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PAPER

Enhanced Radar Emitter Recognition with Virtual Adversarial Training: A Semi-Supervised Framework

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SUMMARY Radar emitter identification (REI) is a crucial function of electronic radar warfare support systems. The challenge emphasizes identifying and locating unique transmitters, avoiding potential threats, and preparing countermeasures. Due to the remarkable effectiveness of deep learning (DL) in uncovering latent features within data and performing classifications, deep neural networks (DNNs) have seen widespread application in radar emitter identification (REI). In many real-world scenarios, obtaining a large number of annotated radar transmitter samples for training identification models is essential yet challenging. Given the issues of insufficient labeled datasets and abundant unlabeled training datasets, we propose a novel REI method based on a semi-supervised learning (SSL) framework with virtual adversarial training (VAT). Specifically, two objective functions are designed to extract the semantic features of radar signals: computing cross-entropy loss for labeled samples and virtual adversarial training loss for all samples. Additionally, a pseudo-labeling approach is employed for unlabeled samples. The proposed VAT-based SS-REI method is evaluated on a radar dataset. Simulation results indicate that the proposed VAT-based SS-REI method outperforms the latest SS-REI method in recognition performance.
key words: *Radar emitter identification (REI), signal recognition, semi-supervised learning (SSL), virtual adversarial training (VAT).*

1. Introduction

In the increasingly complex electromagnetic environment of modern naval and aerial battlefields, radar offense and defense strategies are intensifying. The heart of radar countermeasure information processing, central to modern electronic warfare and surveillance, is radar signal identification [1]. Radar emitter identification (REI) is crucial, involving the recognition and classification of radar signals for defense systems and intelligence. Modern warfare's diverse radar systems and signal characteristics pose significant challenges to REI. The complexity of radar emitter identification (REI) is heightened by the dense electromagnetic spectrum, mixed radar and communication signals, and variability within signal types, further compounded by noise, jamming, and new system signals [2]. This complexity arises from diverse signal modulation techniques, multiple radar operational modes, and environmental noise and interference. Identification typically involves analyzing radar signal features like frequency and modulation, which can be affected by distance and atmospheric conditions. The increasing number and complexity of modern radars challenge the creation of comprehensive databases. Traditional REI, relying on manual analysis and simple algorithms, is inadequate for modern electronic warfare, driving the need for automated, intelligent systems. This has led to the exploration of advanced signal processing and machine learning techniques, with neural networks showing promise in automatic classification.

As a result, numerous REI methods have explored the integration of time-domain complex baseband signals with deep neural networks (DNNs). Wang et al. [5] explored a radar transmitter recognition technique utilizing a deep network model. Their approach involves using the estimated parameter sample plot (EPSD) as the input data format. They employed a deep feedforward network (DFN) to effectively fit the abstract function mapping the input data to its category, significantly enhancing the recognition accuracy of radar transmitters. Madhu et al. [6] implemented DL methods for the efficient processing of large image datasets, leveraging power spectrum and signal noise. They assessed convolutional neural networks across different time-frequency estimators to determine the one yielding the highest accuracy. The optimal estimator is then applied for identifying radar emitters by analyzing the signal-to-noise ratio. Xiao et al. [7] introduced an innovative method for signal feature analysis that utilizes the short-time Fourier Transform (STFT). This approach demonstrates robust performance and effectiveness, particularly in scenarios with low signal-to-noise ratio (SNR), and it also offers notable real-time capabilities. Pan et al. [8] employed a one-dimensional convolutional residual neural network coupled with a convolutional block attention module (1D-CBAM-ResNet) for the automatic learning and identification of one-dimensional intermediate frequency (IF) signals in a single process, thereby enhancing signal emitter identification (SEI) precision. This model integrates a one-dimensional residual building unit (1D-RBV) and a one-dimensional convolution block attention module (1D-CBAM), effectively consolidating channel and spatial data to identify pulse fingerprint features precisely.

The effectiveness of deep learning depends on large amounts of labeled training data [9]. However, collecting and annotating these data in the real world is both challenging and time-consuming. To address the shortcomings of existing

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technologies, we propose a semi-supervised REI method based on virtual adversarial training (VAT) [10], solving the problem of inaccurate device category identification due to insufficient sample volume. Semi-supervised learning can generate decision boundaries, capturing underlying structures more accurately with embedded information. It balances the need for human expertise in feature extraction and the capability of automated systems to handle large-scale data. By utilizing both labeled and unlabeled data, semi-supervised learning (SSL) can improve the accuracy and efficiency of radar transmitter identification, especially in situations where labeled data is scarce or costly to obtain. Considering the dynamic nature of modern electronic warfare, this approach is particularly important, as new radar systems and signal types are continuously evolving. Therefore, exploring SSL techniques in the field of REI is not only a natural evolution of the field but also a necessary step in developing more complex and effective electronic surveillance and countermeasure systems.

This paper proposes a VAT-based REI method using SSL designed for scenarios with a scarcity of labeled training samples. Two objective functions are designed to extract the semantic features of radar signals: computing cross-entropy loss for labeled samples and VAT loss for all samples. Additionally, a pseudo-labeling approach is employed for unlabeled samples. The main contributions of this paper are summarized as follows: (1) We propose a VAT-based SS-REI (SS-VAT) method that incorporates VAT within an SSL framework. This method is designed to address the challenge of REI in situations where labeled training samples are scarce. The process utilizes two objective functions to extract semantic features from radar signals: cross-entropy loss for labeled samples, VAT loss for all samples, and a pseudo-labeling approach for unlabeled samples. (2) We conduct the experiments and verify the proposed method from different aspects. The experimental results demonstrate that the SS-VAT method outperforms existing SS-REI methods regarding recognition performance. This showcases the method's efficacy in leveraging labeled and unlabeled data to achieve superior REI accuracy. (3) We innovatively use VAT within an SSL framework, which helps to enhance the model's robustness and generalization capabilities. This method can effectively utilize many unlabeled data from real-world scenarios.

2. Related Works

2.1 SSL-based Methods

SSL has become increasingly popular in a variety of real-world scenarios. This popularity stems mainly from the challenges and high costs of annotating large datasets. Within this field, there are several methodologies, each offering unique strategies to capitalize on unlabeled data. These include consistency regularization methods, pseudo-labeling methods, deep generative methods, and graph-based methods [15]. Such diverse approaches enable the effective use of unlabeled data, greatly enhancing the versatility and robustness of DL models. This is particularly beneficial when acquiring labeled data is either scarce or expensive.

- Consistency regularization methods, grounded on the smoothness or manifold assumption principles, entail incorporating similarity constraints into the final loss functions. This strategic integration encourages DL models to generate similar predictions for slightly altered versions of the same input signals [18]. Consequently, combining consistency regularization with a supervised classification backbone yields a straightforward and highly effective SSL approach.
- The Pseudo-labeling is a classical self-training method [14]. The pseudo-labeling method uses the probability output of unlabeled training samples as their pseudo-labels. Then, it regularizes the training process of the depth model by using these pseudo-labeled samples [15]. The key is to generate high-confidence pseudo labels so unlabeled training samples can be selected confidently. Yang et al. [16], incorporated pseudo labels into SEI. Longi et al. [17] introduced a SEI method based on pseudo labels. This framework iteratively generated pseudo labels and assigned weighted importance to individual samples based on the number of unlabeled samples and the learning phase.
- Deep generative methods, such as Generative Adversarial Networks (GANs) [19], Convolutional Auto-Encoders (CAEs) [20] and their variants, can learn the data distribution from unlabeled training samples. Therefore, SemiSEI methods based on an unsupervised component such as Auxiliary Classifier GAN (ACGAN) [21], Improved GAN [22] or CAE. In comparison to methods lacking a corresponding generator or decoder, deep generative methods manifest notable enhancements in identification performance, particularly when operating under conditions of limited labeled training samples. Nonetheless, it is imperative to acknowledge the inherent limitations of GAN-based techniques, which are susceptible to training instabilities and are prone to model collapses. Overcoming these issues necessitates the implementation of a myriad of intricate training strategies. Concurrently, CAE, while incorporating unlabeled training samples into the training pipeline solely through target reconstruction, may not fully exploit the latent information embedded within these unlabeled samples.
- In the graph-based method, the distribution of labeled data and unlabeled data is regarded as nodes on the graph, and the label propagation algorithm is used for learning [23].

2.2 Adversarial Training-based Methods

Adversarial training is a crucial technique to strengthen the defenses of neural networks [24, 25]. We introduce slight, carefully crafted disturbances to the input data during training. While these perturbations are small, they can trick the neural network into making errors. The network learns to withstand such disruptions and maintain accuracy by training with these modified inputs. This approach is commonly adopted to protect against adversarial attacks. These attacks involve altering input data minimally yet strategically to fool the model into incorrect predictions. Adversarial training effectively counters such threats, making it a reliable defense mechanism [26]. Moreover, this method is not only defensive. It can also be repurposed to create adversarial attacks [27]. Attackers can generate adversarial inputs that lead a model to make mistakes, exploiting the model's vulnerabilities. In addition to its use in security, adversarial training adapts to semi-supervised learning [28]. It leverages unlabeled data in a method known as Virtual Adversarial Training (VAT). This variation helps improve model performance when labeled data is scarce, using the abundance of unlabeled data to inform the training process.

RF signal fingerprints, uniquely influenced by minor hardware differences in emitters, are typically subtle and can be disrupted by noise, leading to misidentification. We employ adversarial training for our Convolutional Neural Network (CNN) to mitigate this issue. Enriching the training set with adversarial examples bolsters the network's detection capabilities and fortifies its resilience. Central to adversarial training is the generation of these adversarial examples. In practice, a nominal perturbation, denoted as Δx and considered a random variable, is introduced to the input vector of a trained CNN. This randomness is crucial as it allows the model to simulate a range of potential perturbations that might affect the input data, thus reflecting the various types and degrees of noise and distortions that data may encounter in the real world. The variability introduced by this random perturbation forces the model to learn to generalize well across a broader range of input variations, rather than overfitting to specific adversarial examples. This perturbation is calibrated to maximize the network's loss function. When this loss peaks, the input $x + \Delta x$ is deemed an adversarial sample, as discussed by Kokalj-Filipovic and Sadeghi. Such perturbations typically cause the CNN to make classification errors. To combat this, the CNN is trained using the adjusted input $x + \Delta x$ alongside the true label y_{true}. This training step markedly enhances the CNN's proficiency in identifying adversarial examples, thereby substantially improving the robustness of the network against these minute yet effective disturbances, in line with the findings of Kokalj-Filipovic and Sadeghi [26,27].

2.3 VAT-based Methods

The adversarial training algorithm trains a CNN in a supervised learning model, where all the training samples must be labeled. However, in noncooperative communication scenarios, only a small number of signal samples are labeled. Using a small number of labeled samples to train the CNN through adversarial training results in poor generalization capacity. To exploit the information in the unlabeled signals, we adopted VAT [10] to employ the labeled and unlabeled training data and to smoothen the output space of the neural network. This minimized the change in the output of the neural network where its input was locally perturbed. Therefore, VAT proved effective for SSL.

However, in the SSL model, there are many unlabeled training samples such as $q(y \mid x_u)$. Therefore, unlabeled training samples cannot be used to train the CNN through adversarial training algorithms. Note that, for a large amount of labeled training samples, $p(y \mid x, \theta)$ approaches $q(y \mid x)$. We can use virtual labels probabilistically generated from $p(y \mid x, \theta)$ rather than labels unknown to the user. We then compute the adversarial direction based on these virtual labels. The loss function for VAT can be expressed as

$$L_{\mathrm{adv}}(x, \theta) = D[p(y \mid x, \theta), p(y \mid x + r_{\mathrm{adv}}, \theta)], \qquad (1)$$

where θ represents the weight parameters of the neural network in the current training state and r_{adv} represents the virtual adversarial sample: After obtaining the virtual adversarial samples, the full loss function is given by

$$L_{\mathrm{adv}}^{\mathrm{DS}}(x, \theta) = \sum_{(x,y)\in D_l} L(x, y, \theta) + \lambda_{\mathrm{adv}} \sum_{x\in D_u} L_{\mathrm{adv}}(x, \theta), \quad (2)$$

where D_l and D_u represent the labeled and unlabeled training dataset, respectively; $\lambda_{\mathrm{adv}} > 0$ represents the regularization coefficient that needs to be set in advance. $L(x, y; \theta)$ represents the supervised loss function of the CNN.

Labeled data and a large amount of unlabeled data are used to carry out semisupervised training. The labeled data was combined with the unlabeled data to conduct virtual adversarial training. Supervised learning can use labeled data to guide network training. The loss function of VAT $L_{\mathrm{adv}}(x, \theta)$ can be regarded as a measure of the local smoothness of the current network, and its optimization can smooth the network output space. λ_{adv}, as the regularization coefficient, is used to control the relative balance between supervised learning and virtual adversarial training, ensuring the effect of semi-supervised training. Finally, the parameter θ of the CNN is tuned according to the backpropagation algorithm.

Compared to traditional Generative Adversarial Networks (GANs), Virtual Adversarial Training (VAT) offers a more direct and stable method to enhance the model's resistance to data perturbations. Unlike GANs, VAT avoids the instability and mode collapse often seen in training, as it does not rely on the dynamic balance between generators and discriminators. This makes VAT more reliable in practical applications, especially when the number of labeled samples is limited. Through this method, VAT effectively utilizes a large amount of unlabeled data, improving the model's generalization performance and ensuring that the model performs well on new, unknown data regarding classification or prediction capabilities.

3. Signal Model, System Model, and Problem Formulation

The received signal model can be expressed as

$$r(t) = s(t) * h(t) + n(t), \tag{3}$$

where $r(t)$ is the received radar signal at time t, $s(t)$ is the transmitted signal, $h(t)$ is impulse response of the channel between transmitter and receiver, $n(t)$ denotes noise, and $*$ means the convolution operation.

In this paper, we outline a system model rooted in the domain of Radio Emission Identification (REI) using advanced deep learning techniques, as illustrated in Fig. 1. Our systematic methodology unfolds across four distinct yet interconnected phases:

1. **Data Acquisition:** We commence by meticulously gathering a substantial dataset of signal transmissions from an array of devices functioning in real-world scenarios.
2. **Model Training:** Following data collection, we preprocess the data to be compatible with neural network algorithms. The data is then utilized to train the neural network, crafting an intelligent model capable of making accurate predictions.
3. **Model Deployment:** After training, we strategically deploy the sophisticated model onto actual devices within operational environments, ensuring seamless integration.
4. **Model Prediction:** In the final stage, our deployed model stands ready to authenticate and classify signals of unknown origins, effectively discerning between various emission sources.

Acknowledging the inherent complexities of real-world environments and the limitations imposed by the scarcity of labeled data samples, we supplement our approach with a Semi-Supervised Radio Emission Identification (SS-REI) technique. This enhancement is designed to refine the model's efficacy and extend its applicability under constrained conditions.

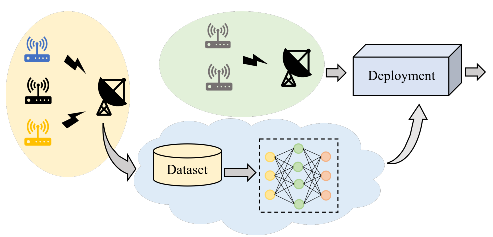


Fig. 1 System model of deep learning-based REI.

Here, we define $\mathcal{X}$ as the input samples space and $\mathcal{Y}$ as the category space. Consider an input sample $x_k \in \mathcal{X}$, representing a radar signal in IQ format, and its true category $y \in \mathcal{Y}$. In the SS-REI problem, the training dataset $\boldsymbol{D}_t$ comprises both labeled and unlabeled data, specifically $\boldsymbol{D}_t = \boldsymbol{D}_l \cup \boldsymbol{D}_{ul}$. Here, $\boldsymbol{D}_l = \{(\boldsymbol{x}_l^n, y_l^n)|n = 1, \cdots, L\}$ is the labeled training dataset, and $\boldsymbol{D}_{ul} = \{(\boldsymbol{x}_{ul}^m)|m = 1, \ldots, N-L\}$ is the unlabeled training dataset, where $\boldsymbol{x}_l^n$ and $\boldsymbol{x}_{ul}^m$ represent the labeled and unlabeled samples, respectively, and y_l^n represents the sample labels, L is the count of labeled samples and $N - L$ is the count of unlabeled samples. Typically, $N - L$ is much greater than L. The objective in a typical machine learning framework for SS-REI is to discover a function $f \in \mathcal{F}$ from $f \in \mathcal{F} : \mathcal{X} \to \mathcal{Y}$ that minimizes the expected error. Formally, this can be represented as:

$$\min_{f\in\mathcal{F}} \epsilon_{\text{em}} = \min_{f\in\mathcal{F}} \mathbb{E}_{(\boldsymbol{x},y)\sim\boldsymbol{D}_l}\mathcal{L}(f(x), y) + \mathbb{E}_{(\boldsymbol{x},y)\sim\boldsymbol{D}_{ul}}\mathcal{L}_{ul}(*), \tag{4}$$

where $\mathbb{E}$ denotes the expected value, $\mathcal{L}(f(\boldsymbol{x}), y)$ is the loss function comparing the predicted $f(\boldsymbol{x})$ with the actual category, and $\mathcal{L}_{ul}(*)$ is an additional loss function that leverages the unlabeled training data to improve the model's accuracy. This auxiliary loss function can be based on Mean Square Error or Kullback-Leibler divergence.

4. The Proposed VAT-based SS-SEI Method

Within this portion of the text, we delve into the specifics of the proposed SS-VAT method. Initially, we provide a comprehensive overview of the framework, elaborating on the functionalities and advantages of each element within the proposed SS-VAT method. Subsequently, we outline the training procedure specific to the proposed SS-VAT method.

The framework of our method is shown in Fig. 2, encapsulating a dual-sample feeding mechanism, a profound deep neural network infrastructure, and a pair of intricately formulated objective functions, meticulously designed to harness the full potential of SSL with VAT. At the heart of our innovative method lies the deployment of a Complex-Valued Neural Network (CVNN) [39], which is specifically adept at extracting and distilling the intricate interplay and coupling information present among the myriad components of radar signals. This specialized capability significantly enhances the overall effectiveness and precision of our SS-VAT methodology. The detailed architecture of the CVNN, showcasing its complex layers and operational intricacies, is vividly illustrated in Fig. 3. Within the realm of real-time testing and application, this meticulously optimized deep neural network is strategically employed to classify and predict outcomes based on a diverse array of test samples fed into the system. This predictive mechanism is not only a testament to the network's advanced analytical capabilities but also underscores the method's adaptability and efficacy in handling real-world radar signal identification and classification challenges, thereby setting a new benchmark in the domain of REI.

The training dataset undergoes a strategic bifurcation

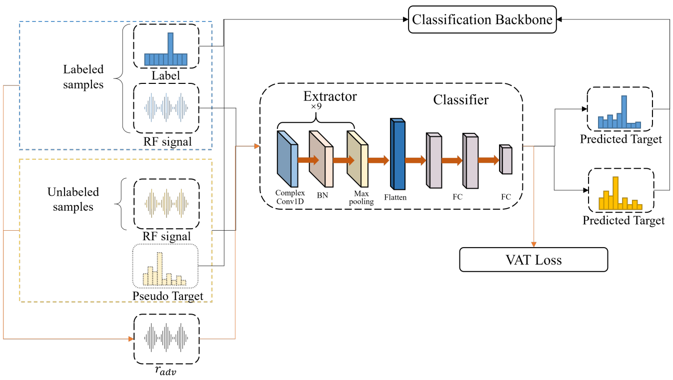


Fig. 2 The frame of SS-VAT method.

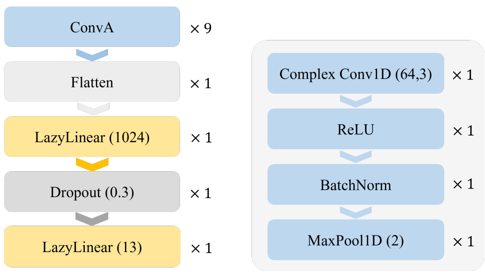


Fig. 3 The structure of CVNN.

into two fundamentally distinct categories: labeled and unlabeled samples, setting the stage for our model to traverse this dual terrain with a nuanced approach. To adeptly navigate through this composite landscape, our framework employs a sophisticated, multifaceted loss function strategy that meticulously balances the model's learning from both terrains. During the initial phases of the model's training, there is a deliberate emphasis on absorbing and integrating knowledge predominantly from the labeled portion of the dataset. This critical phase of learning is rigorously quantified through the application of the cross-entropy loss function. This function serves as a mathematical conduit to measure the divergence between the model's predictions and the actual ground truths, effectively enabling the precise calculation of the supervised loss component of the training process. The essence of the cross-entropy loss lies in its ability to encapsulate the disparity between the expected outcomes and the model's inferences, thereby providing a robust mechanism to guide the model's learning in alignment with the labeled data's inherent truths. This calculated approach ensures that, right from its nascent stages, the model is steered towards achieving a deep, nuanced understanding of the data it is tasked with deciphering, laying a solid foundation for subsequent phases of training where the untapped potential of unlabeled data is progressively harnessed. The cross-entropy loss is expressed as

$$\mathcal{L}_C(f(\boldsymbol{x}_i;\boldsymbol{w}_m), y) = \frac{1}{L}\sum_{i=1}^{L} y_i \log \frac{1}{f(\boldsymbol{x}_i)}, \tag{5}$$

where $\boldsymbol{w}_m$ is hyperparameter space, f is the model, $\boldsymbol{x}_i$ are the labeled samples, L is the number of labeled samples, L_C is the loss of classification backbone.

As the training epochs advance, the model incrementally shifts its focus towards the exploitation of the unlabeled dataset. This is achieved through the model's autonomous generation of pseudo-labels [40], an innovative technique that maximizes the utility of unlabeled datasets. Concurrently, the model also calculates the VAT loss for both labeled and unlabeled datasets, thereby maintaining a balanced learning trajectory. A prominent characteristic of this framework is the integration of VAT, a refined form of adversarial training applicable in SSL contexts. In our proposed SS-VAT method, VAT is employed for the extraction of generalized semantic features from both labeled samples ($\boldsymbol{x}_l$) and unlabeled samples ($\boldsymbol{x}_{ul}$). VAT introduces the concept of local distributional smoothness (LDS), defined as the model's resilience to virtual adversarial directions, gauged through divergence. The VAT loss $\mathcal{L}_{VAT}$ is given by:

$$\mathcal{L}_{VAT}(\boldsymbol{x}_*, \theta) = \boldsymbol{D}[f(y|\boldsymbol{x}_*, \hat{\theta}), f(y|\boldsymbol{x}_* + p_{\text{adv}}, \theta)], \tag{6}$$

where x_* represents either $\boldsymbol{x}_l$ or $\boldsymbol{x}_{ul}$, $\boldsymbol{D}[f, f']$ signifies the Kullback-Leibler divergence in our SS-VAT approach, $\hat{\theta}$ denotes the current model weights, and p_{adv} is the virtual adversarial perturbation.

In summary, the framework elucidated in this study represents a cutting-edge approach in the realm of SSL. By harmonizing the strengths of VAT with a dual dataset utilization strategy, the model demonstrates a heightened performance capability. It is adept at efficiently harnessing both labeled and unlabeled data, exhibiting adaptability across varying proportions of available labels, and achieving commendable levels of accuracy and generalization, even in the face of complex and multifaceted data landscapes. Following the aforementioned design, the target loss function for model optimization during the training phase can be articulated as

$$\mathcal{L}_{objective} = \mathcal{L}_C + \mathcal{L}_{VAT}. \tag{7}$$

For easy understanding of our work, the training procedure is described in **Algorithm 1**.

5. Experimental Setup and Results

Our evaluation of the proposed SS-VAT method utilizes the dataset presented in the paper [11]. The dataset is a synthetic one, designed to closely simulate various conditions of actual radar signal reception. This includes the addition of multipath Rayleigh fading and Gaussian white noise. The synthetic dataset, by simulating potential interferences and signal degradation, aims to approximate real-world conditions as closely as possible, thereby enhancing the model's robustness against various environmental noises and disturbances, making it suitable for evaluating REI methods. Although the synthetic dataset is designed to mimic the

Algorithm 1: Training details of the proposed VAT-based SS-SEI method.

Require:
$\boldsymbol{D}_l$: The dataset consisting of labeled training samples;
$\boldsymbol{D}_{ul}$: The dataset comprising unlabeled training samples;
T: The total count of training iterations;
B: The quantity of batches within each training iteration;
θ_m: Parameters of CVNN;
lr_m: Learning rate of CVNN;
Dataset preprocessing:
$\boldsymbol{D}_l \leftarrow \frac{\boldsymbol{D}_l - \min(\boldsymbol{D}_l \cup \boldsymbol{D}_{ul})}{\max(\boldsymbol{D}_l \cup \boldsymbol{D}_{ul}) - \min(\boldsymbol{D}_l \cup \boldsymbol{D}_{ul})}$;
for $t = 1$ **to** T **do**
  for $b = 1$ **to** B **do**
    Select a batch of data $(\boldsymbol{x}_l, y_l)$ from $\boldsymbol{D}_l$ and a separate batch $(\boldsymbol{x}_{ul})$ from $\boldsymbol{D}_{ul}$.
    Forward propagation:
      Calculate classification backbone loss: (5)
      Calculate VAT loss: (6)
      Calculate objective loss: (7)
    Backward propagation:
      $\theta_m^{b+1} \leftarrow \mathrm{Adam}(\nabla_{\theta_m}, \mathcal{L}_{objective}, lr_m, \theta_m)$;
  end
end

characteristics of real-world data to improve the model's generalization ability in actual environments, there may still be differences in statistical distribution compared to ground truth datasets. The long signal dataset (signal-to-noise ratio (SNR) is 10 dB) with 13 categories is selected as the dataset for evaluation. For our analysis, we established seven SSL scenarios. These scenarios are defined by the varying ratios of labeled training samples to the total training dataset, specified as $\{1\%, 2.5\%, 5\%, 10\%, 20\%, 30\%, 50\%\}$.

Our methods are developed using PyTorch (version 1.12.0 with Python 3.8.13). For parameter optimization, we utilize the Adam optimizer with a learning rate of $lr_m = 0.001$ and the default initial settings of Adam. The model optimization in our study is carried out using a combined loss function. The intensity of the perturbation in VAT is set to $\epsilon = 1.0$. The training is conducted over 300 iterations with a batch size of 32, and the experiments are executed on an NVIDIA GeForce GTX 2080Ti GPU. In our study, the SS-VAT method is benchmarked against three contemporary SS-REI approaches: CVNN [39], SSRCNN [41], and DRCN [42]. To ensure an equitable comparison, while preserving the fundamental concepts of these methods, we employ the identical dataset in IQ format, the same data preprocessing techniques, optimizer, learning rate, and basic network architecture.

The efficacy of the proposed methodologies has undergone stringent assessment via a gamut of experiments, each set against a backdrop of varying proportions of labeled samples. Detailed accounts of the accuracy in identification are encapsulated in Table 1. It suggests a universal trend across all methods: an upsurge in labeled training samples invariably catalyzes enhanced outcomes. This trend is rooted in the reality that an enriched repository of labeled samples furnishes the model with a nuanced comprehension of the intrinsic sample distribution. Such enrichment empowers the model to sculpt more precise decision boundaries, thereby elevating the caliber of identification performance.

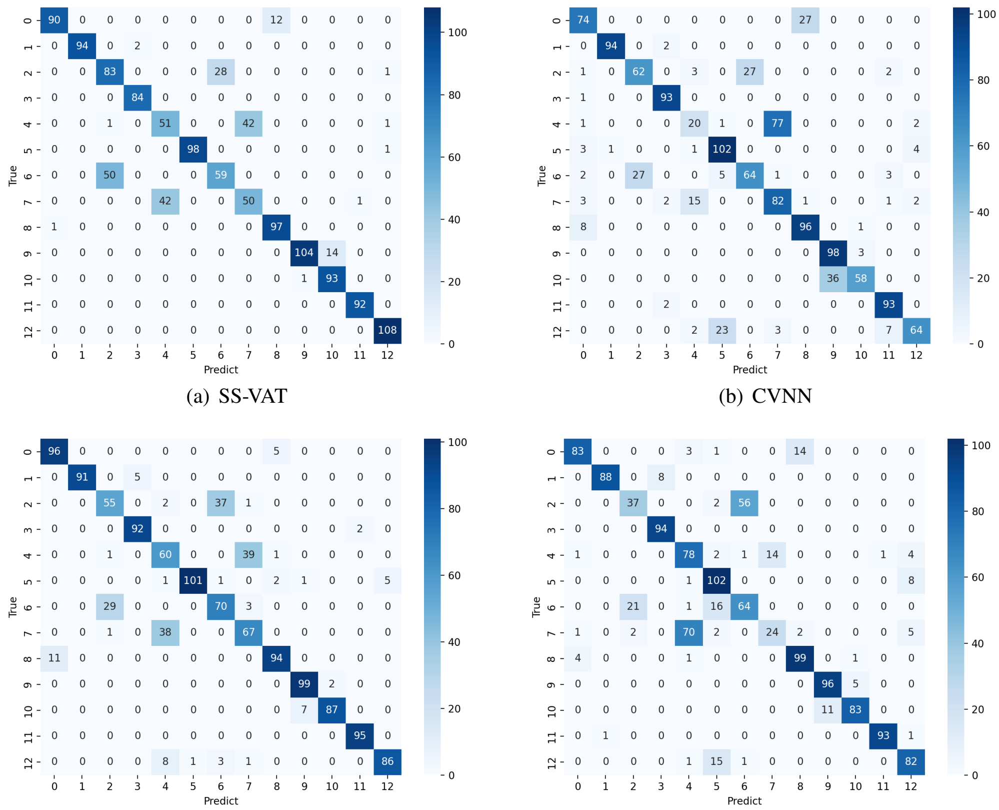
It is noteworthy that our method demonstrates remarkable recognition performance in scenarios where the labeled training samples constitute only 1%, 2.5%, and 5% of the total training dataset, achieving recognition accuracies of 48.69%, 68.15%, and 80.46%, respectively. These figures significantly surpass the capabilities of other methods. Such impressive results under sample scarcity underscore the robustness of the proposed approach. However, in scenarios with 30% and 50% labeled samples, our method shows recognition performance at 88.62% and 92.69%, respectively, slightly below that of the other methods. The reason may lie in the sufficiency of labeled samples, where the added perturbations in our proposed method could limit the enhancement of recognition performance. As shown in Fig. 4, we presented the confusion matrix of the proposed method as well as other comparison methods. It can be observed that, overall, the main classification errors occur in the samples of the fourth, sixth, and seventh categories. Moreover, compared to other methods, which have more or less misclassified samples in other categories, our method's misclassifications are more concentrated, and 50 samples of the sixth category are wrongly classified into the second category, which might be due to the similar spatial distributions that these two categories of samples exhibit.

6. Conclusion

In this paper, a VAT method based on SSL framework was proposed to solve the problem of insufficient labeled dataset and a large number of unlabeled training dataset in the real radar signal recognition scene. Specifically, we designed two objective functions to extract the semantic features of the radar signal. In the early training cycle, the model learns mainly from the labeled data, using the cross-entropy between the model prediction label sample and the real label to calculate the supervised loss for the supervised portion of the data. As the training progresses, it begins to take advantage of the unlabeled data, using pseudo-labels that the model predicts itself. An important advantage of this method is its efficient use of computational resources. By incorporating unlabeled data into the training process, the VAT-based SS-REI method reduces the need for extensive labeled datasets, which are often costly and labor-intensive. This utilization not only extends the practical applicability of the model in environments where labeled data are scarce but also helps maintain the efficiency and scalability of model training. Additionally, this method calculates VAT losses separately for labeled and unlabeled samples, ensuring the model can handle the wide variability and noise common in real radar signal environments. This approach inherently enhances the model's robustness and generalization capabilities. We evaluated the proposed SS-VAT method on a radar dataset. Simulation results show that this method has better recognition performance than

Table 1 The performance of the SS-VAT method in comparison to others.

Method \ Ratio	1%	2.5%	5%	10%	20%	30%	50%
CVNN [39]	33.00%	54.54%	67.77%	76.92%	83.69%	91.69%	**96.08%**
SSRCNN [41]	23.15%	41.38%	71.46%	84.08%	84.15%	88.38%	93.54%
DRCN [42]	38.08%	53.08%	69.15%	78.69%	83.85%	**92.85%**	94.62%
SS-VAT (ours)	**48.69%**	**68.15%**	**80.46%**	**85.08%**	**86.62%**	88.62%	92.69%



(a) SS-VAT (b) CVNN

(c) SSRCNN (d) DRCN

Fig. 4 The confusion matrix of the four methods.

the latest SS-REI method. This shows that our approach improves model robustness and generalization.

References

[1] S. Guo, S. Akhtar, and A. Mella, "A method for radar model identification using time-domain transient signals," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 57, no. 5, pp. 3132–3149, 2021.

[2] S. Guo, R. E. White, and M. Low, "A comparison study of radar emitter identification based on signal transients," in *Proc. 2018 IEEE Radar Conf.*, Oklahoma City, OK, USA, Apr. 2018, pp. 0286–0291.

[3] C. Liu et al. "Overcoming data limitations: a few-shot specific emitter identification method using self-supervised learning and adversarial augmentation," *IEEE Trans. Inf. Forensics Security*, vol. 19, pp. 500–513, 2024.

[4] J.-B. Yu, et al., "A robust RF fingerprinting approach using multisampling convolutional neural network," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 6786–6799, 2019.

[5] H. Wang, Q. Jin, and J. Pu, "Radar emitter type identification effect based on different structural deep feedforward networks," in *Proc. 2020 13th Int. Congr. Image Signal Process.*, Chengdu, China, Oct. 2020, pp. 473–478.

[6] A. Madhu, P. Prajeesha, and A. S. Kulkarni, "Radar emitter identification using signal noise and power spectrum analysis in deep learning," in *Proc. 2022 Fifth Int. Conf. Women Data Sci. Prince Sultan Univ.*, Riyadh, Saudi Arabia, 2022, pp. 52–57.

[7] Z. Xiao, and Z. Yan, "Radar emitter identification based on novel time-frequency spectrum and convolutional neural network," *IEEE Commun. Lett.*, vol. 25, no. 8, pp. 2634–2638, 2021.

[8] J. Pan, et al., "Specific Radar Emitter Identification Using 1D-CBAM-ResNet," in *Proc. 2022 14th Int. Conf. Wireless Commun. Signal Process.*, Nanjing, China, 2022, pp. 483–488.

[9] Y. Lin, Y. Tu, Z. Dou, L. Chen, and S. Mao, "Contour stella image and deep learning for signal recognition in the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 1, pp. 34–46, 2021.

[10] C. Xie, L. Zhang, and Z. Zhong, "Virtual adversarial training-based semisupervised specific emitter identification," *Wireless Commun. Mobile Comput.*, vol. 2022, Article ID: 6309958, 2022.

[11] T. Huynh-The et al. "Accurate LPI radar waveform recognition with CWD-TFA for deep convolutional network," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1638–1642, 2021.

[12] X. Yang, Z. Song, I. King, and Z. Xu, "A survey on deep semi-

supervised learning," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 9, pp. 8934–8954, 2023.
[13] P. Bachman, O. Alsharif, and D. Precup, "Learning with pseudo-ensembles," in *Proc. 27th Conf. Advances Neural Inf. Process. Syst.*, 2014, pp. 3365–3373.
[14] D. H. Lee, "Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks," *Workshop Challenges Representation Learn.*, vol. 3, no. 2, p. 896, 2013.
[15] X. Yang, Z. Song, I. King, and Z. Xu, "A survey on deep semi-supervised learning," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 9, pp. 8934–8954, Sept. 2023.
[16] H. Yang, H. Zhang, H. Wang, and Z. Guo, "A novel approach for unlabeled samples in radiation source identification," *Syst. Eng. Electronics J.*, vol. 33, no. 2, pp. 354–359, 2022.
[17] K. Longi, T. Pulkkinen, and A. Klami, "Semi-supervised convolutional neural networks for identifying Wi-Fi interference sources," in *Proc. 9th Asian Conf. Mach. Learn.*, 2017, pp. 391–406.
[18] P. Bachman, O. Alsharif, and D. Precup, "Learning with pseudo-ensembles," in *Proc. 27th Conf. Advances Neural Inf. Process. Syst.*, 2014, pp. 3365–3373.
[19] T. Jiang, W. Xie, Y. Li, and Q. Du, "Discriminative Semi-Supervised Generative Adversarial Network for Hyperspectral Anomaly Detection," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Waikoloa, HI, USA, 2020, pp. 2420–2423.
[20] J. Masci, et al., "Stacked convolutional auto-encoders for hierarchical feature extraction," in *Proc. Int. Conf. Artif. Neural Networks*, 2011, pp. 52–59.
[21] A. Odena, C. Olah, and J. Shlens, "Conditional image synthesis with auxiliary classifier GANs," in *Proc. 34th Int. Conf. Mach. Learn.*, 2017, pp. 2642–2651.
[22] T. Salimans et al., "Improved techniques for training GANs," in *Proc. 30th Conf. Advances Neural Inf. Process. Syst.*, 2016, pp. 2234–2242.
[23] Z. Song, X. Yang, Z. Xu, and I. King, "Graph-Based Semi-Supervised Learning: A Comprehensive Review," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 11, pp. 8174–8194, 2023.
[24] E. Liu, et al.,"Evaluating generation of chaotic time series by convolutional generative adversarial networks," *IEICE Trans. Inf. Syst.*, vol. 104, no. 5, pp. 709–722, 2021.
[25] Y. Tanaka, and Y. Yamaguti,"MTGAN: extending test case set for deep learning image classifier," *Jpn Soc. Ind. Appl. Math.*, vol. 15, no. 4, pp. 117–120, Sept. 2023.
[26] S. Kokalj-Filipovic, R. Miller, and G. Vanhoy, "Adversarial examples in RF deep learning: detection of the attack and its physical robustness," in *Proc. IEEE Global Conf. Signal Inf. Process.*, Ottawa, Canada, 2019, pp. 1–6.
[27] M. Sadeghi and E. G. Larsson, "Adversarial attacks on deep learning based radio signal classification," *IEEE Wireless Commun. Lett.*, vol. 8, no. 1, pp. 213–216, 2019.
[28] T. Miyato, S. I. Maeda, M. Koyama, and S. Ishii, "Virtual adversarial training: a regularization method for supervised and semi-supervised learning," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 41, no. 8, pp. 1979–1993, 2019.
[29] L. Yang, "An overview of distance metric learning," in *Proc. Comput. Vision Pattern Recognit. Conf.*, 2007.
[30] R. Hadsell, S. Chopra, and Y. LeCun, "Dimensionality reduction by learning an invariant mapping," in *Proc. IEEE Comput. Soc, Conf. Comput. Vision Pattern Recognit.*, 2006, pp. 1735–1742.
[31] F. Schroff, et al., "Facenet: A unified embedding for face recognition and clustering," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, Boston, MA, USA, 2015, pp. 815–823.
[32] K. Sohn, "Improved deep metric learning with multi-class n-pair loss objective," in *Proc. Advances Neural Inf. Process. Syst.*, 2016.
[33] M. Gutmann, and A. Hyvärinen, "Noise-contrastive estimation: A new estimation principle for unnormalized statistical models" in *Proc. Thirteenth Int. Conf. Artif. Intell. Statist.*, 2010, pp. 297–304.
[34] S. Pan, and Q. Yang, "A survey on transfer learning," *IEEE Trans. Knowl. Data Eng.*, vol. 22, no. 10, pp. 1345–1359, Oct. 2010.
[35] M. Long, et al., "Learning transferable features with deep adaptation networks," in *Proc. Int. Conf. Mach. Learn.*, 2015, pp. 97–105.
[36] X. Fu, et al., "Semi-supervised specific emitter identification via dual consistency regularization," *IEEE Internet Things J.*, vol. 10, no. 21, pp. 19257-19269, Nov. 2023.
[37] A. Singh, R. D. Nowak, and X. Zhu, "Unlabeled data: Now it helps, now it doesn't," in *Proc. Conf. Advances Neural Inf. Process. Syst.*, 2008, pp. 1513–1520.
[38] T. Yang, and C. E. Priebe, "The effect of model misspecification on semi-supervised classification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 10, pp. 2093–2103, Oct. 2011.
[39] Y. Wang, et al., "An efficient specific emitter identification method based on complex-valued neural networks and network compression," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 8, pp. 2305–2317, 2021.
[40] D. H. Lee, "Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks," in *Proc. ICML Workshop: Challenges in Representation Learning*, Atlanta, Georgia, USA, Jun. 2013, pp. 1–5.
[41] Y. Dong, X. Jiang, L. Cheng, and Q. Shi, "SSRCNN: A semisupervised learning framework for signal recognition," *IEEE Trans. Cognit. Commun. Networking*, vol. 7, no. 3, pp. 780–789, 2021.
[42] Y. Wang et al., "Transfer learning for semi-supervised automatic modulation classification in ZF-MIMO systems," *IEEE J. Emerging and Sel. Top. Circuits Syst.*, vol. 10, no. 2, pp. 231–239, 2020.

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