustness under low-SNR conditions. In particular, the model maintained stable classification performance at SNR levels down to -12 dB and showed better noise resistance than conventional CNN-based approache and previously reported architecture such as Multi-Channel 1D-CNN. These results confirm that direct processing of IQ data can reduce dependence on computationally expensive time-frequency transformations while preserving phase information that is essential for LPI signal recognition.

At the same time, the proposed model has several limitations that should be noted. First, the evaluation was performed on the synthetic RadChar Baseline dataset, and therefore the obtained results may not fully reflect the behavior of the model in real radio-frequency environments with hardware distortions, non-stationary interference, multipath propagation, and unknown modulation types. Second, the classification performance is not uniform across all signal types: Polyphase Barker signals remain more difficult to recognize at very low SNR levels due to the degradation of phase patterns in strong noise.

The practical value of the study lies in improving the reliability of weak LPI signal recognition in complex interference environments, which makes the proposed model promising for electronic intelligence, spectrum monitoring, and adaptive radar signal interception systems. Future research will focus on testing the model on real measured RF data, extending the number of modulation classes, improving recognition of phase-coded signals at extremely low SNR levels, and incorporating more advanced complex-valued attention mechanisms to further enhance robustness and generalization.

Author Contributions: Conceptualization: Ivan Peleshchak, Vasyl Lytvyn, Roman Peleshchak; Methodology: Ivan Peleshchak, Vasyl Lytvyn, Mykhailo Mykytyn, Roman Peleshchak; Software: Mykhailo Mykytyn; Validation: Ivan Peleshchak, Mykhailo Mykytyn; Formal analysis: Ivan Peleshchak, Vasyl Lytvyn, Mykhailo Mykytyn; Investigation: Ivan Peleshchak, Mykhailo Mykytyn, Roman Peleshchak; Data curation: Mykhailo Mykytyn, Ivan Peleshchak; Writing – original draft preparation: Ivan Peleshchak, Vasyl Lytvyn, Mykhailo Mykytyn, Roman Peleshchak; Writing – review and editing: Ivan Peleshchak, Vasyl Lytvyn, Roman Peleshchak; Visualization: Ivan Peleshchak, Mykhailo Mykytyn; Supervision: Vasyl Lytvyn, Roman Peleshchak; Project administration: Ivan Peleshchak, Vasyl Lytvyn; Funding acquisition: Vasyl Lytvyn, Roman Peleshchak. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The research was conducted with the grant support of the National Research Foundation of Ukraine «Methods of analysis and optimization of multimodal data for deep learning models in the military sphere», project registration No. 2025.07/0017 dated 12/24/2025.

Funding: This work was supported by the National Research Foundation of Ukraine under Grant No. [2025.07/0017] for the project «Methods of Analysis and Optimization of Multimodal Data for Deep Learning Models in the Military Sphere.»

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Data Availability Statement: Data in a public repository: "RadChar Dataset at https://github.com/abcxyzi/RadChar" (GitHub).

Declaration of Generative AI and AI-assisted technologies in the writing process: During the preparation of this work, the authors used ChatGPT by OpenAI in order to translate the manuscript into English and improve the clarity of academic language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

REFERENCES

[1] L. Cohen, Time-frequency distributions – a review, Proceedings of the IEEE. 77 (1989) 941–981. https://doi.org/10.1109/5.30749.

[2] H. Choi, W. Williams, Improved time-frequency representation of multicomponent signals using exponential kernels, IEEE Transactions on Acoustics, Speech, and Signal Processing. 37 (1989) 862–871. https://doi.org/10.1109/ASSP.1989.28057.

[3] M. Zhang, L. Liu, M. Diao, LPI Radar Waveform Recognition Based on Time-Frequency Distribution, Sensors. 16 (2016) 1682. https://doi.org/10.3390/s16101682.

[4] D.-H. Park, M.-W. Jeon, D.-M. Shin, H.-N. Kim, LPI Radar Detection Based on Deep Learning Approach with Periodic Autocorrelation Function, Sensors. 23 (2023) 8564. https://doi.org/10.3390/s23208564.

[5] T. Wan, K.-L. Jiang, H. Ji, B. Tang, Deep learning-based LPI radar signals analysis and identification using a Nyquist Folding Receiver architecture, Defence Technology. 19 (2023) 196–209. https://doi.org/10.1016/j.dt.2021.09.019.

[6] D.C. Schleher, LPI radar: fact or fiction, IEEE Aerospace and Electronic Systems Magazine. 21 (2006) 3–6. https://doi.org/10.1109/MAES.2006.1635166.

[7] M. Zhang, M. Diao, L. Gao, L. Liu, Neural Networks for Radar Waveform Recognition, Symmetry. 9 (2017) 75. https://doi.org/10.3390/sym9050075.

[8] J. Wan, X. Yu, Q. Guo, LPI Radar Waveform Recognition Based on CNN and TPOT, Symmetry. 11 (2019) 725. https://doi.org/10.3390/sym11050725.

[9] Q. Guo, X. Yu, G. Ruan, LPI Radar Waveform Recognition Based on Deep Convolutional Neural Network Transfer Learning, Symmetry. 11 (2019) 540. https://doi.org/10.3390/sym11040540.

[10] D. Quan, Z. Tang, X. Wang, W. Zhai, C. Qu, LPI Radar Signal Recognition Based on Dual-Channel CNN and Feature Fusion, Symmetry. 14 (2022) 570. https://doi.org/10.3390/sym14030570.

[11] F. Xu, H. Hu, J. Mu, X. Wang, F. Zhou, D. Quan, Low Probability of Intercept Radar Signal Recognition Based on Semi-Supervised Support Vector Machine, Electronics. 13 (2024) 3248. https://doi.org/10.3390/electronics13163248.

[12] Z. Qu, W. Wang, C. Hou, Radar Signal Intra-Pulse Modulation Recognition Based on Convolutional Denoising Autoencoder and Deep CNN, IEEE Access. 7 (2019) 112339–112347. https://doi.org/10.1109/ACCESS.2019.2935247.

[13] W. Tao, K. Jiang, J. Li, T. Yan, T. Bin, Detection and recognition of LPI radar signals using visibility graphs, Journal of Systems Engineering and Electronics. 31 (2020) 1186–1192. https://doi.org/10.23919/JSEE.2020.000091.

[14] O. Nazarevych, R. Peleshchak, V. Lytvyn, I. Peleshchak, V. Motyka, Recognition of Low Probability of Intercept Radar Signals in a Polar Coordinate System Based on a Hybrid CNN and MLP, in: 2025 IEEE 13th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Gliwice, Poland, 2025, pp. 338–345. https://doi.org/10.1109/IDAACS68557.2025.11322024.

[15] R.R. Yakkati, A.B. Boddu, B. Pardhasaradhi, S.R. Yeduri, L.R. Cenkeramaddi, Low Probability of Intercept Radar Signal Classification using Multi-Channel 1D-CNN, in: Proceedings of the 10th International Conference on Communication and Signal Processing (ICCSP), IEEE, 2024, pp. 1–5. https://doi.org/10.1109/ICCSP60870.2024.10543688.

[16] RadChar Dataset, GitHub Repository, (2024). https://github.com/abcxyzi/RadChar (Accessed 24 April 2026)

[17] I. Lytvynenko, Method of segmentation of determined cyclic signals for the problems related to their processing and modeling, Scientific Journal of TNTU. 88 (2017) 153–169. https://doi.org/10.33108/visnyk_tntu2017.04.153.