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TEMPORAL-AWARE DATA AUGMENTATION VIA VARIATIONAL MODE DECOMPOSITION AND CONDITIONAL GANS FOR EEG-BASED SEIZURE DETECTION

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ABSTRACT

Automatic detection of epileptic seizures based on electroencephalogram (EEG) signal has been an essential challenge issue in automated clinical diagnostic systems. The imbalance issue in the first place and the lack of labeled seizure data seriously hinder the progress of effective deep learning models. The proposed paper introduces a temporal-aware data augmentation system that fuses Variational Mode Decomposition (VMD) and the Conditional Generative Adversarial Networks (cGANs) in order to produce realistic synthetic EEG seizure data and maintain important temporal and spectral features. The VMD-cGAN model breaks down EEG signals into intrinsic mode functions (IMFs) that represent various frequency components, and the generator learns and reproduces the physiologically realistic seizure patterns. We assess our method using CHB-MIT scalp EEG database, proving that augmented training data significantly enhances seizure detection rates. Our experimental findings indicate 97.84% accuracy, 96.73% sensitivity, and 98.52% specificity, which is 3-5% higher than state-of-the-art techniques. The framework manages the lack of data while preserving temporal relationships and morphological properties required to properly identify seizures.

Keywords: *Electroencephalogram, Seizure Detection, Data Augmentation, Variational Mode Decomposition, Conditional Generative Adversarial Networks*

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders and affects about 65 million people globally [1]. The identification and timely detection of seizures is fundamental in order to ensure patients' safety, treatment refinement and quality of life enhancement. Electroencephalogram (EEG) is the principal method to monitor electrical brain activity and detect seizure events, but manual inspection by neurologists is time-consuming and subjective with significant degrees of inter-rater variations [2]. Machine learning-based automatic seizure detection systems [3] are beginning to emerge as potential solutions for some of these challenges.

Despite the remarkable progress in deep learning-based seizure detection, two critical challenges persist that motivate the present work. First, EEG seizure datasets suffer from severe class imbalance, as seizure events constitute less than 1% of total recording time in most clinical datasets [6]. Second, inter-patient variability in EEG morphology limits the generalizability of models trained on limited labeled data. These twin challenges collectively represent the core problem addressed in this study: the lack of sufficient, high-quality labeled seizure EEG data that faithfully preserves temporal and spectral characteristics critical for accurate detection.

A. Problem Statement

The accurate and automated detection of epileptic seizures from EEG signals remains a critical yet unresolved challenge in clinical neuroscience. Current deep learning models for seizure detection are severely hampered by two interrelated problems: (1) the extreme scarcity of labeled seizure data arising from the rarity of ictal events relative to inter-ictal periods, and (2) the high temporal and spectral complexity of EEG seizure patterns that simple augmentation techniques fail to replicate authentically. Existing generative approaches, such as standard GANs or VAEs, either neglect frequency-specific characteristics of EEG signals or produce physiologically implausible synthetic data, thereby limiting their utility for training robust seizure detectors. Without a principled augmentation strategy that preserves the morphological and temporal integrity of seizure patterns, deep learning models remain prone to overfitting and poor inter-patient generalization.

B. Research Objectives and Research Questions

This study is guided by the following research objectives:

RO1: To develop a frequency-aware data augmentation framework that combines Variational Mode Decomposition (VMD) with Conditional Generative Adversarial Networks (cGANs) for generating physiologically plausible synthetic EEG seizure data.

RO2: To evaluate whether VMD-based decomposition into intrinsic mode functions (IMFs) preserves temporal and spectral seizure characteristics more effectively than direct signal-level generative approaches.

RO3: To assess the impact of the proposed augmentation strategy on the performance of a CNN-based seizure detector, specifically with respect to sensitivity, specificity, and cross-patient generalizability.

These objectives are anchored by the following research questions:

RQ1: Can a VMD-cGAN hybrid augmentation framework generate synthetic EEG seizure data that preserves clinically relevant temporal and spectral features?

RQ2: Does augmenting EEG training data using the proposed VMD-cGAN method significantly improve seizure detection accuracy, sensitivity, and specificity compared to baseline and state-of-the-art augmentation methods?

RQ3: What is the relative contribution of VMD decomposition versus conditional generation to the overall improvement in seizure detection performance?

C. Research Hypothesis

H1 (Main Hypothesis): A temporal-aware data augmentation framework that integrates VMD-based frequency decomposition with conditional GAN synthesis will generate more physiologically plausible synthetic EEG seizure data, leading to significantly higher seizure detection accuracy, sensitivity, and specificity compared to models trained without augmentation or with conventional augmentation strategies.

H2 (Sub-hypothesis): The explicit decomposition of EEG signals into IMFs via VMD, prior to GAN-based generation, will enable the cGAN to learn frequency-band-specific seizure morphology, resulting in synthetic samples that more closely resemble real seizure EEG in both the time and frequency domains compared to direct signal-level generation.

D. EEG-Based Seizure Detection

Early automated seizure detection methods were based on hand-crafted features extracted from EEG [8]. Statistical moments, line length, and nonlinear energy have been extensively employed [9, 10]. Frequency-domain characteristics such as power spectral density, spectral entropy and wavelet coefficients have also been shown to be effective in capturing seizure-related frequency variations [11]. However, a critical limitation of these handcrafted approaches is that they rely on domain expertise for feature selection, limiting their adaptability to diverse patient populations and EEG recording conditions.

The emergence of deep learning has transformed seizure detection. Acharya et al. created a 13-layer CNN that learns hierarchical features from raw EEG signals, achieving 88.67% accuracy without manual feature engineering [13]. Truong et al. proposed a hybrid CNN-LSTM architecture that simultaneously learns spatial patterns and temporal relations, demonstrating better patient-to-patient generalization [14]. More recently, attention mechanisms have been introduced to discover discriminating seizure patterns; Wei et al. suggested a multi-scale attention network that reached 96.2% sensitivity on CHB-MIT data [15].

Transformer-based architectures have demonstrated capabilities to model long-range dependencies in EEG signals. Song et al. designed an EEG transformer with learnable positional encodings that achieved state-of-the-art performance on seizure detection benchmarks [4]. Nevertheless, these advanced architectures typically demand large volumes of labeled training data—a requirement that is at odds with the inherent scarcity of seizure annotations in clinical EEG repositories.

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E. Data Augmentation for EEG Analysis

Conventional data augmentation methods applied to EEG include sliding window segmentation, Mixup, and signal warping. While overlapping window methods enhance sample diversity, they introduce label noise at seizure boundaries [16]. Mixup produces synthetic samples as linear interpolations between training examples, but such interpolations yield physiologically implausible EEG signals [17]. These methods share a critical shortcoming: they operate on the raw EEG signal without respecting its multi-band frequency structure, which is the primary discriminator between ictal and inter-ictal states.

GANs have achieved superior sample quality across many generative tasks. Hartmann et al. used Deep Convolutional GANs (DCGANs) to produce synthetic EEG motor imagery data, reporting improved classification performance [20]. For seizure detection specifically, Luo et al. introduced a Wasserstein GAN with gradient penalty (WGAN-GP) to generate minority class seizure EEG [8], and Zhang et al. proposed a bidirectional LSTM-GAN to retain temporal consistency in generated seizure sequences [21]. Despite these advances, a key limitation shared by all existing GAN-based EEG augmentation methods is that they operate on raw or minimally pre-processed EEG signals, thereby ignoring the rich frequency-band structure that underpins seizure electrophysiology.

F. Research Gap

The preceding literature critique reveals a consistent research gap: while increasingly powerful deep learning architectures have been applied to EEG seizure detection, the data imbalance problem has not been adequately addressed through biologically informed augmentation. Existing generative methods either produce physiologically implausible samples (Mixup, warping) or fail to explicitly model the frequency-band structure of ictal EEG (standard GANs, VAEs). This gap directly motivates the central research question of the present study: Can a VMD-cGAN hybrid framework generate frequency-aware synthetic seizure EEG that improves cross-patient seizure detection beyond the capabilities of existing augmentation strategies?

2. METHODOLOGY

A. Overview of the Proposed Framework

The proposed temporal-aware data augmentation framework comprises three key phases: (1) VMD-based signal decomposition, (2) conditional GAN-based synthetic data generation, and (3) seizure detection with augmented data. The stage of decomposition divides real EEG seizure and non-seizure signals into K intrinsic mode functions based on VMD. The IMFs extract certain frequency parts of the original signal to accomplish a fine-grained analysis of the oscillatory patterns of seizures. The cGAN is then trained to generate realistic IMFs conditional on class labels (seizure, non-seizure). Lastly, to train a CNN-based seizure detector, an augmented sample of real and artificial samples is utilized.

B. Variational Mode Decomposition

VMD breaks down a signal into K discrete sub-signals (modes) uk that have a prescribed sparseness in frequency space. The constrained variational problem is formulated as:

min{uk},{wk} { Σk ||∂t[(δ(t) + j/(πt)) * uk(t)]e^(-jwkt)||^2_2 } subject to: Σk uk = f

The optimization is solved using the Alternate Direction Method of Multipliers (ADMM). For each EEG segment of length L seconds sampled at fs Hz, we apply VMD with K=5 modes, which effectively separates EEG into delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (>30 Hz) frequency bands relevant to seizure analysis.

C. Conditional GAN Architecture

The generator takes as input a latent vector z ∈ R^100 sampled from a standard normal distribution and a one-hot encoded class label c ∈ R^2. These inputs are concatenated and passed through a fully connected layer, followed by reshaping and a series of transposed convolutional layers with batch normalization and LeakyReLU activation. The output is a tensor of shape (K, 64) representing K VMD modes, each with 64 time points.

The discriminator takes either real or generated VMD modes together with the class label in the channel dimension. It comprises spectral normalization convolutional layers to stabilize training. The cGAN is trained with an adversarial loss combined with a feature matching loss that prompts the generator to match statistics of intermediate discriminator features: LFM = E[||Ef(x)[f(x)] - f(G(z|c))||^2_2]. The total generator loss is: LG_total = LG + λFM × LFM, where λFM = 10.

D. Synthetic EEG Reconstruction

Generated K VMD modes are reconstructed to create full EEG records by summing the generated modes: x_synthetic(t) = Σ^K_{k=1} u^synthetic_k(t). To ensure temporal coherence and

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appropriate signal amplitude, post-processing normalizes the reconstructed signal to match the statistical properties of real EEG segments: x_normalized = (x_synthetic - μsynthetic) / σsynthetic × σreal + μreal.

E. Seizure Detection Network

The augmented data is used to train a deep CNN for seizure detection, comprising: (1) Input Layer: 2-second EEG segments (512 points at 256 Hz) across all channels; (2) Three Temporal Convolutional Blocks with Conv1D (filters=64/128/256, kernel=7), BatchNormalization, ReLU, MaxPooling1D, and Dropout(0.3); (3) Self-Attention Mechanism: Attention(Q,K,V) = softmax(QK^T / √dk)V; (4) Global Average Pooling; (5) Fully Connected Layers: two dense layers (256→64→2) with ReLU and dropout.

The network is trained using categorical cross-entropy loss with Adam optimizer (lr=0.001, β1=0.9, β2=0.999). To address remaining class imbalance, class-weighted loss is employed: L = -Σ^C_{i=1} wi × yi × log(ŷi), where wi = N / (C × Ni).

F. Training Procedure

Phase 1 – cGAN Training: Extract EEG seizure and non-seizure segments from the training fold; apply VMD decomposition to obtain K=5 IMFs per segment; train cGAN for 500 epochs with batch size 64, alternating discriminator and generator updates at a 5:1 ratio; generate synthetic seizure IMF sets until the seizure-to-non-seizure ratio reaches 1:1; reconstruct full EEG segments from synthetic IMFs via summation and amplitude normalization.

Phase 2 – Seizure Detection Training: Combine real training segments with synthetic seizure samples to form a balanced training set (1:1 ratio); train the CNN for a maximum of 100 epochs with early stopping (patience=15) monitored on the validation set; select the checkpoint with best validation AUC for final evaluation; evaluate on the held-out test set using accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC.

3. EXPERIMENTS AND RESULTS

A. Dataset and Preprocessing

We tested our approach on the CHB-MIT Scalp EEG Database, a popular standard in seizure detection studies. The data consists of continuous EEG of 23 children (5 males, ages 3-22) with intractable seizures, sampled at 256 Hz with 16-bit resolution using 23 channels in the international 10-20 format. The database contains 664 hours of EEG data including 198 seizure events of 10 to 200 seconds duration. Non-overlapping 2-second segments yielded 8,472 seizure and 1,195,200 non-seizure segments per patient.

Preprocessing steps: (1) Butterworth bandpass filter 0.5-50 Hz to remove baseline drift and high-frequency noise; (2) Artifact removal for segments exceeding ±500 μV; (3) Z-score normalization per channel; (4) Segmentation into 2-second windows with 50% overlap. Patient-specific 5-fold cross-validation was used, with one patient held out for testing per fold and remaining patients split 80:20 for training and validation.

B. Implementation Details

The architecture was implemented in PyTorch 1.12 on NVIDIA RTX 3090 hardware. Key hyperparameters selected via grid search: VMD Parameters: K=5 modes, α=2000, tolerance=1e-7; cGAN: latent dimension=100, learning rates=0.0002, β1=0.5, β2=0.999; Training: batch size=64, discriminator:generator update ratio=5:1, 500 epochs; Detection Network: lr=0.001, batch size=128, max 100 epochs, early stopping patience=15. Augmentation was applied only within training folds.

C. Main Results

Table 1 shows the overall performance comparison of our proposed VMD-cGAN augmentation algorithm and baselines on the CHB-MIT database, averaged across 23 patients using 5-fold cross-validation.

TABLE 1: PERFORMANCE OF PROPOSED METHOD ON CHB-MIT DATABASE

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
Baseline (No Aug.)	93.27±1.82	89.45 ±3.15	94.18±1.67	73.82 ±4.21	80.83±3.44
Traditional Aug.	94.51±1.64	91.23 ±2.87	95.02±1.53	76.54±3.89	83.25±3.12
Standard GAN	95.13±1.55	92.47 ±2.64	95.68±1.48	78.91±3.52	85.13±2.89
cGAN (No VMD)	95.86±1.47	93.28 ±2.51	96.34±1.42	81.05±3.27	86.74±2.71
VMD + Feature Ext.	96.34±1.39	94.16 ±2.38	96.89±1.35	83.27±3.08	88.35±2.56
Proposed VMD-cGAN	97.84±1.12	96.73 ±1.95	98.52±1.08	89.46±2.43	92.93±2.08

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The proposed VMD-cGAN method achieves significant improvements across all evaluation metrics. With respect to RO3, the augmented model improves accuracy by 4.57%, sensitivity by 7.28%, and F1-score by 12.10% over the no-augmentation baseline. The sensitivity improvement is of particular clinical significance, as it confirms that the framework substantially reduces missed seizure detections—the most consequential error type in automated clinical systems. These gains confirm that VMD-cGAN augmentation provides measurably superior improvements compared to both traditional and GAN-only augmentation strategies (RQ2).

D. Comparison with State-of-the-Art Methods

Table II compares our proposed technique with current state-of-the-art seizure detection methods on the CHB-MIT database. All techniques adopt independent evaluation protocols for fair comparison.

TABLE II: COMPARISON WITH STATE-OF-THE-ART METHODS

Method	Year	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
Multi-scale CNN [15]	2022	94.38	92.10	95.20	84.67
LSTM-Attention [26]	2022	95.12	93.45	96.08	86.23
EEG Transformer [4]	2023	95.87	94.28	96.52	87.91
Graph CNN [27]	2023	96.15	94.67	96.84	88.45
WGAN-GP + CNN [8]	2023	96.43	95.12	97.18	89.28
Hybrid CNN-RNN [28]	2024	96.78	95.54	97.45	90.15
Diffusion Model + ResNet [29]	2024	97.21	96.08	97.89	91.34
Proposed VMD-cGAN	2025	97.84	96.73	98.52	92.93

The proposed approach achieves the best performance among all compared methods across all metrics. The VMD-cGAN exceeds the most recent diffusion model approach [29] by 0.63% in accuracy, while offering additional advantages in interpretability through explicit frequency decomposition. Unlike WGAN-GP [8], the proposed method decomposes EEG into physiologically meaningful IMFs before generation, resulting in 1.41% higher accuracy and 1.61% higher sensitivity. Compared to diffusion model augmentation [29], the VMD-cGAN framework is computationally lighter while achieving superior specificity (98.52% vs. 97.89%).

The high performance can be explained by three complementary factors. First (RO2), VMD decomposition enables the generator to learn frequency-specific seizure patterns more efficiently than raw-signal generation, since each IMF corresponds to a distinct physiological frequency band. Second (RO1), conditional generation provides explicit class-level control. Third (RO3), the balanced augmented training set enables the CNN detector to learn more generalizable discriminative features. Several open issues remain for future work: evaluation on adult populations and multi-centre datasets, automatic patient-adaptive selection of K, formal neurophysiological validation of synthetic signal fidelity, and extension to real-time clinical seizure monitoring systems.

4. CONCLUSION

This paper presented a temporal-aware data augmentation framework for EEG-based epileptic seizure detection that integrates Variational Mode Decomposition (VMD) and Conditional Generative Adversarial Networks (cGAN). The proposed VMD-cGAN approach resolves the scarcity of high-quality, class-balanced seizure EEG data by generating physiologically plausible synthetic seizure data that preserves the frequency-specific temporal and spectral characteristics of ictal EEG—characteristics that simpler augmentation strategies consistently fail to reproduce.

Extensive experimentation on the CHB-MIT Scalp EEG Database confirmed state-of-the-art performance: 97.84% accuracy, 96.73% sensitivity, and 98.52% specificity. These results directly validate the main research hypothesis H1. The 7.28% improvement in sensitivity over the no-augmentation baseline is of particular clinical importance, demonstrating the framework's effectiveness at reducing missed seizure events—the primary safety concern in automated clinical detection systems. The sub-hypothesis H2 was also confirmed by the ablation study, which showed that VMD-based frequency decomposition prior to generation consistently outperformed direct EEG-level GAN generation.

Future work should extend the evaluation to adult and multi-centre EEG databases, explore patient-adaptive VMD parameter selection, incorporate formal neurophysiological validation of synthetic signal quality, and investigate the integration of the framework with real-time clinical seizure monitoring systems.

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