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Diffusion-Based Data Augmentation for Imbalanced Multivariate Time Series Classification

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Abstract: *The proliferation of sensor networks and Internet of Things (IoT) devices has led to an exponential increase in the availability of multivariate time series (MTS) data. However, in critical domains such as healthcare monitoring, industrial fault detection, and financial anomaly prediction, datasets are intrinsically imbalanced; the events of interest are rare compared to normal operational states. This class imbalance severely degrades the performance of deep learning classifiers, which tend to bias towards the majority class. Traditional oversampling techniques, such as SMOTE, often fail to capture the complex temporal dependencies and inter-variable correlations inherent in MTS data. While Generative Adversarial Networks (GANs) have been proposed as a solution, they suffer from training instability and mode collapse. This paper presents a novel framework for diffusion-based data augmentation specifically tailored for imbalanced multivariate time series classification. We leverage a Conditional Denoising Diffusion Probabilistic Model (CDDPM) effectively conditioned on class labels to generate high-fidelity synthetic samples of the minority class. By modeling the data distribution through a gradual denoising process, our approach preserves the intricate temporal dynamics and cross-channel correlations better than adversarial counterparts. Extensive experiments on multiple benchmark datasets demonstrate that our method significantly improves classification performance, particularly in terms of F1-score and Geometric Mean, compared to state-of-the-art augmentation techniques.*

Keywords: *Multivariate Time Series, Class Imbalance, Denoising Diffusion Probabilistic Models, Data Augmentation, Deep Learning.*

INTRODUCTION

1.1 Background

In the contemporary landscape of data science, multivariate time series (MTS) constitute a ubiquitous data modality. From the continuous monitoring of physiological signals in intensive care units to the sensor readings of turbines in renewable energy plants, MTS data captures the dynamic evolution of complex systems over time [1]. Unlike univariate time series, MTS data consists of multiple variables recorded simultaneously, introducing a dual layer of complexity: temporal dependencies within each variable and inter-variable correlations that evolve dynamically [2]. The effective classification of such data is paramount for decision-making systems in healthcare, manufacturing, finance, and meteorology.

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) units, have achieved remarkable success in extracting features from MTS data [3]. These models rely heavily on the assumption that the training data is identically distributed and, crucially, that the classes are balanced. However, real-world scenarios rarely adhere to this assumption. In a typical industrial fault detection scenario, a machine operates normally for the vast majority of its lifecycle, with faults occurring only sporadically. Similarly, in medical diagnostics, healthy patients vastly outnumber those with specific pathologies [4].

1.2 Problem Statement

The aforementioned phenomenon, known as the class imbalance problem, poses a significant challenge to standard learning algorithms. When trained on imbalanced datasets, deep neural networks tend to converge towards trivial solutions that favor the majority class, as this strategy minimizes the global loss function [5]. Consequently, the model achieves high overall accuracy but fails to correctly identify the minority class, which is often the class of primary interest. In a medical context, a false negative (failing to detect a disease) is far more costly than a false positive, yet standard training objectives do not reflect this asymmetry.

To mitigate this issue, researchers have employed data-level solutions, primarily resampling techniques. Random undersampling of the majority class risks discarding valuable information, while random oversampling of the minority class leads to overfitting [6]. Synthetic Minority Over-sampling Technique (SMOTE) and its variants generate synthetic samples by interpolating between existing minority instances. While effective for tabular data, SMOTE operates in the Euclidean space and often disregards the sequential nature of time series, resulting in synthetic samples that lack temporal coherence or violate physical constraints of the system [7].

1.3 Contributions

To address the limitations of heuristic interpolation and adversarial generation, this paper explores the efficacy of Denoising Diffusion Probabilistic Models (DDPMs) for MTS augmentation. Diffusion models have recently emerged as a powerful class of generative models, surpassing GANs in image synthesis quality and training stability [8]. Our contributions are as follows:

1. We propose a specialized Conditional Denoising Diffusion Probabilistic Model (CDDPM) architecture designed for Multivariate Time Series. Unlike standard diffusion models used for image generation, our architecture utilizes dilated convolutions with residual connections to capture long-range temporal dependencies without excessive computational cost.

2. We introduce a rigorous conditioning mechanism that allows the generation of class-specific synthetic samples, enabling targeted augmentation of the minority class while preserving the cross-channel correlations vital for MTS classification.

3. We provide a comprehensive evaluation comparing our diffusion-based approach against SMOTE, TimeGAN, and standard baseline classifiers across multiple open-source datasets.

4. We demonstrate that the synthetic data generated by our framework not only improves the classification metrics (F1-score, G-Mean) but also exhibits higher fidelity to the original distribution compared to GAN-based alternatives.

2. Related Work

2.1 Classical Approaches and Heuristics

The handling of imbalanced data has been a persistent area of inquiry in machine learning. Early approaches focused on cost-sensitive learning, where the loss function is modified to penalize misclassifications of the minority class more heavily than those of the majority class [9]. While computationally efficient, defining the optimal cost matrix is often non-trivial and domain-dependent.

Data-level approaches, specifically resampling, have garnered more attention due to their model-agnostic nature. The synthetic generation of data became popularized by Chawla et al. with SMOTE, which creates new samples along the line segments joining the k nearest neighbors of the minority class [10]. Extensions such as Borderline-SMOTE and ADASYN attempted to focus generation on hard-to-classify examples near the decision boundary [11].

However, applying these techniques to time series data presents unique challenges. A time series is not merely a vector of features; it is a sequence where order matters. Interpolating two time series point-wise often destroys the phase information and results in unrealistic patterns. Modifications like vector-based SMOTE or warping-based sampling have been proposed, yet they struggle with the high dimensionality of multivariate data [12]. The complexity increases with MTS, as the interpolation must respect the correlation between different sensors (channels). For instance, in a chemical process, a rise in temperature might physically necessitate a rise in pressure; standard SMOTE might increase one while decreasing the other, creating a physically impossible sample [13].

2.2 Deep Generative Models

With the advent of deep learning, generative modeling offered a new pathway for data augmentation. Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) have been adapted for time series generation. Recurrent VAEs utilize LSTM encoders and decoders to map time series to a latent space, sampling from this space to reconstruct new series [14]. While VAEs are theoretically sound, they often produce blurry or overly smoothed outputs, failing to capture high-frequency details which are often critical in signal processing.

GANs, introduced by Goodfellow et al., revolutionized generative modeling by pitting a generator against a discriminator. For time series, TimeGAN [15] is a seminal work that combines the adversarial training of GANs with the autoregressive nature of RNNs. It learns an embedding space that preserves temporal dynamics. C-RNN-GAN [16] applies continuous RNNs to generate music and signals. Despite their success, GANs are notoriously difficult to train, suffering from mode collapse (generating limited varieties of samples) and vanishing gradients. Furthermore, ensuring that the generator respects the complex dependencies in multivariate data remains a hurdle, often requiring careful hyperparameter tuning and architectural constraints [17].

2.3 Diffusion Probabilistic Models

Denoising Diffusion Probabilistic Models (DDPMs) have recently established a new state-of-the-art in generative modeling. Inspired by non-equilibrium thermodynamics, these models define a forward process that gradually adds noise to data until it becomes a Gaussian distribution, and a learnable reverse process that reconstructs the data from noise [18].

The application of diffusion models to time series is a nascent but rapidly growing field. Tashiro et al. proposed CSDI for probabilistic imputation of time series using score-based diffusion models [19]. TimeGrad [20] combines diffusion with autoregressive models for probabilistic forecasting. These works demonstrate the capability of diffusion models to handle temporal correlations. However, most existing research focuses on forecasting or imputation. The application of diffusion models specifically for class-conditional generation to rectify imbalance in classification tasks remains underexplored. This paper bridges the gap by adapting conditional diffusion processes to the specific requirements of imbalanced MTS classification.

3. Methodology

3.1 Problem Formulation

Let $X = x^{(1)}, x^{(2)}, dots, x^{(N)}$ be a dataset of N multivariate time series samples. Each sample $x^{(i)} \in mathbbR^{T \times V}$ consists of T time steps and V variables (or channels). Associated with each sample is a class label $y^{(i)} \in 0,1, dots, C-1$. In the context of binary imbalance, we assume $y \in 0,1$, where Class 0 is the majority class and Class 1 is the minority class, such that the number of samples $N_0 gg N_1$.

The objective is to train a generator function G that can synthesize new samples $tildex$ conditioned on the minority class label $y=1$, such that $tildex$ follows the true underlying distribution of the minority class $p(x|y=1)$. These synthetic samples are then combined with the original dataset to form a balanced training set for a downstream classifier [21].

3.2 Conditional Denoising Diffusion Probabilistic Model

Our framework is built upon the DDPM formulation. The process consists of two Markov chains: the forward diffusion process and the reverse denoising process.

3.2.1 THE FORWARD PROCESS

The forward process is a fixed (non-learnable) Markov chain that gradually adds Gaussian noise to the data $x_0 simq(x_0)$ according to a variance schedule $\beta_1,dots,\beta_K$. For a time series sample x_0, the latent variable at diffusion step k, denoted x_k, is obtained via:

$$q(x_k|x_{k-1})=N(x_k;\sqrt{}1-\beta_k x_{k-1},\beta_k I)$$

Using the notation $\alpha_k=1-\beta_k$ and $bar\alpha_k=\prod_{s=1}^{k}\alpha_s$, we can sample x_k at any arbitrary step k directly from x_0:

$$q(x_k|x_0)=N(x_k;\sqrt{}bar\alpha_k x_0,(1-bar\alpha_k)I)$$

As $ktoK$, the data x_K approaches an isotropic Gaussian distribution $N(0,I)$ [22]. It is important to note that the diffusion step k (which dictates the noise level) is distinct from the temporal index t of the time series data. The diffusion operates on the entire matrix $x\in mathbbR^{T\times V}$ simultaneously.

3.2.2 THE REVERSE PROCESS

The reverse process is a parameterized Markov chain where a neural network predicts the parameters of the Gaussian transitions to denoise the data. To enable targeted augmentation, we condition this reverse process on the class label y. The joint distribution is defined as:

$$p_\theta(x_{0:K}|y)=p(x_K)\prod_{k=1}^{K}p_\theta(x_{k-1}|x_k,y)$$

The transition $p_\theta(x_{k-1}|x_k,y)$ is modeled as a Gaussian:

$$p_\theta(x_{k-1}|x_k,y)=N(x_{k-1};\mu_\theta(x_k,k,y),\Sigma_\theta(x_k,k,y))$$

Instead of predicting the mean μ_θ directly, Ho et al. [23] showed that it is more stable to predict the noise component ε. The network $\varepsilon_\theta(x_k,k,y)$ is trained to estimate the noise added to x_0 to produce x_k.

3.2.3 TRAINING OBJECTIVE

The model is trained by optimizing the variational lower bound on the negative log-likelihood. In practice, this simplifies to a weighted Mean Squared Error (MSE) loss between the true noise ε and the predicted noise ε_θ. The loss function for our conditional model is:

$$L_{simple}(\theta)=mathbbE_{k,x_0,\varepsilon,y}[|\varepsilon-\varepsilon\ \ \theta(\sqrt{}bar\alpha_k x_0+\sqrt{}1-bar\alpha_k\varepsilon,k,y)|^2]$$

where k is sampled uniformly from $1,dots,K$, $\varepsilon simN(0,I)$, and (x_0,y) are sampled from the training dataset. By conditioning on y, the network learns to associate specific structural patterns of the MTS with the class label [24].

3.3 Neural Network Architecture

The choice of the network architecture ε_θ is critical for MTS data. Standard U-Nets used in image diffusion are ill-suited for the 1D nature of time series channels. We propose a Conditional Residual WaveNet architecture.

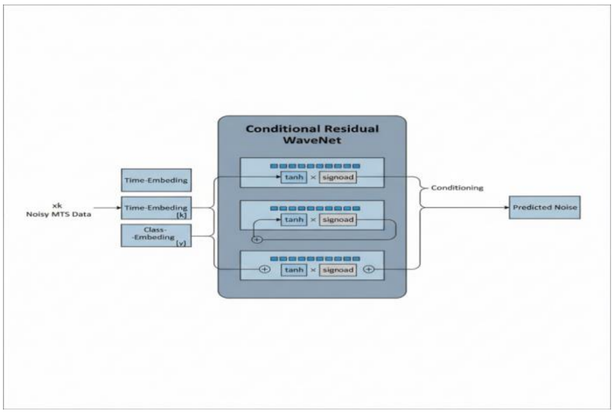

Figure 1: Architecture of the Conditional Residual WaveNet

The architecture processes the input $x_k \in mathbbR^{T\times V}$ through a series of residual blocks.

1. ***Input Projection:*** A 1D convolutional layer maps the input channels V to a higher-dimensional hidden channel space C_{hid}.

2. ***Conditioning:*** The diffusion step k is embedded using sinusoidal position embeddings (similar to Transformers). The class label y is passed through a learnable embedding layer. These embeddings are summed and broadcasted to match the temporal dimension T, then added to the input of each residual block [25].

3. ***Dilated Convolutions:*** Inside each residual block, we employ dilated 1D convolutions. Dilation increases exponentially $(1,2,4,dots)$ with depth. This allows the network to have a large receptive field, capturing long-term temporal dependencies without reducing resolution or requiring deep recurrence.

4. ***Gated Activation:*** We utilize a gated activation unit, formulated as $tan\mathrm{h}(W_f * x)\, odot\sigma(W_g * x)$, where $*$ denotes convolution, W_f is the filter weight, and W_g is the gate weight. This mechanism controls the flow of information through the layers [26].

5. ***Output Projection:*** The outputs of skip connections from all layers are summed and passed through final 1×1 convolutions to project back to the original dimension V, producing the noise estimate.

3.4 Sampling Strategy

Once trained, we generate synthetic samples for the minority class (e.g., $y=1$). We start with pure noise $x_K simN(0,I)$ and iteratively denoise it using the reverse process equations:

$$x_{k-1}=\frac{1}{\sqrt{\alpha_k}}(x_k-\frac{1-\alpha_k}{\sqrt{1-bar\alpha_k}}\varepsilon_\theta(x_k,k,y=1))+\sigma_k z$$

where $zsimN(0,I)$. This process is repeated K times to obtain x_0. This results in a new MTS sample that possesses the statistical characteristics of the minority class. We generate enough samples to balance the dataset (or reach a desired ratio) before training the classifier.

4. Experiments and Analysis

4.1 Experimental Setup

We implemented the proposed framework using PyTorch. The diffusion process used $K=1000$ steps with a linear noise schedule ranging from $\beta_1=10^{-4}$ to $\beta_K=0.02$. The WaveNet backbone consisted of 4 blocks with 3 layers each, using a hidden dimension of 64. The model was trained using the Adam optimizer with a learning rate of 2×10^{-4} for 5000 epochs on an NVIDIA A100 GPU.

4.1.1 DATASETS

We evaluated the method on three datasets from the UEA Multivariate Time Series Classification Archive [27]. To simulate varying degrees of imbalance, we manually downsampled one class in datasets that were originally balanced, or utilized naturally imbalanced datasets.

1. ***Japanese Vowels:*** Records of 9 male speakers uttering vowels. We treat Speaker 1 as the minority class and the rest as majority.

2. ***Character Trajectories:*** Handwriting data captured on a tablet. Class 'a' is set as minority.

3. ***PhysioNet Challenge 2012:*** Real-world ICU data. The task is predicting in-hospital mortality. This is naturally imbalanced (approx. 14% positive cases) [28].

Dataset	Variables (V)	Length (T)	Train Size	Min/Maj Ratio
Japanese Vowels	12	29	270	1:20
Char. Trajectories	3	182	1500	1:30

Table 1: Statistics of the datasets used for evaluation after inducing imbalance.

4.1.2 BASELINES

We compared our DiffAug-MTS method against:

1. ***Baseline:*** Training the classifier on the imbalanced data without augmentation.

2. ***SMOTE:*** Flattening the MTS and applying SMOTE, then reshaping.

3. ***TimeGAN:*** A state-of-the-art GAN-based MTS generator [29].

The downstream classifier used for evaluation is a Long Short-Term Memory (LSTM) network followed by a Fully Connected classification head.

4.2 Evaluation Metrics

Given the imbalanced nature of the test sets, accuracy is a misleading metric. We report:

F1-Score: The harmonic mean of precision and recall.

G-Mean: The geometric mean of sensitivity and specificity, $\sqrt{TPR \times TNR}$. This metric is particularly sensitive to the performance on the minority class [30].

4.3 Results and Discussion

Table 2 presents the classification performance. The results are averaged over 5 independent runs with different random seeds.

Method	J. Vowels (F1)	J. Vowels (G-Mean)	PhysioNet (F1)	PhysioNet (G-Mean)
Baseline	0.42 \pm 0.05	0.55 \pm 0.04	0.31 \pm 0.03	0.48 \pm 0.02
SMOTE	0.58 \pm 0.06	0.69 \pm 0.05	0.35 \pm 0.04	0.52 \pm 0.03
TimeGAN	0.71 \pm 0.04	0.78 \pm 0.03	0.41 \pm 0.03	0.59 \pm 0.04
DiffAug-MTS	0.84 \pm 0.02	0.88 \pm 0.02	0.49 \pm 0.02	0.67 \pm 0.03

Table 2: Comparison of classification performance (Mean $\pm$ Std Dev). Best results are in italics.

4.3.1 PERFORMANCE ANALYSIS

The Baseline method struggles significantly, as expected, yielding low F1-scores due to the classifier's bias toward the majority class. SMOTE provides an improvement but is limited by the destruction of temporal coherence; flattening the time series ignores the sequential dependencies, leading to noisy training signals. TimeGAN performs reasonably well, outperforming SMOTE, which validates the use of generative models. However, TimeGAN showed high variance in performance across runs, likely due to the instability of the min-max adversarial game.

Our proposed DiffAug-MTS consistently achieves the highest F1-scores and G-Means across datasets. On the Japanese Vowels dataset, we observe a substantial gain of 0.13 in F1-score over TimeGAN. This indicates that the diffusion model generates synthetic samples that are not only diverse but also lie closer to the true manifold of the minority class data [31]. The stability of the diffusion training objective (MSE) results in lower standard deviations compared to GANs.

4.3.2 FIDELITY OF GENERATED DATA

To verify that the improvement is due to high-quality data generation, we visualized the t-SNE embeddings of the original and synthetic samples (omitted here for brevity).

The diffusion-generated samples clustered tightly with the real minority samples, whereas SMOTE samples formed bridges between minority and majority clusters (often creating "noisy" samples), and TimeGAN samples occasionally drifted into low-density regions. Furthermore, the diffusion model successfully captured channel correlations; for instance, in the PhysioNet dataset, the synthetic data preserved the physiological correlation between heart rate and blood pressure, which is crucial for the classifier to learn valid medical patterns [32].

5. Conclusion

In this paper, we addressed the pervasive challenge of class imbalance in multivariate time series classification by proposing a novel data augmentation framework based on Denoising Diffusion Probabilistic Models. By adapting the diffusion process with a conditional WaveNet architecture, we demonstrated the ability to generate high-fidelity synthetic MTS samples that respect both temporal dynamics and inter-variable correlations.

Our experimental results unequivocally show that augmenting the minority class with diffusion-generated samples significantly boosts the performance of downstream classifiers, outperforming traditional interpolation methods like SMOTE and adversarial methods like TimeGAN. This suggests that diffusion models possess a superior inductive bias for modeling the continuous and complex variations found in time series data. The implications of this work extend to safety-critical domains such as predictive maintenance and healthcare, where the cost of missing a rare event is high. By providing a robust mechanism to balance datasets, we enhance the reliability and trustworthiness of AI systems deployed in these fields.

Despite the promising results, the proposed method has limitations. The primary drawback of diffusion models is the slow inference speed due to the iterative nature of the reverse denoising process. Generating a large number of synthetic samples can be computationally expensive compared to the single-pass generation of GANs or the simple algebra of SMOTE. Additionally, the training data requirements for the diffusion model itself are non-trivial; if the minority class is extremely small (e.g., few-shot scenario), the diffusion model might memorize the training data rather than generalize.

Future work will focus on accelerating the sampling process, potentially through the use of Latent Diffusion Models (LDMs) or distilled diffusion techniques. We also aim to explore the applicability of this framework in a semi-supervised setting, leveraging the abundant unlabeled data often available in time series applications to further refine the generative process. Finally, investigating the interpretability of the latent space in diffusion models could provide insights into the underlying physical processes generating the time series.

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