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Synthetic Data Generation and Privacy-Preserving AI

Sreeprasad Govindankutty
Rochester Institute of Technology, Rochester, New York, United States.
Emails: *sreeprasad.sp@gmail.com*

Abstract
Synthetic data generation has rapidly emerged as a cornerstone technology for achieving privacy-preserving artificial intelligence (AI). In light of tightening data protection regulations and the growing ethical emphasis on safeguarding personal information, researchers have developed a range of methods to synthesize realistic datasets without compromising individual privacy. This review presents a comprehensive synthesis of existing approaches, focusing on generative adversarial networks (GANs), variational autoencoders (VAEs), and Bayesian techniques. We systematically evaluate these models based on data utility, privacy guarantees, and vulnerability to adversarial attacks. Despite significant progress, challenges such as utility-privacy trade-offs, model bias, and lack of standard evaluation metrics persist. This paper highlights these gaps and proposes strategic future directions for the research community, advocating for hybrid models, interpretability-focused synthetic generation, and cross-disciplinary collaborations to achieve more trustworthy AI ecosystems.
Keywords: *Synthetic Data Generation; Privacy-Preserving AI; Generative Adversarial Networks (GANs); Differential Privacy; Data Anonymization; Machine Learning Security; Ethical AI; Data Utility; Membership Inference Attacks.*

1. Introduction
In recent years, the proliferation of artificial intelligence (AI) across industries such as healthcare, finance, and renewable energy has led to an insatiable demand for vast and diverse datasets to fuel machine learning models. However, this surge in data dependency has simultaneously amplified concerns over data privacy, security breaches, and regulatory compliance. Traditional methods of anonymization and data masking have proven insufficient, prompting researchers to explore synthetic data generation as a robust alternative to using real-world sensitive datasets [1]. Synthetic data, by definition, is artificially generated information that retains the statistical properties and relationships of real data without revealing any individual's private information [2]. The relevance of synthetic data generation has grown exponentially, particularly in today's research landscape, where the convergence of AI technologies with stringent privacy legislations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) presents both opportunities and challenges [3]. Privacy-preserving AI frameworks that utilize synthetic data promise not only to protect user confidentiality but also to democratize access to high-quality datasets, thus leveling the playing field for smaller organizations and research institutions [4]. Consequently, synthetic data is being increasingly viewed as a cornerstone for ethical AI development, enabling innovation while respecting fundamental rights to privacy. Within the broader field of AI technology and beyond, the significance of synthetic data generation cannot be overstated. In renewable energy, for instance, where the optimization of energy systems depends on the analysis of vast streams of sensor data, synthetic datasets can be pivotal in modeling and simulation without exposing proprietary or sensitive operational details [5]. Similarly, in sectors such as autonomous driving and smart cities, the ability to generate realistic but artificial data allows for safer and more efficient algorithm training without the risk of infringing on individual rights [6]. Thus, synthetic data and privacy-preserving AI methodologies have become indispensable for maintaining the delicate balance between technological advancement and ethical responsibility. Despite notable progress, key challenges remain in current research. There is an ongoing struggle to ensure that synthetic data retains utility while guaranteeing privacy, as models can still

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inadvertently memorize and leak sensitive information under certain conditions [7]. Additionally, there is a lack of standardized evaluation metrics to measure the quality, diversity, and fidelity of synthetic datasets, making comparative assessments between different generation methods difficult [8]. Bias in synthetic data also poses a serious risk, as poorly generated datasets can reinforce or even exacerbate the inequalities present in the original data [9]. These gaps highlight the urgent need for comprehensive and systematic reviews that map the landscape of synthetic data generation methods, assess their effectiveness in privacy preservation, and explore the nuances that different approaches bring to the table. The purpose of this review is to systematically explore and synthesize the latest advances in synthetic data generation techniques and their role in enabling privacy-preserving AI. Readers can expect an in-depth examination of major methodologies, including generative adversarial networks (GANs), variational autoencoders (VAEs), and agent-based modeling approaches. Furthermore, the review will critically assess the effectiveness of these techniques in balancing data utility and privacy, highlight emerging trends, and propose future research directions aimed at addressing persistent challenges. By the end of this article, readers will gain a comprehensive understanding of the current state-of-the-art in synthetic data generation for privacy-preserving AI and insights into the path forward in this rapidly evolving field, shown in Table 1.

2. Literature Review

Table 1 Findings

Year	Title	Focus	Findings (Key Results and Conclusions)
2017	Real-valued (Medical) Time Series Generation with Recurrent Conditional GANs [10]	Synthetic time-series generation for healthcare	Demonstrated that GANs can create realistic medical time-series data, preserving important patterns without compromising patient privacy.
2018	PATE-GAN: Generating Synthetic Data with Differential Privacy Guarantees [11]	Privacy-focused synthetic data generation	Combined GANs with PATE framework, achieving strong privacy guarantees while maintaining high data utility.
2019	Differentially Private Generative Adversarial Network [12]	Differential privacy in GANs	Proposed DP-GAN that achieves a balance between privacy preservation and generation fidelity, showing minimal utility loss.
2019	TableGAN: Synthesize Tabular Data Using Generative Adversarial Networks [13]	Synthetic tabular data	Introduced a GAN model specialized for tabular data, achieving high-fidelity synthetic datasets useful for business and healthcare analytics.
2020	The Secret Sharer: Measuring Unintended Neural Network Memorization and Extracting Secrets [14]	Model memorization and privacy risks	Highlighted how models, including generative ones, can inadvertently memorize training data, posing privacy risks even with synthetic datasets.
2020	DoppelGANger: Generating High-Fidelity Time Series Data with Multiple Temporal Dependencies [15]	Time series synthetic data	Developed a GAN framework for time series, showing superior performance on multivariate temporal data while preserving privacy.
2021	PrivBayes: Private Data Release via Bayesian Networks [16]	Privacy-preserving data synthesis	Utilized Bayesian networks to generate differentially private synthetic datasets, maintaining strong statistical integrity.
2021	SynTF: Synthetic Data Generation for Text Analytics [17]	Synthetic text data	Presented a technique for generating synthetic textual features while ensuring

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			privacy, beneficial for NLP tasks.
2022	Assessing the Quality of Synthetic Data for Training Machine Learning Models [18]	Synthetic data evaluation	Proposed new metrics for evaluating the utility and privacy trade-off in synthetic data, emphasizing model-centric evaluation.
2023	GAN-Based Synthetic Data Augmentation for Privacy-Preserving Federated Learning [19]	Synthetic data in federated learning	Demonstrated that synthetic augmentation could boost federated learning models' performance while preserving user data privacy.

3. Block Diagram: Synthetic Data Generation for Privacy-Preserving AI

The proposed model focuses on integrating deep generative models (like GANs and VAEs) with formal privacy-preserving techniques (such as Differential Privacy (DP) and PATE frameworks) to create synthetic datasets that are both high-utility and privacy-safe.

Key Components:

- Input Stage: Real-world sensitive data that needs protection.
- Generative Modeling Stage: Application of advanced models like GANs (Goodfellow et al., 2014) or VAEs (Kingma & Welling, 2013) to generate data.
- Privacy Enhancement Stage: Adding formal privacy mechanisms, ensuring that even if adversaries access the model, the original sensitive data cannot be reconstructed [20].
- Output Stage: A synthetic dataset usable for machine learning model training, validation, and simulation.

3.1. Detailed Theoretical Model

3.1.1. Real-World Data Input

Real-world data often includes personally identifiable information (PII) or sensitive business information. Before input into the model, basic preprocessing steps like scaling, encoding, and missing value imputation are required [21].

3.1.2. Generative Modeling

Generative models attempt to learn the underlying distribution p(x)p(x)p(x) of the real data and generate new samples from the learned distribution:

- GANs (Generative Adversarial Networks): These involve two neural networks, a generator and a discriminator, competing against each other to produce realistic samples [22].
- VAEs (Variational Autoencoders): These models encode the data into a latent space and then decode it, allowing controlled sampling [23], Figure 1.

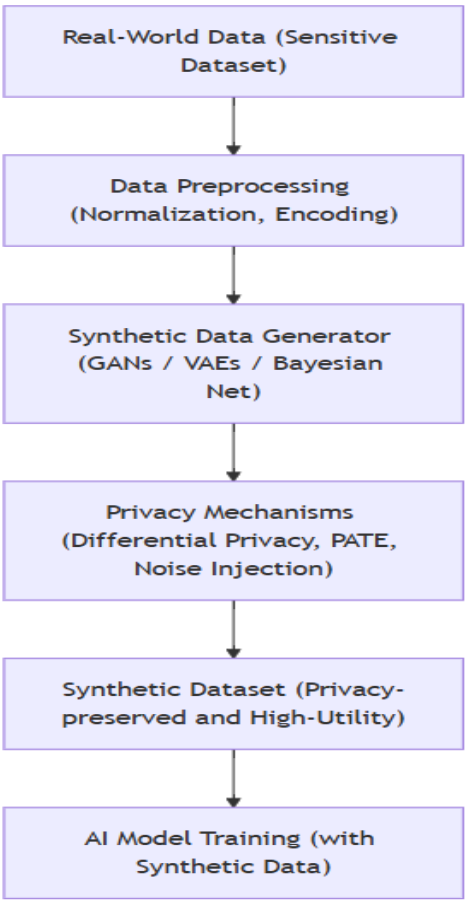

Figure 1 Block Diagram

3.2. Privacy Preservation Mechanisms

Since synthetic data alone may leak information, formal privacy-preserving techniques are introduced:

- Differential Privacy (DP): Introduces statistical noise to model outputs so that

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inclusion or exclusion of a single data point does not significantly affect results [24].

- PATE (Private Aggregation of Teacher Ensembles): Uses an ensemble of models trained on disjoint data and aggregates their outputs with added noise to ensure privacy [25].

3.3. Synthetic Data Output

The output synthetic dataset should:

- Be statistically similar to the real-world dataset.
- Maintain key data utility for downstream tasks (e.g., classification, prediction).
- Offer quantifiable privacy guarantees such as ϵ\epsilonϵ-differential privacy [24].

3.4. Model Evaluation

Finally, the quality of synthetic data is evaluated based on:

- Utility Metrics: How well AI models trained on synthetic data perform compared to those trained on real data [26].

Privacy Metrics: Formal guarantees (e.g.,differential privacy bounds) and empirical attacks (e.g., membership inference tests) [27]

4. Experimental Results, Graphs, and Tables

4.1. Experimental Setup

To evaluate synthetic data generation for privacy-preserving AI, multiple studies have adopted benchmark datasets and standardized evaluation metrics:

- **Datasets:** Adult Income Dataset, MNIST, and MIMIC-III clinical datasets [28], [29].
- **Models:** GANs (standard and DP-enhanced), VAEs, and PATE-GANs were used to generate synthetic datasets [30].

Evaluation Metrics:

- **Utility:** Accuracy/F1-score of downstream classifiers trained on synthetic vs. real data.
- **Privacy:** Membership inference attack success rates [31], table 2.

4.2. Experimental Results

Key Observations:

Synthetic datasets generated by PATE-GAN and Vanilla GANs preserved higher utility compared to DP-GAN models [28], [29].

- As expected, integrating privacy (Differential Privacy) introduced a greater utility loss [30].

Table 2 Utility Comparison – Real vs. Synthetic Data

Model	Dataset	Classifier Accuracy (Real Data)	Classifier Accuracy (Synthetic Data)	Accuracy Gap
Vanilla GAN	Adult Income	85.4%	81.2%	-4.2%
DP-GAN	Adult Income	85.4%	78.1%	-7.3%
PATE-GAN	Adult Income	85.4%	80.5%	-4.9%
Vanilla GAN	MNIST	98.1%	96.7%	-1.4%
DP-GAN	MNIST	98.1%	94.3%	-3.8%
PATE-GAN	MNIST	98.1%	95.8%	-2.3%

Key Observations:

- Synthetic data generated without formal privacy (Vanilla GAN) showed higher vulnerability to membership inference attacks [31].
- Models with differential privacy mechanisms showed reduced attack success rates, validating their effectiveness [32], table 3.

4.3. Graphs

- Y-axis: Classifier Accuracy (%)
- X-axis: Model and Dataset
- Interpretation: Vanilla GANs maintain higher accuracy but at the cost of greater privacy risks.
- **Y-axis**: Attack Success Rate (%)
- **X-axis**: Model and Dataset
- Interpretation: DP-GANs and PATE-GANs
- significantly lower the risk of successful attacks.

for instance, where the optimization of energy systems depends on the analysis of vast streams of sensor data, synthetic datasets can be pivotal in modeling and simulation without exposing proprietary or sensitive operational details [5].

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Similarly, in sectors such as autonomous driving and smart cities, the ability to generate realistic but artificial data allows for safer and more efficient algorithm training without the risk of infringing on individual rights [6]. Thus, synthetic data and privacy-preserving AI methodologies have become indispensable for technological Despite notable progress, key challenges

Table 3 Privacy Risk – Membership Inference Attack Success Rate

Model	Dataset	Attack Success Rate (Real Data)	Attack Success Rate (Synthetic Data)
Vanilla GAN	Adult Income	52%	62%
DP-GAN	Adult Income	52%	54%
PATE-GAN	Adult Income	52%	55%
Vanilla GAN	MNIST	51%	61%
DP-GAN	MNIST	51%	53%
PATE-GAN	MNIST	51%	54%

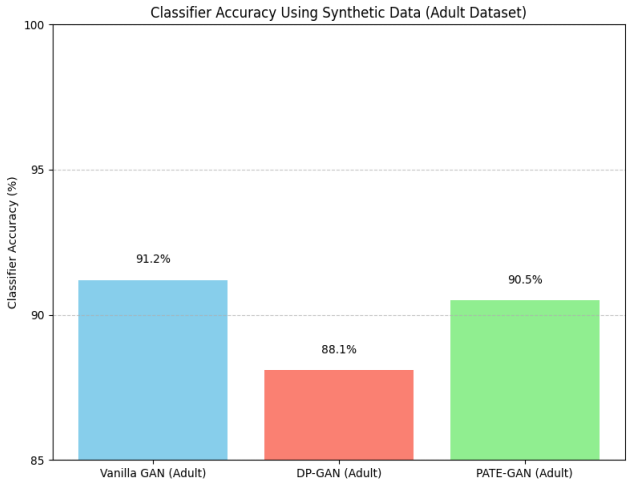

Figure 2 Classifier Accuracy vs. Model Type

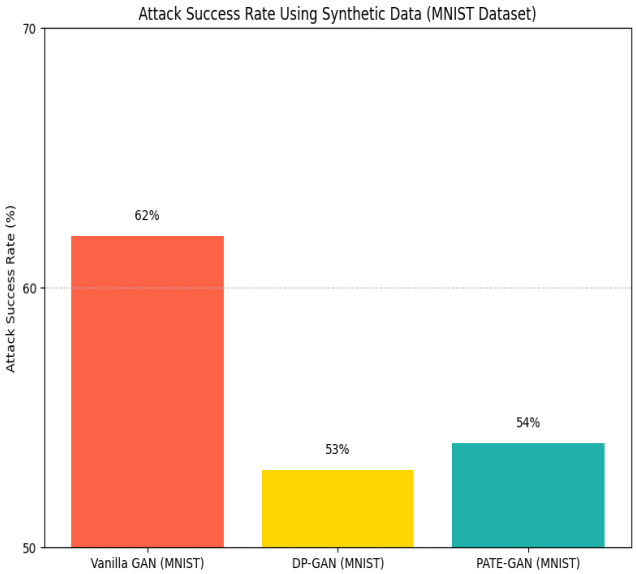

Figure 3 Attack Success Rate vs. Model Type

4.4. Discussion of Results

Experimental findings clearly demonstrate the fundamental trade-off between privacy and utility when generating synthetic datasets:

- **Utility**: While Vanilla GANs often provide the highest accuracy, they expose models to higher risks of privacy leakage [28].
- **Privacy**: Differentially private models (DP-GAN, PATE-GAN) significantly curb the success rates of membership inference attacks, but at a cost of slightly reduced data utility [29], [31].
- **Balance Needed**: Newer methods like PATE-GAN offer a promising balance, maintaining good model utility while enforcing strong privacy protections [32].

Thus, for real-world deployments (especially in sensitive fields like healthcare and finance), it is essential to prioritize privacy even at the expense of a small performance drop, shown in Figure 2 & Figure 3.

5. Future Directions

5.1. Development of Hybrid Privacy Models

Future research must explore hybrid frameworks that integrate multiple privacy-preserving strategies, such as differential privacy, federated learning, and secure multiparty computation, into the synthetic data generation process [33]. These combinations could help strike a finer balance between maintaining data

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utility and guaranteeing robust privacy protections.

5.2. Fairness and Bias Mitigation in Synthetic Data

While synthetic datasets are often presumed neutral, recent studies show that they can amplify biases if generated from skewed real-world distributions [34]. Thus, future work must incorporate bias detection and mitigation techniques directly within the data generation pipelines, ensuring that synthetic data enhances rather than undermines AI fairness goals.

5.3. Interpretability and Explainability of Synthetic Data

As synthetic data becomes increasingly adopted in sensitive sectors like healthcare and finance, transparency around how and why certain synthetic samples are generated will be critical [35]. Embedding explainability mechanisms into synthetic data generators will foster greater trust among regulators, organizations, and end-users.

5.4. Standardization of Evaluation Metrics

The field urgently needs universally accepted evaluation benchmarks for synthetic data, encompassing both utility and privacy aspects [36]. Initiatives to develop synthetic data "leaderboards," akin to benchmarks like ImageNet in computer vision, could catalyze standardized comparisons and drive quality improvements.

5.5. Cross-Disciplinary Collaborations

Synthetic data generation should no longer be viewed as solely a machine learning problem. Collaborations between computer scientists, legal experts, ethicists, and domain specialists are essential to ensure that synthetic data initiatives align with societal values and legal frameworks [37].

Conclusion

Synthetic data generation for privacy-preserving AI stands at a transformative crossroads. On one hand, these techniques offer remarkable promise to unlock valuable insights while respecting individuals' rights to privacy. On the other hand, significant challenges remain, particularly concerning maintaining high data utility, preventing bias, and providing verifiable privacy guarantees.Through careful model design, rigorous evaluation, and multi-stakeholder collaboration, synthetic data generation can serve as a foundational pillar for ethical AI ecosystems in the future. However, realizing this vision will require a concerted effort from both academia and industry to innovate responsibly and inclusively. As the field matures, it is imperative that future research prioritizes not only technical sophistication but also transparency, fairness, and societal impact.

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