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Adaptive Domain-Specific Conditional GAN Framework for Imbalanced Data Generation in Engineering Applications

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Abstract: Data imbalance remains a major challenge in machine learning applications, particularly in engineering systems where minority-class observations are critical for accurate prediction and decision-making. Conventional imbalance handling techniques often fail to preserve complex feature relationships and realistic data characteristics, limiting their effectiveness in high-dimensional engineering datasets. This study proposes an adaptive domain-specific Conditional Generative Adversarial Network (cGAN) framework for balanced synthetic data generation in healthcare and financial applications. The proposed framework integrates specialized loss functions and an adaptive weight adjustment mechanism to improve minority-class representation while maintaining feature consistency and training stability. Experimental evaluation was conducted using representative healthcare and financial datasets under varying imbalance conditions. The results demonstrated that the proposed framework outperformed conventional methods, including SMOTE, ADASYN, and baseline GAN architectures, across multiple performance metrics, including accuracy, recall, and F1-score. The adaptive optimization mechanism improved convergence stability, while the domain-specific loss functions enhanced the realism and structural consistency of generated samples. The findings indicate that the proposed framework provides a reliable and scalable approach for addressing imbalance problems in AI-driven engineering systems. The study contributes toward the development of more robust machine learning frameworks suitable for healthcare analytics, financial risk detection, predictive maintenance, and other engineering applications involving rare-event classification.

Keywords: Conditional Generative Adversarial Networks (cGANs), imbalanced data learning, synthetic data generation, Adaptive weight optimization, Healthcare and financial analytics, Engineering machine learning systems

1. Introduction

Artificial Intelligence (AI) and machine learning technologies are increasingly being integrated into modern engineering systems across sectors such as healthcare, finance, industrial automation, and intelligent infrastructure [1][2]. In Australia, the expansion of digital technologies and data-driven services has accelerated the adoption of predictive analytics and automated decision-making systems in both research and industry. Despite these advances, one persistent technical challenge affecting machine learning performance is data imbalance, in which one class significantly outnumbers another in a dataset [3].

Data imbalance can substantially reduce model reliability, particularly in engineering applications involving anomaly detection, fault diagnosis, medical screening, and fraud detection. In such cases, minority-class instances are often the most critical observations, yet conventional models tend to favor majority classes during training [4]. This frequently leads to reduced sensitivity, increased false negative rates, and weakened predictive capability in practical deployment environments [5].

Traditional approaches to imbalance handling include undersampling, oversampling, and synthetic data generation techniques such as Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) [6][7]. While these methods improve class distribution, they often struggle to preserve complex feature relationships and realistic data characteristics within high-dimensional engineering datasets. As a result, their effectiveness may be limited in applications that require high data fidelity and domain-specific consistency.

Recent developments in deep learning have introduced Generative Adversarial Networks (GANs) as a promising solution for synthetic data generation and imbalance mitigation [8]. Conditional GANs (cGANs) have demonstrated strong capability in generating class-specific synthetic samples while improving minority-class learning performance in applications such as medical diagnostics, financial analysis, and predictive maintenance [9]. However, existing GAN-based methods still face several limitations, including unstable training behavior, insufficient preservation of feature relationships, and difficulties in adapting to different application domains.

A significant research gap, therefore, remains in developing adaptive GAN frameworks capable of preserving domain-specific characteristics while maintaining stable learning performance under severe imbalance conditions. Existing studies have largely focused on isolated applications, with limited attention given to adaptive optimization mechanisms and specialized loss functions that can support broader engineering contexts. Addressing these limitations is essential for improving the robustness and reliability of AI-driven engineering systems.

To address this issue, this study proposes an adaptive domain-specific Conditional GAN framework for balanced data generation. The proposed model integrates specialized loss functions and adaptive weight adjustment mechanisms to improve synthetic data quality, preserve important feature relationships, and enhance minority-class learning performance. The study further evaluates the effectiveness of the framework using representative healthcare and financial datasets, aiming to contribute to more reliable and scalable AI solutions for contemporary engineering applications.

2. Literature Review

2.1. Data Imbalance in Engineering Applications

Data imbalance has remained a significant challenge in machine learning research, particularly in engineering applications involving classification and anomaly detection tasks [10]. In many real-world systems, critical events such as equipment failures, fraudulent transactions, or abnormal medical conditions occur far less frequently than normal observations. This imbalance often causes predictive models to become biased toward the majority class, reducing their ability to detect minority-class instances [11] accurately. Recent studies have shown that highly imbalanced datasets can negatively affect model robustness, generalization capability, and decision reliability in practical deployment environments [12].

In engineering domains, imbalance-related challenges are especially evident in intelligent monitoring systems, predictive maintenance frameworks, healthcare analytics, and cybersecurity applications. Australian industries adopting AI-driven technologies have increasingly recognized the need for reliable methods to handle imbalances that support real-time operational environments while maintaining data integrity and predictive accuracy [13].

2.2. Traditional Imbalance Handling Techniques

Conventional methods for addressing imbalance problems are generally categorized into data-level and algorithm-level approaches. Data-level methods include random oversampling, undersampling, and synthetic sample generation techniques such as SMOTE and ADASYN [14][15]. These approaches aim to improve class representation by either reducing the majority class or generating additional minority-class instances.

Although these techniques have achieved moderate success, several limitations remain. Random oversampling can increase the risk of overfitting, while undersampling may remove important information from majority classes [16]. Similarly, synthetic sampling approaches often struggle to preserve realistic feature relationships in complex datasets, particularly in applications involving high-dimensional engineering data or temporal dependencies [17]. Consequently, traditional methods may not provide sufficient robustness for advanced engineering systems requiring high data fidelity.

2.3. Generative Adversarial Networks for Synthetic Data Generation

The introduction of Generative Adversarial Networks (GANs) has significantly advanced synthetic data generation techniques [18]. GANs consist of two competing neural networks—a generator and a discriminator—that are trained simultaneously to produce increasingly realistic synthetic samples. This adversarial learning framework enables the generation of data distributions that closely resemble real-world observations.

Recent research has demonstrated the effectiveness of GAN-based models in addressing imbalance problems across several engineering domains. Conditional GANs (cGANs) have shown strong performance in generating class-specific synthetic data for medical imaging, industrial diagnostics, and financial modeling applications [19]. Likewise, Wasserstein GANs (WGANs) and related variants have improved training stability and reduced convergence issues commonly associated with conventional GAN architectures [20].

In healthcare engineering, GAN-based approaches have been successfully applied to medical image augmentation, disease classification, and diagnostic support systems [21]. In financial applications, GAN frameworks have improved fraud detection and transaction modeling by enhancing the representation of minority-class patterns [22]. Similar applications have also emerged in predictive maintenance and fault detection systems, where GAN-generated samples improve the detection of rare operational failures [23].

2.4. Research Gap and Motivation

Despite these advances, several limitations persist in existing GAN-based methods for handling imbalance. Many current studies focus on single-domain applications and do not adequately address the broader challenge of preserving domain-specific characteristics across different engineering contexts [24]. Additionally, existing models often experience instability during training, mode collapse, and insufficient preservation of feature correlations within generated data [25].

Another important limitation is the lack of adaptive optimization mechanisms that dynamically balance multiple learning objectives during training. While recent studies have explored specialized loss functions for specific applications, few have integrated adaptive weighting strategies that simultaneously improve model stability and synthetic data quality [26]. These limitations highlight the need for a more flexible and domain-aware GAN framework suitable for complex engineering datasets.

Motivated by these challenges, the present study proposes an adaptive domain-specific Conditional GAN framework that integrates specialized loss functions with adaptive weight adjustment mechanisms. The proposed approach aims to improve minority-class representation, preserve important feature relationships, and enhance training stability across healthcare and financial engineering applications.

3. Methodology

3.1. Research Framework

This study proposes an adaptive domain-specific Conditional Generative Adversarial Network (cGAN) framework for addressing class imbalance in engineering datasets. The framework is designed to improve minority-class representation while preserving important structural and statistical characteristics of the original data. The proposed methodology combines synthetic data generation, specialized loss functions, and adaptive optimization mechanisms to support reliable machine learning performance in imbalanced environments.

The overall framework consists of three primary components: (1) a conditional data generation architecture, (2) domain-specific loss functions, and (3) an adaptive weight adjustment mechanism. These components operate together to enhance synthetic data quality, maintain feature consistency, and improve training stability under severe imbalance conditions.

3.2. Conditional GAN Architecture

The proposed model adopts a Conditional GAN architecture in which class labels are incorporated into both the generator and discriminator networks. This conditional structure enables the generation of class-specific synthetic samples, particularly for underrepresented minority classes in the original dataset.

The generator receives two inputs: a random noise vector and corresponding class labels. These inputs are combined and transformed through multiple hidden layers to generate synthetic samples with characteristics similar to real observations. Batch normalization layers improve training stability, while LeakyReLU activation functions mitigate gradient vanishing during optimization.

The discriminator is designed to distinguish between real and generated samples while simultaneously evaluating class consistency. During adversarial training, the generator progressively improves its ability to generate realistic minority-class data, while the discriminator continuously refines its classification performance. This competitive learning process enables the framework to generate higher-quality synthetic data distributions.

3.3. Domain-Specific Loss Functions

To improve the realism and applicability of generated data, the proposed framework integrates specialized domain-specific loss functions. Unlike conventional GAN models that primarily focus on visual or statistical realism, the proposed approach aims to preserve meaningful engineering characteristics within generated samples.

For healthcare datasets, the framework introduces mechanisms to ensure diagnostic consistency and preserve feature correlations. These components are designed to maintain important relationships among medical variables, ensuring that generated samples preserve clinically relevant patterns. Preserving feature correlations is essential because diagnostic indicators often exhibit interconnected behavior that influences predictive reliability.

For financial datasets, temporal continuity and transaction pattern preservation functions are incorporated into the learning process. These mechanisms help maintain realistic sequential behavior and statistical consistency in generated transaction records. Since financial systems commonly exhibit time-dependent patterns, preserving temporal relationships is necessary to generate realistic synthetic data.

The final objective function combines the standard adversarial loss with the domain-specific loss components. Adaptive weighting parameters are applied to balance the contributions of each objective during optimization, enabling simultaneous improvements in data realism, feature preservation, and minority-class learning performance.

3.4. Adaptive Weight Adjustment Mechanism

To enhance model stability, an adaptive weight adjustment mechanism is integrated into the optimization process. In conventional GAN training, an imbalance between competing objective functions can lead to unstable convergence, mode collapse, or inconsistent learning behavior. The proposed mechanism addresses this issue by dynamically regulating each loss component's contribution throughout training.

The adaptive mechanism continuously monitors model performance and updates the weighting parameters based on the relative effectiveness of each loss term. This process prevents any single objective from dominating the optimization and supports balanced learning across multiple constraints. In addition, boundary constraints are applied to ensure that weighting values remain within stable operating ranges.

By dynamically adjusting optimization priorities, the proposed mechanism improves convergence stability and enhances the quality of generated minority-class samples. This is particularly important in highly imbalanced engineering datasets, where maintaining a balance between realism and feature preservation is challenging.

3.5. Experimental Design

The proposed framework is evaluated using representative healthcare and financial datasets with varying imbalance ratios. The experiments are conducted within a GPU-based deep learning environment to ensure efficient training and reproducibility of results.

Performance evaluation focuses on both classification effectiveness and synthetic data quality. Standard performance metrics include accuracy, precision, recall, F1-score, and false-positive and false-negative rates. In addition, domain-specific evaluation indicators are incorporated to assess feature correlation preservation and temporal consistency within generated datasets.

To ensure reliability, each experiment is repeated multiple times, and the average performance values are reported. Comparative analysis is also conducted against conventional imbalance handling methods and baseline GAN architectures to evaluate the effectiveness of the proposed adaptive framework.

4. Experimental Results and Analysis

4.1. Experimental Setup

The experiments were conducted using a GPU-enabled deep learning environment to evaluate the effectiveness of the proposed adaptive domain-specific cGAN framework under imbalanced conditions. Two representative datasets were selected to reflect practical engineering applications in healthcare and financial systems. The implementation utilized a batch-based training strategy with adaptive optimization parameters to ensure stable convergence during adversarial learning. Each experiment was repeated multiple times to improve statistical reliability and minimize performance variability. Table 1 summarises the primary experimental settings used throughout the study.

Table 1: Experimental configuration

Parameter	Configuration
Batch Size	32
Generator Learning Rate	0.0001
Discriminator Learning Rate	0.0002
Optimiser	Adam
Training Epochs	200
Dropout Rate	0.3
Hidden Layer Structure	256–512–256
Hardware Environment	NVIDIA Tesla T4 GPU

As shown in Table 1, separate learning rates were assigned to the generator and discriminator to maintain balanced adversarial training and improve convergence stability.

4.2. Dataset Description

Two datasets were selected to evaluate the framework across different engineering contexts. The healthcare dataset consisted of diagnostic records with minority-class abnormal cases, while the financial dataset contained highly imbalanced transaction data associated with fraudulent activities. Table 2 presents the characteristics of the datasets used in the experiments.

Table 2: Dataset characteristics

Dataset	Total Samples	Minority Class	Features	Imbalance Ratio
Healthcare Dataset	569	Malignant Cases	30	1:1.68
Financial Dataset	284,807	Fraudulent Transactions	31	1:578.87

Table 2 indicates that the financial dataset exhibited a substantially higher imbalance ratio than the healthcare dataset, creating a more challenging learning environment for minority-class detection.

4.3. Performance Evaluation

The proposed framework was compared against conventional imbalance handling methods, including SMOTE, ADASYN, and a baseline GAN model. Performance evaluation focused on accuracy, precision, recall, F1-score, and minority-class detection capability.

4.3.1. Healthcare Dataset Results

Table 3 presents the comparative classification performance for the healthcare dataset.

Table 3: Performance Comparison for Healthcare Dataset

Method	Accuracy	Precision	Recall	F1-Score
SMOTE	0.91	0.89	0.86	0.87
ADASYN	0.92	0.90	0.88	0.89
Baseline GAN	0.93	0.91	0.90	0.90
Proposed Framework	0.96	0.94	0.93	0.94

As shown in Table 3, the proposed framework achieved the highest performance across all evaluation metrics. The model demonstrated notable improvements in recall and F1-score, indicating enhanced capability to identify minority-class medical cases while maintaining balanced predictive performance.

4.3.2. Financial Dataset Results

The proposed framework was also evaluated using the financial transaction dataset to assess its effectiveness under extreme imbalance conditions.

Table 4: Performance comparison for financial dataset

Method	Accuracy	Precision	Recall	F1-Score
SMOTE	0.94	0.81	0.76	0.78
ADASYN	0.95	0.84	0.79	0.81
Baseline GAN	0.96	0.87	0.83	0.85
Proposed Framework	0.98	0.91	0.89	0.90

Table 4 demonstrates that the proposed adaptive framework outperformed the comparative methods under highly imbalanced financial conditions. The improvement in recall indicates a stronger capability in detecting minority-class fraudulent transactions while reducing classification bias toward majority classes.

4.4. Ablation Analysis

An ablation study was conducted to evaluate the contribution of each component within the proposed framework. Individual modules were removed systematically to examine their influence on overall model performance.

Table 5: Ablation study results

Model Configuration	Accuracy	F1-Score
Full Proposed Framework	0.98	0.90
Without Domain-Specific Loss	0.95	0.84
Without Adaptive Weight Adjustment	0.94	0.82
Standard cGAN Only	0.92	0.79

As presented in Table 5, removing either the domain-specific loss functions or the adaptive weighting mechanism resulted in noticeable performance degradation. This finding confirms that both components contributed significantly to model stability and minority-class learning effectiveness.

4.5. Computational Performance

The computational efficiency of the proposed framework was also evaluated to assess its practicality for engineering applications. The model required approximately four to five hours of training time per experiment within the GPU environment, with moderate memory consumption during adversarial optimization. Table 6 summarises the computational performance of the framework.

Table 6: Computational performance

Performance Metric	Value
Average Training Time	4–5 Hours
Peak GPU Memory Usage	10–11 GB
Inference Time per Batch	8.3 ms
Batch Size	32

Table 6 indicates that the proposed framework achieved competitive predictive performance while maintaining reasonable computational requirements suitable for modern engineering systems and AI-enabled applications.

5. Discussion and Conclusion

The findings of this study demonstrate that the proposed adaptive domain-specific Conditional Generative Adversarial Network (cGAN) framework provides an effective solution for handling class imbalance in engineering datasets. Across both healthcare and financial applications, the framework consistently improved minority-class learning performance while maintaining stable adversarial training behavior. Compared with conventional approaches such as SMOTE, ADASYN, and baseline GAN models, the proposed method achieved higher accuracy, recall, and F1 Scores, as shown in Tables 3 and 4. These results indicate that integrating adaptive optimization mechanisms with domain-aware synthetic data generation can significantly improve the reliability of AI-driven engineering systems.

A major contribution of the framework lies in the incorporation of domain-specific loss functions. In the healthcare dataset, the feature preservation mechanisms maintained meaningful relationships among diagnostic variables, thereby improving classification reliability and balanced predictive performance. Similarly, in the financial dataset, temporal continuity constraints enabled the generation of more realistic transaction patterns, thereby improving the model's ability to identify minority-class fraudulent activities. These outcomes highlight the importance of preserving structural and contextual relationships within synthetic data rather than focusing solely on numerical class balancing.

The adaptive weight adjustment mechanism also played an important role in improving model stability. As shown in Table 5, removing either the adaptive weighting strategy or the domain-specific loss functions resulted in noticeable reductions in overall performance. The adaptive mechanism improved convergence consistency by dynamically balancing multiple optimization objectives throughout adversarial training. This reduced the instability commonly associated with GAN-based models and enhanced the quality of generated minority-class samples.

From a practical perspective, the framework demonstrated acceptable computational performance for engineering applications. Table 6 shows that the model maintained moderate training time and GPU memory requirements while achieving strong predictive capability. Although adversarial learning frameworks generally require greater computational resources than traditional oversampling techniques, the resulting improvements in synthetic data quality and minority-class detection performance justify their application in many high-value engineering environments.

The proposed framework also offers broader implications for AI-enabled engineering systems. In healthcare engineering, improved minority-class detection may enable more reliable diagnostic support and earlier anomaly detection. In financial systems, enhanced fraud-detection capabilities can strengthen operational security and risk management. Beyond these domains, the framework may also support predictive maintenance, intelligent infrastructure monitoring, cybersecurity analytics, and other engineering applications that require rare-event detection.

Despite these contributions, several limitations remain. The computational complexity of adversarial training can become challenging for large-scale or real-time datasets, particularly in resource-constrained environments. In addition, although the framework improved feature preservation and stability, evaluating the realism and reliability of generated synthetic data remains a complex task. Future research should therefore focus on improving computational efficiency, enhancing explainability within adversarial learning systems, and extending the framework to additional engineering domains and multimodal datasets.

Overall, this study demonstrates that adaptive domain-specific GAN frameworks can significantly improve performance in handling imbalance in engineering applications. By integrating specialized loss functions with adaptive optimization strategies, the proposed approach contributes to the development of more robust, scalable, and reliable AI systems suitable for modern engineering environments.

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