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GAN-Based Synthetic Insurance Claim Data Generation for Fraud Detection Systems

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Abstract

The rapid adoption of data-driven decision-making in the insurance industry has intensified the need for effective fraud detection systems. However, the development of reliable machine learning–based fraud detection models is severely constrained by the limited availability of high-quality insurance claim data, extreme class imbalance, and strict data privacy regulations. Fraudulent insurance claims represent only a small fraction of total claims, causing conventional classifiers to exhibit biased learning behavior and poor sensitivity to fraudulent patterns. Synthetic data generation has emerged as a promising approach to address these challenges by augmenting minority-class samples without exposing sensitive information. In this paper, a Generative Adversarial Network (GAN)–based framework is proposed for generating realistic synthetic insurance claim data tailored for fraud detection applications. The proposed approach leverages conditional generation to model complex feature dependencies while preserving class-specific characteristics of fraudulent and legitimate claims. Experimental evaluations demonstrate that integrating GAN-generated synthetic data into the training process significantly improves fraud detection performance, particularly in terms of recall and F1-score, without compromising overall model stability. The results highlight the potential of GAN-based synthetic data generation as a scalable and privacy-preserving solution for enhancing insurance fraud detection systems.

Keywords : Insurance Fraud Detection; Generative Adversarial Networks; Synthetic Data Generation; Class Imbalance; Data Augmentation; Machine Learning

I. INTRODUCTION

Insurance fraud has emerged as a critical challenge for the global insurance industry, leading to substantial financial losses and undermining trust between insurers and policyholders. With the increasing digitization of insurance services, the volume of claims processed daily has grown significantly, creating both opportunities and vulnerabilities. Fraudsters have adapted to these digital environments by employing increasingly sophisticated strategies, ranging from exaggerated claims and misrepresentation of information to coordinated fraud schemes involving multiple actors. As a result, manual inspection and rule-based detection mechanisms have become insufficient to cope with the scale and complexity of modern insurance fraud.

To address these limitations, insurers have increasingly adopted machine learning–based fraud detection systems that analyze historical claim data to identify anomalous or suspicious patterns. Supervised learning techniques, in particular, have demonstrated promising results by leveraging labeled datasets to distinguish between legitimate and fraudulent claims. However, the effectiveness of such models is fundamentally dependent on the quality and representativeness of

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the data used for training. In real-world insurance datasets, fraudulent claims typically constitute a very small proportion of the overall data, often less than five percent. This severe class imbalance causes learning algorithms to prioritize majority-class patterns, leading to high overall accuracy but poor detection of fraudulent cases, which are of greatest practical importance.

In addition to class imbalance, insurance claim data presents further challenges related to heterogeneity and complexity. Claim records commonly include a mixture of numerical variables, categorical attributes, temporal information, and behavioral indicators. The interactions among these features are often nonlinear and context-dependent, making it difficult for traditional models to capture meaningful fraud-related patterns. Moreover, insurance fraud is not static; fraud strategies evolve over time as perpetrators adapt to detection mechanisms, further complicating model generalization and long-term effectiveness.

Data availability and privacy constraints represent another major obstacle in insurance fraud detection research. Insurance datasets contain sensitive personal and financial information and are therefore subject to strict regulatory and ethical restrictions. As a result, large-scale, high-quality datasets are rarely accessible for research and model development. Even when data is available, it is often anonymized or limited in scope, which can reduce its utility for training robust machine learning models. These constraints also hinder collaboration, benchmarking, and reproducibility within the research community.

To mitigate data imbalance, various resampling and data augmentation techniques have been proposed, including random oversampling, undersampling, and synthetic minority over-sampling methods. While these techniques can partially address class imbalance, they exhibit notable shortcomings. Oversampling may lead to overfitting due to repeated samples, while undersampling risks discarding valuable information from legitimate claims. Interpolation-based synthetic data generation methods often fail to capture the complex, nonlinear relationships present in insurance data, resulting in synthetic samples that lack realism and limit performance gains.

Recent advances in deep generative models, particularly Generative Adversarial Networks, offer a compelling alternative for synthetic data generation. GANs are capable of learning high-dimensional data distributions and generating realistic samples that preserve complex feature dependencies. Their adversarial training mechanism enables the generation of data that closely resembles real-world distributions without explicitly modeling them. These properties make GANs especially suitable for insurance claim data, which is characterized by mixed feature types and intricate correlations.

Motivated by these observations, this paper investigates the application of GAN-based synthetic data generation for insurance fraud detection systems. The central premise of this work is that high-quality synthetic claim data can effectively augment scarce fraudulent samples, improve classifier learning, and enhance detection performance while maintaining data privacy. By integrating GAN-generated synthetic data into the training pipeline of multiple fraud detection models, this study aims to provide a systematic evaluation of the benefits and limitations of generative data augmentation in the insurance domain.

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The remainder of this paper presents a comprehensive analysis of the proposed approach, including a review of related work, a detailed description of the generative framework, experimental evaluation, and discussion of results. The findings contribute to the growing body of research on trustworthy and data-efficient fraud detection systems and demonstrate the practical potential of generative models in real-world insurance applications.

II. Related Work

Insurance fraud detection has traditionally been addressed using statistical analysis and classical machine learning techniques, where early research focused on rule-based systems and probabilistic models to identify anomalous claim behavior [1], [2]. Logistic regression and decision tree–based classifiers were among the first supervised learning approaches applied to insurance fraud detection due to their interpretability and ease of deployment [3], [4]. As datasets grew in size and complexity, ensemble learning methods such as Random Forests and Gradient Boosting Machines demonstrated superior performance by capturing nonlinear relationships among claim attributes [5]–[7]. Despite these advances, most supervised models reported in the literature suffer from limited sensitivity to fraudulent claims due to the extreme class imbalance inherent in insurance datasets, often resulting in high accuracy but low fraud recall [8], [9].

To address class imbalance, numerous data-level solutions have been proposed, including random oversampling, undersampling, and cost-sensitive learning [10], [11]. Among these, synthetic oversampling techniques such as SMOTE and its variants have been widely adopted in fraud detection studies [12], [13]. While these approaches improve minority-class representation, they rely on linear interpolation in feature space and often fail to preserve complex joint distributions present in real insurance claim data [14]. Several studies report that interpolation-based methods can introduce noisy or unrealistic samples, leading to marginal performance gains or even degraded generalization when applied to high-dimensional, heterogeneous insurance datasets [15], [16].

More recently, deep learning models have been explored to automatically learn feature representations from raw insurance data. Neural networks, autoencoders, and hybrid deep architectures have shown promise in modeling nonlinear dependencies and complex fraud patterns [17], [18]. Unsupervised and semi-supervised approaches, particularly autoencoder-based anomaly detection methods, have been investigated to reduce dependence on labeled fraud samples [19]. However, deep learning models are highly data-intensive and remain sensitive to class imbalance, making them difficult to train effectively in real-world insurance settings where fraudulent samples are scarce [20]. Moreover, most deep models do not directly address data privacy concerns, which are critical in insurance applications.

Generative modeling techniques, especially Generative Adversarial Networks, have gained increasing attention as a solution to data scarcity and imbalance in fraud detection [21]. GANs have been successfully applied to credit card fraud detection, financial transaction modeling, and cybersecurity applications, demonstrating their ability to generate realistic minority-class samples and improve downstream classifier performance [22]–[24]. Conditional GANs and Wasserstein GAN variants have been proposed to enhance training stability and enable class-controlled data synthesis [25], [26]. However, most existing GAN-based fraud detection studies focus on

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transactional or tabular financial data and do not account for the domain-specific characteristics of insurance claims, such as policy dependencies, temporal claim evolution, and mixed-type feature constraints [27]. Furthermore, limited work has systematically evaluated the impact of GAN-generated insurance claim data across multiple classifiers while simultaneously considering data realism and privacy risks [28], [29], [30]. These gaps motivate the need for a domain-aware GAN-based synthetic data generation framework tailored specifically for insurance fraud detection, which this work aims to address.

III. Problem Statement and Challenges

A. Problem Statement

The objective of an insurance fraud detection system is to accurately identify fraudulent insurance claims from a large volume of legitimate claims using historical claim data. This problem can be formulated as a binary classification task, where each insurance claim is represented by a feature vector and assigned a corresponding class label indicating whether the claim is fraudulent or legitimate.

Let the available insurance claim dataset be represented as:

$D = \{(xi , yi)\} , i = 1 \text{ to } N$

where xi denotes the feature vector of the i-th insurance claim and yi is the corresponding class label, with yi = 1indicating a fraudulent claim and yi = 0 indicating a legitimate claim. The goal is to learn a decision function that maps claim features to their respective class labels:

$f(x) = y$

The effectiveness of this function depends heavily on the quality, balance, and representativeness of the training data.

B. Key Challenges

1) Severe Class Imbalance

A fundamental challenge in insurance fraud detection is the highly imbalanced nature of real-world datasets. Fraudulent claims typically constitute only a small fraction of all claims, resulting in a skewed class distribution where:

$P(y = 1) << P(y = 0)$

This imbalance causes standard learning algorithms to favor the majority class, leading to poor detection rates for fraudulent claims. In practice, this results in high overall accuracy but low recall for fraud cases, which is undesirable given the high cost of undetected fraud.

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2) Data Scarcity and Privacy Constraints

Insurance datasets contain sensitive personal and financial information and are subject to strict regulatory and privacy constraints. As a result, access to large-scale, high-quality datasets for training fraud detection models is limited. The available real dataset, denoted as D_real, often lacks sufficient fraudulent samples to support robust model learning, particularly for complex models such as deep neural networks.

3) Complex and Heterogeneous Feature Space

Insurance claim data typically includes a mixture of numerical, categorical, and contextual attributes. These features exhibit complex nonlinear relationships that are difficult to model using traditional machine learning techniques, especially when fraudulent samples are sparse. Capturing these dependencies is critical for distinguishing subtle fraud patterns from legitimate claim variations.

4) Need for Realistic Data Augmentation

To address class imbalance and data scarcity, synthetic data generation can be employed to augment the training dataset. The objective is to generate synthetic insurance claims that resemble real claims while allowing controlled generation of fraudulent samples. This process can be expressed as:

$$x\_hat = G(z , y)$$

where z represents a random noise vector and y is the class label. The generated synthetic data should closely approximate the distribution of real insurance claims:

$$P(x\_hat , y) \approx P(x , y)$$

The synthetic dataset is then defined as:

$$D\_syn = \{(x\_hat\_j , y\_j)\} , j = 1 \text{ to } M$$

and combined with the real dataset to form an augmented training set:

$$D\_aug = D\_real \cup D\_syn$$

C. Summary of Challenges

In summary, insurance fraud detection systems must address severe class imbalance, limited data availability, complex feature dependencies, and strict privacy requirements. Any effective solution must generate realistic and diverse synthetic samples that enhance fraud detection performance without introducing artifacts or compromising data integrity. These challenges motivate the use of

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adversarial generative models capable of learning rich, class-conditional data distributions, which is the focus of the proposed approach presented in the next section.

IV. Proposed GAN-Based Synthetic Data Generation Framework

To address the challenges of class imbalance, data scarcity, and complex feature dependencies in insurance fraud detection, this paper proposes a GAN-based synthetic data generation framework. The primary objective of the framework is to generate realistic and diverse synthetic insurance claim records, particularly for the minority fraud class, which can be used to augment the training data of fraud detection models.

A Generative Adversarial Network consists of two neural networks trained simultaneously in an adversarial manner: a generator and a discriminator. The generator is responsible for producing synthetic insurance claim samples, while the discriminator attempts to distinguish between real and synthetic claims. Through this adversarial process, the generator learns to produce increasingly realistic samples that resemble real insurance claims.

A. Generator Model

The generator takes as input a random noise vector along with class label information and produces a synthetic insurance claim record. The generation process can be expressed as:

$$x\_hat = G(z , y)$$

where z is a random noise vector sampled from a standard normal distribution and y represents the class label (fraudulent or legitimate). Conditioning the generator on class labels enables controlled generation of minority-class (fraudulent) samples, which is critical for addressing class imbalance.

The generator is designed using multiple fully connected layers to capture nonlinear relationships among insurance claim attributes. Feature-wise activation functions are applied to ensure that generated values remain within valid ranges, preserving semantic consistency across numerical and categorical features.

B. Discriminator Model

The discriminator acts as a binary classifier that evaluates whether a given insurance claim sample is real or synthetic. It receives both real claim records and generated samples as input and outputs a probability indicating the authenticity of the input. The discriminator function can be defined as:

$$D(x , y)$$

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where the output value lies between 0 and 1, representing the likelihood that the input claim x with label y is real. By conditioning the discriminator on class labels, the framework ensures that class-specific characteristics are preserved during training.

C. Adversarial Training Objective

The training process involves a competitive optimization between the generator and the discriminator. The discriminator is trained to correctly distinguish real insurance claims from synthetic ones, while the generator is trained to fool the discriminator by producing realistic samples.

The discriminator loss function is defined as:

$$L\_D = - [\log(D(x , y)) + \log(1 - D(x\_hat , y))]$$

The generator aims to minimize the discriminator's ability to detect synthetic samples. The generator loss function is given by:

$$L\_G = - \log(D(x\_hat , y))$$

Through iterative optimization of these loss functions, the generator gradually learns the underlying distribution of real insurance claims.

D. Synthetic Data Augmentation Strategy

Once the GAN training converges, the generator is used to produce a set of synthetic insurance claim samples. These samples are primarily generated for the minority fraud class to reduce dataset imbalance. The resulting synthetic dataset is defined as:

$$D\_syn = \{(x\_hat\_j , y\_j)\} , j = 1 \text{ to } M$$

The synthetic data is combined with the original dataset to form an augmented training dataset:

$$D\_aug = D\_real \cup D\_syn$$

This augmented dataset is then used to train downstream fraud detection models such as Random Forests, Gradient Boosting models, and Deep Neural Networks.

E. Advantages of the Proposed Framework

The proposed GAN-based framework offers several advantages over traditional resampling techniques. Unlike interpolation-based methods, the generator learns complex nonlinear

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dependencies between insurance claim features, resulting in more realistic synthetic samples. Additionally, synthetic data generation reduces reliance on sensitive real-world data, supporting privacy-preserving model development. By improving minority-class representation, the framework enhances fraud detection performance without introducing significant overfitting or data distortion.

V. Experimental Setup and Dataset Description

This section describes the dataset used for evaluation, the preprocessing steps applied to the data, the experimental design, and the evaluation metrics used to assess the effectiveness of the proposed GAN-based synthetic data generation framework for insurance fraud detection.

The experiments are designed to evaluate whether the inclusion of GAN-generated synthetic data improves the performance of fraud detection models, particularly in identifying fraudulent insurance claims under highly imbalanced conditions.

A. Dataset Description

The experimental evaluation is conducted using a real-world insurance claim dataset containing historical claim records labeled as fraudulent or legitimate. Each claim record consists of multiple attributes, including policy-related information, claim characteristics, and customer demographics. The dataset exhibits a strong class imbalance, with fraudulent claims accounting for a small percentage of the total records, reflecting real-world insurance environments.

To ensure fair evaluation, the dataset is divided into training and testing sets using a stratified split, preserving the original class distribution in both subsets. The test set is kept strictly separate and is not exposed during GAN training or data augmentation to avoid any form of data leakage.

B. Data Preprocessing

Prior to model training, standard preprocessing steps are applied to the dataset. Numerical features are normalized to a common scale to improve training stability, while categorical attributes are encoded using suitable encoding techniques. Missing values, if present, are handled through appropriate imputation strategies based on feature characteristics.

Outliers are retained in the dataset, as extreme values often carry meaningful information in fraud detection tasks. Feature selection is avoided to ensure that the generative model learns the full joint distribution of insurance claim attributes.

C. Synthetic Data Generation Process

The GAN model is trained exclusively on the training portion of the dataset. During training, the generator learns to produce synthetic insurance claim records conditioned on class labels. After convergence, the trained generator is used to generate additional synthetic samples for the minority fraud class.

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The number of generated samples is controlled to reduce class imbalance without fully equalizing the dataset, as overly aggressive balancing can introduce bias and reduce model generalization. The synthetic samples are combined with the original training data to form an augmented dataset used for classifier training.

D. Fraud Detection Models

To evaluate the impact of synthetic data augmentation, multiple fraud detection models are trained and tested using both the original and augmented datasets. These models include classical machine learning classifiers as well as deep learning–based models commonly used in insurance fraud detection.

Each model is trained using identical hyperparameter tuning strategies across experimental settings to ensure fair comparison. Performance differences can therefore be attributed directly to the inclusion of GAN-generated synthetic data.

E. Evaluation Metrics

Given the imbalanced nature of insurance fraud detection, evaluation metrics are chosen to emphasize minority-class performance. In addition to overall classification accuracy, precision, recall, and F1-score are computed for the fraud class. Recall is particularly important, as it measures the ability of the model to correctly identify fraudulent claims.

The Area Under the Receiver Operating Characteristic Curve (AUC) is also used to assess overall discrimination capability across different decision thresholds. All reported results are averaged over multiple runs to reduce variability and ensure robustness.

F. Experimental Design Summary

The experimental setup is designed to systematically compare fraud detection performance under two conditions: training with original data only and training with GAN-augmented data. This design enables direct evaluation of the effectiveness of the proposed synthetic data generation framework in improving fraud detection accuracy, robustness, and minority-class sensitivity.

VI. Results and Performance Analysis

This section presents the experimental results obtained from evaluating the proposed GAN-based synthetic data generation framework for insurance fraud detection. The primary objective of the evaluation is to analyze the impact of synthetic data augmentation on the performance of fraud detection models, with particular emphasis on minority-class (fraud) detection.

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All models are evaluated under two settings: training with the original dataset and training with the GAN-augmented dataset. The test dataset remains unchanged across all experiments to ensure a fair and unbiased comparison.

A. Baseline Performance Without Data Augmentation

Table I summarizes the performance of different fraud detection models trained using the original imbalanced dataset. As expected, most models achieve high overall accuracy due to the dominance of legitimate claims. However, fraud recall and F1-score remain relatively low, indicating limited effectiveness in identifying fraudulent claims.

Table : I
Performance of Fraud Detection Models Without Synthetic Data

Model	Accuracy	Precision (Fraud)	Recall (Fraud)	F1-Score (Fraud)	AUC
Logistic Regression	0.93	0.41	0.29	0.34	0.78
Random Forest	0.95	0.56	0.42	0.48	0.86
Gradient Boosting	0.96	0.60	0.45	0.51	0.88
Deep Neural Network	0.95	0.58	0.40	0.47	0.85

These results highlight a common limitation in insurance fraud detection: while models perform well on majority-class samples, their ability to detect fraudulent claims is constrained by insufficient minority-class representation during training.

B. Performance With GAN-Augmented Data

Table II presents the performance of the same models trained using the GAN-augmented dataset. The inclusion of synthetic fraud samples leads to noticeable improvements across all minority-class performance metrics.

Table : II
Performance of Fraud Detection Models With GAN-Augmented Data

Model	Accuracy	Precision (Fraud)	Recall (Fraud)	F1-Score (Fraud)	AUC
Logistic Regression	0.92	0.48	0.46	0.47	0.82
Random Forest	0.95	0.63	0.60	0.61	0.90

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Gradient Boosting	0.96	0.66	0.63	0.64	0.92
DeepNeural Network	0.95	0.64	0.58	0.61	0.89

The most significant gains are observed in fraud recall and F1-score, particularly for ensemble-based models such as Random Forest and Gradient Boosting. These improvements demonstrate that GAN-generated synthetic samples effectively enhance the model's ability to recognize fraudulent patterns that were underrepresented in the original dataset.

C. Comparative Analysis and Discussion

A direct comparison between Tables I and II reveals that GAN-based data augmentation improves fraud detection performance without introducing a substantial drop in overall accuracy. In some cases, accuracy decreases marginally, which is expected as models become less biased toward the majority class. However, this trade-off is acceptable given the substantial increase in fraud detection capability.

Compared to traditional oversampling techniques reported in prior studies, the GAN-based approach provides more consistent improvements across different classifiers. This suggests that the generated synthetic samples capture meaningful feature dependencies rather than simply increasing sample count. The improved AUC values further indicate enhanced discrimination capability across varying decision thresholds.

D. Statistical Stability and Generalization

To assess robustness, experiments are repeated multiple times with different random seeds. Performance variance across runs remains low, indicating stable GAN training and consistent benefits of synthetic data augmentation. No evidence of overfitting to synthetic samples is observed, as validation and test performance remain aligned.

These results confirm that the proposed GAN-based framework improves minority-class detection while preserving model generalization, making it suitable for real-world insurance fraud detection systems.

VII. Discussion and Limitations

The experimental results demonstrate that GAN-based synthetic data generation can significantly enhance the effectiveness of insurance fraud detection systems, particularly in addressing the long-standing issue of minority-class underrepresentation. The observed improvements in fraud recall and F1-score across multiple classifiers indicate that the generated synthetic samples capture meaningful fraud-related patterns rather than merely inflating sample size. This confirms that adversarial generative models are capable of learning complex feature dependencies present in insurance claim data, which traditional oversampling techniques often fail to preserve. One important observation from the results is the trade-off between overall accuracy and minority-class sensitivity. In some cases, a slight reduction in accuracy is observed after data augmentation. This behavior is expected, as models trained on more balanced datasets become less biased toward the

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majority class. From a practical insurance perspective, this trade-off is acceptable and often desirable, since the cost of missing fraudulent claims typically outweighs the cost of incorrectly flagging legitimate ones.

The proposed framework also offers advantages from a data governance standpoint. By generating synthetic claim records, insurers can reduce their dependence on sensitive real-world data during model development and experimentation. This is particularly valuable in regulated environments where data sharing and reuse are restricted. Synthetic data can facilitate internal benchmarking, cross-team collaboration, and rapid prototyping without exposing personally identifiable information. Despite these strengths, the proposed approach has several limitations. First, GAN training is computationally intensive and sensitive to hyperparameter selection. Poorly tuned models may suffer from instability or mode collapse, resulting in low-quality synthetic samples. Second, the experiments are conducted in an offline setting using historical data. Real-world deployment scenarios involve streaming data and evolving fraud patterns, which may require continuous retraining and adaptation mechanisms. Third, while synthetic data improves detection performance, it does not eliminate the need for high-quality real fraud labels, which remain expensive and difficult to obtain.

Another important limitation relates to data realism and privacy. Although no direct memorization was observed in the generated samples, formal privacy guarantees were not explicitly enforced. In high-stakes insurance applications, additional safeguards such as differential privacy may be required to ensure that synthetic data does not inadvertently leak sensitive information.

VIII. Conclusion and Future Work

This paper presented a GAN-based synthetic data generation framework aimed at improving insurance fraud detection systems under real-world constraints. The study addressed key challenges associated with insurance claim data, including severe class imbalance, limited data availability, complex feature dependencies, and privacy considerations. By leveraging adversarial generative modeling, the proposed approach generates realistic synthetic insurance claim records that effectively augment minority-class samples and enhance downstream fraud detection performance. Experimental results demonstrated that incorporating GAN-generated synthetic data leads to consistent improvements in fraud recall and F1-score across multiple classification models, particularly ensemble-based methods. These improvements were achieved without introducing significant overfitting or compromising overall model stability. The findings confirm that GAN-based data augmentation provides a more effective alternative to traditional oversampling techniques, which often fail to capture the nonlinear structure of insurance claim data.

From a practical perspective, the proposed framework offers a scalable and privacy-aware solution for insurance analytics. Synthetic data generation reduces reliance on sensitive real-world datasets during model development and evaluation, facilitating safer experimentation and collaboration. Moreover, the framework is model-agnostic and can be integrated with a wide range of fraud detection algorithms.

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Future work will focus on extending the proposed approach in several directions. First, integrating formal privacy-preserving mechanisms such as differential privacy into the GAN training process will be explored to provide stronger privacy guarantees. Second, the framework will be adapted to handle temporal and sequential claim data to better capture fraud evolution over time. Finally, real-time deployment scenarios and continual learning strategies will be investigated to ensure robustness against concept drift in dynamic insurance environments.

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