INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

WebApp-Based Digital Modulation Waveform Generator for Automatic Modulation Classification in Wireless Communication Systems

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DOI: https://doi.org/10.51583/IJLTEMAS.2026.150700045

Received: 22 July 2026; Accepted: 27 July 2026; Published: 07 August 2026

ABSTRACT

To alleviate the issue of data scarcity in the context of communication systems, a viable solution is the capacity to generate realistic wireless signal constellation diagrams with Generative Adversarial Networks (GANs). While it was possible to train stable GANs for multi-class (20 classes) image data for some time, the situation where it is launched with strict calculation resources such as only using the CPU and High Performance Storage(HPS) in a small amount, and is trained for a large number of classes (260 classes) has been difficult until recently. In this paper, we propose two lightweight GANs, an improved vanilla generator-dominant GAN (G:D ratio 3.28) and an improved vanilla GAN (G:D ratio 1.43), along with a novel hybrid GAN model with the incorporation of DCGAN components and class conditioning: a Conditional Least Squares GAN (LSGAN Hybrid, G:D ratio 2.0) is made. All models were trained on 52,000 constellation images with four successive epochs (5, 10, 15, 20) using a standard Intel Core i7 CPU. The LSGAN Hybrid achieved outstanding training stability with monotonically decreasing loss throughout training, and with the smallest epoch-to-epoch correlation variance ($\sigma = 0.0073$) with only 720K parameters, which is more than 55% reduction from its vanilla counterpart. All architectures had 100% discriminative accuracy (ACC) when tested against the test dataset; the vanilla models, however, were suffering from serious discriminator dominance, with the ratio reaching up to 18.57 for the 10th epoch, which reflects the occurrence of the gradient becoming saturated. SGD statistical distribution analyses (t-tests) showed that the LSGAN was the only algorithm to make significant distributional changes at subsequent epochs ($p < 0.05$ after 15 epochs and 20 epochs of generation), which validates its continuous improvement capacity for generation. These results paved the way for parameter-efficient constellation generation algorithm on a controlled constellation in an ideal back nook for LSGAN Hybrid for strict constellation generation requirements, especially under hardware constraints scenarios.

Keywords: Communication Systems, Constellation, Generative Adversarial Networks.

INTRODUCTION

The availability of large-scale and labeled wireless signal constellations is a major limitation in (modern) communication systems research. Traditional data collection relies primarily on a lab testbed using cost-prohibitive, specialized Software-Defined Radios (SDRs) such as the HackRF platform, with one SDR used as the transmitter, and another SDR acting as the receiver. This equipment-intensive approach, frequently achieved via a simulated approach (e.g., using GNU Radio Companion to create a realistic communication scenario), is very expensive, not to mention being very time-consuming. To overcome the vast and continuous channel space, one has to sweep over a range of Signal-to-Noise Ratio (SNR) and a variety of fading environments. Therefore,

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

the huge economic and temporal expenses for obtaining full datasets are still seriously hindering the development of data-driven applications like Automatic Modulation Classification (AMC), spectrum management, cognitive radios' applications, etc.

This study suggests another approach to overcoming these limitations: the use of Generative Adversarial Networks (GANs) for the generation of synthetic data that would allow the reproduction of constellation diagrams, these being the most crucial cornerstones of visualization in digital modulation. The parameter space set to be targeted by the generator is intentionally wide and practically pertinent: the generator has to be able to produce constellation images for 10 different modulation techniques: 8PSK, 16PSK, BPSK, QPSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, and 1024QAM. Besides that, the synthesis process should be dependent on two important parameters of the communication system: (1) the channel type (Rayleigh fading channel and Rician fading channel) and (2) the signal-to-noise (SNR) value sampled at every 5 dB over a wide range of 40 dB up to -20 dB. This forms a noiseless order of recording, and two channel types result in 260 individual channel classification cases (10 modulations x 13 SNR levels x 2 channels). An experimental setup, built with two HackRF radios and GNU Radio, was carefully optimized to produce an underlying data source that simulated the deleterious propagation effects of an actual channel and propagation path and was later injected with programmatically custom-based Python post-processing scripts to generate the SNR and channel variations.

Although a full dataset of 52,000 images (representing 200 samples per class) was generated to ensure statistical representativeness, the lifting of the signature resource capacity constraints of the intended deployment platform determines the need to judiciously shrink the training footprint. All experiments were performed on a Lenovo T480s laptop with Intel Core i7 processor, 8 G of RAM, a small 512 GB SSD and Windows 11 Pro. This limit on hardware, which doesn't allow for the powerful GPUs that accelerate generation, meant there was a pragmatic 40% partitioning of the main dataset for the generation task, which made the training set for this task, despite having 20,800 samples across the 260 classes, a manageable but challenging collection. The overall objective is to find out which of these lightweight GAN architectures is able to learn the highly complex constellation patterns from this subset while preserving the ability to generalize for the entire SNR range and channel conditions.

In addition to the confirmation of the research hypothesis, this work provides a deployable tool to the wireless communications community. Once the optimal architecture has been found, the model is encapsulated in a Streamlit web app for local testing and inference. The application is an easy-to-use on-demand constellation simulator, enabling researchers to create realistic labelled modulation data without reimplementing the hardware costs. The planned instrument will be used for various downstream wireless applications, such as single-task or multi-task AMC, multimodal and multitasking applications, complex spectrum sensing, and dynamic spectrum management. Through this tool, we hope to fill the gap between handmade hardware-based data gathering and the need for extensive and annotated training sets in the field of wireless artificial intelligence, given the increasing popularity in the field, particularly in the domain of cognitive radio networks.

In this review, scholars in [1] focused on image and signal-based applications of Generative Adversarial Networks (GANs) for generating synthetic data in the healthcare sector. The importance of generating large, high-quality medical datasets has spurred the motivation of the present study. Generating large, high-quality medical datasets is motivated because of the increased need to generate these kinds of datasets, which, if obtained, could be generally restricted by privacy, ethics, and cost issues of acquiring such datasets. The aim was to investigate whether GANs could be effective for the purpose of generating realistic synthetic medical images and physiological signals that would not impact patient privacy, but would benefit the machine learning models. They did so by using a systematic literature review methodology, identifying, screening, and reviewing published literature on the subject of GANs and Synthetic Data Generation. The reviewed studies encompassed various applications, including medical image synthesis, disease diagnosis, segmentation of medical images, electrocardiogram (ECG) signal modeling, electroencephalogram (EEG) synthesis, and data augmentation in deep learning models. Selected cases were analysed based on the GAN architecture, data quality produced by the model, evaluation metrics, privacy preservation, and some effects on predictive model performance. The review resulted in the following findings: the GAN-generated datasets make a huge contribution to dataset diversity, class imbalance, maintain good patient privacy, and also improve the accuracy of machine learning models. Although these benefits have been observed, the authors found that there are some persistent problems, such as instability in training, model collapse, high computational cost, etc., in the quality assessment of the synthesized data. Furthermore, the research only focused on healthcare applications and not on other potential applications such as the wireless communication sector, digital modulation signals, etc. It was also not taken into account that lightweight GAN architectures existing for hardware-constrained communication devices would be considered. This constraint poses an important research challenge to build efficient GAN models that can generate realistic multi-class constellations for wireless communication embedded systems to enhance other practical applications.

In [2], the authors discussed the design of the next-generation communication system using deep learning autoencoders. The study has shown that conventional communication methods optimize the performance of the transmitter and receiver components separately, which reduces the communication performance in complex wireless environments. The aim was to explore how the concept of autoencoding communication systems evolved, how they were used in various communication scenarios, and what the current challenges for the practical application of such systems were all about. The authors used a comprehensive survey technique and analyzed all the recent studies on relevant deep learning autoencoder architectures for wireless communications. The applications that were surveyed included channel coding, channel estimation, signal detection, multiple-input multiple-output (MIMO) communications, orthogonal frequency division multiplexing (OFDM), visible light communications, semantic communications, and end-to-end communication system optimization. Various comparative characteristics based on communication reliability, computational needs, robustness, learning strategies, architecture design, and feasibility of implementation were examined. The review illustrated that deep learning autoencoders give better communication reliability, communication channel adaptability, better signal representation, and better end-to-end optimisation than traditional communication systems design. Despite this, the authors highlighted that their practical implementation is not easy due to the computational complexity and time requirements, massive data needs, a lack of explainability, and hardware implementation constraints. Additionally, few studies examined in the review were limited to discriminative deep learning models and didn't explore the use of lightweight Generative Adversarial Networks (GANs) for communication signal generation or digital modulation constellation synthesis. Therefore, efficient lightweight generative models that can generate various types of constellations to satisfy hardware resources still need to be significantly investigated, which also created an open research gap to be filled by the study.

Researchers [3] looked into the theoretical explanations that cause the instability in training Generative Adversarial Networks. When assessing the performance of classic GANs, the authors noted that many problems landed into mode collapse, vanishing gradients, and strong fluctuations in optimization progress toward directions of little overlap with the real data distribution. The study aimed to formulate a principled theoretical model that could identify the various optimization failures and find alternative mathematical metrics that better describe the optimal game of stable adversarial learning. The method employed was a theoretical approach, having included thorough analysis based on the theory of probability, optimal transport theory, and statistical learning. The appropriate probability distance measure for analysing their suitability in stable adversarial training in the GAN was investigated. The authors showed that by mathematically analyzing the Wasserstein distance, they can learn smoother and more informative gradients than their traditional counterparts so that meaningful optimization is possible even when the distributions are significantly different. The researchers found that in addition to topological changes, the type of distance metric used in the GAN network is more fundamental for generating a stable network. The results provided a foundation to build upon for the advancement of Wasserstein-based GANs and showed considerable advantage in terms of convergence stability and fewer modes collapsed.

But this work was theoretical in most traceable senses, and did not delve so deeply into lightweight network designs or into any real hardware environment. In addition, the computational complexity, memory consumption, inference latency, and energy efficiency were not discussed. Signal generation and multi-class constellation synthesis for communications under the constraint of hardware advantages are thus important research still to be explored and developed using these approaches and theories.

In the paper [4], the authors introduced an in-depth survey of wireless communication recipients' application of deep learning techniques. For this, the study was motivated by the complexity of modern wireless communication systems and the need from the engineers' side to develop efficient receiver algorithms that operate with fading, interference, hardware impairments, and nonlinear distortions, to handle communication in dynamic communication environments. The purpose of the survey was to explore the recent developments in deep learning-based receiver architectures, analyze their performance for the various communication tasks, and draw future research directions for intelligent wireless communication systems. The authors employed a systematic survey approach to the state-of-the-art of deep neural networks, convolutional neural networks, recurrent neural networks, transformers, autoencoders, and hybrid learning models for channel estimation, modulation classification, signal detection, equalization, channel decoding, and end-to-end receiver optimization. Performance criteria like bit error rate, communication accuracy, computational complexity, robustness to channel variations, and implementable techniques were evaluated for comparative analysis. The survey showed that deep learning receivers could consistently outperform traditional signal processing methods in various complex wireless environments, as they could achieve better channel estimation accuracy, symbol detection, interference suppression, and communication reliability. But the authors added that many of the proposed models demand a lot of computational resources, extensive training sets, and high-performance processing devices; otherwise, they are not able to be practically applied to edge communication devices. Moreover, the underlying premise of the survey was receiver optimization, which was its main emphasis, neglecting any study on lightweight Generative Adversarial Networks (GANs) to generate the communicated signals and multi-class constellation synthesis. However, the lack of adversarial learning methods designed for hardware, model compression methods, and easy-to-implement generator architectures creates a strong research motivation for the current research.

Recently, [5] developed an update for the training strategy used in Wasserstein Generative Adversarial Networks (WGANs) that reduces the limitations caused by clipping weights in the original Wasserstein GAN. The authors noted that weight clipping may inhibit the learning ability of the discriminator to avoid over-optimization, weak convergence, and poor-quality generated samples. The aim of the study was to create a more stable framework which enforced the Lipschitz continuity constraint while preserving the adversarial learning quality and reliability. In order to achieve this goal, the authors developed the Wasserstein GAN with Gradient Penalty (WGAN-GP), removing the need for the Lipschitz constraint to be enforced by weight clipping by adding a gradient penalty term to the discriminator loss function. The proposed approach is tested on datasets such as CIFAR10, LSUN Bedrooms, Imagenet, and language modeling datasets. Conventional GANs, the original WGAN, and WGAN-GP were compared using the evaluation metrics of convergence stability, robustness, consistency of training, and quality of generated samples. The findings showed that WGAN-GP successfully generated high-quality synthetic images, had lower optimization failures, and higher testing stability while training compared with the current methods in traditional GANs. Another optimization method that was motivated by the gradient penalty, therefore eliminating many of the optimization issues caused by weight clipping, became one of the most influential stable methods in today's GAN research. However, the framework that was proposed and developed was mostly intended for creating images and other large-scale deep learning applications and was not designed with consideration of computational efficiency for embedded systems. However, the extra gradient calculation during training results in higher computational complexity and makes it challenging to deploy on those communication devices that have limited computing resources. Moreover, the study didn't explore the topic of generating communication signals, the digital modulation constellation, lightweight GAN architectures, or hardware-conscious methods for optimizing the constellation. Therefore, there is still a great demand for lightweight adversarial models that can retain the training stability of WGAN-GP and in situ lower the computational complexity to achieve efficient multi-class constellation synthesis under hardware requirements.

In Article [6], a comprehensive survey and tutorial were presented relating to the use of Generative Artificial Intelligence (Generative AI) for improving secure communications in Space–Air–Ground Integrated Networks (SAGINs). The study was driven by the evolving complexity of future communication networks, where simultaneous and ubiquitous access to the ground, air, and space domains will be required, while attacking these networks become more innovative and complex due to the rise of cyber threats. The study aimed to explore the potential of the newly emerging General AI (GenAI) technologies such as Generative Adversarial Networks (GANs), diffusion models, foundation models, and large language models for the advancement of communication security and intelligent networking, adaptive resource management, and better and smarter decision-making in integrated communication systems. Using a systematic survey methodology, the authors sifted through recent research on various aspects of communication security using AI, physical-layer authentication techniques, anomaly detection, secure channel estimation, intrusion detection, spectrum utilization, creation of synthetic data, and intelligent channel utilization optimization. The reviewed techniques were categorized based on the architectures, communication applications, implementation strategies, and security features. According to the survey, the use of Generative AI greatly enhances the security of communications, with applications such as generating realistic communications for attack simulation, intelligent anomaly detection, and adaptive communication authentication mechanisms. Generative AI greatly enhances communication security, such as applications that simulate attacks using realistic communications, intelligent anomaly detection, adaptive communication authentication mechanisms, synthetic communication data generation, and improved machine learning performance under limited training data conditions, the survey revealed. The authors found that Generative AI (GAI) will be an essential enabler for the intelligent communication systems of the future. But they pointed out that current generative models are CPU and memory-intensive, have long training durations, and are costly, so they are difficult to implement in embedded communication devices in practice. Although adding the ability to generate synthetic communications data is seen as a promising area of GAN applications, the study was not done on the design of lightweight architectures for digital modulation constellation synthesis. Likewise, no explanation was given for the compression of the models, low-power deployment, sparse-receptive adversarial learning, or real-time constellation generation constraints on the hardware. These limitations present a significant driving point to develop an efficient multi-class constellation synthesis for practical wireless communication systems based upon lightweight generation of GAN.

Thus, in a comparative study, [7] investigated the various Generative Adversarial Network (GAN) architecture options for the generation of synthetic data in various application areas. The study was inspired by the recent emergence of a number of GAN variants proposed and the scarcity of comparative studies for their performance under similar experimental conditions. The aim was to assess the performance of popular GANs, based on synthetic data quality, statistical similarity, convergence properties, efficiency, and suitability to establish them for further machine learning applications. The authors experimented with various widely used architectures for GANs on standard datasets and compared the results by analysing the natural and synthetic data from them statistically, assessing their similarity using various metrics, comparing their ability to learn predictive models and analyzing them visually with respect to the quality of the synthetic data produced. The convergence stability, the diversity of the sample, computation time and training efficiency for the models under test were compared. The results showed there were no architecture of GAN showing robust performance regarding all the evaluation criteria. Some architectures achieved very realistic synthetic data sets; however, they needed a much longer training time and much more computing power; other architectures gathered faster, but the quality of the gathered samples was lower. Based on the results of this study, the choice of a specific GAN architecture will vary depending on the specific application, computational resources, and the desired level of efficiency and accuracy. The study, however, concentrated mainly on general synthetic data generation and did not take into account the synthesis of a communication signal or the generation of the digital modulation constellation. The computational complexity was mentioned, but there was little attempt to tailor the GAN architectures to work optimally in the context of embedded wireless communication systems. Therefore, the generation of accurate multi-class constellation configurations to serve in hardware-limited communication platforms, but with the ability to adapt to the computational requirements during training, is still associated with important research challenges.

Emphasized and critically discussed the principles, application, and evolution of signal generator technologies in electronic engineering, communication systems, scientific research, and industrial testing. The research acknowledged that signal generators have advanced beyond being just analogue oscillators to provide complex and accurate waveforms programmed to run by a digital machine, for use in various engineering functions. The goal is to analyse the working principle of different kinds of signal generator technologies, discuss their engineering applications, and explore future technological developments enabled by technological advancement of digital electronics and signal processing. A method was developed to review all available work that included analogue signal generators, function generators, arbitrary waveform generators, radio-frequency signal generators, and digitally synthesized waveform generation techniques. The evaluation of these technologies was carried out comparatively considering the following: waveform accuracy; frequency stability; programmability; operational flexibility; and application suitability. The review revealed that the precision of the waveforms, control of the frequency, automation, flexibility and variety of signals obtainable using modern digital signal generators over those attainable with conventional analogue signal generators are significant. The researchers found that ongoing developments of digital electronics and signal processing would provide further capabilities of enhanced signal generation technologies. While it covered the conventional method of generating the waveforms through the use of hardware, the study didn't explore the possibility of using artificial intelligence-based approaches to signal synthesis. Specifically, GAN, deep generative learning, synthetic communication constellation generation, and intelligent waveform synthesis were not a part of the study. Moreover, lightweight neural network architectures, hardware-aware optimization strategies, and deployment approaches for the embedded system were not addressed. From the above limitations, it is clear that lightweight approaches that are based on GANs to generate realistic multi-class communication constellations that still meet the hardware and computation requirements of modern wireless communication systems have not been catered to [8].

In [9], Mobile Edge Computing (MEC) from the communication point of view is analyzed in detail with the motivation that Internet of Things (IoT) devices, intelligent wireless applications, and latency-critical applications that cannot be efficiently supported by the traditional cloud computing infrastructures are growing rapidly. The authors noted that centralized cloud computing is plagued with unnecessary communication delays, bandwidth congestion, and increased energy use, which can constrain the performance of new wireless communication networks. The study aimed to survey the architecture of Mobile Edge Computing, filter out the computation offloading methods, resource allocation methods, communication protocol, mobility management and security issues, and explore the future research directions for intelligent edge communications. The approach taken was an extensive review of the literature about MEC technologies. Research studies were divided into the categories of communication architecture, computation models, optimization algorithms, resource management techniques, application scenarios, and implementation strategies and were then comparatively studied. The review showed that Mobile Edge Computing (MEC) can successfully reduce communication latency, increase bandwidth utilization, improve energy efficiency and find real-time intelligent processing for emerging wireless applications. The authors also highlighted as a possible technology trend to be used in future for edge intelligence, Artificial Intelligence (AI) and Deep Learning (DL) which may be effective where computational complexity can be managed effectively. Although these have contributed to the study in general, the study has not been structured to specifically explore Generative Adversarial Networks or the use of Generative Adversarial Networks for communication signal generation. Moreover, a lightweight adversarial learning method, a synthetic modulation constellation generation, a compression of the model, and hardware-aware optimization techniques suitable for edge communication devices were not investigated. Therefore, there exists a vast need for researchers to develop lightweight GAN architectures for multi-class communication constellation generation that would meet the computational and energy requirements of Mobile Edge Computing platforms.

Based on the observation that in traditional GAN training the generator and discriminator interact in the process of adversarial optimization, [10] explored the instability that was found. It is noteworthy that the authors noticed that in standard GAN training, the generator typically exhibits oscillatory behaviour and mode collapse issues since it is trained based on the state of the discriminator at a specific instance, given a rapidly changing discriminator architecture. The study aimed to increase the stability of the training process for GAN by letting the generator predict future updates of the discriminator while optimizing. To achieve this goal, they put forward the Unrolled Generative Adversarial Network (Unrolled GAN), where the discriminator is unrolled, and a number of optimization steps happen before the generator is optimized. The proposed approach was tested with synthetic examples, as well as benchmark image datasets (MNIST and CIFAR). The authors investigated various metrics, including convergence stability, sample diversity, mode coverage, and training behaviour and found that the proposed Unrolled GAN outperforms conventional GANs in comparative experiments. The results of the experiments validated that the proposed approach significantly reduced the mode collapse, stabilized the convergence, and produced more realistic and varied synthetic samples than the general training methods for GANs. The model had the generator predict the discriminator's outcome which provided a more balanced adversarial learning and better optimization results. But this improvement had to be paid for by using a more powerful computational device, since several steps in optimizing the discriminators had to be performed for each update to the generator. Such computational complexity restricts the applicability of the proposed approach in embedded communication devices, mobile platforms, Internet of Things (IoT) nodes, and other hardware-limited systems. Furthermore, the study concentrated only on image synthesis and ignored the generation of communication signals, the synthesis of digital modulation constellations, the lightweight generation of GAN architectures, and the efficient generation of adversarial learning from the perspective of hardware. Additionally, this study was limited to image synthesis and did not explore the generation of image-specific communication signals, the synthesis of digital modulation constellations, the lightweight generation of GAN architectures, or the efficient, hardware-efficient generation of adversarial learning. Then, the need for dataset generation in the domain of wireless communication that considers low device cost.

To solve the challenge of training GANs, [11] suggested an efficient regularization method called "spectral normalization" by normalizing the trainable weights. The motivation for the study was the fact that in many cases sudden changes of the weights of the discriminators result in unstable optimization, gradient explosion, and poor quality of discriminator samples generated. The goal was to find a normalization mechanism that is both efficient and simple to compute and is compatible with the Lipschitz continuity condition with as little computation as possible. The method proposed was to normalize the spectral norm (largest singular value) of each discriminator weight matrix by power iteration. When comparing this to gradient penalty methods, Spectral Normalization needs minimal extra computation and is easily added to popular existing GAN architectures. The proposed approach was tested on benchmark image generation datasets such as CIFAR-10, STL-10, and ImageNet and compared to several traditional methods that are used for implementing the stabilization in GANs. The results indicated that while the computational cost of the spectral normalization method is lower than some of the previous regularization techniques, the improvement in training stability, convergence speed, generation quality, and competitive results make it a worthy method to investigate. One of the very popular GAN

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

stabilization techniques is spectral normalization due to its simplicity and efficiency in practical use. However, the study focused only on computer vision and did not focus on the generation of communication signals or wireless communication systems. Similarly, lightweight NN architectures, model pruning, quantization, optimization with consideration of the hardware, and deployment of the NN on communication devices embedded with hardware were not discussed. Thus, efficient use of the Spectral Normalization in small-size GAN architectures for multi-class constellation generation under the limitation of hardware is still an important research topic.

A low-cost signal generator, suitable for educational laboratory and electronic testing applications, was designed and built by [12]. Commercially available signal generators are expensive, and therefore generally not available in research laboratories or educational institutes, especially in developing areas of the world, leading to the motivation of the study. The investigation aimed to design a low-cost signal generator that can generate stable waveforms of output frequencies with acceptable frequency accuracy using the widely available electronic components. The approach taken was to create the signal generator by employing oscillator circuits, shaping circuits to generate the desired waveform, a set of amplification stages to increase the amplitude, power supply circuits to provide operating power, and a set of circuits to control the frequency. A prototype of this was fabricated and tested experimentally to check out its stability, frequency accuracy, reliability of operation, and overall performance in various modes of operation. The experimental results showed that the designed signal generator was able to create sine, square, and triangular waveforms in the desired frequency band and also it has good stability of the waveforms and satisfactory accuracy of measurement that can be used for educational and laboratory purposes. The outcome of the developed prototype also fulfilled the aim of giving an affordable alternative to available signal generators. Unfortunately, the study did not consider integrating AI, machine learning, or deep generative models into the detection of shapes for the generation of waveforms, and only conventional hardware or digital hardware-based signal generation was considered. Moreover, the output signals were standard analog signals, not digitally generated communication constellations needed in present-day wireless communication systems. The study continues not to address adaptive signal generation, synthetic communication datasets, lightweight neural network architectures, and hardware-aware optimization approaches. It thus stands that there is still a huge gap in research on how to build lightweight Generative Adversarial Networks with reasonable hardware constraints that can generate realistic signals of communication constellations with a small number of classes.

Similarly, if privacy laws prohibit sharing data, confidentiality issues may arise, or in many financial sectors, the sector simply does not have the data to begin with, then the use of synthetic data generation is the solution to this restricted data [13]. The study was driven by the need for realistic synthetic financial datasets that would play a crucial role in applications that involve fraud detection, credit risk analysis, algorithmic trading, and predictive modelling without any leakage in sensitive customer information. The research aimed to investigate the ability of various GAN architectures to produce synthetic financial time series that maintain crucial statistical properties and analytical value of real-time data with data privacy. In order to accomplish this goal, the authors applied various versions of the GAN network to create synthetic financial records and compared the generated assets with similarity measures in terms of statistical distribution analysis, correlation coefficients, and quality assessment metrics. Further, machine learning models were trained both on synthetic data and on original data, and it was then determined whether the generated data could be helpful for predictive analytics. The experimental findings illustrated that the generated datasets could closely emulate authentic financial data in relation to their statistical distributions, relationships of the features, and their predictive powers. The simulated samples captured necessary features of the underlying datasets, avoiding any leakage of sensitive information, and are compatible with various financial applications. Despite these accomplishments, the study concentrated on the financial tabular datasets and excluded wireless communication signals and digital modulation constellation generation. Moreover, the proposed GAN model focused on data quality rather than computational efficiency, and lightweight network architecture, model compression, model inference latency, optimizing the model to run on fewer resources, or the energy efficiency of using the model on a hardware-constrained system were not included. This fact highlights the important research challenge of developing lightweight architectures of GANs with a comprehensive ability to generate synthetic datasets with communication constellation images of several classes efficiently and adaptable to the deployment on communication embedded computer hardware.

In light of the growing and urgent necessity of implementing complex AI models in traditional satellites and UAVs together with other resource-limited remote sensing platforms, [14] offered a thorough review of various methods of deployment on the board of these platforms for remote sensing foundation models. While large scale foundation models have shown spectacular results in image analysis and intelligent perception related applications, they have an extremely large computation load, which becomes a difficult challenge to run on embedded hardware, the authors noted. The purpose of the study was to analyze the intelligent remote sensing foundation models, to discuss the optimization method for implementation on the platform, and to examine the feasibility hardware platform for the implementation of intelligent remote sensing foundation model. The authors used a systematic review approach based on the examination of recent studies that employed transformer-based foundation models, self-supervised learning, knowledge distillation, model pruning, quantization, and hardware acceleration. Performance metrics, including computational complexity, required memory, inference time, energy consumption, viability for deployment, and predictive accuracy, were used in comparative analysis. It was shown that techniques employed for optimization, such as pruning, quantization, lightweight networks, knowledge distillation, and specialized hardware for accelerating models, significantly enhance deployment efficiency, while preserving model performance. The authors found that improving AI system performance and cost-effectiveness in terms of balancing predictive accuracy with computational efficiency remains a key challenge for embedded AI systems. The focus of the review, however, was on remote area sensing and not on wireless communication systems. It didn't researched Generative Adversarial Networks for communication signal generation, digital modulation constellation synthesis or light weight adversarial learning techniques. Similarly, a simultaneous optimization of the GAN with synthetic communication signals using hardware-aware optimization was not investigated. The limitations will create an important avenue of research into lightweight GAN models which generate high quality multi-class constellation databases that possess the characteristics required by the available computational resources of practical communication hardware.

In [15], 2-Dimensional Array reared his head again by discussing the advancements of deep learning in wireless physical layer communications; wireless networks of the future will need intelligent algorithms to adapt to ever prominent and dynamic communication scenarios. The study was inspired by the formidable development of 6th generation communication (6G) technologies and the more and more use of Artificial Intelligence in the realm of wireless communication technology. The goal was to review the latest trends in deep learning technologies at the physical layer and understand the existing methodologies and their limitations, and suggest future research ideas on intelligent communication system design. A comprehensive survey method was chosen by the authors, where they took into account the latest studies conducted in the areas related with channel estimation, channel decoding, signal detection, modulation recognition, beamforming, semantic communications, resource allocation, and intelligent wireless networking. To compare the different NN architectures from the following categories for their information fidelity, robustness, scalability, computational complexity, and implementations, these categories include convolutional neural networks, recurrent neural networks, graph neural networks, transformers, reinforcement learning models, and generative models. The review revealed that deep learning techniques can greatly support the communication process through accurate channel estimation, decrease the bit error rate, increase the spectral efficiency, and introduce adaptive signal processing in a wireless environment with a rapidly changing channel. The authors additionally stressed that in the near future AI will be an essential part of any intelligent communication system. Some of the currently unaddressed challenges highlighted by the survey were however, computational complexity, model lack of generalization, inadequate communication sets, hardware challenges, and the lack of model interpretation. While it was known that generative models have potential as technologies, this study did not specifically explore lightweight Generative Adversarial Networks

INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

(GANs) for synthetic communication signal generation nor digital modulation constellation synthesis. Furthermore, there was no consideration of lightweight generator architecture, hardware-aware optimization, computational efficiency, memory reduction, or of deploying in real-time onto embedded communication platforms. The above-mentioned drawbacks are a clear incentive to the current research for the development of an efficient multi-class constellation synthesis using a lightweight Generative Adversarial Network (GAN) under low configuration-based hardware constraints on a device.

METHODS

The research methodology follows a structural pattern from the dataset generation to the preprocessing and model formulation, training, and testing. Figure 1 below is the system diagram showing the experimental pipeline of the entire procedure, and dowm to the conclusion of the system.

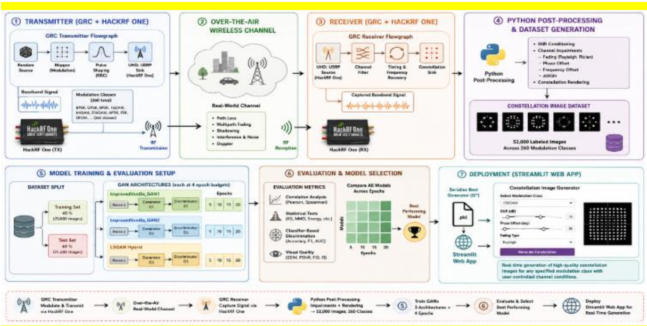

Figure 1: System Diagram of the complete Experimental Pipeline

Experimental Platform and Dataset Generation

The experiments were conducted on a benchmark Lenovo T480s notebook having an Intel UHD Graphics 620, 8 GB RAM, Intel Core i7 8th Generation and Windows 11 Pro operating system. As GPU acceleration is unavailable, it is necessary to design all models to be efficient during CPU-only training.

Using GNU Radio Companion (GRC), a hardware-in-the-loop communication platform was created using two Software-Defined Radios (SDRs), HackRF One. Both HackRFs were used in a separate mode: one as a transmitter and the other as a receiver. The SDR platform was used to transmit ten different digital modulation types: BPSK, QPSK, 8PSK, 16PSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM and 1024QAM.

The captured constellation data were processed using Python scripts to simulate Additive White Gaussian Noise (AWGN), Rayleigh fading, and Rician fading at different SNRs of –20 dB, –15 dB, ..., +5 dB, 10 dB, ..., 40 dB in 5 dB steps. Twenty-six classes of communication were gathered from 10 modulation schemes and 13 SNR levels and two channel models to provide the complete dataset of 260 communication classes. We generated 52,000 RGB constellation images, such that there are 200 images in every class of size 64 x 64 pixels. Due to the low hardware configuration, we considered 20,800 images (40%) to be used for training, and 31,200 images (60%) were reserved for the test. The images used for training the model were all re-scaled to the range [-1,1]. Figure 2 shows the experimental hardware setup; Figure 3 shows the GRC flowgraph representation of how the QAM dataset was generated, while Tables 1 and 2 show the experimental modalities and radio configuration parameters.

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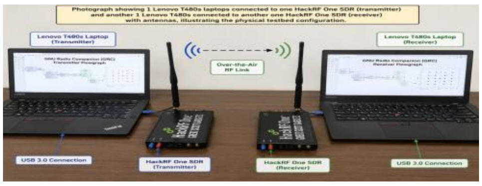

Figure 2: Experimental Hardware Setup

Table 1: GNU Radio Companion Transmitter Flowgraph Parameters

Parameter	**Setting**	**Description**
Signal Source		
Modulation Type	BPSK, QPSK, 8PSK, 16PSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 1024QAM	Selected via Constellation Modulator block
Symbol Rate	1 Msps	Symbols per second
Samples per Symbol	4	Oversampling factor
Constellation Modulator		
Constellation Object	digital. constellation_*	Generated from PSK/QAM constellation objects
Differential Encoding	False	Standard encoding
Excess Bandwidth	0.35	Root-raised cosine filter roll-off
Osmocom Sink (HackRF Transmitter)		
Sample Rate	4 Msps	Must be between 2–20 Msps for HackRF One
Frequency	2.45 GHz	ISM band (adjustable per experiment)
RF Gain	14 dB	Controls RF amplifier
IF Gain	20 dB	Intermediate frequency gain
VGA Gain	20 dB	Selected via Constellation Modulator block
Antenna	SMA Female	External antenna connection

Table 2: GNU Radio Companion Receiver Flowgraph Parameters

Parameter	**Setting**	**Description**

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Osmocom Source (HackRF Receiver)		
Sample Rate	4 Msps	Matches transmitter sample rate
Frequency	2.45 GHz	Matches transmitter frequency
RF Gain	14 dB	RF amplifier gain
IF Gain	20 dB	Intermediate frequency gain
VGA Gain	20 dB	Variable gain amplifier
Digital Signal Processing		
Frequency Correction	Enabled	Fine frequency offset correction
Symbol Timing Recovery	Mu = 0.5, Omega = 4	Gardner timing error detector
Costas Loop	8PSK/QPSK mode	Carrier phase recovery
Constellation Decoder		
Constellation Object	Matches transmitter	Identical constellation for decoding
Output Format	Complex (I/Q)	Raw constellation points
QT GUI Constellation Sink		
Number of Points	1024	Displayed constellation points
Auto Scale	Enabled	Automatic amplitude scaling
Update Rate	10 Hz	Display refresh rate

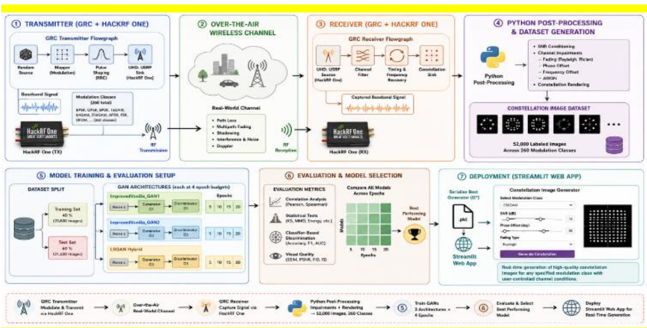

Figure 3: GNU Radio Companion Flowgraphs for 16 QAM (a) Transmitter System; and (b) Receiver System

GAN Architectures

Three lightweight generative adversarial networks (GANs) were developed for comparative evaluation.

The first architecture, ImprovedVanillaGAN1, used the standard Binary Cross-Entropy (BCE) adversarial loss with Spectral Normalization and Batch Normalization to enhance convergence. No changes were made to the parameter ratio of the generator vs the discriminator (1.43:1).

The second architecture, ImprovedVanillaGAN2, had a larger generator size, but a smaller discriminator. A generator-dominant parameter ratio of 3.28:1 was achieved. This design examined the possibility of using more parameters in the generator to yield better constellation synthesis.

To alleviate the vanishing gradient (VGP) issue, the proposed LSGAN Hybrid was based on Mean Squared Error (MSE) loss instead of BCE loss. Furthermore, conditional embedding was taken into consideration to allow the generation of the constellation picture based on the modulation type, channel conditions, and SNR level. In comparison to vanilla models, the proposed model architecture only uses 737,666 trainable parameters, which is more than a 55% reduction in the number of parameters and still comparable generation performance.

Model Training and Performance Evaluation

The Adam optimizer was used with all models, a learning rate of 0.0002, a batch size of 32, and a latent dimension of 100. Seven independent lengths of training: 5 epochs, 10 epochs, 15 epochs, and 20 epochs. Vanilla GAN models have been applied with smoothing on labels, and the LSGAN Hybrid model has been applied with Mean Squared Error adversarial loss and Cross-Entropy loss for conditional label classification.

The combined quantitative and qualitative approach was used for performance evaluation. Structural similarity of the generated images to the real images was quantified using Pearson Correlation Coefficient and statistical similarity using Independent Two-Sample t-tests for the distribution of the images' pixels. A Random Forest (RF) external classifier was used for the discrimination of the generated samples from actual samples. Adversarial stability was examined by analysing the generator and discriminator loss curves, and the positive influence of the constellation images was checked qualitatively by comparing the actual and generated constellation images in visualization. Figure 2 shows the architectural pipeline of the entire work.

RESULT AND DISCUSSIONS

The results of the three lightweight GAN designs are presented and thereafter discussed extensively over different metrics like structural similarities, stability of the training, statistical and computational performance, visual assessment, balance ratio, statistical distribution analysis, classification and discriminative performance, etc., and other assessments under the condition of training only on low-configuration computer hardware.

Structural Similarity

Based on the Pearson correlation analysis, it can be noticed that the proposed LSGAN Hybrid can maintain the minimum difference in a stable range during the training process, as it can be seen that it has correlation values between 0.6981 and 0.7155, and its mean value during the training is 0.7087 with the smallest standard deviation ($\sigma = 0.0073$). This low variance indicates proof of the same generation of images under all the epoch range configurations.

The improvedVanillaGAN1 had the greatest peak correlation for 20 epochs; however, there was large variability between each experimental run. ImprovedVanillaGAN2 achieved a middle ground in its correlation performance, but showed significant variations in performance over long training runs. Technically, improvedVanillaGAN1 had a better maximum correlation, but the proposed LSGAN Hybrid achieved a better generator when compared to other models, considering its parameters, that is fewer, and poses a reasonable overall cost reduction in the model.

Training Stability

There were substantial differences in adverse convergence evidenced in the generator and discriminator loss curves. The model's LSGAN Hybrid converged smoothly monotonic during the training procedure. The generator loss continuously dropped from 2.0078 to 0.9337, and the discriminator loss gradually declined from

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2.1439 to 0.4868 from epoch 5 to 20, which showed that adversarial learning is balanced.

However, when using ImprovedVanillaGAN1, after 10 epochs the generator loss slightly increased for a large portion of epochs while the discriminator loss continued to be very low near 0, which means the discriminator became dominant (soft-loss convergence by its extremely low value with vanishing gradients. When compared with the other methods, ImprovedVanillaGAN2 maintained its performance fairly well throughout training, but dropped significantly after 20 epochs. The above observations show that the utilization of Least Squares optimization to replace Binary Cross Entropy loss significantly boosts adversarial stability. Figure 4 explains the loss curve of the generator and discriminator for the three GAN architectures.

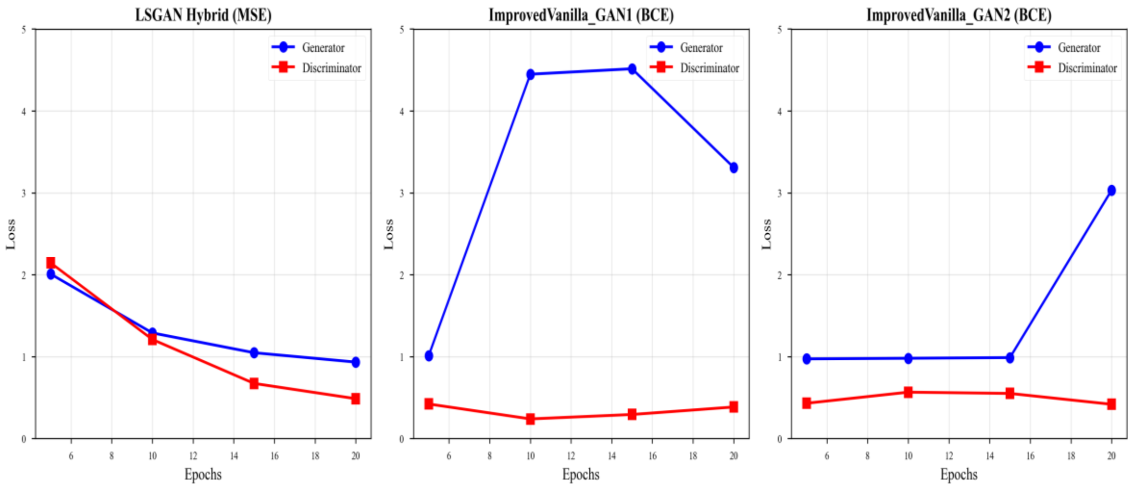

Figure 4: Generator and discriminator loss curves for the three GAN architectures

Statistical and Computational Performance

Independent Two-Sample t-tests additionally validated the advantages of the suggested structure. After 15 and 20 training epochs, the LSGAN Hybrid data further refined its statistics and had a large increase in its similarity to the real constellation images. In contrast, the vanilla architectures either did not show a significant improvement or even worsened after a long training period.

The proposed LSGAN Hybrid needed just 737,666 trainable parameters instead of more than 1.6 million parameters for both vanilla models. The optimized number of parameters decreased the memory usage and training duration, making this model very appropriate to be deployed in CPU-based systems. Table 3 shows the architectural parameter budgets, revealing the total parameters in each GAN model.

Table 3: Architectural Parameter Budgets

Model	Generator Params	Discriminator Params	Total Params	G:D Ratio
ImprovedVanilla_GAN1	957,699	667,905	1,625,604	1.43
ImprovedVanilla_GAN2	1,288,131	392,513	1,680,644	3.28
LSGAN Hybrid	491,291	246,375	737,666	1.99

Visual Assessment

The overall geometry of constellation diagrams (CDs) of constellation diagrams available in real datasets could

INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

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be well reproduced by comparing the proposed LSGAN Hybrid with real CDs in a visual manner for various modulations, SNR values, and channel conditions.

Fine texture and noise distribution changes were inevitable; however, the created constellation images retained the structural features required for Wireless Communication applications such as Automatic Modulation Classification (AMC), spectrum sensing, and cognitive radio applications. Figure 5 shows the correlation analysis for the generated images when compared to the real images.

The vanilla GAN models were able to produce reasonable pictures in the early phases but gradually became more visually distorted as the adversarial imbalance increased.

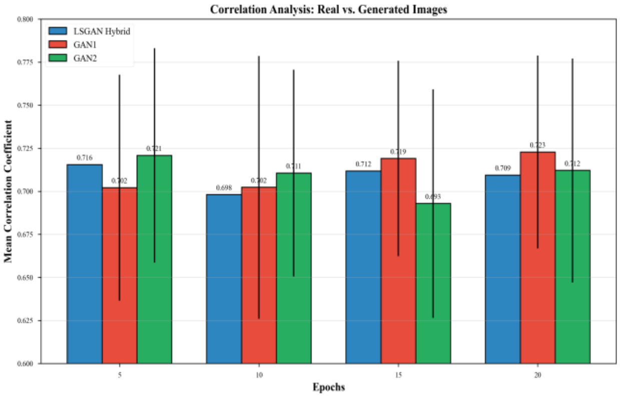

Figure 5: Comparison between real constellation images and images generated by the LSGAN Hybrid.

Balanced Ratio Evolution

LSGAN Hybrid

Balance was very close to optimal with the LSGAN Hybrid. The balance ratio was maintained in the stable range (0.5–2.0) from 5 epochs of observation up to 15 epochs (and even up to 20 epochs) and remained stable at 0.94 at 5 epochs, 1.07 at 10 epochs, 1.56 at 15 epochs, and 1.92 at 20 epochs, respectively. As can be seen in Figure 6, this is a smooth, monotonic rise, showing that the transition has not reached the limit of instability and is moving towards a dominant generator.

ImprovedVanilla_GAN1

The ImprovedVanilla_GAN1 showed significant excursions of the balance ratio. The ratio of “balances” first rose to a moderate level of 2.40 after 5 epochs, but then jumped to a catastrophic score of 18.57 at 10 epochs, meaning the discriminator was overly confident. It was still high at 15.36 across 15 epochs, but then began to climb back up towards 8.59 at 20 epochs. These values are also much higher than the stable region (0.5–2.0), indicating that BCE loss with spectral normalization did not keep adversarial equilibrium.

ImprovedVanilla_GAN2

Compared to the all-time baseline results of ImprovedVanilla_GAN2, it remained stable for epochs 5-15, after which it diverged from the baseline results. The balance ratios at 5, 10, and 15 epochs were 2.26, 1.73, and 1.79, respectively, both lying within and close to the stable region in the balance diagram. The ratio was still high, however, at 20 epochs, 7.25, which represents an end-of-period failure. This architecture gives one a sense that the generator side lines up the stability, yet it goes on to experience the same decline in the gradient problem.

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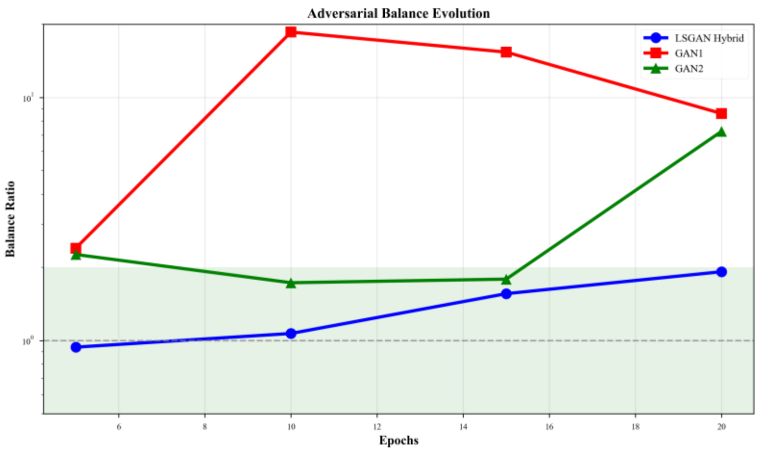

Figure 6: Balance Ratio Evolution] – Line chart showing balance ratio evolution across epochs on a logarithmic scale.

Statistical Distribution Analysis

LSGAN Hybrid

Progressive refinement of distributions with training time was achieved for the LSGAN Hybrid. No statistically significant difference between real and fake distributions was observed for any of the epochs (p-value = 0.5614 at 5 epochs). The p-value fell further to 0.1810 at 10 epochs, but did not reach significance or noticeable changes. The obtained p-value was just below its significance threshold at 15 epochs ($p = 0.0469 < 0.05$), meaning that the generated distribution became statistically different from the real distribution. The p-value also decreased to 0.0122 at 20 epochs, thus indicating a significantly changed generated distribution of mean value.

ImprovedVanilla_GAN1

All epochs were tested for the ImprovedVanilla_GAN1, but none of them had any statistically significant difference. Whereas at 5 epochs, the p-value was 0.1024, which is close but not statistically significant. The p-value decreased slightly at 10 epochs (0.0865) and 15 epochs (0.0642) but never crossed 0.05. At epoch 20, the p-value went up to 0.8761, meaning that the distribution learnt was not different from the real distribution, but on successful training, the generator has been producing ‘meaningless’ data.

ImprovedVanilla_GAN2

The ImprovedVanilla_GAN2 had a transient significant increase at epoch 5 followed by a decrease at epoch 10. The p-value at the 5 epochs was 0.2844, which is not significant. Using the 10 epochs of data indicates a distributional shift at the 0.0298 ($p < 0.05$) threshold. Until epoch 15, though, the p-value wasn't significant (0.1300), and by the 20th epoch, it shot up to 0.9795, indicating that training had failed. Figure 7 shows the significance variation for all models.

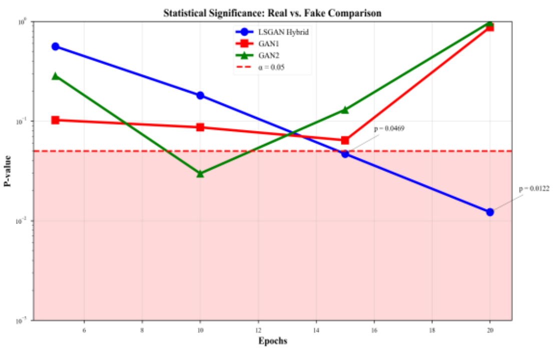

Figure 7: Statistical Significance P-values from T-tests comparing real and fake pixel distributions across

epochs

Classification and Discriminative Performance

The confusion matrix used in the classification task, where the data is separated into real vs generated samples, is shown in Figure 8. In all configurations and architectures, classification results of the external Random Forest Classifier on the set of test samples were 100.00% accuracy and an F1 Score of 1.0000 when differentiating them from the generated test set to the real test set. This optimal separation means that the resulting distributions are located in a different subspace of the feature space, which can readily be separated by ensemble classifiers.

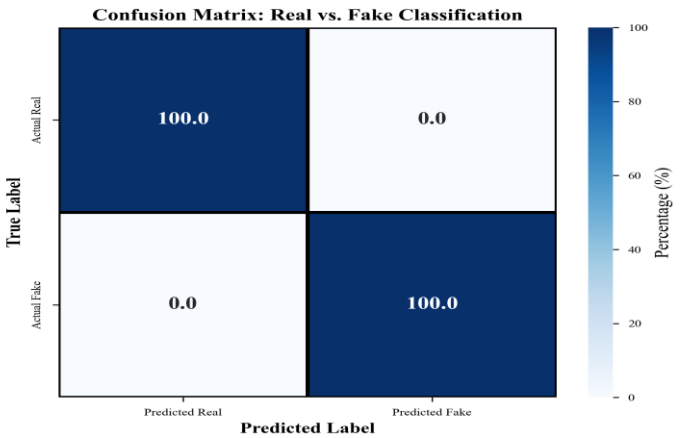

Figure 8: Confusion Matrix – Confusion matrix showing 100% accuracy in distinguishing real from fake samples across all models and epochs.

DISCUSSION

Training stability makes greater contributions than just capacity increase in the network, as shown by the comparative evaluation. There were a few occasions on which the vanilla architectures attained slightly greater correlation values; their unstable optimisation resulted in variable convergence and inferior image quality.

Least Squares adversarial learning and conditional generation were used to overcome these limitations in the proposed LSGAN Hybrid. The stable convergence, less computational complexity, high degree of statistical similarity and small number of parameters are favorable for practical constellation image synthesis when the hardware resources are limited.

Limitation & Future Work

Although this work shows excellent overall performance, there are still some limitations that leave room for future work: (1) Image Fidelity Regularization: The lack of complete subspace alignment is one of the challenges in the current framework. It enables the external classifiers to distinguish between the real images and synthetic images. Current work is directed towards the integration of new forms of regularization methods and feature matching loss weight parts to fill this gap. This will be given in later work, and (2) Evaluation Metric Breadth: Validation to date is limited to Pearson and t-tests (quantitative). An increased number of validations and quantification of visual realism will be done in the future versions of this work. The constellation-specific Inception Distance (FID) and Inception Score (IS) calculations are being actively developed. In upcoming publications, expanded metrics will be fully captured, and a (3) publicly hosted website will be part of the next evolution for use by researchers in the domain of CRN as a subfield of wireless communication. The work currently is limited to only a locally hosted Streamlit web app, and it shows appreciable results reflecting statistically charactistics of the LSGAN Hybrid system.

CONCLUSION

This study introduced a lightweight conditional LSGAN Hybrid model for multi-class constellation image synthesis with computational constraints only on a CPU. Three lightweight GAN architectures were quantitatively compared using a constellation dataset with 52 000 constellation images, covering ten digital modulation schemes, thirteen SNRs (SNR point modulation), and two wireless channel models.

Results showed the proposed LSGAN Hybrid to be the most stable adversarially trained model with an average structural correlation of around 0.71 (with the smallest variance) and reduced model complexity by over 55% relative to the vanilla GAN models. The Least Squares loss proved to be very effective in overcoming the adversarial instability and producing high-quality constellation images with reasonable computing power requirements.

The proposed model in particular proves to be a highly efficient framework for synthetic data generation, which is useful for wireless communication research, especially in Automatic Modulation Classification, spectrum sensing, cognitive radio applications, and channel modelling, as well as data augmentation scenarios where ample labelled data is often absent. Future work will include exploring GPU-based training, investigating additional constellation synthesis resolutions, examining additional fading environments, and advanced GAN variants to further enhance image fidelity and generalization performance.

ACKNOWLEDGEMENTS

The authors would like to thank the management of the Federal University of Technology, Ilaro (FUTI), Ogun State, Nigeria, for the support of this study under the Year 2024–2025 TETFund Intervention in Research Project (RP), Batch 10, with reference number AD/RDC/38/VOL.II/131, Tertiary Education Trust Fund (TETFund) as part of the Institution-Based Research (IBR) Intervention. The authors are also grateful to the unwavering support of the Director, RESDEC, Engr. Dr. S.A. Odunlami, for his facilitation and the financing support of the TETFund and the Federal Government of Nigeria for the study.

Funding Information

The research work has been funded by the Tertiary Education Trust Fund (TETFund) as part of the Institution-Based Research (IBR) Intervention, Research Project (RP) Batch 10, Year 2024 – 2025, Federal University of Technology, Ilaro (FUTI), Ogun State, Nigeria, under the grant reference number: AD/RDC/38/VOL.II/131.

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