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Experimental Evaluation of Generative Adversarial Network for Addressing Class Imbalance in Machine Learning

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ABSTRACT

Class imbalance poses a significant challenge in machine learning, especially in critical domains like fraud detection and healthcare. The dominance of majority classes often overshadows minority classes, leading to models that inadequately recognize rare but pivotal events, such as fraudulent transactions. This imbalance can compromise predictive accuracy and fairness. Traditional methods, including resampling techniques and ensemble methods, often suffer from overfitting and inadequate representation. This study explores the use of Generative Adversarial Networks (GANs) to enhance predictive performance on an imbalanced dataset of credit card transactions, comprising 95% legitimate and 5% fraudulent transactions. The GAN architecture consists of a generator producing synthetic samples of the minority class and a discriminator distinguishing between real and synthetic data. Experimental results indicate models augmented with GANs achieve high accuracy, with Random Forest models reaching 99.98%, Gradient Boosting models achieving 99.99%, and Decision Tree models obtaining 99.82%. These findings underline GANs' effectiveness in addressing class imbalance, enhancing predictive performance for minority classes and providing reliable results in practical applications.

Keywords: Class Imbalance, Machine Learning, Classification Tasks, Generative Adversarial Network

1. INTRODUCTION

Class imbalance is a prevalent concern in various fields, including medicine, banking and fraud detection, where class distributions within datasets are significantly skewed. In these scenarios, models trained on imbalanced datasets tend to favor the majority class, leading to suboptimal predictive performance for the minority class. For instance, in credit card fraud detection, a dataset comprising 95% legitimate transactions and only 5% fraudulent transactions can allow a model to achieve high overall accuracy by predominantly predicting transactions as legitimate [1]. However, this frequently results in elevated false negative rates and potential financial repercussions for banks and customers due to undetected fraud.

In healthcare, the early detection of rare diseases, such as specific cancers, is crucial. A dataset that includes 98% healthy patients and merely 2% with rare cancers can lead models to predominantly predict health [2], resulting in missed diagnoses and delayed treatments, adversely affecting patient outcomes. The implications of data imbalance in this context include an inability to accurately diagnose rare diseases, with potentially severe consequences for patient health [3].

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To enhance prediction accuracy for minority classes, several strategies can be employed. Traditional approaches for managing class imbalance often utilize resampling techniques, such as oversampling the minority class or undersampling the majority class. While these methods can help achieve a more balanced dataset, they come with notable limitations. Oversampling involves increasing the number of instances in the minority class, which can inadvertently lead to overfitting, as the model may memorize duplicated samples rather than learning to generalize from them [4]. Conversely, undersampling entails reducing the number of instances in the majority class, risking the loss of valuable information and obscuring vital patterns within the data. Both traditional methods primarily modify existing data points instead of generating new ones, limiting their ability to accurately reflect the underlying distribution of the minority class [5]. Therefore, there is a pressing need for advanced techniques capable of generating new, realistic samples to improve model performance and ensure reliable predictions for minority classes.

GANs have emerged as a powerful solution to challenges associated with imbalanced datasets. By employing a dual architecture consisting of a generator and a discriminator [6], GANs are capable of generating realistic samples from minority classes, enriching the dataset and improving balance [7]. This paper investigates the application of GANs to improve the performance of machine learning models on imbalanced classification tasks, enhancing model accuracy and ensuring robust generalization to unseen data. The findings underscore GANs' ability to effectively address the limitations of traditional resampling methods, such as overfitting and information loss [8].

Experimental results highlight that the GAN-based methodology significantly enhances the predictive performance of minority classes, yielding more reliable and equitable outcomes across diverse applications. This work offers valuable insights into the evolving landscape of GANs, paving the way for future research and practical applications aimed at improving the accuracy and reliability of machine learning models in imbalanced classification scenarios.

This article is structured as follows: Section 1 presents the study of imbalanced datasets, while Section 2 reviews related work. Section 3 details the GAN methodology used to address imbalanced datasets. Section 4 discusses performance evaluation results for each machine learning classifier. Finally, Section 5 summarizes main findings and outlines avenues for future research.

2. LITERATURE REVIEW

Dealing with imbalanced datasets presents a significant challenge in ML, particularly as many real-world applications demonstrate skewed class distributions. An imbalanced class distribution occurs when examples from different classes are represented unevenly, with one class (the majority class) containing more samples than another (the minority class) [9]. This imbalance complicates the training of ML models and can lead to biased predictions.

Various traditional methods have been documented to address this issue, including resampling techniques, cost-sensitive learning, and synthetic data generation. Resampling methods can be divided into two main categories: minority class oversampling and majority class undersampling. For instance, the Synthetic Minority Oversampling Technique (SMOTE) generates synthetic examples to enhance classifier performance. However, it may also lead to overfitting by creating overly similar instances of the minority class [10]. Conversely, undersampling the majority class can result in the loss of valuable information, negatively impacting model performance. Recent studies indicate that traditional methods often fall short in addressing the complexities inherent in highly imbalanced datasets, underscoring the need for advanced techniques [11].

Recent advances in machine learning have introduced more sophisticated methods for balancing datasets, as summarized in Table 1. One notable approach is cost-sensitive learning, which assigns different misclassification costs to classes. This technique encourages the model to prioritize minority classes, but it often requires careful tuning of cost parameters, complicating implementation [12][13]. Additionally, ensemble methods, such as Balanced Random Forests, have demonstrated potential for improving classification performance in imbalanced scenarios. These methods train a set of classifiers on balanced subsets of the data, leveraging the strengths of multiple algorithms to enhance overall prediction accuracy [14].

Despite their advantages, both cost-sensitive learning and ensemble methods have limitations, particularly in situations characterized by extreme class imbalance. Evaluations across various domains have shown that their effectiveness can diminish when class distribution disparities are pronounced [3]. This situation highlights the necessity for innovative solutions to tackle persistent challenges posed by imbalanced datasets in machine learning.

Table 1 Imbalanced datasets method

Author	Method	Title	Technique Used
[15]	Resampling	Handling class imbalance in credit card fraud using resampling methods	• SMOTE • ROS • RUS
[16]	Class Weight	Weighting methods for rare event identification from imbalanced datasets	• Adaptive algorithm • Boosting style algorithm
[17]	Ensemble Methods	A novel ensemble method for classifying imbalanced data	• Random splitting (SplitBal) • Clustering (ClusterBal) • Ensemble rule
[18]	Cost-Sensitive Learning	Cost-sensitive decision tree ensembles for effective imbalanced classification	• Evolutionary algorithm
[19]	Algorithm Selection	A hybrid supervised ML classifier system for breast cancer prognosis using feature selection and data imbalance handling approaches	• Nature-inspired algorithms • Wrapper-based feature selection approach
[20]	Data Augmentation	Solving the class imbalance problem using a counterfactual method for data augmentation	• Counterfactual Augmentation (CFA)
[21]	Anomaly Detection	The optimized anomaly detection models based on an approach of dealing with imbalanced dataset for credit card fraud detection	• AdaBoost • Isolation Forest (IForest) • One-Class Support Vector Machine (OCSVM)

Given the limitations of traditional methods for addressing class imbalance, GANs have emerged as a compelling alternative. GANs consist of two neural networks—a generator and a discriminator—that are trained concurrently. This architecture facilitates the generation of effective artificial samples for the minority class, tackling the core issue of class imbalance by enriching the dataset with realistic examples that closely mimic the underlying distribution of the minority class [22]. GAN framework can be seen in Figure 1.

The generator's primary function is to create new data points from random noise, learning to produce samples indistinguishable from authentic instances of the minority class [23]. Simultaneously, the discriminator evaluates whether these samples are real or synthetic. Through this adversarial training process, both networks enhance their respective capabilities: the generator becomes more proficient at crafting realistic samples, while the discriminator improves its accuracy in distinguishing between real and generated data [8]. This dynamic interplay makes GANs particularly well-suited for mitigating class imbalance. Empirical studies, as summarized in Table 2, demonstrate that GANs can outperform traditional resampling methods by generating diverse and representative samples.

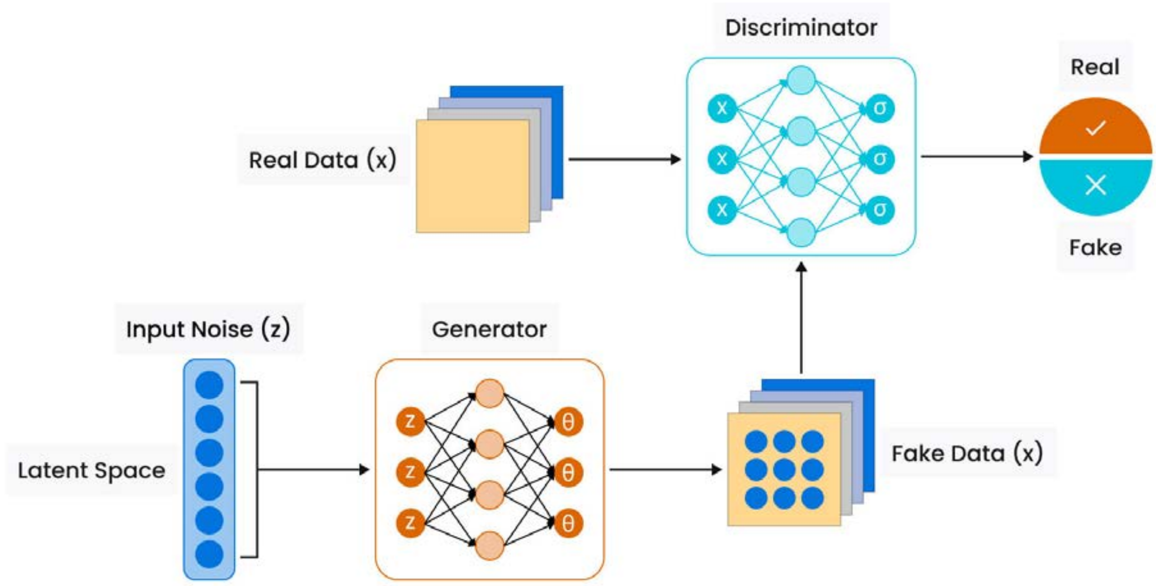

Figure 1. The framework of GAN [24]

To improve the efficiency of GANs in generating samples for balanced datasets, several variants have been proposed. One notable variant is the Conditional GAN (cGAN), which enables targeted generation by conditioning on class labels. This feature allows for the production of specific examples of minority classes, making cGANs particularly useful in scenarios where precise control over the generated samples is required [25]. Additionally, techniques such as Wasserstein GANs (WGANs) have been developed to enhance both training stability and the quality of generated samples. By reformulating the loss function, WGANs address issues related to mode collapse and provide a more meaningful measure of the distance between distributions. This results in more reliable and diverse sample generation, which is critical for effectively addressing class imbalance [26]. These advancements highlight the adaptability of GANs across various contexts, including medical imaging and fraud detection, where class imbalances are prevalent. By leveraging these specialized GAN variants, researchers and practitioners can better tackle the challenges posed by imbalanced datasets, ultimately improving the performance and reliability of ML models in critical applications.

The literature outlines a diverse array of techniques for managing class imbalance, encompassing both traditional resampling methods and advanced generative models such as GANs. While conventional approaches offer certain benefits, they frequently fall short in complex scenarios marked by substantial class imbalance.

The advent of GANs and their various derivatives signifies a promising direction for future research. These models not only provide innovative solutions for generating realistic synthetic samples but also enhance the overall robustness of ML algorithms. By refining strategies to effectively manage imbalanced datasets, GANs hold the potential to significantly improve predictive performance in a wide range of applications, ultimately leading to more accurate and reliable outcomes. As research continues to evolve, exploring the capabilities of GANs and their adaptations will be crucial in addressing the ongoing challenges posed by class imbalance in ML.

Table 2 Imbalanced datasets applications with GAN

Author	Technique Used	Contribution	Findings
[27]	• CNN • GAN	Implement code visualization methods and use GANs to generate more samples of malicious code variants	CNN as well as GAN models can achieve higher classification accuracy than related work
[28]	• Dynamic ensemble algorithm	Propose a dynamic ensemble algorithm for anomaly detection in the Internet of Things (IoT)	The proposed algorithm outperforms comparative anomaly detection methods in IoT scenarios
[29]	• Hybrid deep learning (CBGRU)	Propose a new hybrid deep learning model named CBGRU that combines different word embedding techniques	The CBGRU model shows superior performance in vulnerability detection compared to previous models
[30]	• RGAN-EL	Introduces a hybrid framework called RGAN-EL, which combines GAN with ensemble learning to improve classification performance on imbalanced datasets	RGAN-EL significantly outperforms six common ensemble learning methods
[31]	• WGAN	Investigates the use of WGAN as a technique for dealing with imbalanced data sets in ML	WGAN outperforms basic GAN and enhanced GAN in producing high-quality and diverse synthetic data

3. GENERATIVE ADVERSARIAL NETWORKS (GANs) FOR IMBALANCED DATASETS

This section outlines the methodology employed to address the challenges of imbalanced datasets using GANs.

3.1 Data Selection and Preprocessing

The process initiates with the selection of a credit card transaction dataset sourced from [32]. This dataset is loaded using the Pandas library, from which the target variable, 'Class', is extracted. This operation results in two distinct variables: x for features and y for labels. Following this extraction, the data undergoes normalization using StandardScaler, ensuring that the GAN operates on normalized values and facilitates effective training and sample generation [33]. To address class imbalance, both the majority and minority classes are identified and isolated. The majority class is then further divided into training and test sets ("20:80", "30:70", and "40:60"). This structured approach balances the dataset while preparing it for GAN training, ultimately enhancing the model's ability to generate realistic minority class samples.

3.2 GANs Architecture

GANs comprise two primary components: the generator and the discriminator. The generator is responsible for creating synthetic data from random noise. It employs several dense layers equipped with ReLU (Rectified Linear Unit) activation functions, along with batch normalization to balance the training process. The output layer utilizes a Tanh activation function, which is well-suited for adjusting to the feature scale of the real dataset. This design enables the generator to produce high-quality synthetic samples that closely mimic the characteristics of the actual data.

Conversely, the discriminator's role is to accurately distinguish between real and fake data. It features a dense layer with dropout to mitigate the risk of overfitting. The discriminator ultimately produces a sigmoid output representing class probabilities that indicate the likelihood of a sample being real or fake. This dual architecture is effective in generating high-quality synthetic data that aligns firmly with the underlying distribution of the minority class, as supported by previous research. The interplay between the generator and discriminator fosters an adversarial training process that enhances the overall performance of the GAN [8][24].

3.3 Training Procedure

The training of the GAN is conducted in two main steps. The process utilizes the Adam optimizer with a learning rate of 0.0002 and a batch size of 64. Initially, the discriminator is trained using batches of both real and synthetic data generated by the generator. During this phase, the loss for both datasets is computed and smoothed to enhance training stability. Following the discriminator's training, the generator is then trained with the goal of deceiving the discriminator into classifying its synthetic samples as real. The loss for the generator is calculated based on the discriminator's ability to discriminate between real and fake data. This cyclic training process is replicated for a predetermined number of epochs, set at 10 in this instance. Throughout the training, loss values are recorded to monitor progress. Figure 2 shows the GAN algorithm used.

Algorithm 1: GAN Training

```
INITIALIZE G (Generator)
INITIALIZE D (Discriminator)

FOR each epoch DO
        # Train Discriminator (D)
        D_loss = - (log(D(real)) + log(1 - D(fake)))
        UPDATE D USING D_loss

        # Train Generator (G)
        G_loss = - log(D(fake))
        UPDATE G USING G_loss

        PRINT D_loss
        PRINT G_loss
END FOR
```

Figure 2. GAN training algorithm

3.4 Data Augmentation

After the successful training of the GAN, synthetic samples of the minority class are generated to create a balanced dataset. The extent of this expansion is determined by the original class distribution, with the goal of achieving a balanced 1:1 ratio between the minority and majority classes. The newly generated synthetic examples are then integrated into the original dataset, ensuring a diverse representation of both classes. This method aligns with findings that demonstrate GANs' capability to synthesize diverse data that accurately reflects the distribution of the minority class [7][34]. By enriching the dataset with these realistic samples, the model's performance on minority class predictions is significantly enhanced.

3.5 Model Evaluation

To assess the impact of synthesized data on model performance, several classifiers—including Random Forest (RF), Gradient Boosting (GB) and Decision Tree (DT)—are evaluated using both the original imbalanced dataset and an augmented dataset that includes synthetic samples. The performance of these models is measured based on key metrics such as precision, recall, F1 score, and accuracy. This rigorous methodology is crucial for validating the effectiveness of synthetic data in enhancing classification tasks, ensuring that improvements in model performance are both measurable and significant [3].

4. RESULTS AND DISCUSSION

This section presents the results obtained from the experiments addressing the challenges of GAN using imbalanced datasets.

Table 3 summarizes the findings from our experiments. The RF classifier performs exceptionally well across all data splits, consistently achieving perfect precision (1.00). This indicates the model is always correct when predicting positive results, a significant advantage in applications where false positives can incur substantial costs. However, while precision remains high, recall varies, particularly showing lower values in the 40:60 split. Nevertheless, RF's computational efficiency is commendable, delivering results within a reasonable timeframe, making it suitable for scenarios where speed is critical.

Table 3 Model evaluation

	Techniques	Accuracy	Precision	Recall	F1-Score	Time (s)
20:80	Random Forest	0.999772	1.00	0.845238	0.916129	36.05
	Gradient Boosting	**0.999877**	0.987342	0.928571	0.957055	243.09
	Decision Tree	0.998982	0.632653	0.738095	0.681319	4.70
30:70	Random Forest	0.999754	1.00	0.838462	0.912134	33.14
	Gradient Boosting	**0.999895**	0.991870	0.938462	0.964427	196.32
	Decision Tree	0.999356	0.790698	0.784615	0.787645	3.96
40:60	Random Forest	0.999552	1.00	0.722826	0.839117	28.01
	Gradient Boosting	**0.999763**	0.943503	0.907609	0.925208	178.56
	Decision Tree	0.999228	0.792683	0.706522	0.747127	3.20

GB is noted for its accuracy, particularly in the 30:70 split, where it achieves the highest accuracy of 0.999895. Additionally, it demonstrates impressive recall across all splits, indicating its effectiveness in identifying true positives. GB balances precision and recall well, as reflected in its high F1 scores, which are the best among the classifiers tested. However, this performance comes with a trade-off in computational time, suggesting it may be better suited for applications where accuracy takes precedence over speed.

Despite being the fastest of the classifiers, DT exhibits lower overall performance metrics. Its accuracy ranges from 0.998982 to 0.999228, but precision and recall are comparatively lower, especially in the 20:80 and 40:60 splits. The simplicity of DT facilitates rapid calculations, making it a viable option for scenarios requiring quick predictions. However, its limitations in precision and recall suggest it may not be optimal for tasks where accuracy is paramount.

GB emerges as the best classifier due to its highest accuracy, recall and F1 scores, reflecting its capability to handle the classification task effectively. It identifies positive instances while maintaining a high level of precision. Conversely, RF remains a strong contender, particularly for applications prioritizing computational efficiency and minimizing false positives. Ultimately, the selection of a classifier should be guided by the specific demands of the task, weighing the need for accuracy against computational speed and the significance of precision in predictions.

5. CONCLUSION

Addressing class imbalances continues to pose significant challenges across various domains, particularly in applications where accurate predictions for minority classes—such as in healthcare and fraud detection—can have substantial consequences. Traditional resampling methods, including oversampling and undersampling, often fail to capture the complexity of minority class distributions. This limitation can lead to suboptimal model performance, as these methods may not adequately reflect the intricate characteristics of minority classes.

This paper demonstrates that GANs offer a robust alternative by generating realistic synthetic samples that enhance the learning process of ML models. By integrating GANs into the data preprocessing pipeline, model accuracy and generalization can be significantly improved, resulting in enhanced performance on imbalanced classification tasks.

Additionally, the study underscores the importance of carefully designing GAN architectures to maximize their effectiveness. This includes optimizing the training process, ensuring diversity in generated samples, and appropriately balancing the ratio of real to synthetic data. Future research should explore further enhancements to GANs and evaluate their applicability across various imbalanced datasets, ultimately aiming to refine predictive models and achieve more equitable outcomes in machine learning applications.

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