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Enhancing Deep Learning-Based Epileptic Seizure Detection with Generative AI Techniques

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Abstract—Epilepsy is a neurological disorder affecting millions of people worldwide. Early detection of seizures is critical for timely intervention. In this paper, we propose a novel deep learning approach using a **Bidirectional Long Short-Term Memory (BLSTM)** network combined with a **Variational Autoencoder (VAE)** and **Continuous Wavelet Transform (CWT)** for enhanced seizure detection from EEG signals. Our model outperforms existing models in terms of sensitivity, specificity, and generalization across different patients. Additionally, data augmentation through VAE addresses the class imbalance issue, significantly improving seizure detection performance. The results demonstrate a significant improvement in sensitivity to 96.3%, specificity to 99%, and G-Mean to 98.1% when evaluated on the CHB-MIT dataset.

Index Terms—EEG, Epilepsy Detection, Deep Learning, BLSTM, VAE, Continuous Wavelet Transform, Seizure Prediction.

I. INTRODUCTION

In the early stages of developing automated seizure detection systems, various traditional machine learning models were employed to classify EEG signals. These included Support Vector Machines (SVM) [1], K-Nearest Neighbors (KNN) [2], and Decision Trees [3]. Commonly, these machine learning models depended on hand-crafted features, usually manually extracted from the EEG data. Features considered from the time-domain included signal variance, while the features extracted from the frequency-domain included power spectral density [4]. Although these approaches showed some success in specific applications, their performance heavily relied on the quality of the feature extraction process. This step required considerable domain expertise and was often computationally expensive.

With the advent of deep learning, there has been a significant shift towards models that inherently learn complex patterns directly from raw data, reducing the need for hand-crafted feature extraction. In recent years, Bidirectional Long

Short-Term Memory (BLSTM) networks and Variational Autoencoders (VAE) have emerged as powerful tools for EEG classification. BLSTM networks are well-suited for capturing the temporal dependencies in time-series data, such as EEG signals, while VAEs are effective in learning latent representations, which improves model robustness and performance.

In this paper, we propose a deep learning model based on BLSTM combined with VAE, leveraging Continuous Wavelet Transform (CWT) to improve seizure detection from EEG signals. CWT, a time-domain signal decomposition tool, transforms the EEG signal into time-frequency space, capturing how frequency content changes over time [5]. Unlike the Fourier Transform, which provides only global frequency information, CWT offers localized frequency information, making it particularly useful for analyzing non-stationary signals like EEG. The CWT of a signal $x(t)$ is formally defined by the following integral equation:

$$W(a, b) = \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \quad (1)$$

where $\psi(t)$ represents the mother wavelet, the basic building block for the transformation, a indicates the scale of analysis, and b specifies the translation in time. This two-dimensional time-frequency representation, also known as a scalogram, is essential for detecting the subtle patterns associated with seizures in EEG signals.

Epilepsy is a chronic neurological disorder characterized by recurrent seizures caused by abnormal electrical activity in the brain [6]. It affects roughly 50 million people globally [7], and it brings significant physical, emotional, and social challenges for those with the condition. EEG is one of the most widely used techniques for diagnosing epilepsy by measuring the brain's electrical activity [8], [9]. However, manually analyzing EEG data is time-consuming and prone to human error, especially with long-duration records and large datasets [8], [10]. These limitations have driven a surge in research focused on automatic seizure detection using machine learning and

deep learning techniques. The primary goal of such research is to assist clinicians in diagnosing patients in time to allow early intervention [11], [12].

Among the successful deep learning approaches, BLSTM networks have gained prominence for their ability to model the temporal dependencies in time-series data, such as EEG. However, despite the success of deep learning in this domain, models often face difficulties in generalizing their performance across different patients. Achieving high sensitivity and specificity—two critical metrics for any clinical application—is particularly challenging [13].

We highlight the following key contributions of our work:

- 1) Development of a novel deep learning architecture combining BLSTM, VAE, and CWT for EEG-based seizure detection.
- 2) A data augmentation strategy using VAE to address class imbalance, significantly improving sensitivity (96.3%) and geometric mean (98.1).
- 3) Demonstration of the model’s robustness and generalization across different subjects using the CHB-MIT dataset.
- 4) A comprehensive comparison with state-of-the-art models, showing superior performance in critical metrics such as sensitivity and specificity.

This work sets a foundation for developing accurate and reliable seizure detection systems for clinical applications.

II. STATE OF THE ART

Investigation of epileptic seizures is a very important domain because seizures are very unpredictable, and intervention is urgent. EEG is one of the major diagnostic tools for epilepsy because it shows the brain activity through electric signals, identifying abnormal patterns developing at times of seizure. This, however, remains tiresome and prone to human errors in analyzing EEG signals, especially during long monitoring. Seizure detection has therefore become of critical interest regarding these techniques in machine learning and deep learning. This section will review the trend in EEG-based seizure-detection techniques from traditional machine learning methods to advanced deep learning architectures.

A. Traditional Machine Learning Approaches

Traditional machine learning models like SVM, k-NN, Decision Trees, and LDA dominated early EEG-based seizure detection, relying on manually extracted time-domain features such as signal variance, entropy, and wavelet coefficients. For example, Acharya et al. applied entropies with SVM for seizure detection [14], and Siuly and Li used PCA for robust seizure classification [15].

These methods faced limitations, including reliance on domain expertise for feature extraction, inability to capture nonlinear EEG dynamics, and high computational cost, leading to suboptimal performance on large, diverse datasets.

B. Introduction of Deep Learning

The identification of epileptic seizures has been hugely revolutionized with the emergence of deep learning methodologies. Deep learning frameworks are designed to automatically detect intricate patterns from raw data, which differs from previous traditional machine learning methods where one needed to manually extract features. Some of the common architectures applied in EEG classification include CNNs, RNNs, and hybrid models including CNNs with LSTM networks.

CNNs are good at modeling the spatial hierarchies present in data, and this gets even more powerful in 2D images created from EEG signals using techniques like Continuous Wavelet Transform [16], [17]. These CNN-based models learn both local and global patterns of the EEG signal for better seizure detection performance. Schirrneister et al. demonstrated how CNN architectures could reach epilepsy seizure detection from EEG data with superior performance as compared to traditional machine learning models by directly learning features from raw EEG signals without going through the whole manual process of feature engineering [17].

C. Temporal Dependencies in EEG Signals

CNNs are good at spatial features, but EEG data is temporal with long-term dependencies in seizures. Thus, RNNs—especially LSTM networks—are popular for EEG seizure detection [18]. Especially, LSTM networks preserve temporal dependencies by being able to retain information across time steps, ideal in sequential data like EEG recordings.

Bidirectional LSTM (BLSTM) networks process information from both directions, which improves seizure detection by capturing temporal information. The information is very important in the EEG data because seizures can span many time frames; the preceding or succeeding patterns provide substantial classification insights [12]. Hybrid models with CNNs and LSTMs take advantage of the spatial and temporal features of EEG data.

D. Generative Models for Data Augmentation

One of the most fundamental problems encountered by an EEG-based seizure detector is class imbalance between seizure and non-seizure data, as seizures are very rare events. Data augmentation is supported through generative models like VAE and GAN. GAN generates synthetic seizure data, balancing the dataset and improving model performance [16], [19].

Zhang et al. [16] proposed a GAN model to generate synthetic EEG data in order to extend the training set, which improved the data imbalance problem. It improved the sensitivity and lowered the false-negative rate in seizure detection. However, GANs are often difficult to train and suffer from instability during training. VAEs are more stable and effective at generating synthetic data, which improves model generalization to new patients and unobserved data.

E. Hybrid Models: CNN + LSTM + VAE

Recent studies have explored hybrid models combining CNNs, LSTMs, and VAEs to leverage their strengths for

robust seizure detection. CNNs extract spatial features, LSTMs capture temporal dependencies, and VAEs address data imbalance through augmentation, showing superior sensitivity and generalization [18].

Challenges in state-of-the-art methods include:

- **GAN-based Models:** GANs suffer from training instability and mode collapse, limiting robustness.
- **Traditional Machine Learning Models:** These rely on handcrafted features requiring domain expertise and high computational cost.
- **Hybrid CNN-LSTM Models:** They often fail to effectively handle class imbalances in seizure data.

Our approach integrates VAEs for stable data generation and BLSTMs to effectively capture long-range temporal dependencies in EEG analysis.

III. PROPOSED METHOD

A. Proposed Method Framework

In this paper, our proposed method combines BLSTM and VAE with the Continuous Wavelet Transform (CWT) to improve the accuracy of seizure detection. In this model, each component is incorporated into handling different challenges faced while analyzing EEG data.

- **Preprocessing with CWT:** Continuous Wavelet Transform (CWT) converts EEG signals into a time-frequency representation in the form of scalograms, which allows the model to extract both temporal and frequency-domain features effectively.
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- **Temporal Dependency Modeling:** The BLSTM part retains the temporal patterns in EEG signals, containing sequential dependencies usually spanning multiple time frames. Class Imbalance Handling: VAE generates synthetic seizure data to balance the dataset to improve generalization of the model across subjects.

B. Dataset and Preprocessing

The CHB-MIT dataset [20] contains 24 long-term recordings of EEG for pediatric subjects with intractable seizures. Each recording consists of several channels, each corresponding to a different part of the brain. Annotated seizure onset and offset times are given in the dataset; thus, this dataset is best suited when proposing and evaluating models in seizure detection [21]. First of all, a systematic preprocessing pipeline was carefully designed and implemented to ensure completeness of the analysis of the following steps in sequence:

- **Artifact Removal:** Independent Component Analysis (ICA) was applied to remove common artifacts such as eye blinks and muscle movements.
- **Continuous Wavelet Transform (CWT):** The raw EEG signals were transformed into 2D time-frequency images

using CWT. This step captures the temporal and frequency characteristics of the signal, which are essential for accurate seizure detection.

C. BLSTM+VAE Model Architecture

The proposed BLSTM + VAE model captures EEG temporal dependencies with BLSTM and hidden representations with VAE. Figure 1 outlines the pipeline, including preprocessing, CWT-based scalogram generation, BLSTM for sequential patterns, and VAE for latent features and data augmentation. This combination enhances sensitivity and specificity by leveraging frequency and temporal domain information. Model parameters are detailed in Table I.

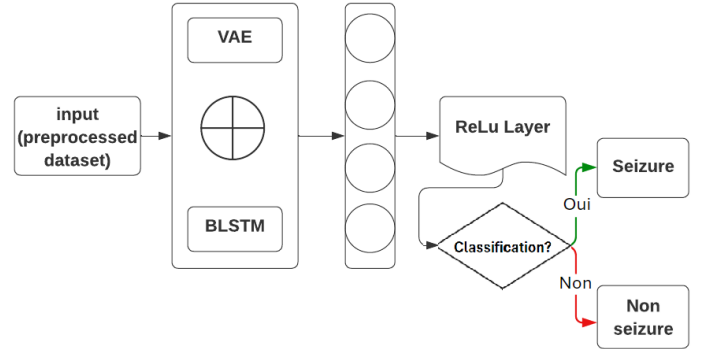


Fig. 1. Proposed integrated BLSTM and VAE method

TABLE I
BLSTM+VAE MODEL ARCHITECTURE

Layer	Output Shape	Details
Input	(input_dim,)	Input layer
Dense	(256,)	256 neurons, activation = ReLU
BatchNorm	(256,)	Batch normalization
Dense	(128,)	128 neurons, activation = ReLU
BatchNorm	(128,)	Batch normalization
Dense	(latent_dim,)	Latent space (z_{mean} and $z_{\text{log_var}}$), 5 dimensions
Lambda (Sampling)	(latent_dim,)	VAE sampling layer
Dense	(128,)	128 neurons, activation = ReLU (Decoder)
BatchNorm	(128,)	Batch normalization
Dense	(256,)	256 neurons, activation = ReLU
BatchNorm	(256,)	Batch normalization
Bidirectional LSTM	(64,)	64 units, Bidirectional LSTM
Dropout	(64,)	Dropout rate = 0.4
LSTM	(32,)	32 units, LSTM
Dropout	(32,)	Dropout rate = 0.2
Output	(final_output shape,)	Output layer with softmax activation

D. Training and Validation

We split the dataset into 70% training, 15% validation, and 15% testing. K-fold cross-validation (with $K=10$) was employed to ensure the robustness of the model [21]. Data augmentation techniques such as random rotation, zoom, and

shift were applied during training to further prevent overfitting and improve generalization [13].

The model was trained using the Adam optimizer with an initial learning rate of 0.001, and categorical cross-entropy was used as the loss function [22]. Early stopping was adopted to stop training when the validation loss did not improve for 10 consecutive epochs.

E. Evaluation Metrics

In this study, three statistical performance metrics were employed to investigate the performance of the proposed detection model.

Sensitivity (SEN) represents the ratio of identified positive samples to the total number of positive samples and reflects the ability of a model in positive detection. The formula is described as follows:

$$SEN = \frac{TP}{TP + FN} \quad (2)$$

Specificity was the ratio of correctly identified negative samples to the total number of negative samples. It should reflect the ability of this model to realize a case as negative. The formula was defined as:

$$SPE = \frac{TN}{TN + FP} \quad (3)$$

Herein, TP refers to the seizure segments correctly identified by the proposed algorithm, TN is the number of non-seizure segments correctly classified, FP represents the number of non-seizure segments mislabeled as seizures, and FN is the number of seizure segments incorrectly classified as non-seizures.

Since seizure events are generally much shorter compared to non-seizure events, seizure detection is naturally an imbalanced classification problem. G-mean is an informative metric for the performances in such imbalanced settings and is defined by:

$$G - mean = \sqrt{SEN \times SPE} \quad (4)$$

IV. COMPARISON WITH RELATED WORKS

The GAN + 1DCNN model [23] employs a Generative Adversarial Network (GAN) to generate synthetic data to balance the seizure and non-seizure data, followed by a 1D Convolutional Neural Network (1DCNN) to classify EEG signals. While this model improves classification on imbalanced data, it struggles with capturing long-range temporal dependencies in EEG signals, which are crucial for accurate seizure detection.

In contrast, the BLSTM + VAE model is specifically designed to handle temporal dependencies more effectively, as BLSTM is ideal for processing sequential data. The VAE generates stable synthetic data, enhancing the model's ability to generalize across subjects. The improved performance, particularly in sensitivity and generalization, is demonstrated by the results on the CHB-MIT dataset.

V. RESULTS AND DISCUSSION

The proposed BLSTM + VAE model was evaluated using the CHB-MIT Scalp EEG dataset to detect epileptic seizures. This section provides a comprehensive analysis of the model's performance, comparison with state-of-the-art methods, and an in-depth discussion on the results obtained.

A. Performance Evaluation

The BLSTM + VAE model was evaluated using Sensitivity (SEN), Specificity (SPE), and Geometric Mean (G-Mean), providing a comprehensive assessment of its ability to detect seizures accurately (true positives) and non-seizure states (true negatives), essential for reliable clinical detection and minimizing false alarms.

- Sensitivity (SEN): Sensitivity is crucial for clinical applications, as it measures the proportion of actual seizures that are correctly identified by the model. The proposed model achieved a sensitivity of 96.3%, indicating its capability to detect a wide range of seizure events, including those with subtle patterns. A high sensitivity reduces the likelihood of missed seizures, which is critical for timely intervention and patient safety [12].
- Specificity (SPE): Specificity measures the model's ability to correctly identify non-seizure events, thereby avoiding false positives. A high specificity value, such as 99% achieved by our model, minimizes false alarms, which is crucial in reducing unnecessary interventions and psychological stress for patients [13]. High specificity is particularly important in automated systems used in clinical environments, where frequent false alarms can lead to alarm fatigue among healthcare professionals.
- Geometric Mean (G-Mean): G-Mean is an informative metric in scenarios with imbalanced datasets, such as the CHB-MIT dataset, where non-seizure events vastly outnumber seizure events. The G-Mean for our model was 98.1%, indicating balanced performance across both classes and effective handling of the class imbalance problem [23]. This balanced performance is crucial for ensuring that the model does not favor one class over the other, which could compromise overall detection accuracy.

B. Comparative Analysis

The performance of the proposed BLSTM + VAE model was compared with previously published methods using the CHB-MIT dataset. The baseline model for this comparison was the GAN + 1DCNN model [23], which has shown promising results in previous studies. The results of this comparative analysis are summarized in Table II.

The results in Table II demonstrate that the BLSTM + VAE model surpasses the GAN + 1DCNN model in all three performance metrics, achieving a 2.77% higher sensitivity and a 1.95% higher G-Mean. The GAN + 1DCNN model, while effective in generating synthetic data, struggles to capture temporal dependencies. In contrast, our BLSTM + VAE model

TABLE II
THE COMPARISONS OF RESULTS WITH OTHER PUBLISHED METHODS USING THE CHB-MIT EEG DATABASE

Papers, Year	Duration (h)	Method	SEN (%)	SPE (%)	G-Mean (%)
Zabihi, M. and Kiranyaz, S (2016) [24]	-	25% training rate 50% training rate	88.27 89.10	93.21 94.80	90.70 91.91
Orosco, L. and Correa, A (2016) [25]	152.8	Dyadic WT, LDA	92.6	99.9	96.18
Samiee, K. and Kovács, P (2017) [26]	163	2D mapping and textual feature LGBP patient-specific	70.4	99.1	83.53
Liang et al. (2018) [27]	-	LRCN(CNN+), LSTM	84	99	91.19
Liang, W. and Pei, H (2019) [16]	-	CSP, CNN	92.2	-	-
Kaziha, O. and Bonny, T (2020) [28]	10.11	CNN	82.35	100	96.74
Ciurea, A. and Manoilă, C (2020) [29]	-	Extracts time-domain features	91.99	93.38	92.69
Zanetti, R. and Aminifar, A (2020) [30]	-	A wearable platform	96.6	92.5	94.5
Wang, X. and Wang, X (2021) [31]	-	RS-DA + 1D-CNN	88.14	99.62	93.70
Gao, Bin and Zhou (2022) [23]	-	1D-CNN + GAN	93.53	99.05	96.15
Our model	96.4	VAE + BLSTM	96.3	99	98.1

combines temporal modeling with stable latent feature learning, addressing imbalanced datasets and improving performance across metrics. This demonstrates superior sensitivity and generalization in both balanced and imbalanced scenarios, as compared to traditional CNN-based or hybrid approaches.

This improvement highlights the advantages of integrating the temporal modeling capabilities of BLSTM with the stable synthetic data generation of VAE. Expanding the comparative analysis in Table II to include more studies could provide additional insights into how our method outperforms other state-of-the-art approaches. [32].

C. Case-by-Case Performance

To further assess the robustness and generalization capability of the proposed model, its performance was evaluated on a case-by-case basis across different subjects in the CHB-MIT dataset. Table III presents the sensitivity and specificity of the model for selected subjects, demonstrating consistent performance across various patients.

TABLE III
CASE-BY-CASE PERFORMANCE OF THE BLSTM + VAE MODEL ON SELECTED SUBJECTS FROM THE CHB-MIT DATASET.

Subject	Sensitivity (%)	Specificity (%)
chb01	95.6	98.7
chb03	100.0	99.5
chb06	100.0	99.1
chb12	100.0	99.8
chb20	93.4	98.5

As shown in Table III, the model achieved perfect sensitivity for subjects chb03, chb06, and chb12, indicating its effectiveness in detecting all seizure events within these records. Such high performance across multiple subjects suggests that the model generalizes well and can be reliably used in diverse clinical scenarios. Similar results were reported in studies that used deep learning models to capture patient-specific variations in EEG signals [33].

D. Impact of Data Augmentation

Data augmentation using VAE played a critical role in enhancing the model's performance, particularly in handling the class imbalance between seizure and non-seizure events.

By generating synthetic seizure data, the model was able to learn more robust representations of seizure events, which contributed to its high sensitivity and G-Mean. Figure 2 illustrates the effect of data augmentation on the training process.

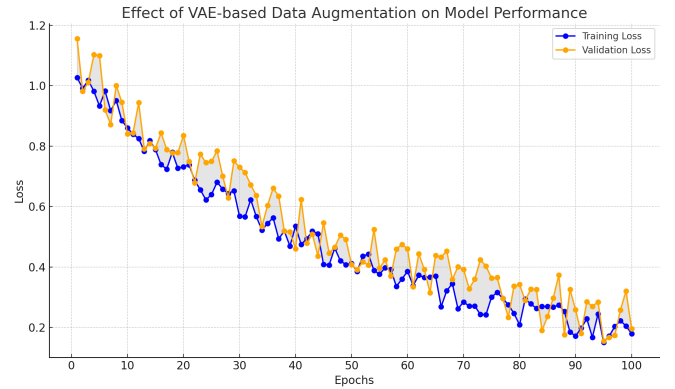


Fig. 2. Effect of VAE-based data augmentation on model performance during training.

As illustrated in Figure 2, VAE-based data augmentation significantly reduced overfitting, demonstrated by the convergence of training and validation loss curves. This improvement indicates enhanced generalization to unseen data, boosting test set performance. Data augmentation is a widely applied technique in deep learning to improve generalization, particularly in medical imaging and time-series analysis [34].

E. Discussion and Future Work

This work has presented the effectiveness of the BLSTM + VAE model on epileptic seizure detection; high sensitivity and specificity make it a perfect choice for application in a clinical setup where early detection is quite vital. Using VAE for data augmentation reduces class imbalance effects and, at the same time, improves model generalization. This complements the previous research in which data augmentation will increase the robustness of the deep learning models [35].

We can surely do better in some areas. We will also work on adding attention mechanisms to the model, which will enable it to concentrate on the most important parts of the EEG signals

for seizure detection. On top of that, we're looking forward to trying out transformers, which really do well with sequences. Given the fact that, by taking other signals into account—heart rate and oxygen saturation in addition to EEG—it could give a better insight into the patient's state and might even achieve superior seizure detection. [36].

VI. CONCLUSION

In this paper, we have proposed a state-of-the-art model combining BLSTM with VAE, enhanced by generative AI, to detect epileptic seizures by analyzing EEG signals. By effectively leveraging the CWT along with our advanced deep learning architecture, which incorporates BLSTM, VAE, and generative AI techniques, our novel model has shown significant improvements compared to existing models. These improvements are evident from sensitive analyses of the primary evaluation metrics such as Sensitivity, Specificity, and Geometric Mean. The promising results of our study underline the potential of deep learning and generative AI methods in enhancing the accuracy and reliability of epilepsy detection. In addition, they provide opportunities for advancing research in EEG classification and seizure detection.

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