Generative Adversarial Networks for Synthetic Electronic Health Record Data Generation and Privacy Preservation in Healthcare Systems

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Abstract

The adoption of electronic health records (EHRs) has revolutionized healthcare data management, enabling large-scale clinical analytics, precision medicine, and population health monitoring. However, concerns regarding patient privacy, regulatory compliance, and data scarcity hinder the use of EHRs for research and model development. Generative Adversarial Networks (GANs), a class of deep learning models capable of producing realistic synthetic data, offer a compelling solution to these challenges. This study investigates the design, implementation, and evaluation of GAN-based frameworks for generating synthetic EHR data while preserving patient privacy and supporting downstream machine learning applications. Leveraging multimodal healthcare datasets, including structured clinical codes, laboratory values, and temporal treatment sequences, we demonstrate that GANs can synthesize high-fidelity data that accurately mimics real-world distributions. Furthermore, we explore privacy-preserving strategies, including differential privacy and adversarial regularization, to mitigate disclosure risks. Experimental results indicate that GAN-generated synthetic EHRs maintain statistical properties and predictive utility comparable to real datasets, enabling robust model training without compromising sensitive patient information. This research advances the integration of AI-driven synthetic data generation in healthcare, providing scalable solutions for secure data sharing, research reproducibility, and privacy-preserving analytics.

Keywords: Electronic Health Records, Generative Adversarial Networks, Synthetic Data, Privacy Preservation, Deep Learning, Healthcare AI

1. Introduction

The proliferation of electronic health records (EHRs) has enabled unprecedented opportunities for **data-driven medicine**, ranging from predictive modeling of disease progression to individualized treatment recommendations (Fatunmbi, 2023). Despite these advances, **access to high-quality, comprehensive EHR datasets** remains limited due to privacy regulations such as HIPAA and GDPR, ethical considerations, and institutional policies that restrict data sharing. Consequently, researchers and healthcare organizations face **data scarcity and privacy challenges** that limit the training of machine learning models, particularly in rare disease cohorts or multimodal data contexts.

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2014), are composed of a **generator** and a **discriminator** in a zero-sum game framework. The generator produces synthetic

samples, while the discriminator attempts to distinguish real from synthetic data. Through iterative adversarial training, the generator learns to produce data indistinguishable from real-world distributions. GANs have shown remarkable success in image synthesis, text generation, and time-series simulation, and have recently been adapted to **healthcare applications**, including synthetic EHR generation, medical imaging, and physiological signal modeling (Fatunmbi, 2023; Choi et al., 2017).

The primary contributions of this study are:

1. **Design of GAN architectures tailored for EHR data**, capable of handling heterogeneous data types including categorical diagnosis codes, continuous laboratory values, and temporal sequences of treatments.
2. **Integration of privacy-preserving mechanisms**, such as differential privacy regularization and membership inference attack mitigation, ensuring synthetic data does not compromise patient confidentiality.
3. **Evaluation of synthetic data utility**, demonstrating the preservation of statistical distributions, predictive performance in downstream tasks, and applicability to multimodal machine learning models.

This paper is structured as follows: Section 2 reviews related work in **synthetic healthcare data generation** and GAN architectures; Section 3 describes the **methodology**, including dataset preprocessing, GAN model design, and privacy-preserving mechanisms; Section 4 presents **experimental results**, quantitative evaluation, and discussion; Section 5 explores **practical implications, limitations, and future research directions**; finally, Section 6 concludes the study.

2. Literature Review

2.1 Synthetic Data Generation in Healthcare

Synthetic data generation aims to produce artificial datasets that retain the **statistical and structural properties** of real-world data while preventing the disclosure of sensitive information. In healthcare, synthetic EHR data enables:

- **Research without compromising privacy**
- **Model training in data-scarce domains**
- **Benchmarking and reproducibility**

Previous methods include **rule-based simulations, variational autoencoders (VAEs), and probabilistic graphical models**, each with limitations in capturing high-dimensional, heterogeneous, and temporally dependent EHR data (Esteban et al., 2017). GANs overcome these limitations by **learning complex joint distributions** directly from data, supporting high-fidelity synthetic generation for structured, unstructured, and sequential records (Xu et al., 2019).

2.2 Generative Adversarial Networks (GANs)

GANs operate on a **minimax objective**, where the generator G attempts to create samples indistinguishable from real data, and the discriminator D attempts to correctly classify real versus synthetic samples:

minGmaxDV(D,G)=Ex∼Preal(x)[logD(x)]+Ez∼Pz(z)[log(1−D(G(z)))]\min_G \max_D V(D,G) = \mathbb{E}_{x \sim P_\text{real}(x)}[\log D(x)] + \mathbb{E}_{z \sim P_z(z)}[\log(1-D(G(z)))]GminDmax V(D,G)=Ex∼Preal(x)[logD(x)]+Ez∼Pz(z)[log(1−D(G(z)))]

This adversarial framework enables **implicit density modeling**, essential for high-dimensional EHR data, which includes categorical codes (ICD, CPT), continuous lab values, and temporal sequences. Variants such as **Conditional GANs (CGANs)** allow conditioning on patient demographics or treatment categories, improving **realism and utility** of synthetic datasets (Mirza & Osindero, 2014).

2.3 Privacy Preservation in GANs

The application of GANs in healthcare introduces **privacy concerns**, particularly membership inference attacks and reconstruction risks. Several strategies have been proposed:

1. **Differential Privacy (DP):** Adds calibrated noise to model updates, providing a mathematical guarantee of privacy at the expense of potential data utility loss (Abadi et al., 2016).
2. **Adversarial Regularization:** Discriminator networks are regularized to reduce memorization of individual patient records, enhancing privacy while maintaining synthetic data fidelity.
3. **Evaluation of Privacy Risks:** Metrics such as **membership inference accuracy and attribute disclosure probability** quantify the likelihood of patient information leakage (Xie et al., 2018).

2.4 Applications of GANs in Healthcare

Recent research demonstrates GANs for:

- **Medical imaging synthesis** (e.g., MRI, CT scans)
- **Time-series physiological signal generation** (e.g., heart rate, EEG)
- **Synthetic EHR creation** for predictive modeling, clinical trials, and multi-institutional research (Choi et al., 2017; Xu et al., 2019)

GAN-generated synthetic EHRs have been shown to **retain predictive performance** for downstream machine learning models, supporting tasks such as disease onset prediction, treatment recommendation, and mortality risk assessment, while mitigating patient privacy risks (Fatunmbi, 2023).

3. Methodology

3.1 Data Acquisition and Preprocessing

3.1.1 Dataset Description

The study utilized **multimodal EHR datasets** comprising structured patient information, including demographic variables (age, gender, ethnicity), diagnosis codes (ICD-10), procedural codes (CPT), laboratory measurements, medication records, and temporal treatment sequences. Data were sourced from a **large tertiary hospital network**, ensuring diversity in clinical conditions, treatment pathways, and temporal resolutions. The dataset included **approximately 50,000 patient encounters**, providing a sufficient basis for training high-capacity deep learning models such as GANs (Fatunmbi, 2022).

3.1.2 Data Cleaning

Preprocessing steps were critical to handle **missing, inconsistent, and noisy entries**, which are common in real-world EHRs. The following procedures were applied:

1. **Missing Value Imputation:** Continuous variables were imputed using **K-nearest neighbor imputation** and median substitution where appropriate. Categorical variables utilized **mode imputation** and category consolidation for rare labels.
2. **Outlier Handling:** Values exceeding three standard deviations from the mean were clipped or transformed using **logarithmic scaling** to maintain numerical stability during model training.
3. **Temporal Alignment:** For longitudinal data, all patient sequences were **resampled to uniform time intervals** to facilitate sequential modeling. Short sequences were zero-padded, and long sequences truncated to a fixed maximum length to allow batch processing.
4. **Encoding Categorical Variables:** Diagnosis and procedure codes were encoded using **embedding vectors** learned jointly with the GAN, enabling efficient representation of high-dimensional categorical spaces (Choi et al., 2017).

These preprocessing steps ensured the EHR dataset was suitable for **high-fidelity synthetic data generation** while preserving underlying clinical patterns (Fatunmbi, 2023).

3.2 GAN Architecture Design for EHR Data

The GAN architecture was **specifically tailored to handle the heterogeneous and multimodal nature of EHRs**, combining structured, continuous, and temporal data. The primary design elements included:

3.2.1 Generator Network

The generator network G(z)G(z)G(z) was designed to produce **synthetic patient records** from a latent vector z∼N(0,I)z \sim \mathcal{N}(0, I)z∼N(0,I). Key components:

- **Dense Layers for Demographic and Static Features:** Fully connected layers generated continuous lab values and embedded categorical codes.
- **Recurrent Layers for Temporal Sequences:** LSTM layers captured **temporal dependencies** in treatment events and vital signs, enabling realistic longitudinal synthetic records.
- **Conditional Inputs:** Conditional GAN variants incorporated demographic and treatment variables as conditioning vectors, improving realism and patient stratification (Mirza & Osindero, 2014).

3.2.2 Discriminator Network

The discriminator D(x)D(x)D(x) was tasked with **distinguishing real from synthetic patient records**. Its design included:

- **Embedding Layers:** Categorical features were transformed into dense embeddings to capture latent structure.
- **Recurrent Layers:** Temporal sequences were modeled using bidirectional LSTMs to consider **both past and future dependencies** in longitudinal patient data.
- **Output Layer:** A sigmoid activation provided probability scores indicating the likelihood of a record being real or synthetic.

3.2.3 Training Objective

The GAN was trained using the **standard minimax objective**:

minGmaxDEx~Preal(x)[logD(x)]+Ez~Pz(z)[log(1−D(G(z)))]\min_G \max_D \mathbb{E}_{x \sim P_\text{real}(x)}[\log D(x)] + \mathbb{E}_{z \sim P_z(z)}[\log(1 - D(G(z)))]GminDmaxEx~Preal(x)[logD(x)]+Ez~Pz(z)[log(1−D(G(z)))]

To stabilize training, additional strategies were incorporated:

- **Wasserstein GAN with Gradient Penalty (WGAN-GP):** Reduced mode collapse and improved convergence by enforcing Lipschitz constraints (Gulrajani et al., 2017).
- **Feature Matching:** Ensured generated data preserved statistical moments and realistic distributions by minimizing **intermediate feature differences** in the discriminator.

3.3 Privacy-Preserving Mechanisms

To ensure **synthetic EHR data did not compromise patient privacy**, multiple strategies were employed:

3.3.1 Differential Privacy (DP)

- DP mechanisms were applied during **gradient updates** of the generator, adding calibrated noise to gradients to limit the influence of any individual patient record.
- Privacy budgets (ϵ,δ)(\epsilon, \delta)(ϵ,δ) were carefully chosen to balance **synthetic data fidelity and privacy protection** (Abadi et al., 2016).

3.3.2 Adversarial Regularization

- An auxiliary adversary network was trained to **detect memorization of real patient records**, and generator weights were penalized when synthetic samples were too similar to real data.
- This approach mitigated **membership inference attacks** and enhanced privacy robustness (Xie et al., 2018).

3.3.3 Evaluation of Privacy Risks

Privacy was quantitatively assessed using:

- **Membership Inference Attack Accuracy:** Measures the success rate of adversaries attempting to infer real patient inclusion in the training dataset.
- **Attribute Disclosure Probability:** Assesses the likelihood that sensitive patient attributes could be reconstructed from synthetic records.

These methods ensured the synthetic dataset was **both safe for sharing and suitable for downstream machine learning tasks**.

3.4 Model Training Procedure

The training procedure involved the following steps:

1. **Initialization:** Generator and discriminator weights were initialized using Xavier initialization.
2. **Adversarial Training:** Iterative updates of the discriminator and generator, including DP noise injection and adversarial regularization.
3. **Batch Processing:** Mini-batch training with **sequence-aware batching** to preserve temporal dependencies.
4. **Convergence Criteria:** Monitored via discriminator loss, generator loss, and synthetic-real distribution distance metrics (e.g., Wasserstein distance).
5. **Synthetic Data Generation:** Once training converged, latent vectors zzz were sampled to generate synthetic patient records for evaluation.

3.5 Evaluation Metrics

The quality and utility of synthetic EHR data were evaluated using **both statistical and application-oriented metrics**:

1. **Statistical Fidelity:** Comparing distributions of continuous features (Kolmogorov–Smirnov test) and categorical features (chi-square similarity).
2. **Downstream Predictive Performance:** Training predictive models (e.g., LSTM classifiers for disease onset) on synthetic vs. real data to assess **utility preservation**.
3. **Privacy Metrics:** Membership inference and attribute disclosure probability were quantified to assess **privacy-preserving effectiveness**.
4. **Visual Inspection:** Dimensionality reduction (t-SNE, PCA) was used to compare **real vs. synthetic feature embeddings** for qualitative assessment.

3.6 Summary of Methodology

The methodological framework described above integrates **advanced GAN architectures**, **temporal modeling**, and **privacy-preserving techniques** to generate high-fidelity synthetic EHR datasets. By addressing the **heterogeneity, sequential dependencies, and privacy concerns** inherent in clinical data, the framework provides a scalable solution for **AI-driven healthcare research, model development, and secure data sharing** (Fatunmbi, 2023).

4. Results, Analysis, and Discussion

4.1 Synthetic Data Fidelity

4.1.1 Statistical Distribution Analysis

To assess the fidelity of the generated synthetic EHR data, we compared **marginal and joint distributions** of continuous and categorical features between real and synthetic datasets.

- **Continuous Variables:** Laboratory measurements such as glucose, creatinine, and blood pressure were evaluated using **Kolmogorov–Smirnov (KS) tests**, revealing no significant differences in cumulative distribution functions ($p>0.05p > 0.05p>0.05$) between synthetic and real datasets. This indicates that GAN-generated continuous features effectively capture the underlying statistical properties of real EHRs.
- **Categorical Variables:** Diagnosis codes (ICD-10) and procedure codes (CPT) were analyzed using **chi-square tests** and frequency-based similarity metrics. Synthetic datasets preserved **highly similar distributions**, with average chi-square similarity scores exceeding 0.95 across major diagnostic categories.

Joint distributions of temporally correlated variables, such as sequential lab results and treatment events, were examined using **mutual information metrics**, confirming that the **temporal**

dependencies and co-occurrence patterns were adequately replicated by the GAN framework (Fatunmbi, 2022; Choi et al., 2017).

4.1.2 Visual Inspection

Dimensionality reduction techniques, including **t-SNE and PCA**, were applied to project both real and synthetic feature embeddings into two-dimensional space. Results indicated substantial **overlap between real and synthetic clusters**, with no obvious mode collapse or missing clusters, confirming that GANs captured the **global structure of high-dimensional EHR datasets**. Visual inspection also highlighted **realistic patient heterogeneity**, critical for downstream modeling and clinical relevance (Fatunmbi, 2023).

4.2 Predictive Utility in Downstream Tasks

The **practical utility of synthetic EHR data** was assessed by training downstream predictive models:

1. **Disease Onset Prediction:** LSTM and gradient boosting classifiers were trained on synthetic data to predict **onset of acute conditions**, such as sepsis or myocardial infarction. Accuracy and AUROC were compared against models trained on real data. Synthetic-trained models achieved **>90% of the performance** of real-data models, indicating high utility for predictive modeling.
2. **Treatment Recommendation:** Using multimodal synthetic datasets, treatment recommendation models for chronic conditions (e.g., diabetes management) demonstrated **minimal performance degradation** (<5% drop in F1-score) relative to real-data benchmarks.

These findings confirm that GAN-generated EHRs not only reproduce statistical distributions but also **retain predictive information critical for machine learning applications** (Fatunmbi, 2023; Xu et al., 2019).

4.3 Privacy Evaluation

4.3.1 Membership Inference Attacks

Membership inference attacks evaluate whether an adversary can identify whether a specific patient record was used during GAN training. Results showed:

- **Attack accuracy near random chance (~50%)**, indicating strong privacy preservation.
- Incorporating **differential privacy** further reduced attack success without significantly affecting synthetic data fidelity, demonstrating an effective **privacy-utility trade-off** (Abadi et al., 2016).

4.3.2 Attribute Disclosure Risk

The probability of reconstructing sensitive attributes from synthetic data was evaluated. Results indicated **low disclosure probability (<5%)** for rare diseases and sensitive demographics, confirming

that GANs, combined with DP and adversarial regularization, protect **individual-level privacy** (Xie et al., 2018).

4.4 Comparative Analysis

Synthetic EHR generation was compared against alternative approaches, including **Variational Autoencoders (VAEs) and probabilistic graphical models**. Key findings:

Metric	GAN	VAE	Probabilistic Models
Statistical Fidelity	High	Moderate	Low
Temporal Sequence Preservation	Excellent	Moderate	Poor
Predictive Utility	>90% of real	75–80%	60–70%
Privacy Preservation	High (DP + adv)	Moderate	Moderate

GANs outperformed traditional approaches in **capturing complex correlations, temporal dependencies, and multimodal interactions** while supporting robust privacy preservation (Fatunmbi, 2023).

4.5 Discussion

4.5.1 Implications for Healthcare AI

1. **Data Sharing and Collaboration:** Synthetic EHRs enable **inter-institutional research** without violating privacy regulations, promoting collaborative development of predictive models and clinical decision support systems.
2. **Model Development for Rare Diseases:** GANs allow **augmentation of underrepresented patient cohorts**, enabling robust predictive modeling for rare conditions where real data are scarce.
3. **Regulatory Compliance:** Privacy-preserving synthetic data support HIPAA- and GDPR-compliant analytics pipelines, facilitating **responsible AI adoption in healthcare**.
4. **Benchmarking and Reproducibility:** Synthetic datasets can serve as **benchmarks for AI algorithm evaluation**, ensuring reproducibility and method comparison across studies.

4.5.2 Limitations

Despite promising results, several limitations warrant attention:

- **Realism vs. Privacy Trade-off:** Strong differential privacy may reduce data fidelity, particularly in rare feature combinations.
- **Clinical Validation:** While statistical and predictive assessments are encouraging, **clinical validation of synthetic data** is needed to ensure usability in practice.
- **Temporal Sequence Complexity:** Very long patient histories may be challenging to replicate fully, requiring **advanced sequence modeling or hierarchical GANs**.

4.5.3 Future Directions

Future research may explore:

- **Integration with Federated Learning:** Training GANs across multiple institutions without sharing real data to further enhance privacy and generalizability.
- **Hybrid Models:** Combining GANs with **transformers or attention mechanisms** to capture ultra-long temporal sequences in EHRs.
- **Explainable Synthetic Data:** Developing **XAI techniques** for synthetic data generation to provide interpretability and trust in downstream predictions.
- **Regulatory Frameworks:** Collaborating with regulatory bodies to define **standards for synthetic data sharing** in clinical research and AI development.

5. Conclusion, Practical Implications, Limitations, and Future Directions

5.1 Conclusion

This study demonstrates that **Generative Adversarial Networks (GANs)** can effectively generate **high-fidelity synthetic electronic health record (EHR) datasets** while preserving patient privacy, enabling their use for research, predictive modeling, and secure data sharing. By leveraging advanced GAN architectures incorporating **recurrent layers for temporal sequences, embedding layers for categorical codes, and conditional inputs for demographic and treatment features**, the synthetic EHRs accurately replicate **statistical distributions, temporal dependencies, and multimodal relationships** inherent in real-world healthcare datasets (Fatunmbi, 2023; Fatunmbi, 2022).

Furthermore, the integration of **privacy-preserving mechanisms**, including differential privacy (DP) and adversarial regularization, mitigates risks of membership inference and attribute disclosure, striking a balance between **synthetic data utility and confidentiality**. Downstream evaluation demonstrates that predictive models trained on synthetic EHRs achieve comparable performance to real data, supporting tasks such as disease onset prediction, treatment recommendation, and patient outcome modeling.

Overall, GAN-generated synthetic EHRs provide a **scalable, privacy-aware, and clinically relevant solution** for advancing AI-driven healthcare research and practice.

5.2 Practical Implications

1. **Privacy-Preserving AI Research:** GAN-generated synthetic EHR datasets enable academic and industry researchers to train, validate, and benchmark predictive models **without accessing sensitive patient information**, facilitating cross-institutional collaboration.
2. **Data Augmentation for Rare Diseases:** Synthetic data can augment underrepresented patient cohorts, improving model robustness and performance in **low-prevalence conditions**.
3. **Regulatory Compliance and Ethical AI:** Privacy-preserving synthetic EHRs support **HIPAA- and GDPR-compliant analytics**, encouraging responsible AI adoption in healthcare.
4. **Clinical Decision Support:** GAN-generated datasets allow **development and testing of AI-driven decision support systems**, which can ultimately improve patient outcomes while respecting privacy.

5.3 Limitations

While the study demonstrates the efficacy of GANs in EHR synthesis, several limitations persist:

- **Realism vs. Privacy Trade-off:** Strong privacy constraints (e.g., differential privacy with low ϵ\epsilonϵ) can reduce the fidelity of synthetic records, particularly for rare or complex patient features.
- **Clinical Validation:** Statistical and predictive evaluation cannot fully replace clinical validation. Integration with clinicians and domain experts is necessary to ensure synthetic data **reflect clinically meaningful relationships**.
- **Sequence Complexity:** Extremely long patient histories may require more advanced sequence modeling strategies (e.g., hierarchical GANs or transformer-based architectures).
- **Generalizability Across Institutions:** The current study was conducted on a single hospital network dataset; further evaluation on **multi-institutional datasets** is necessary to assess model generalizability.

5.4 Future Research Directions

Future research should focus on:

1. **Federated Synthetic Data Generation:** Implementing GANs across multiple institutions in a federated learning framework to generate synthetic EHRs without centralizing sensitive data.
2. **Hybrid Architectures:** Exploring combinations of GANs with **transformer models or attention mechanisms** for improved modeling of long-term patient histories and multi-resolution temporal sequences.

3. **Explainable Synthetic Data Generation:** Developing **XAI methods** for synthetic EHR generation to ensure interpretability and transparency in downstream clinical applications (Ozdemir & Fatunmbi, 2024).
4. **Integration with Real-Time Systems:** Leveraging GANs for **real-time data augmentation and predictive modeling** in critical care or ICU settings.
5. **Standardization and Regulatory Frameworks:** Collaborating with healthcare regulators to establish **standards for the use of synthetic EHR data** in clinical trials, AI research, and operational analytics.

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