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Geometric generative adversarial net based multiple methods for spectrum sensing in cognitive radio networks

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ABSTRACT

The majority of recently developed approaches require a significant number of labelled samples. The proposed system are dedicated to using less marked samples for automatic modulation detection in the cognitive radio domain. The proposed signal classifier generative adversarial nets (GANs) methodology is a semi-supervised learning framework that focuses on adversarial analysis GANs are a major step forward in the development of competitive generative networks, and they've spawned a slew of apparently unrelated versions. The discovery of a single geometric form in GAN and its derivatives is one of the paper's key contributions. In three geometric stages, by demonstrate how to train an adversarial generative model: updating the discriminator parameter away from the separating hyperplane, looking for the separating hyperplane, and updating the generator along the usual vector route of the separating hyperplane. The shortcomings in current approaches are shown by this geometric intuition, leading us to suggest a new geometric GAN formulation that maximizes the margin using SVM separating hyperplane. An equilibrium is reached between the discriminator and generator in the geometric GAN, according to our theoretical research. Furthermore, detailed computational results showing the superior efficiency of the GAN engineering network were obtained.

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1. INTRODUCTION

The goal of cognitive radio is to identify and employ restricted and varied spectrum capacity across time, frequency, and spatial dimensions [1]. Cognitive radios can now perform monitoring, grouping, and prediction functions, thanks to the introduction of low-cost software-defined radio (SDR) devices (such as spectrum sensing and automated modulation recognition) [2], [3]. Machine learning could be able to solve the innate need for automated decision making by encouraging cortical radios Without explicit or rigorous coding, learn something new.Traditional machine learning approaches such as the support vector machine (SVM) may be used to classify modulation [4]. Spectrum sensing with convolutional neural networks would be other example [5]. As a consequence, it is necessary or beneficial to restrict the sensing time to a small number of training samples. When several networks are available to sense, the situation can become more complicated or difficult [6].

Classifiers trained on historical data obtained under a limited or limited range of spectrum circumstances (e.g., in offline laboratory measurements) cannot be applied safely to fresh data (such as those needed for external experiments). This is because it misrepresents the content of current research findings. It addresses these challenges by generating synthetic training data for machine learning using the suggested spectrum adaptation with generative adversarial network (SAGA) technique. SAGA makes use of and supports the use of generative adversarial networks (GANs), Deep learning and auto encoders are used to help[7] Where the number of training samples is inadequate or the world described by the initial training data varies over time, synthetic data is generated to retrain machine learning classifiers. Adversarial training is handled by GANs [8] By teaching complex neural network architectures, it is possible to learn the underpinning representations of complex data sources more effectively [9], [10]. The geometric GAN, a new McGAN engineering circular was influenced by the recent discovery that McGAN is made up of three geometries in the function space [11]:

- Separate super-level search: This approach focuses on locating the linear classifier's super-level dividing class [12]-[14].
- Using the following technique, separate the discriminant from the hyperplane: This method updates the discrimination parameter away from the hyperplan using the random gradient direction (SGD) [15].
- Updating the generator against the hyperplane: Using the random gradient direction, this technique modifies the generator parameter in the usual vector direction of the independent superplane (SGD) [16].

This engineering understanding can be applied to the vast majority of GANs and variants currently in use due to its broad scope [17]. The key differences between current algorithms are the geometric scaling factors of feature vectors and the inclusion of distinct super-layers of a linear classifier on the feature field [18]. The propose new engineering interpretations based on this experience. Our computational analyses showed that the proposed engineering GAN is more stable than current or traditional GANs in both data sets.

In conventional spectrum sensing devices, power detection is commonly used [19], detection based on toroidal robust characteristics [20], eigenvalue based detection [21], frequency band detection [22], and the force continuum's de-segmentation [23]. Because of its ease, energy detection is one of the most widely used methods, but it has a drawback or problem in that it suffers from extreme noise instability [24]. In low-noise signal (SNR) scenarios, the cyclostationary dependent detection technique is superior, but it has issues with mathematical operations, has a high numerical complexity, and needs prior signal knowledge. In the presence of noise power uncertainty, eigenvalues-driven discovery allows for an optimal or secure decision dependent on eigenvalues. In the frequency domain, the entropy-based model depends on changing noise and signal distributions [25].

The authors proposed several collective sensing algorithms in [26] using a SVM, the nearest K-weighted neighborhood, averaging of K averages, and a Gaussian mixture model. The feature's vector was generated using the signal energy received. The function vectors in [27] were low dimensional likelihood vectors, and the K-mean and SVM clustering techniques were used. In [28] proposes a shared sensing approach based on a convolutional neural network (CNN) that increases sensor accuracy while lowering computational complexity and long arithmetic operations. To investigate the ultra-high-dimensional and nonlinear signal processing capabilities of linear KBL methods.

Kernel-based learning approaches (KBL) have been used extensively in cognitive radio networks (CRNs) to address difficulties such as cooperative spectrum sensing [29]. Machine learning techniques for single-node spectrum sensing are either new or in the early stages of development. Power ratio and probability test statistics may be used as input characteristics in an artificial neural network (ANN) based sensor technique [30]. In [31] A spectrum sensing ANN was fed data on power and toroidal stability. Cyclic qualities may be used in the same way.

Research by Ding *et al.* [32] for spectrum sensing, they switched to a CNN architecture. Neural networks are used in many of these investigations to recognize traits that have been pre-selected beforehand. Success would thus be highly determined by the advantages and disadvantages of the earlier removed functionalities.

According to D. Han *et al.* [33] explain how to utilize a stacked autocoder to recognize OFDM signals in a wireless network. Deep neural networks such as CNN and RNN are also used by the authors to identify radar emissions in the 3.5 GHz band, in addition to employing spectrograms to do so in [34] they find a higher and more accurate as compared to traditional detection strategies. These two articles, on the other hand, are more concerned with signal detection than with spectrum sensing in general.

Research by O'Shea *et al.* [35] categorize changed analog transmission signals; they suggested the use of an ANN. This experiment demonstrated how antimicrobial resistance can be combated using deep learning. In [36] and [37] they proposed CNN with a time-domain signal in phase and quadrature as an input to modulate domain recognition (IQ). One of their most significant contributions was the development of a dataset with a number of typical modifications, which has since become an AMR technique or norm.

Li *et al.* [38] used ADTP signals to train DNNs for co-modulation/bitrate classification synchronization, and their approach was validated using multipath channel simulation. With low signal-to-noise ratios, an anti-noise computing technique and a deep hierarchical CNN have been presented. This solution employs CNN to segregate the signal time spectrum, thus considerably boosting the accuracy and resilience of the algorithm. A large portion of this strategy was based on manual attribute extraction and adaptive categorization.

According to Tang *et al.* [39] signal processing and computer vision were successfully related in the GAN application. The main theory is to derive classification characteristics for modifications using a constellation diagram. It aimed to develop a fusion model that can process signal data directly. The paradigm incorporates both CNN and long short term memory (LSTM) [40]. Research by Hauser *et al.* [41] revolve around how sampling rate and frequency offsets affect modulating signal classification precision. According to the findings, CNN preparation to balance frequency and sampling rate has no bearing on progress. The current curricula will be built on two main pillars: The first is that they ignore or rely entirely on supervised learning, with most current approaches focusing on signal pre-processing rather than fully leveraging the potential to evoke or obtain deep learning features. The results showed the systems' ability to respond to existing and unexpected cognitive radio sensitivity issues have been compromised. According to this strategy, deep neural networks' memory capacity is not fully used; rather, it is merely a method for making deep learning models simpler to practice.

Research by Mirza and Osindero [42] conditional obstetric adversarial network (COAN) is an acronym for conditional obstetric adversarial network (CGAN). By applying conditional variables to GANs when modeling D and G, they were able to provide more accurate and coherent instruction. A series of important architectural designs have been proposed in [43] for replacing GANs' erratic learning style and obtaining special training examples for CNNs using a concept called DCGAN. A DCGAN introduced the batch-normalize (BN) has been proposed in [44] to prevent a network failure, switch to G and D networks (the 45th.) Larsen and his coworkers work as a unit. To reuse features developed by GANs, they added a package of automatic variable encoder (VAE) and GANs. VAE, which is a fusion of GAN and VAE, had to be replicated. CNN demonstrates the stability of translation by proposing complete layers of aggregation. However, due to the usually minimal spatial variety of maximal aggregation, the CNN lacks a stability feature for such artificial transformations such as rotation, distortion, and so on. CNN accumulation is unconstrained, but the predominant bidirectional IQ signal in CR can only aggregate in the time domain [45].

Research by Davaslioglu and Sagduyu [46] effort resulted in the development of a spatial transformer network (STN), which creates a parameter for the spatial transformation of an input picture or feature map. It is necessary to apply a global spatial modification to the original picture in order to get the final standard spot, which is based on this parameter. As part of regression parametric translation, an approved localization network is used, and a trained discriminant classifier is used to decide how a class is graded.

2. THE PROPOSED GEOMETRIC GAN METHOD

Linear classifiers with a huge number of observations and a small sample size. The discriminant relies on discriminating between individual samples during vigorous feature space training {(xi)} ni=1 and the fake samples {Φζ (gθ (zi))} ni=1. The HDLSS problem derives its name from the fact that in real life, the scale of the minibatch n is much smaller than the dimensions of the function space d [46]. The average difference (MD) classifier is one of the most widely used HDLSS methods. The MD classifier precisely defines the hyperbolic degree halfway between the two class roots. Getting the class differential for the individual superplane implies having the normal vector w:

$$w_{MD}=\frac{1}{n}\sum_{i=1}^{n}\Phi_\zeta(x_i)-\frac{1}{n}\sum_{i=1}^{n}\Phi_\zeta(g_\theta(z_i)) \tag{1}$$

When the parameters are first averaged and then evaluated by standard deviation, the mean variance equals the naive Bayes classifier. There is always a cumulative data accumulation path (MDP) in HDLSS Due to the fact that several points in each class are projected onto the line enlarged by the normal vector. HDLSS shows that SVMs and their various versions are among the most commonly researched and utilized classification techniques. SVM is energized by engineering inference, which leads directly to the optimization problem: maximizing the margin between two forms of separable data, since the fitment of the statistical distribution of data catalyzes the above-mentioned classification algorithms [46].

The proposed system is based on the RadioML2016.10b dataset compiled a large data collection that researchers can use for free. Eight optical modifications and two analog modulations are among the ten types of modulated signals in the dataset. The SNR values are used, as well as the form of modification. SNR values range from -20 dB to +18 dB in 2 dB increments. As positive tests, by using eight different forms of digitally transformed signals with various SNR levels. Negative samples are Gaussian noise with zero-scale spherical symmetry and the same dimensions as the input signal (CSCG). The deep neural network was fed training samples in two n vectors, each containing 'n' samples, consisting of step and quadrature components separated into complicated time samples Table 1 contains a description of the dataset's parameters. A total of three parts have been created in the dataset: training, assessment, and tracking.

Table 1. Table of the parameters of our dataset

Parameters	Value
Modulation scheme	BPSK, QPSK, 8PSK, QAM16, QAM64, CPFSK, GFSK and PAM4
Sample length	64,128,256,512
SNR range	-20 db -18 in 2 db increment
Training sample	153,000
Validation sample	51,000
Testing sample	51,000

3. METHOD

The SVM soft margin linear classifier was used to build the proposed engineering GAN due to its generality. There are two sections concern with introduction to this work:

a. In the context of a certain spectrum, synthetic data samples are added to the current training data set as part of the training data augmentation process. There is evidence to suggest that retraining the classifier using data from a high-performance or high-resolution sensor enhances the accuracy of spectrum sensing and returns it to a more default state. Conditional GAN (C-GAN) is a neural network that is composed of two neural networks, namely the alternator or generator (G) and the discriminator (D). Remember that labels are also sent into the discriminator and generator (also known as the alternator).
b. A different approach, known as field adaption, yields training results that are more closely replicable in a given spectrum environment. Adversarial learning is used to train a new classifier for new spectrum circumstances using high-performance or fidelity synthetic research data. Using a classifier based on the old spectrum context results in a significant decrease in spectrum sensing performance in the current environment, as shown by this study. With current spectrum settings, the classifier approaches the default (optimal) state in terms of accuracy.

4. RESULTS AND DISCUSSION

The proposed system results compared with the engineering GAN of three representative forms of GANs: i) Jenson Shannon (GAN) [1]; ii) the main difference in l (Wasserstein GAN) [7]; ii) the main difference in l2 (Wasserstein GAN) [9].

The behavior of the maximum margin separating the super level engineered GAN is compared to the methods described above. Furthermore, for each hostile training strategy. As seen in the bellow, the generator and characterizer are constructed using multi-layered and completely linked neural network architecture.

To train these networks based on Vanilla GAN with a momentum of $\beta 1=0.5$ (without any of Lipschitz's restrictions). As a starting point, the learning rate was set to 0.001. When doing weight struncation; the parameters are sheared in the function mapping$\varphi\zeta(x)$ in the range [0.01, 0.01]. When applying a weight drop to the unit norm l2, use the following rule, p=min{1,1/kpk2}×p described in [9] for each iteration to update some parameter p. The weight decay factor is set to 0.001 for weight loss. On both experiments, the batch size was set to 500. In terms of the number of characterizer Kd and generator Kg updates, it set them as 1, i.e. (Kd=1, Kg=1).

- Discrimination: FC (2, 128) -ReLU-FC (128, 128) -ReLU-FC (128, 128) -ReLU-FC (128, 1).
- Alternator: FC (4, 128) -BN-ReLU-FC (128, 128) -BN-ReLU-FC (128, 128) -BN-ReLUFC (128, 2). The results exaplained in Figure 1 to Figure 12.

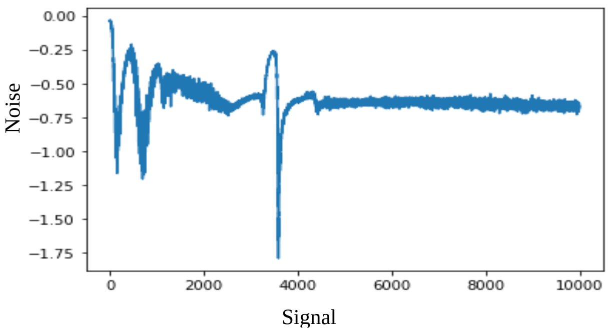

Figure 1. Before it's begin, plot the linear relationship between signal and noise effects hyperplane GAN

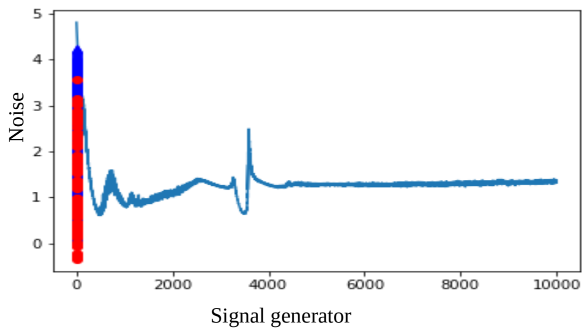

Figure 2. Plot the generator and discriminator losses (hyperplane GAN nois)

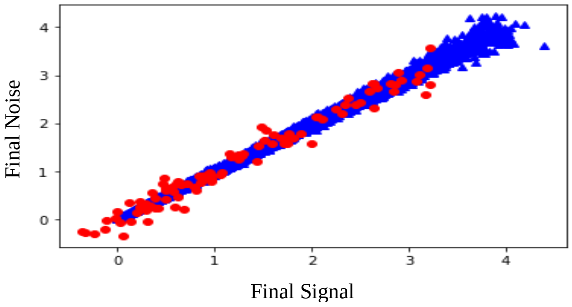

Figure 3. Plot the final signal after it has been trained (hyperplane GAN noise)

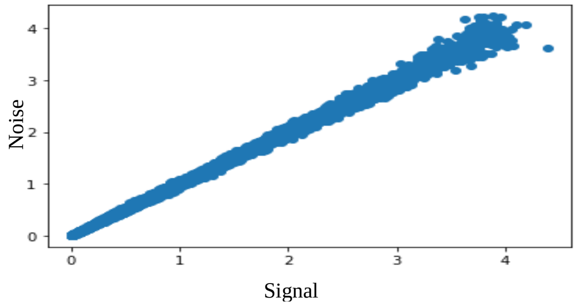

Figure 4. Before it's begin, plot the linear relationship between signal and noise effects (hyperplane GAN)

In addition, Figure 5 and Figure 6 demonstrate the outcome of the experiment with a mixture of 25 Gaussians. About the limitations of Lipschitz continuity control, the geometric GAN in this experiment showed less mode breakup than the other GAN variants.

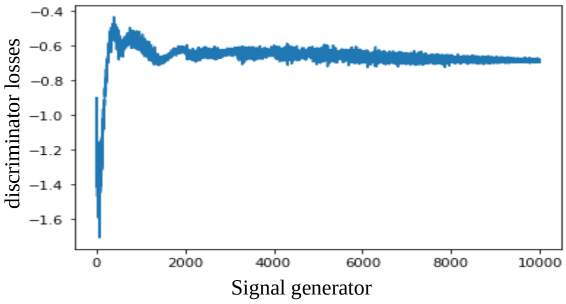

Figure 5. Plot the generator and discriminator losses (hyperplane GAN)

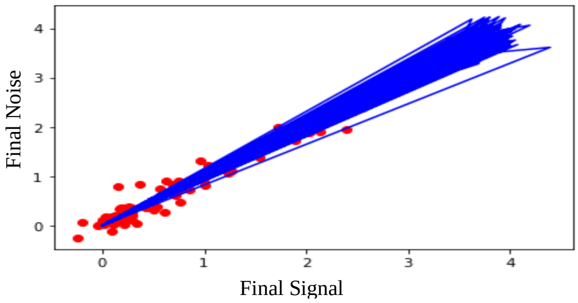

Figure 6. Plot the final signal after it has been trained (hyperplane GAN)

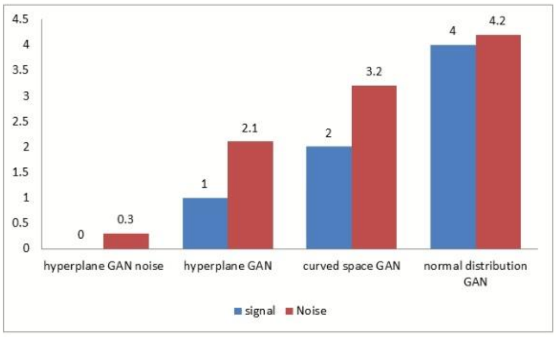

Figure 7. Before it's begin, plot the linear relationship between signal and noise effects

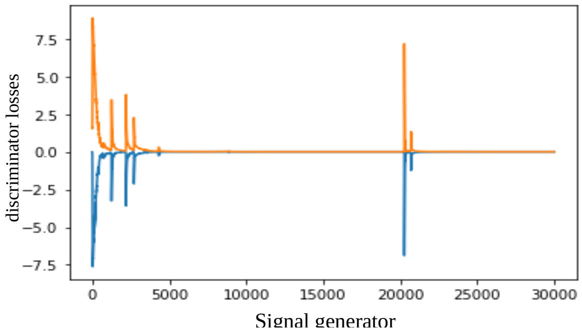

Figure 8. Plot the generator and discriminator losses (curved space GAN)

Under the same Lipschitz density restrictions as the nonlinear interval hyperplane of the original GAN, the linear hyperplane solution revealed less mode breakup behaviors, the average difference powered Wasserstein GAN or McGAN superchargers to the generators, based on the features of the mean difference, which linked an expected number of modes in the individual distributions based on the mean difference. True distributions were preferred by the geometric GAN in an obvious and consistent manner. The proposed system compared with the other related works as follow in Table 2. It showed that the used method decreased the noise value into -1 which eliminate interference to the signal and which effects on the signal strength.

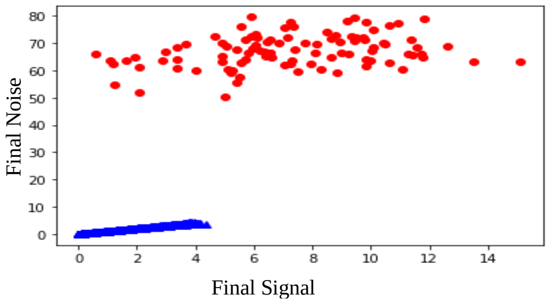

Figure 9. Plot the final signal after it has been trained (curved space GAN)

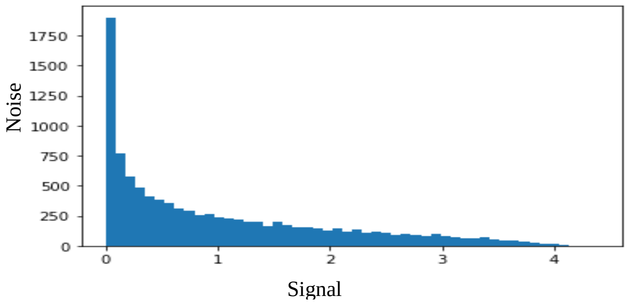

Figure 10. Before it's begin, plot the linear relationship between signal and noise effects (normal distribution GAN)

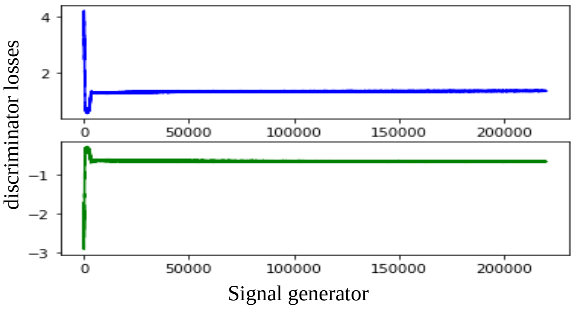

Figure 11. Plot the generator and discriminator losses (normal distribution GAN)

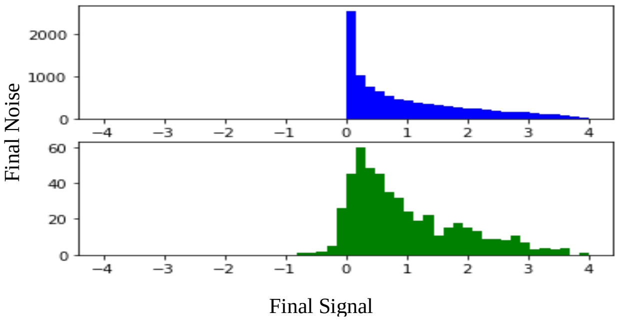

Figure 12. Plot the final signal after it has been trained (normal distribution GAN)

Table 2. System compareison with other related works

Ref, Nom	Method	Final signal	Final noise
Kemal, [46]	GAN	4	-4
The proposed system	GAN	4	-1

5. CONCLUSION

Since the previous rigorous training methodology revealed engineering insight, this paper proposed a new engineering GAN that distinguishes the super plane using SVM. The SVM, which separates superjets with the largest possible margins between them, is the subject of GAN engineering. Geometric GAN derivation, like SVM derivation, is based on geometric intuition, unlike other conventional or existing approaches that rely on mathematical design principles. The suggested solution resulted in a smaller breakdown function reduction and more consistent training operation in detailed numerical trials. It also supports the idea that the proposed algorithm converges to a structural and geometric Nash equilibrium between the generator and the discriminant. To deal with the fact that spectrum sensing is a two-class classification issue, it developed a deep learning-based technique. When it comes to performance, it was shown that a suggested solution outperforms the frequency domain technique and the minimal value method. A process's effectiveness or dependability may be judged on the basis of how subjective it is. The generalizability of the system allows it to recognize a broad variety of untrained signals. When interacting with real-world signals, it will make adjustments to those parameters in order to further enhance the performance of our suggested system. With pink noise, standard approaches suffer greatly since they cannot dynamically learn noise characteristics from the data, while the utilized methodology can retain its performance. Most of the experiments in this paper are based on simulations, with the exception of a few that use real-world data. As a result of these tests and the usage of the marker or heuristics network, it will be possible to better understand the method's capacity to function in the real world, and to enhance the efficiency of classifiers when there is a lack of tagged data and training time grows in the future. The age and parameter direction of rising batch size.

REFERENCES

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," in *IEEE Personal Communications*, vol. 6, no. 4, pp. 13-18, Aug. 1999, doi: 10.1109/98.788210.

[2] C. Clancy, J. Hecker, E. Stuntebeck, and T. O'Shea, "Applications of Machine Learning to Cognitive Radio Networks," in *IEEE Wireless Communications*, vol. 14, no. 4, pp. 47-52, Aug. 2007, doi: 10.1109/MWC.2007.4300983.

[3] D. Janu, K. Singh, and S. Kumar, "Machine learning for cooperative spectrum sensing and sharing: A survey," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 1, 2022, doi: 10.1002/ett.4352.

[4] Y. Liu, Y. Liu and C. Yang, "Modulation Recognition With Graph Convolutional Network," in *IEEE Wireless Communications Letters*, vol. 9, no. 5, pp. 624-627, May 2020, doi: 10.1109/LWC.2019.2963828.

[5] Z. Chen, Y. -Q. Xu, H. Wang and D. Guo, "Federated Learning-Based Cooperative Spectrum Sensing in Cognitive Radio," in *IEEE Communications Letters*, vol. 26, no. 2, pp. 330-334, Feb. 2022, doi: 10.1109/LCOMM.2021.3114742.

[6] I. Goodfellow *et al*., "Generative adversarial nets," *Advances in neural information processing systems*, vol. 27, 2014.

[7] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, no. 5786, pp. 504-507, Jul. 2006, doi: 10.1126/science.1127647.

[8] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, Nov. 2016.

[9] M. Katzef, A. C. Cullen, T. Alpcan, and C. Leckie, "Generative Adversarial Networks for anomaly detection on decentralised data," *Annual Reviews in Control*, 2021, doi: 10.1016/j.arcontrol.2021.10.002.

[10] M. Arjovsky and L. Bottou, "Towards principled methods for training generative adversarial networks," *arXiv preprint arXiv:1701.04862*, Jan. 2017, doi: 10.48550/arXiv.1701.04862.

[11] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein generative adversarial networks," *International conference on machine learning*, Jul. 2017, pp. 214-223.

[12] A. Müller, "Integral probability metrics and their generating classes of functions," *Advances in Applied Probability*, vol. 29, no. 2, pp. 429-443, Jul. 2016, doi: 10.2307/1428011.

[13] X. Qiao, H. H. Zhang, Y. Liu, M. J. Todd, and J. S. Marron, "Weighted distance weighted discrimination and its asymptotic properties," *Journal of the American Statistical Association*, vol. 105, no. 489, pp. 401-414, 2010, doi: 10.1198/jasa.2010.tm08487.

[14] I. Carmichael, and J. S. Marron, "Geometric insights into support vector machine behavior using the KKT conditions," *Electronic Journal of Statistics*, vol. 15, no. 2, pp. 6311-6343, 2021, doi: 10.48550/arXiv.1704.00767.

[15] I. Carmichael and J. S. Marron, "Geometric insights into support vector machine behavior using the KKT conditions," *arXiv preprint arXiv:1704.00767*, 2017, doi: 10.48550/arXiv.1704.00767.

[16] J. Ahn and J. S. Marron, "The maximal data piling direction for discrimination," *Biometrika*, vol. 97, no. 1, pp. 254-259, Mar. 2010, doi: 10.1093/biomet/asp084.

[17] S. Nowozin, B. Cseke, and R. Tomioka, "f-gan: Training generative neural samplers using variational divergence minimization," *Proceedings of the 30th International Conference on Neural Information Processing Systems*, 2016, pp. 271-279.

[18] J. Zhao, M. Mathieu, and Y. LeCun, "Energy-based generative adversarial network," arXiv preprint arXiv:1609.03126, 2016, doi: 10.48550/arXiv.1609.03126.

[19] B. Schölkopf, A. J. Smola, and F. Bach, *Learning with kernels: support vector machines, regularization, optimization, and beyond*. MIT press, 2002.

[20] F. F. Digham, M. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *IEEE International Conference on Communications, 2003. ICC '03.*, vol. 5, pp. 3575-3579, 2003, doi: 10.1109/ICC.2003.1204119.

[21] J. Lunden, S. A. Kassam, and V. Koivunen, "Robust Nonparametric Cyclic Correlation-Based Spectrum Sensing for Cognitive Radio," in *IEEE Transactions on Signal Processing*, vol. 58, no. 1, pp. 38-52, Jan. 2010, doi: 10.1109/TSP.2009.2029790.

[22] Y. Zeng and Y. Liang, "Eigenvalue-based spectrum sensing algorithms for cognitive radio," in *IEEE Transactions on Communications*, vol. 57, no. 6, pp. 1784-1793, Jun. 2009, doi: 10.1109/TCOMM.2009.06.070402.

[23] Zhang, Y., Zhang, Q., & Wu, S. (2010). Entropy-based robust spectrum sensing in cognitive radio. *IET communications*, *4*(4), 428-436. Y. Zhang, Q. Zhang, and S. Wu, "Entropy-based robust spectrum sensing in cognitive radio," *IET communications*, vol. 4, no. 4, pp. 428-436, Mar. 2010, doi: 10.1049/iet-com.2009.0389.

[24] Q. Pei-Han, L. Zan, S. Jiang-Bo, G. Rui, "A robust power spectrum split cancellation-based spectrum sensing method for cognitive radio systems," *Chinese Physics B*, vol. 23, no. 12, p. 128401, Oct 2014.

[25] S. Das *et al*., "The Atacama Cosmology Telescope: temperature and gravitational lensing power spectrum measurements from three seasons of data," *Journal of Cosmology and Astroparticle Physics*, vol. 2014, no. 4, p. 014, Apr 2014.

[26] Gismalla, E. H., & Alsusa, E. (2011). Performance analysis of the periodogram-based energy detector in fading channels. *IEEE Transactions on Signal Processing*, *59*(8), 3712-3721. E. H. Gismalla and E. Alsusa, "Performance Analysis of the Periodogram-Based Energy Detector in Fading Channels," in *IEEE Transactions on Signal Processing*, vol. 59, no. 8, pp. 3712-3721, Aug. 2011, doi: 10.1109/TSP.2011.2153849.

[27] K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine Learning Techniques for Cooperative Spectrum Sensing in Cognitive Radio Networks," in *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 11, pp. 2209-2221, Nov. 2013, doi: 10.1109/JSAC.2013.131120.

[28] Y. Lu, P. Zhu, D. Wang, and M. Fattouche, "Machine learning techniques with probability vector for cooperative spectrum sensing in cognitive radio networks," *2016 IEEE Wireless Communications and Networking Conference*, 2016, pp. 1-6, doi: 10.1109/WCNC.2016.7564840.

[29] W. Lee, M. Kim, and D. H. Cho, "Deep sensing: Cooperative spectrum sensing based on convolutional neural networks," *arXiv preprint arXiv:1705.08164*, May 2017, doi: 10.48550/arXiv.1705.08164.

[30] G. Ding, Q. Wu, Y. Yao, J. Wang, and Y. Chen, "Kernel-Based Learning for Statistical Signal Processing in Cognitive Radio Networks: Theoretical Foundations, Example Applications, and Future Directions," in *IEEE Signal Processing Magazine*, vol. 30, no. 4, pp. 126-136, Jul. 2013, doi: 10.1109/MSP.2013.2251071.

[31] M. R. Vyas, D. K. Patel, and M. Lopez-Benitez, "Artificial neural network based hybrid spectrum sensing scheme for cognitive radio," *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2017, pp. 1-7, doi: 10.1109/PIMRC.2017.8292449.

[32] Y. Tang, Q. Zhang, and W. Lin, "Artificial Neural Network Based Spectrum Sensing Method for Cognitive Radio," *2010 6th International Conference on Wireless Communications Networking and Mobile Computing (WiCOM)*, 2010, pp. 1-4, doi: 10.1109/WICOM.2010.5601105.

[33] D. Han *et al*., "Spectrum sensing for cognitive radio based on convolution neural network," *2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 2017, pp. 1-6, doi: 10.1109/CISP-BMEI.2017.8302117.

[34] E. Azzouz and A. K. Nandi, “Automatic modulation recognition of communication signals,” M.S. thesis, School of Engineering Blekinge Institute of Technology, Blekinge, Sweden, 2013.

[35] T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," *International conference on engineering applications of neural networks*, vol. 629, pp. 213-226, Aug. 2016, doi: 10.1007/978-3-319-44188-7_16.

[36] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-Air Deep Learning Based Radio Signal Classification," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 168-179, Feb. 2018, doi: 10.1109/JSTSP.2018.2797022.

[37] F. N. Khan, C. Lu, and A. P. T. Lau, "Joint modulation format/bit-rate classification and signal-to-noise ratio estimation in multipath fading channels using deep machine learning," *Electronics letters*, vol. 52, no. 14, pp. 1272-1274, Jun. 2016, doi: 10.1049/el.2016.0876.

[38] R. Li, L. Li, S. Yang, and S. Li, "Robust Automated VHF Modulation Recognition Based on Deep Convolutional Neural Networks," in *IEEE Communications Letters*, vol. 22, no. 5, pp. 946-949, May 2018, doi: 10.1109/LCOMM.2018.2809732.

[39] B. Tang, Y. Tu, Z. Zhang, and Y. Lin, "Digital Signal Modulation Classification with Data Augmentation Using Generative Adversarial Nets in Cognitive Radio Networks," in *IEEE Access*, vol. 6, pp. 15713-15722, 2018, doi: 10.1109/ACCESS.2018.2815741.

[40] A. Graves, "Long short-term memory," *Supervised sequence labelling with recurrent neural networks*, vol. 385, pp. 37-45, Feb. 2012, doi: 10.1007/978-3-642-24797-2_4.

[41 S. C. Hauser, W. C. Headley, and A. J. Michaels, "Signal detection effects on deep neural networks utilizing raw IQ for modulation classification," *MILCOM 2017-2017 IEEE Military Communications Conference (MILCOM)*, 2017, pp. 121-127, doi: 10.1109/MILCOM.2017.8170853.

[42] M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, Nov. 2014, doi: 10.48550/arXiv.1411.1784.

[43] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," *arXiv preprint arXiv:1511.06434*, Nov. 2015, doi: 10.48550/arXiv.1511.06434.

[44] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," *International conference on machine learning*, Jun. 2015, pp. 448-456.

[45] A. B. L. Larsen, S. K. Sønderby, H. Larochelle, and O. Winther, "Autoencoding beyond pixels using a learned similarity metric," *International conference on machine learning*, Jun. 2016, pp. 1558-1566.

[46] K. Davaslioglu and Y. E. Sagduyu, "Generative Adversarial Learning for Spectrum Sensing," *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1-6, doi: 10.1109/ICC.2018.8422223.

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