Generative AI for Data Augmentation in Wireless Networks: Analysis, Applications, and Case Study

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Abstract—Data augmentation is a powerful technique to mitigate data scarcity. However, owing to fundamental differences in wireless data structures, traditional data augmentation techniques may not be suitable for wireless data. Fortunately, Generative Artificial Intelligence (GenAI) can be an effective alternative to wireless data augmentation due to its excellent data generation capability. This article systemically explores the potential and effectiveness of GenAI-driven data augmentation in wireless networks. We first briefly review data augmentation techniques, discuss their limitations in wireless networks, and introduce generative data augmentation, including reviewing GenAI models and their applications in data augmentation. We then explore the application prospects of GenAI-driven data augmentation in wireless networks from the physical, network, and application layers, which provides a GenAI-driven data augmentation architecture for each application. Subsequently, we propose a general generative diffusion model-based data augmentation framework for Wi-Fi gesture recognition, which uses transformer-based diffusion models to generate high-quality channel state information data. Furthermore, we develop residual neural network models for Wi-Fi gesture recognition to evaluate the role of augmented data and conduct a case study based on a real dataset. Simulation results demonstrate the effectiveness of the proposed framework. Finally, we discuss research directions for generative data augmentation.

Index Terms—Wireless networks, data augmentation, GenAI, Wi-Fi gesture recognition, diffusion models.

I. INTRODUCTION

As an indispensable and fundamental technology, wireless networks enable users to access the Internet, connect devices, and communicate wirelessly. The growing complexity and diversity of wireless networks have facilitated the development of Deep Learning (DL)-based wireless communications and networking [1]. Since wireless networks generate large amounts of data from user activities, channel states, and network conditions, DL can efficiently distill high-level features and information from these data, which have complex structures and inner correlations [1], and enable intelligent

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applications such as Digital Twins (DTs), autonomous driving, and metaverse. Nevertheless, the availability of vast amounts of high-quality wireless data is a major determinant of the effectiveness of DL models [2]. Specifically,

- *Dynamic wireless channels:* Due to multipath fading, shadowing, and interference, the environment in wireless channels is highly variable [3], which makes it difficult to collect high-quality wireless data.
- *Limited measuring equipment:* High-quality wireless data collection often requires extensive deployment of specialized hardware and software equipment [3], which is costly and time-consuming.

Therefore, obtaining high-quality and diverse wireless data for the progress of DL-based wireless communications and networking is challenging [2], [3].

Data augmentation is an effective technique to solve the problem of limited labeled datasets in model training [4]. The core idea of data augmentation is to synthetically increase the size of training datasets by modifying existing data, thus enhancing the robustness and generalization of learning algorithms [4]. Data augmentation techniques have been extensively applied in fundamental domains. For example, in Computer Vision (CV), data augmentation methods apply geometric or color transformations, such as cropping, flipping, and color channel changes [5]. However, traditional data augmentation methods may not be applicable to wireless data. Specifically, traditional data augmentation methods are carefully designed for certain domains and only perform simple transformations on the original datasets, rather than enriching data features from existing data [4]. Most importantly, traditional data augmentation methods lack consideration of the inherent characteristics and structures of wireless data [5], which cannot guarantee the quality and diversity of augmented wireless data. Hence, novel techniques for effective wireless data augmentation are urgently needed.

Generative Artificial Intelligence (GenAI) is obtaining the full spotlight after the release of Large Language Model (LLM)-based chatbots by tech giants such as OpenAI's ChatGPT, Google's Bard, and Microsoft's Bing Chat [6]. Unlike discriminative AI models that focus primarily on explicitly learning decision boundaries between classes, GenAI models excel at learning the underlying distribution, patterns, and features of input data, thus generating new data instances that resemble the original dataset [7]. Due to its transformative power in data generation, GenAI has recently gained significant attention in the realm of wireless networks [6],

where real-world wireless data is often scarce, incomplete, costly to acquire, and difficult to model or comprehend [2], enabling the emergence of GenAI-driven data augmentation. Specifically, GenAI models can generate high-quality and diverse wireless data as a supplement, and the synthetic data can be combined with real data to augment the training dataset [6], which solves the wireless data acquisition challenge and can effectively improve the performance of DL models in wireless communication and networks.

There are currently some preliminary studies on using GenAI models for data augmentation in wireless networks [2]–[4], [8]. For instance, the authors in [2] utilized conditional latent diffusion models to generate high-diversity and high-quality Radio Frequency (RF) data at low costs. In [3], the authors leveraged a Denoising Diffusion Probabilistic Model (DDPM) to generate channel data in multiple speed scenarios, where the DDPM can capture the underlying distribution of wireless channel data with limited data volume. Finally, a CsiNet model was used to validate the effectiveness of the proposed approach. However, the above works do not provide a general tutorial on how to implement data augmentation using GenAI technology in wireless networks. To this end, this paper focuses on answering two questions, i.e., "*Why GenAI is conducive to data augmentation in wireless networks*" and "*How to use GenAI techniques to achieve wireless data augmentation.*" *To the best of our knowledge, this is the first work that systemically explores the potential and effectiveness of generative data augmentation in wireless networks.* Our main contributions are summarized as follows:

- We begin with a brief review of data augmentation techniques in the basic domains of images, text, and graphics, then discuss potential advantages brought by effective data augmentation techniques in wireless networks, and finally present the limitations of traditional data augmentation techniques in wireless networks.
- We review typical GenAI models and their applications in data augmentation, and summarize the benefits of generative data augmentation. We then explore the effectiveness of GenAI-driven data augmentation for wireless applications from the physical, network, and application layers, which presents a specific GenAI-driven data augmentation architecture for each application.
- We propose a general Generative Diffusion Model (GDM)-based data augmentation framework for Wi-Fi gesture recognition, where we use transformer-based diffusion models to generate high-quality and diverse Channel State Information (CSI) data. We finally conduct a case study based on a real dataset, where we develop Residual neural Network (ResNet) models to evaluate the performance gains achieved by augmented CSI data. Simulation results demonstrate the effectiveness of the proposed framework.

II. OVERVIEW OF DATA AUGMENTATION

A. Data Augmentation

As a cornerstone technique in DL, data augmentation has been extensively applied and proven to be effective and efficient when facing data collection challenges [2], [5]. A primary function of data augmentation is to artificially enlarge training datasets by creating modified copies of existing data, thus countering the overfitting of AI models [5]. Data augmentation techniques have achieved success for image and text data, and there is a growing trend in augmenting graph data. We present a summary of non-AI and GenAI methods for image, text, and graph data augmentation in Table I.

In the progress of DL-based wireless communications and networking, data augmentation has been explored to enrich the data characteristics of wireless communications and enhance the robustness of DL models [2], [4]. We summarize several critical advantages of effective data augmentation applied in wireless communications and networking:

1) Enhancing insufficient training datasets: Since wireless data, such as RF data, are sensitive and time-dependent to the open-space propagation environment [2], obtaining large amounts of high-quality training datasets for DL models in wireless communications is a costly and challenging endeavor. Fortunately, using effective data augmentation techniques can artificially increase the dataset size by generating variations of existing data, and subsequently mixing the existing training data with the augmented data into DL models, thus improving the performance and robustness of learning algorithms [4].

2) Boosting performance in security applications: In wireless security applications, anomaly detection is often affected by imbalanced datasets, where normal behavior far outweighs malicious events [9]. Especially, in an operational mechanical system that works under normal conditions most of the time, the collected sensor data representing positive training samples is sufficient [9], while machine operation failures are rare, and the corresponding collected sample is limited compared to positive samples. By using effective data augmentation techniques, training datasets with synthetic fault samples can improve the ability of DL models to detect rare events.

In the realm of machine learning and AI, several techniques are closely related to data augmentation but have distinct meanings, i.e., data synthesis and data enhancement. Specifically, data synthesis focuses on generating entirely new data instances that are not directly derived from existing data but created using GenAI models, while data enhancement is a complementary approach that aims to improve the quality of existing data, including augmented or synthesized data so that the data can be used more effective for training tasks.

B. Limitations of Non-AI Data Augmentation Techniques in Wireless Networks

Traditional (i.e., non-AI) data augmentation techniques resolve around simple transformations, such as cropping, rotations, and transformation [5]. Although traditional data augmentation techniques have been shown to significantly improve model performance, as wireless datasets grow in complexity, a series of intricate challenges are emerging:

- **Limited data diversity and balance:** One of the challenges of data augmentation is to create enough diversity and balance in the data [3], especially for imbalanced

TABLE I: A Summary of Traditional Non-AI and GenAI Methods for Typical Data Augmentation.

Data Types	Technologies		Principles	Characteristics
Image	Traditional non-AI methods	Pixel Erasing	Mask some information from the original input space or the feature space.	• Critical features needed for classification may be inadvertently erased. • Difficult to control which parts of the image are erased.
		Image Cropping	Select different regions from the original image and remove other parts of the image.	• Increase complexity in multi-object scenarios. • Might lead to an unbalanced representation of certain parts of the image.
		Image Mixup	Combine two images pixel-wise, and each pixel of the augmented image is produced by interpolating the pixels from the original images.	• Might not perform well for fine-grained tasks. • Require careful parameter tuning.
	GenAI methods	GANs	The generator creates synthetic images from random noise, and the discriminator tries to distinguish between real and synthetic images.	• Powerful for generating realistic and detailed images based on the adversarial training.
		VAEs	Encode input images into a latent space and decode from this latent space to generate synthetic images.	• Offer stable and efficient training by relying on probabilistic modeling.
		GDMs	Iteratively refine random noise to generate realistic images, modeling the distribution of images by learning how to gradually transform noise into data.	• Excel in generating high-quality, detailed images with stable training.
Text	Traditional non-AI methods	Token Addition	Add extra tokens to the original text, thus enriching the sentences and making them more informative.	• Might disrupt the meaning of the text. • Might be less effective for tasks requiring nuanced understanding of syntax and semantics.
		Sentence Cropping	Use dependency trees to extract the relationships between subjects and objects of the sentence and produce multiple smaller sentences.	• Might limit the ability of models to generalize to full-text scenarios. • Rely heavily on sentence structure.
		Text Mixup	Combine (or mix) two or more original text samples and interpolating their labels.	• Less suitable for tasks requiring coherent language. • Depend on carefully tuning the interpolation ratio.
	GenAI methods	VAEs	Adapt the variational autoencoder to text by using single-layer LSTM RNNs for both the encoder and the decoder, essentially forming a sequence autoencoder.	• Enable to produce diverse, coherent sentences through purely deterministic decoding and that they can interpolate smoothly between sentences.
		LLMs	Trained on large-scale text data to perform a wide range of natural language understanding and generate coherent text based on input prompts.	• Capable of performing a wide range of text generation tasks, including paraphrasing, completion, and content creation, which is highly versatile for augmentation.
Graph	Traditional non-AI methods	Node Attribute Augmentation	Modify the features or attributes of nodes in a graph while keeping the topology unchanged.	• Potentially limit effectiveness for structure-based tasks. • Lead to overfitting to specific feature modifications.
		Naive Topology Perturbation	Modify a single node or edge component or consider a set of nodes as a whole and modify the substructure.	• Might disrupt critical structures or relationships in the graph because of randomly adding or removing edges.
		Graph Propagation	Spread information from one node to other nodes along the graph.	• Introduce additional computational complexity. • Might not be effective in non-homophilic graphs.
	GenAI methods	GANs	The generator attempts to learn the graph distribution and generate new graphs, while the discriminator tries to distinguish the real graph from the generated graph.	• Able to capture complex graph distributions, including various node and edge types.
		VAEs	Train a probabilistic graph encoder to map the graph space to a low-dimensional continuous embedding, and a graph decoder to reconstruct new data.	• Provide a smooth latent space, enabling interpolation between different graph structures.
		GDMs	Iteratively denoise and refine random graph structures to produce realistic graphs.	• Excel at stably generating high-quality and detailed graph structures.

datasets and Non-IID[1] data. Data diversity refers to the variety and richness of data features, while data balance refers to the distribution and proportion of data labels. Classical data augmentation methods, such as rotation, flipping, and scaling, can generate only limited variations in the original data, which may not be sufficient to capture the variability and complexity of real-world data [5].

- **Domain-specific augmentation:** Different domains have their own unique needs when it comes to data augmentation [4]. For instance, in medical imaging, the augmentation of medical images must be done cautiously to ensure the integrity of the data and avoid the introduction of artifacts that could compromise diagnosis. Thus, traditional augmentation techniques are often designed for specific types of data and are not universally applicable.
- **Loss of semantic information:** Certain traditional data augmentation techniques may distort raw data in a way that alters semantic meanings [5]. For example, flipping an image horizontally may change the interpretation of content. In addition, the biases inherent in the original data are still present in the augmented data, and may even be reinforced.
- **Limited effectiveness for large datasets:** Traditional data augmentation can be computationally intensive when applied to extensive datasets. The time required to perform augmentations on each data point can significantly lengthen the training process of DL models. This challenge is exacerbated when working in real-time or resource-constrained situations where efficiency and responsiveness are critical.

In summary, current traditional data augmentation methods still face difficulties in capturing the complexities of real-world data and generating scalable data, especially in wireless networks with a dynamically changing environment. Hence, more sophisticated augmentation strategies, such as generative

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[1]Non-IID means that data is not identically distributed.

data augmentation, are urgently needed.

III. Generative Data Augmentation

A. Generative AI

Pre-trained on large-scale datasets or fine-tuned on the target dataset, GenAI models are capable of effectively capturing complex patterns of real-world samples and generating various types of customized data based on provided prompts [7]. Due to its data processing capability, GenAI can surpass the traditional data augmentation paradigm through synthetic data generation. In the following, we review typical GenAI models and their applications for data augmentation in different fields:

- **Variational Autoencoders (VAEs):** VAEs work by encoding the input data into a latent space and then decoding it back to the original space [7]. By sampling from decoding and the latent space, VAEs can generate new data that are closely consistent with the original distribution. In [10], VAEs are applied to augment intrusion detection data to enhance the performance of network security protection.
- **Generative Adversarial Networks (GANs):** GANs consist of generator and discriminator networks that are trained simultaneously. The generator generates new data, while the discriminator tries to distinguish synthetic data from real data [7]. GANs are capable of dealing with the limitations of data expansion. For example, in [4], GANs are adopted for wireless channel data augmentation by learning the distribution of the original channel data.
- **Generative Diffusion Models:** GDMs consist of the sampling procedure, the forward diffusion process, and the denoising process. The goal of GDMs is to learn to reverse the diffusion process to generate new data samples from the Gaussian noise [7]. GDMs are effective in data augmentation with the advantages of training straightforwardly and avoiding typical problems like model collapse [8]. For instance, in [8], GDMs are integrated with an attention module, which can generate high-quality and time-series RF data.
- **Transformers:** Transformers involve self-attention mechanisms that learn complex dependencies and generate coherent contextual instances [7], which are the fundamental technology of LLMs. LLMs have demonstrated the ability to augment textual data. For example, LLMs can facilitate the generation of high-quality data by automating augmentation instruction generation and selection.

B. Benefits of Generative Data Augmentation

Generative data augmentation offers numerous advantages and promising applications across various fields [6], [8]. We summarize the potential benefits as follows:

- **Data diversity augmentation:** GenAI models can generate a wide variety of realistic and high-fidelity synthetic samples [6], thus augmenting the data diversity in the original dataset. This approach is especially beneficial when the original dataset lacks variability.

- **Data imbalance mitigation:** Data imbalance issues are common in many real-world datasets, which can negatively impact the performance of DL models. To mitigate this issue, GenAI models can generate more samples of underrepresented classes to balance the dataset, which can also reduce model bias.
- **Privacy preservation:** GenAI models can enable data augmentation without breaching privacy [6]. For example, GenAI models can generate synthetic datasets that resemble the original dataset without directly using sensitive data. Moreover, GenAI models can enhance federated learning systems by compensating for the missing portion of local data, where models are trained collaboratively without sharing raw data.

IV. Generative AI-driven Data Augmentation for Wireless Applications

In this section, we explore how GenAI techniques play a role in data augmentation in wireless networks from the physical, network, and application layers. The overview of GenAI-driven data augmentation for wireless applications is shown in Fig. 1.

A. Physical Layer

1) GenAI-driven data augmentation for wireless channel modeling: Wireless channel modeling involves simulating the propagation of electromagnetic waves between transmitters and receivers. However, collecting real-world channel data in different environments and under diverse conditions is often labor-intensive and has high overhead [4]. Fortunately, GenAI can generate a variety of synthetic channel responses, allowing for the creation of diverse training datasets that enhance the performance of DL-based wireless communication algorithms. For example, in [4], the authors developed a GAN-based network for channel data augmentation in an intelligent industrial wireless communication environment. Then, GAN-generated data is leveraged to train the DL-based channel state information feedback algorithm for performance enhancement. Simulation results demonstrate that for the accuracy of CSI feedback algorithms, the proposed GAN-based approach can obtain at most 3 dB performance improvement compared with traditional data augmentation approaches.

2) GenAI-driven data augmentation for radio-frequency sensing: RF sensing is a field assisting vision technology that uses radio signals to capture surrounding information, enabling intelligent applications such as human activity recognition [2]. Due to the dynamic nature of the RF spectrum and the high cost of collecting RF datasets [2], GenAI models, especially GDMs, can be used to synthesize realistic RF data to augment existing datasets. For example, in [8], the authors proposed a time-frequency diffusion theory to instruct diffusion models to effectively generate time-series and high-quality RF data. The authors redesigned the denoising process by integrating attention-based diffusion blocks to extract RF features. Numerical results demonstrate the generation quality of the proposed diffusion model outperforms DDPMs by up to 42.4%.
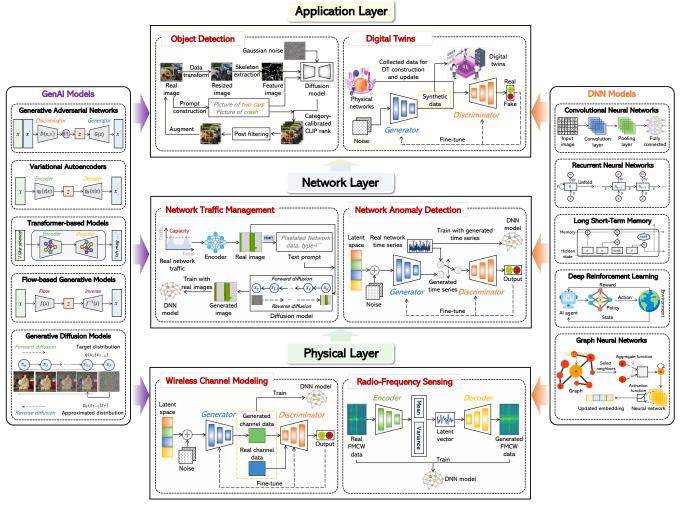
Fig. 1: Overview of GenAI-driven data augmentation for wireless applications. We show how GenAI techniques can improve data augmentation to boost the performance of wireless applications at the physical, network, and application layers. In particular, we present a GenAI-driven data augmentation architecture for each application.

B. Network Layer

1) GenAI-driven data augmentation for network traffic management: Wireless networks are increasingly reliant on DL models for a wide range of management tasks, including estimating future traffic data volume to intelligently manage and optimize wireless networks. However, the high costs and privacy concerns of data collection and sharing lead to the scarcity of labeled network datasets [11], hindering the training of robust DL models that can accurately extract real conditions in wireless networks. To address this challenge, GenAI models can generate traffic data that approximates real traffic patterns, thus providing a more comprehensive dataset for model training. For example, the authors in [11] leveraged controlled and fine-tuned stable diffusion models to generate network traffic traces, which introduced a conversion process to transform raw packet captures into image representations. Simulation results demonstrate that by integrating the network traffic generated by the proposed approach into the real dataset, the performance of decision tree models can be significantly improved, which outperforms the NetShare

approach by 86.36%.

2) GenAI-driven data augmentation for network anomaly detection: Network anomaly detection is widely recognized as a crucial component of wireless network security. Traditional anomaly detection systems heavily rely on real-world data to learn the patterns of normal and abnormal behavior. However, gathering enough data to represent all possible exception types can be challenging. Generative data augmentation provides a feasible solution for enhancing network anomaly detection. For example, in [12], the authors proposed a GAN-based method called TAnoGan for unsupervised anomaly detection when time series data points are small. Numerical results demonstrate that the proposed TAnoGan ranks higher than baseline models in F_1 score, which is the most important indicator in anomaly detection [12].

C. Application Layer

1) GenAI-driven data augmentation for object detection: In wireless networks, object detection tasks mainly involve identifying and tracking the location of users or devices.
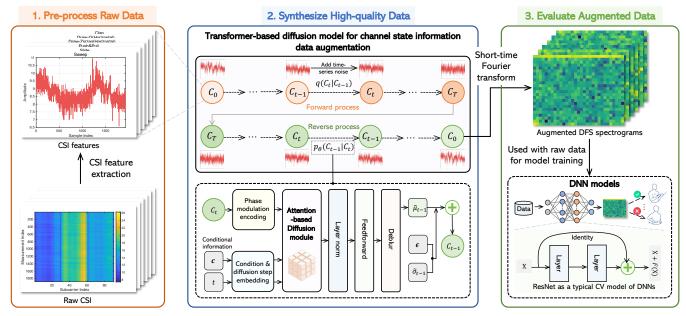
Fig. 2: A GDM-based data augmentation framework for Wi-Fi gesture recognition. The framework consists of three parts: *Part 1* is the pre-processing raw CSI data; *Part 2* is the use of transformer-based diffusion models to synthesize high-quality CSI data; *Part 3* is the evaluation of augmented data.

However, object detection requires not only target labels in each image but also precise bounding boxes [13]. This extra work makes the management of these datasets for training object detection models more laborious than image classification [13]. An alternative approach to effectively manage datasets for object detection is generative data augmentation. For example, the authors in [13] proposed a data augmentation pipeline based on contrastive language-image pertaining and controllable diffusion models, which can generate images with high-quality bounding box annotations.

2) GenAI-driven data augmentation for digital twins: DTs have been recognized as an important enabler of wireless networks [14]. The core elements of DT construction are data-driven physical-virtual modeling and synchronization. However, wireless DT construction is predicted to be much more data-hungry in the future [14]. The application of generative data augmentation provides a feasible solution. Specifically, GenAI models can generate diverse synthetic network data, such as the state and behavior of physical objects, thus enhancing wireless DT construction. For instance, the authors in [14] leveraged a GAN model to generate a sufficient augmented dataset, and the dataset can be used to train the policy-level DT model that consists of multi-layer neural networks through supervised learning.

D. Lesson Learned

Current wireless applications may lack sufficient data to support DL model training to meet performance requirements. Generative data augmentation is transforming wireless networks from the physical, network, and application layers. A unified GenAI model can generate jointly data for multiple layers coherently. This cross-layer or multi-layer data augmentation can improve DL models used in communications and networking.

V. CASE STUDY: GENERATIVE DIFFUSION MODELS FOR DATA AUGMENTATION IN WI-FI GESTURE RECOGNITION

In this section, we propose a GDM-based data augmentation framework for Wi-Fi gesture recognition and conduct a case study based on a real dataset to evaluate the effectiveness of the proposed framework.

A. Background Description

Due to its advantages in ubiquitous deployment and non-invasive sensing, Wi-Fi-based gesture recognition is an emerging and innovative application for constructing privacy-preserving and contact-free wireless sensing systems [8]. The use of DL to develop Wi-Fi-based gesture recognition systems has recently garnered significant attention [5], [8], and is not yet mature. One of the biggest challenges in driving the development of this technology is building comprehensive wireless sensing datasets for model training [5]. However, since Wi-Fi sensing is heavily dependent on the surrounding environment, collecting and labeling Wi-Fi sensing data (e.g., CSI data) is costly and energy-intensive [5]. Besides, due to the fundamental differences in wireless data structures, traditional data augmentation methods may not be applicable to Wi-Fi sensing data [5]. To this end, we propose a general GDM-based data augmentation framework for Wi-Fi gesture recognition, as shown in Fig. 2. Specifically, GDMs are leveraged to increase the diversity of Wi-Fi sensing datasets. Then, the raw datasets with the synthesized CSI data can be used to train Deep Neural Network (DNN) models to evaluate the impact of data augmentation.
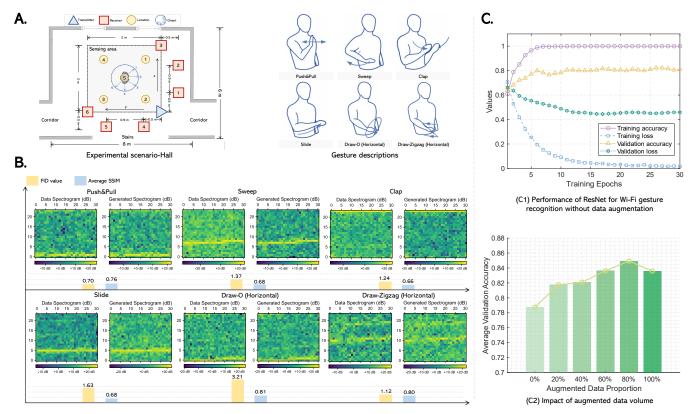
Fig. 3: A case study on evaluating the effectiveness of the proposed GDM-based data augmentation framework for Wi-Fi gesture recognition. *Part A* shows the experiment design, where figures are modified based on [15]. *Part B* presents the generative performance of the transformer-based diffusion model. *Part C* illustrates the impact of augmented data on the model performance for Wi-Fi gesture recognition.

B. Proposed Framework

The proposed framework showcases how GDMs can implement CSI data augmentation and boost the performance of Wi-Fi-based gesture recognition systems, which is composed of three parts:

1) Pre-processing raw CSI data: In Wi-Fi sensing systems, CSI is estimated on multiple subcarriers [5], providing environmental information on how each Wi-Fi subcarrier is affected during transmission. CSI features lay the foundation of wireless sensing, including the amplitude and phase of signals transmitted between Wi-Fi devices. Before CSI data synthesis by GDMs, it is necessary to pre-process the original CSI data based on feature extraction, as shown in the left part of Fig. 2. The processed data consists of CSI features and condition information, where the features are represented as a complex matrix in double precision, and the condition information is used for conditional generation, including the gestures, orientations, and locations of users.

2) Synthesizing high-quality CSI data: Based on the processed CSI data, we use the transformer-based diffusion model to synthesize high-quality CSI data [8], as shown in the middle part of Fig. 2. In the forward diffusion process, time-series noise is progressively added to the input data until following the Gaussian distribution. Then, the diffusion model utilizes the denoising network to iteratively eliminate the noise and restore the original data distribution. The reverse restoration

process is designed with a hierarchical architecture, which can fully reveal the time-frequency characteristics of CSI data. Moreover, the denoising network is essentially a complex-valued neural network with an embedded Transformer module to further extract CSI data features, thus generating high-quality and time-series CSI data.

3) Evaluating augmented data: As shown in the right part of Fig. 2, we use DNN models to evaluate the impact of augmented data on the performance of Wi-Fi-based gesture recognition systems. Nowadays, Doppler Frequency Shift (DFS) spectrograms are generally used as inputs to DL models [5]. DFS spectrograms are extracted from CSI data without intensive computation and reflect the movement and activities of the target, which is capable of striking a balance between denoising raw data and preserving signals for learning [5]. Thus, we transform both the raw and generated CSI data to DFS spectrograms through Short-Term Fourier Transform (STFT). Specifically, STFT can truncate the time series of signals using a fixed-length sliding time window and perform a fast Fourier transform on each window [5]. Finally, both the original and generated DFS spectrograms can be used in the training of DNN models in the form of images.

C. Simulation Experiments

We implement the GDM-based data augmentation framework for Wi-Fi gesture recognition by using PyTorch on

NVIDIA GeForce RTX 3080 Laptop GPU and evaluate its effectiveness on a real dataset from Widar 3.0 [15], where Widar 3.0 is the largest WiFi sensing public dataset [5], [8]. Our project is available here[2].

1) Experiment design: The Widar 3.0 dataset is collected from 17 users. Users stand in 5 different locations within the range of 6 receivers equipped with Intel 5300 network cards, oriented in 5 different directions towards a transmitter, and perform 22 gestures [5], [15]. Due to the non-uniform distribution of gesture data, we select one user with corresponding 6 gestures as the dataset for the evaluation of the proposed framework. The experimental scenario is a hall, and the 6 gestures are pushing and pulling, sweeping, clapping, sliding, horizontally drawing O, and horizontally drawing zigzag, respectively, as shown in the *Part A* of Fig. 3. In addition, we develop a ResNet[3] model to evaluate the impact of augmented CSI data on Wi-Fi gesture recognition performance, where we utilize the Adam algorithm for gradient optimization and set the network learning rate as 0.0001.

2) Simulation results: As shown in the *Part B* of Fig. 3, we present the ground truth DFS spectrogram and the generated DFS spectrogram for 6 gestures, along with their corresponding Fréchet Inception Distance (FID) values and average Structural Similarity Index Measure (SSIM) values. The SSIM and the FID are two common image quality indexes that can evaluate the generative quality of transformer-based diffusion models, where the SSIM is a perceptual method to quantify the similarity between two images and the FID is an effective metric used to access the realism and diversity of generated images [8]. Note that the SSIM value is $[-1, 1]$, where the closer the value is to 1, the better the image quality, and the FID value is $[0, \infty)$, where the smaller the value, the closer the distribution of the generated image and the real image. We can observe that the transformer-based diffusion model can generate high-quality DFS spectrograms close to real data distribution.

In the *Part C* of Fig. 3, we explore the impact of synthesized data ratio. Firstly, since the ResNet is one of the most commonly used backbone CV models [5], we develop a ResNet model for Wi-Fi gesture recognition without data augmentation, and the proposed ResNet model can effectively recognize Wi-Fi gestures, as shown in the result module (C1). To evaluate the impact of synthesized data on the performance of Wi-Fi gesture recognition systems, we use the generated DFS spectrograms with the original DFS spectrograms to retrain the ResNet model. As can be seen from the result module (C2), the average validation accuracy of the ResNet model first increases and then decreases as the proportion of augmented data increases. The reason is that a small amount of augmented data can enrich the diversity of training datasets and improve the performance of DL models. However, as the augmented data gradually increases, the original data distribution may be replaced by the generated data distribution, potentially resulting in model collapse.

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[2]https://github.com/JinboWen00/GDA-for-Wi-Fi-Gesture-Recognition
[3]https://www.geeksforgeeks.org/residual-networks-resnet-deep-learning/

VI. FUTURE DIRECTIONS

A. Generative Data Augmentation for Next-Generation Networks

Next-generation networks are expected to support ultra-reliable low-latency communications, massive machine-type communications, and high-precision localization, enabling intelligent and promising applications, such as autonomous vehicles and immersive extended reality. However, these applications may present unique challenges, such as data hungry [14], which cannot be effectively addressed by using traditional DL models and datasets. Therefore, future research can focus on utilizing generative data augmentation to create synthetic data that can enhance traditional datasets and accurately reflect the diverse conditions of these novel applications, thus enabling better DL model training.

B. Multi-modal Generative Data Augmentation for Wireless Networks

Traditional data augmentation often focuses on single data modalities. However, the next generation of wireless networks, especially with the advent of six-generation networks, will need to process multiple types of data simultaneously, such as spatial, temporal, and contextual data. Therefore, the realization of multi-modal generative data augmentation technology is significant and promising for future research in data augmentation. The Mixture of Experts (MoE) model is expected to promote the realization of multi-modal generative data augmentation technology. Specifically, in the MoE architecture, each expert can be specialized to handle a specific modality and generate data within its domain.

C. High-quality Data Augmented by Generative AI

The effectiveness of DL-based wireless communications and networking largely depends on the quality of training datasets. Low-quality or unrealistic training data can cause models to perform poorly or behave unpredictably in real wireless networks. As GenAI plays an increasingly pivotal role in augmenting data for wireless networks, ensuring the quality of the generated data becomes critically important. Therefore, how to evaluate and guarantee the quality of data augmented by GenAI models is a critical future direction.

VII. CONCLUSION

In this article, we have explored the potential and effectiveness of GenAI-driven data augmentation in wireless networks. We have discussed the limitations of traditional data augmentation methods in wireless networks and introduced generative data augmentation. Then, we have explored GenAI-driven data augmentation for wireless applications from the physical, network, and application layers. Subsequently, we have proposed a general generative diffusion model-based data augmentation framework for Wi-Fi gesture recognition and developed ResNet models to evaluate the impact of augmented CSI data on Wi-Fi gesture recognition performance. Simulation results demonstrate the effectiveness of the proposed framework through case studies based on a real dataset from

Widar 3.0. Finally, we have investigated potential open research directions for generative data augmentation.

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