Cramer Distance: A Deep Learning Approach for Better Epileptic Seizure Prediction

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Abstract – Epilepsy is a neurological condition that is found in most people all over the world, and the ability to accurately anticipate seizures in epileptic patients has a significant impact on both their level of protection and their overall quality of life. This research proposes a unique patient-specific seizure prediction approach based on Deep Learning (DL) using long-term scalp electroencephalogram (EEG) recordings to predict seizure onset. Preictal brain states should be adequately detected and differentiated from the prevalent interictal brain states as early as possible to make this technology acceptable for real-time use. A single automated system has been designed for the Features Extraction (FE) and classification processes. The raw EEG signal that has not been pre-processed is considered the input to the system, and the signal is further reduced using subsequent computations. An innovative reconstruction approach using Variational Auto-Encoder Generative Adversarial Networks (VAE+C+GAN) with the Cramer Distance (CD) and a Temporal-Spatial-Frequency (TSF) loss function is presented in this research work. The machine that discriminates receives instructions to differentiate between created tests and actual samples, while the generator is verified to produce false samples that the discriminator does not recognize as fake. The proposed VAE+C+GAN's experimental results have been examined, and a classification accuracy of 95% has been achieved. According to the experiment's findings, the VAE-C-GAN performs better than the current EEG classification system and has excellent potential for real-time applications.

Keywords – Seizure, Cramer Distance, Variational Autoencoder, Electroencephalogram, Epilepsy Diagnosis and Detection.

I. INTRODUCTION

Epilepsy is an ancient known disease now considered the most common neurological disease. The Greek physician Hippocrates was the first to recognize Epilepsy as a brain disorder rather than a divine punishment (Sacred Disease), as the Society believed. Religious beliefs, however, prevented the systematic and scientific study of Epilepsy until the 18th century. After the 18th century, brain metastases were categorized based on their type as Idiopathic, symptomatic, and sympathetic [1]. A change in brain activity leads to idiopathic Epilepsy. Sympathetic Epilepsy arises from the lower brain and spreads through the spinal cord. Despite several approaches, an effective epileptic detection system is required for early prediction and diagnosis [2].

The human body is a multitasking system that is measured by the brain. It performs numerous tasks with the help of sensory and motor signals generated by the brain. These sensory and motor signals are called biomedical signals that could be electrical, magnetic, mechanical, acoustic, optical, or chemical. These signals provide a plethora of information about the physiological processes that happen in the human body. These Electrical signals are used in some biomedical measurements such as Electrocardiography (ECG), which is performed to check the function of the heart; Electromyography (EMG), which measures muscle activity; Electroencephalography (EEG), which measures brain

signals; Electrogastrography (EGG) for measuring stomach signals, Electrooptigraphy (EOG) for measuring eye dipole fields, and so on [3].

A seizure is a short-term *"abnormal, excessive or simultaneous neuronal activity in the brain"*. The apparent effects differ slightly, ranging from severe disability (onset of tension zone) to loss of consciousness (onset of the defect). Epilepsy is a syndrome with frequent seizures for no reason, but seizures may also occur in people who do not have Epilepsy. Generalized Epilepsy and partial Epilepsy are the two types of Epilepsy that differ in the severity with which the brain region is affected. Focal seizures, on the reverse side, can take place in single epileptic foci or multiple epileptic foci but are localized to a specific area of the brain, whereas generalised seizures impact both hemispheres of the brain simultaneously. After the first seizure, treatment is not mandatory if either EEG or brain imaging is free from specific problems [4]. Depending on the type, the signs and symptoms of a seizure may vary. Approximately two-thirds begin with a localized seizure and proceed to a generalized seizure, while the others $1/3^{rd}$ begin with a generalized seizure.

Epilepsy Detection (ED) is a critical area of research and medical application focusing on identifying and predicting epileptic seizures. In computation techniques, various data analysis, Machine Learning (ML), and signal processing methods are used to develop efficient and accurate ED systems. Before applying any ML algorithms, the EEG data, a shared data source for ED, undergoes preprocessing. Techniques such as filtering, noise reduction, artifact removal, and Feature Extraction (FE) enhance the signal quality and extract relevant features for analysis [5].

Various ML techniques are used for ED, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Deep Learning (DL) models (*e.g.,* Convolutional Neural Networks (CNN) or Long Short-Term Memory (LSTM) networks), Random Forests (RF), and more. These algorithms are trained on labelled EEG data to learn patterns distinguishing between epileptic and non-epileptic states. In clinical settings, real-time ED is essential for timely intervention. Implementing efficient algorithms and optimizing computational resources becomes crucial to ensure real-time monitoring of EEG signals.

ED in the context of computation techniques is an interdisciplinary field that integrates signal processing, ML, and computing methodologies to create accurate, efficient, and real-time systems for early diagnosis and intervention, leading to better management and treatment of epilepsy patients. It's important to continually explore and develop innovative computational techniques to improve the performance and accessibility of ED systems in real-world scenarios.

Researchers work to incorporate cutting-edge DL and Artificial Intelligence (AI) approaches into improving healthcare practice. Early illness identification and disease prediction are essential objectives in healthcare because they allow for prompt preventive measures [6]. This is particularly true for Epilepsy, which is marked by unexpected and repeated episodes. If we can predict in advance in some way, this study will spare patients from the ill effects of epileptic seizures. Despite decades of research, seizure prediction remains an open problem. There are two significant categories of research is going on.

One is the Analog designer who designed a device and predicted it as quickly as possible, and the second one is the AI-based designer who developed excellent algorithms to predict Epilepsy from the features. These two categories have their advantages and disadvantages. It solves this problem by combining the two categories and bringing them into one umbrella to achieve highly accurate predictions. This work identifies gaps, challenges, and pitfalls in current research and recommends future directions.

A hybrid model for mathematical Generative Adversarial Networks (GANs) combines the power of GANs with other mathematical modelling techniques to enhance the generation and manipulation of mathematical content. This hybrid model combines the strengths of Variational Auto-Encoders (VAEs) and GANs. VAEs can learn a low-dimensional representation of complex data, while GANs generate realistic samples. Incorporating VAEs into the GAN permits the hybrid model to learn a more structured latent space representation and generate mathematically meaningful samples [7].

The Cramer Distance (CD), or the Cramer-von Mises distance, is a statistical measure used to quantify the discrepancy or dissimilarity between two probability distributions. It is based on the Cumulative Distribution Functions (CDF) of the distributions being compared. Given two probability distributions, let's call them ‘F’ and ‘G’, the CD measures the difference between their CDFs. It evaluates how much the CDFs deviate from each other, indicating the dissimilarity between the distributions.

Following are the sections of the research work that are highlighted: Previous research and literature are described in Section 2, the proposed VAE+C+GAN with the CD and a TSF loss function is explained in Section 3, In Section 4, the statical results of the experiment are presented, and the discussion and conclusions section wraps up the DL approach by providing recommendations for the future study.

II. RELATED WORKS

Most researchers work on ED, but only 20 % work on epilepsy prediction. The traumatic pain caused by Epilepsy is more than the pain of Epilepsy itself. One of the crucial points to note is that Epilepsy is an abrupt and unpredictable disorder. As a result, studying seizure prediction lowers the risk of seizures and enhances the quality of life for an epilepsy patient. These characteristics are essential for seizure prediction. Scientists have used ML techniques for functional categorization, such as SVM, Linear Discriminant Analysis (LDA), RF, and Neighbourhoods (k-NN) [8].

Healthcare professionals visualize several EEG signal patterns to predict seizures. They use prior knowledge from medical procedures to automatically FE from the brain. However, numerous researchers have used DL technology to

anticipate the onset of epileptic seizures via automatic Feature Extraction (FE) and categorization [9]. DNN, SOM, DenseNet, and Bi-LSTM are the most predominant DL algorithms. The accuracy of these DL approaches in predicting Epilepsy has been demonstrated. Typical data can be used to FE using DL. Before entering DL, most researchers make minor adjustments to the raw EEG data. The Continuous Wavelet Transforms (CWT), Short-Time Fourier Transform (STFT), and Discrete Wavelet Transform (DWT) are the three most widely utilized transformations. Meanwhile, the DL technique turns raw EEG data into images [10].

One of the most significant jobs in ED is EEG data processing for FE. To extract statistical features, this method requires the use of well-defined and structured signal analysis techniques [11]. Numerous signal analysis techniques exist, including Fast Fourier Transform Techniques (FFT), STFT, CWT, and DWT. The Fourier transform in the time domain depicts the signal's frequency and amplitude. The information not displayed in the time domain can be displayed in the frequency domain; signals can also be recorded in the frequency domain.

Although FFT is the most extensively used transform method, many other techniques are available, such as STFT, Hilbert transform, Wigner distribution, Radon transform, and wavelet transform [12]. The FFT has the drawback of being unable to evaluate signals simultaneously in the time and frequency domains. Long Short-Term Memory (LSTM) is utilized to classify Epilepsy efficiently. If the signal is turned off, there is no need for this transition [13]. The frequency of a stop signal does not change over time. The frequency components inherent in a stop signal remain constant during the signal's duration. In most situations, this conversion method puts the entire signal through high-pass and low-pass filters. These filters divide the signals into groups of high and low-frequency signals, repeating the process several times [14-18].

The study included a large dataset of continuous multi-channel newborn EEG ranging from 18 neonates to 834 hours and 1389 seizures and publicly studied neonates collected from EEG waveforms in children from Helsinki University Hospital. The AUC with more than 90% specificity was 86.9% for the 18 study subjects. In this study, the flaws in the current systems are considered and fixed [19]. To reduce the quantity of labelled data needed, Deep Neural Networks (DNN) are integrated with the massive semi-supervised learning approach and annotated datasets by adopting VAE+C+GAN with the CD and a TSF loss function for a deep learning setting [20].

III. PROPOSED SEIZURE PREDICTION USING VAE+C+GAN

VAE+C+GAN with the CD and a TSF loss function is a DL model used for ED, particularly with EEG data. VAE is a generative model that learns to encode input data (EEG signals) into a lower-dimensional latent space and then decode it back to reconstruct the original data. VAEs are unsupervised models that can be used for generative tasks, and they are beneficial for learning meaningful representations of high-dimensional data. GAN is a neural network model that uses a generator, discriminator, and filter to produce realistic EEG signals while simultaneously identifying and removing false signals. This asymmetrical process improves the generation algorithm's ability to generate viable EEG signals through repeated iterations.

To evaluate how closely synthetic EEG data correlates with the distribution of accurate EEG data, GANs use the coefficient of dispersion. The CD is minimized to generate EEG signals identical to real-world EEG data regarding TSF characteristics. During training, the loss function is a key element of EEG data modelling, as it permits synthetic EEG signals to share the same TSF features as accurate EEG signals.

EEG Signal Reconstruction

EEG signal reconstruction in LSS is represented by $z \in S^{N\times TS_1\times R}$ from the D_L distribution, while in HSS, it is represented by $x \in S^{N\times TS_2\times R}$ from the D_H distribution. TS1 indicates LSS-EEG, TS2 indicates HSS-EEG, N indicates channel count, and R indicates motor task count. A function $f_n(z)$, where *'z'* is the LSS-EEG signal and *'x'* is the HSS+EEG signal, is reconstruction's primary goal.

$$\text{fn(z):z}\rightarrow\text{x} \tag{1}$$

The research goal is to change a specific distribution near the true distribution DH by deviating the function *fn(z)*, which translates the samples of LSS-EEG from D_L into D_C, which is a given distribution, during the reconstruction phase. With GAN, the rebuilding process involves two different approaches. The item modifies EEG samples during creation, moving them from the distribution D_L to D_C. The change of an EEG signal from one distribution to another is called the EEG reconstruction process. Reconstruction involves mapping LSS+EEG samples from DL to DC to deviate the function $f_n(z)$ to change a distribution close to D_H.

GAN reconstruction shifts EEG samples from DL to DC distribution due to non-stationary and non-linear signals, and the noise model complicates and maps the reconstruction connection unevenly. There is no obvious indication of where the signals are associated in the HSS and LSS+EEG distribution. Utilising conventional methods is a challenging approach for LSS-EEG reconstruction. By learning high-level non-stationary and non-linear features and displaying reconstruction distribution using signal patches of reasonable size, DNN reduces noise model uncertainties and their impact on reconstruction mapping. A modified GAN architecture with TSF loss and CD reconstructs HSS-EEG signals from LSS-EEG data, while DNN-based GANs reconstruct EEG data.

VAE+GAN with CD Computation

VAE+C+GAN combines two powerful DL models: Variational Auto-Encoders (VAEs) and Generative Adversarial Networks (GANs). It leverages the strengths of both models to achieve improved generative capabilities and better control over the generated data. VAE-C-GAN generates high-quality data samples, such as images, audio, or time series data, while learning meaningful data representations.

The VAE component is responsible for learning meaningful latent representations of the EEG data and generating similar EEG signals. The encoder takes pre-processed EEG data as input and maps it into a latent space distribution (usually Gaussian with mean and variance). The decoder (generator) takes samples from the latent space and reconstructs EEG signals. Training the VAE to minimise reconstruction loss and KL divergence between original and reconstructed EEG signals promotes a simple latent space distribution.

The GAN component is responsible for generating realistic EEG signals that are indistinguishable from real EEG data. The generator in the GAN takes random noise as input and generates fake EEG signals. The GAN's discriminator uses adversarial training to reduce the generator's ability to distinguish between real and fake EEG signals.

To combine VAE+GAN for ED, the decoder (generator) from the VAE component would be integrated as the generator in the GAN. The GAN's discriminator would evaluate the realism of the generated EEG signals, while the VAE component would ensure that the generated EEG signals have similar temporal, spatial, and frequency patterns as the accurate EEG signals. The VAE+C+GAN would be trained to minimize the reconstruction loss and KL divergence in the VAE and the adversarial loss in the GAN to generate realistic EEG signals that closely match the accurate EEG data. Once the VAE+C+GAN is trained, it can be used for ED by feeding new EEG data into the model. The model's output can be a threshold to classify EEG recordings as either indicating Epilepsy or not.

The CD has a disadvantage known as sample unbiased gradient and shares comparable distance features with the Wessertein metric. For HSS, the EEG signal is represented by $x \in S^{N\times TS_2\times R}$ for signal D_H and $z \in S^{N\times TS_1\times R}$ for signal D_L, based on two different distributions. The formula for the LSS and HSS-CD is EQU (2)

$$C_2^2(L,H) \coloneqq \int_{-\infty}^{\infty}(D_L(x) - D_H(x))^2\,dx \tag{2}$$

The appropriate member of the metric family C_p and the square root of the CD are provided as EQU (3)

$$C_p(L,H) \coloneqq \left(\int_{-\infty}^{\infty}|(D_L(x) - D_H(x))|^p dx\right)^{1/p} \tag{3}$$

The integral probability and the dual versions of the CD metric are as follows:

$$C_p(L,H) = \sup_{fn\in F_q}|_{x\sim L}^{E} fn(x) - _{x\sim H}^{E} fn(x)| \tag{4}$$

where F_H:={f_n:f}is generally continuous, $\left\|\frac{df}{dx}\right\|_q \leq 1\}$ where H is the conjugate exponent of L that is $L^{-1}+H^{1}=1$. It is a dual form that is utilised to prove the CD.

Using two Neural Networks (NN), the discriminator DI and generator GE, the VAE-GAN optimises the *Min-Max* issue in two layers. The discriminator determines the EEG signal reconstruction ($DI_{\theta_{DI}}$) and generator ($GE_{\theta_{GE}}$), which are specified as EQU (5)

$$\min_{\theta_{GE}}\max_{\theta_{DI}} L_{GAN}(DI_{\theta_{DI}}, GE_{\theta_{GE}}) = E_{x\sim D_H}\left[logDI_{\theta_{DI}}(x)\right] + E_{z\sim D_L}\left[\log\left(1 - DI_{\theta_{DI}}\left(GE_{\theta_{GE}}(z)\right)\right)\right] \tag{5}$$

where the expectation vector is denoted by E(.). When the discriminator meets the accurate data, it will gratify $DI_{\theta_{DI}}(x) = 1$ to discriminate the accurate data Here, $DI_{\theta_{DI}}(x) = 1$ influences the anticipation for $LogDI_{\theta_{DI}}(x)$. When the discriminator meets the created information, it can gratify $DI_{\theta_{DI}}\left(GE_{\theta_{GE}}(z)\right) = 0$ to create information that is discriminated, EQU (6).

$$\text{Here, } DI_{\theta_{DI}}\left(GE_{\theta_{GE}}(z)\right) = 0 \text{ attains the expectation for } (1\text{-}DI_{\theta_{DI}}\left(GE_{\theta_{GE}}(z)\right) = 0) \tag{6}$$

As a result, the expectation operator creates the minimax's optimum function. The typical approach to reconstruction is to educate a generator to be able to deceive a different discriminator that has been trained to distinguish between fake and real HSS+EEG signals. Instead of using Jensen-Shannon divergence to compare sample distribution, the VAE+C+GAN design uses the CD to train non-stationary and non-linear EEG signals. According to the VAE+C+GAN specification, the optimisation of the *Min-Max* problem is accomplished by $DI_{\theta_{DI}}$ and $GE_{\theta_{GE}}$ EQU (7),

$$\min_{\theta_{GE}} \max_{\theta_{DI}} L_{CGAN}(DI_{\theta_{DI}}, GE_{\theta_{GE}}) = E_{x\sim D_H}\left[DI_{\theta_{DI}}(x)\right] + E_{z\sim D_L}\left[DI_{\theta_{DI}}\left(GE_{\theta_{GE}}(z)\right)\right] + \lambda E_{\tilde{x}\sim D_R}[(\|\nabla_{\tilde{x}}(D(\tilde{x}))\|)_2 - 1)^2] \quad (7)$$

The first two terms determine the Min-Max problem's CD, gradient penalty is the gradient penalty for regularising the network, and DR is the uniform distribution of samples along lines. The parameter is a penalty term for a constant weighting parameter 'λ', and the symbol indicates the gradient estimator $\nabla_{\tilde{x}}(\cdot)$. In *Min-Max* training, the VAE+C+GAN architecture removes the log function and final sigmoid layer to maintain gradient value while optimising and updating the discriminator $DI_{\theta_{DI}}$ and $GE_{\theta_{GE}}$ generator alternately.

Loss function of TSF-MSE

The loss function requires VAE+C+GAN architecture, with generator modification enabling information distribution from low to sensitive high sampling rates. The details and content of the EEG signals will be preserved using this method. A frequently used loss function for the Mean Square Error (MSE) loss function's detail and information content. EQU (8) predicts temporal MSE by reducing the time-sampling error between LSS+HSS+EEG patches, while a signal processing error measures point-wise MSE.

$$L_{T-MSE}(GE_{\theta_{GE}}) = E_{(x,y)}\left[\frac{1}{T^2}\left\|GE\left(z(t)\right) - x(t)\right\|_P^2\right] \quad (8)$$

Instead of images, EEG signals are multi-channel time-series data that must be reconstructed using spatial and frequency factors. In order to encourage the VAE+C+GAN architecture to create more precise HSS-EEG signals, it is required to consider the spatial MSE+L_{SMSE} across channels, the frequency MSE LFMSE among signal batches, and the temporal MSE+L_{TMSE} among time steps.

Frequency data is extracted from EEG signals using Power Spectral Density (PSD) characteristics and spatial information using Common Spatial Patterns (CSP). The PSD method computes power levels on specific frequencies, while the CSP method creates projection vectors to transfer the EEG signal to a new space for optimal spatial resolution and discrimination across signal classes. The spatial MSE+L_{S-MSE} and the frequency MSE+L_{F-MSE} for the generator are calculated using these two methods, EQU (9) and EQU (10)

$$L_{S-MSE}(GE_{\theta_{GE}}) = E_{(x,z)}\left[\frac{1}{C^2}\left\|GE\left(CSP(z(c)\right) - CSP(x(c))\right\|_F^2\right] \quad (9)$$

$$L_{F-MSE}(GE_{\theta_G}E) = E_{(x,z)}\left[\frac{1}{N^2}\left\|GE\left(PSD(z(n)\right) - PSD(x(n))\right\|_F^2\right] \quad (10)$$

where CSP() and PSD(), respectively, are the FE for CSP(·) and PSD(·). The channel, count, batch, and count within the produced signal batch are all provided for the real and generated EEG signals, respectively. Three MSE losses are weighed to estimate the TSF loss for accessibility, EQU (11).

$$L_{TSF-MSE}(G_{\theta_G}) = \lambda_T . L_{S-MSE}(G_{\theta_G}) + \lambda_S . L_{S-MSE}(G_{\theta_G}) + \lambda_F . L_{S-MSE}(G_{\theta_G}) \quad (11)$$

where λ_T, λ_S, λ_F are the weights of three diversified MSE losses. Additionally coherent in both space and time, the EEG signals are generated using a generator that employs a regularisation loss $L_{TV}(GE_{\theta_{GE}})$ based on total deviation, EQU (12)

$$L_{TV}(GE_{\theta_{GE}}) = \frac{1}{CT}\sum_{c=1}^{C}\sum_{t=1}^{T}\left\|\nabla_z GE_{\theta_{GE}}(z)_{c,t}\right\| \quad (12)$$

When the gradient estimator is represented by the symbol $\nabla_z(\cdot)$, the gradient regularisation loss will improve the spatial and temporal coherence of the reconstruction. The following total joint reconstruction loss function is created by combining the equations VAE+C+GAN, TSF loss, and regularisation loss, EQU (13)

$$\min_{\theta_{GE}} \max_{\theta_{GE}} L_{TSF-MSE}(GE_{\theta_{GE}}) + \lambda_1 L_{CGAN}(DI_{\theta_{DI}}, GE_{\theta_{GE}}) + \lambda_2 L_{TV}(GE_{\theta_{GE}}) \quad (13)$$

The trade-off of the controlling weights is labelled as λ_1 and λ_2 between the VAE+C+GAN adversarial loss, the TSF+MSE loss, and the TV loss. The architecture of the VAE+C+GAN+EEG, which has been trained using several batches of EEG readings, is used in each experiment. The framework has been refined to detect Epilepsy in the EEG output with accuracy.

VAE+C+GAN with the CD and a TSF loss function is a specialized DL model designed for ED using EEG data. It leverages the power of VAE+GAN to learn meaningful representations of EEG signals and generate realistic EEG data. Using the CD and the TSF loss function ensures that the generated EEG signals closely match the accurate EEG data,

making the model more effective in identifying patterns indicative of Epilepsy and assisting in early diagnosis and treatment.

IV. RESULT AND DISCUSSION

The Bern-Barcelona EEG database, which includes non-focal and focal channels sampled at 1024 Hz from epilepsy patients, is used to classify Epilepsy using recommended and existing methods. A public EEG database with 3750 pairs of signals divided into 10240 samples randomly selected 50 focal and non-focal signals. The experiment was run in MATLAB with Intel® Core™ i7 Processor; 1000 GB Capacity; 16 GB Memory CPU, and accuracy, precision, F1-score, and recall were assessed. **Fig 1** and **Fig 2** show the EEG signal with Epilepsy as the recommended method is compared to SVM, DNN, and LSTM.

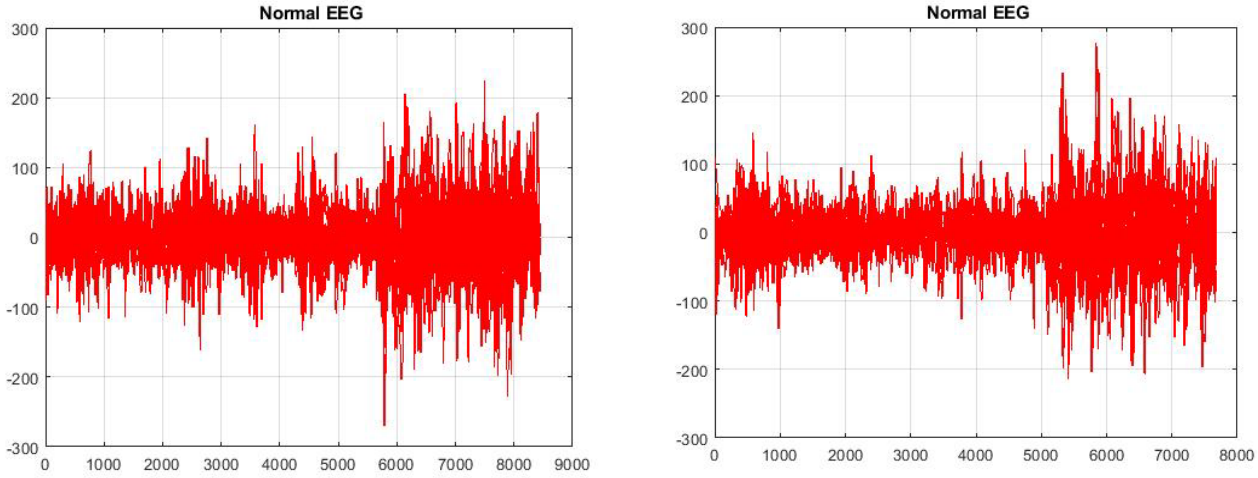

Fig 1. Visual Representation of Normal EEG.

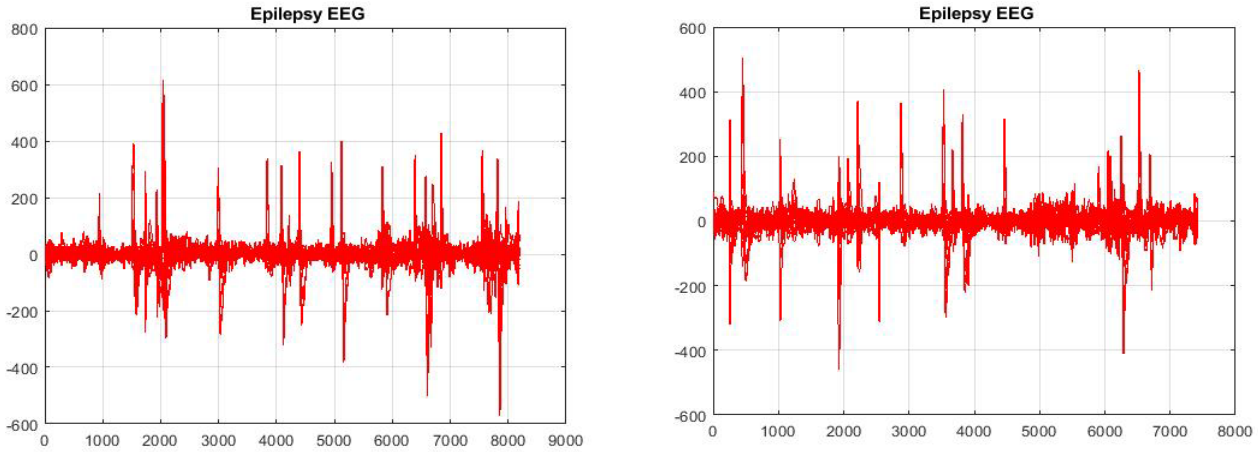

Fig 2. Illustration of EEG with Epilepsy.

Accuracy

The accuracy of the VAE+C+GAN with CD and a TSF loss function for ED refers to the model's ability to correctly distinguish between EEG recordings that indicate the presence of Epilepsy and those that do not. A higher accuracy indicates that the model is better at identifying instances of Epilepsy, while a lower accuracy implies that the model is less reliable in ED. **Fig 3** and **Table 1** shows the comparison of accuracy.

Table 1. Comparison of Accuracy

Iteration	SVM	DNN	LSTM	VAE-C-GAN
100	86	89	88	89
200	87	90	89	92
300	89	92	91	93
400	91	93	92	95

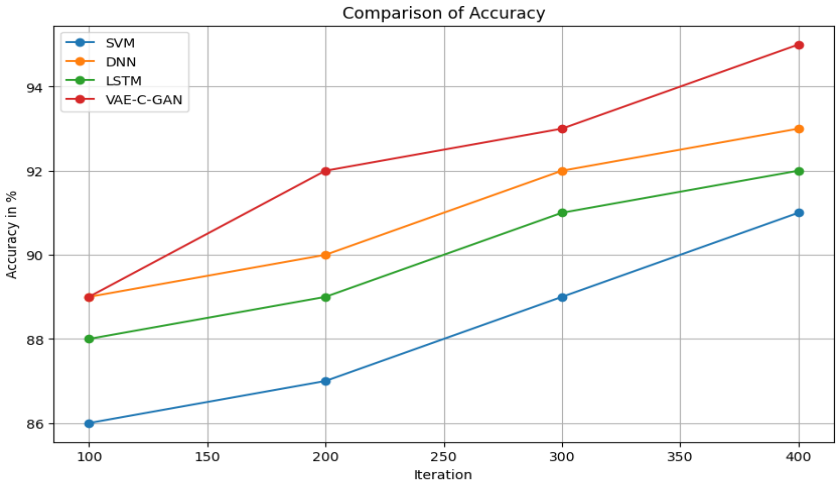

Fig 3. Comparison of Accuracy.

The VAE+C+GAN model achieved the highest mean accuracy (92.25%), indicating better overall performance than the other models. VAE+C+GAN stands out as the best-performing model in terms of mean accuracy, but it also shows higher variability in its results.

Sensitivity

Sensitivity measures the proportion of True Positive (TP) cases (correctly identified epilepsy instances) that the model correctly detects among all actual positive cases in the EEG data. It is calculated as EQU (14)

$$Sensitivity = \frac{TP}{TP+FN} \tag{14}$$

where TP is the number of correctly identified epilepsy cases, False Negatives (FN) are the number of epilepsy cases not detected by the model (missed).

A high sensitivity score indicates that the VAE+C+GAN model is effective in correctly detecting most of the epilepsy cases in the EEG data. It is essential in medical applications like ED, as missing TP cases could have severe consequences for patient diagnosis and treatment.

Table 2. Comparison of Sensitivity

Iteration	SVM	DNN	LSTM	VAE-C-GAN
100	81	83	87	91
200	83	84	87.5	92
300	85	86	89	93.5
400	86	87	90	94

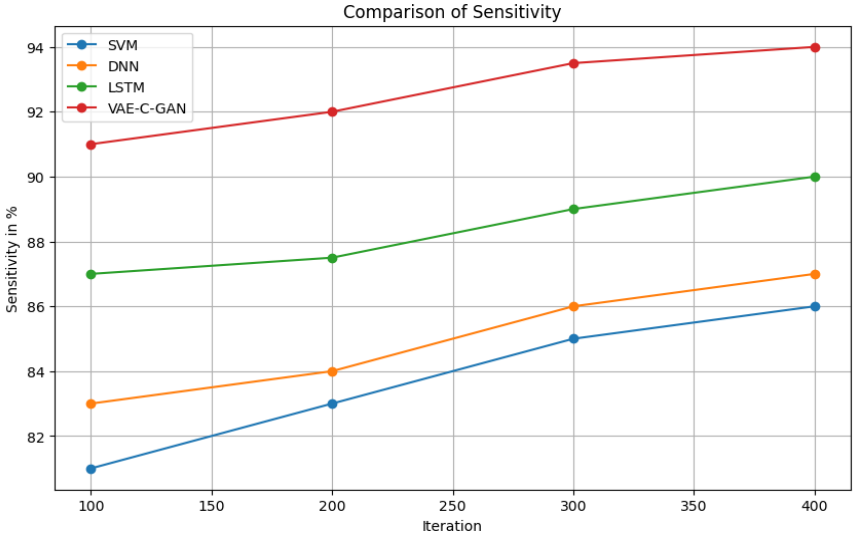

Fig 4. Comparison of Sensitivity.

VAE+C+GAN achieved the highest mean sensitivity (92.88%), indicating that it correctly identified the TP instances most accurately among all models. VAE+C+GAN and LSTM appear to be the best-performing models in sensitivity, correctly identifying the positive instances with higher accuracy. DNN+SVM shows relatively lower sensitivities in comparison. **Fig 4** and **Table 2** shows the comparison of sensitivity.

Specificity

Specificity measures the proportion of TN cases (correctly identified non-epilepsy instances) that the model correctly detects among all actual negative cases in the EEG data. It is calculated as EQU (15)

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positives} \tag{15}$$

where TN is the number of correctly identified non-epilepsy cases, and FP is the number of non-epilepsy cases incorrectly identified as epilepsy cases by the model.

A high specificity score indicates that the VAE+C+GAN model effectively identifies most non-epilepsy cases in the EEG data. This is important as it helps to reduce false alarms and avoid unnecessary interventions or treatments for patients who do not have Epilepsy. In medical applications like epilepsy detection, sensitivity, and specificity are crucial metrics for evaluating the model's performance and ensuring its clinical utility.

Table 3. Comparison of Specificity

Iteration	SVM	DNN	LSTM	VAE-C-GAN
100	81.5	82	85	91.5
200	83	83	86.5	92
300	85.5	84	88	93
400	86.5	86	89	93.5

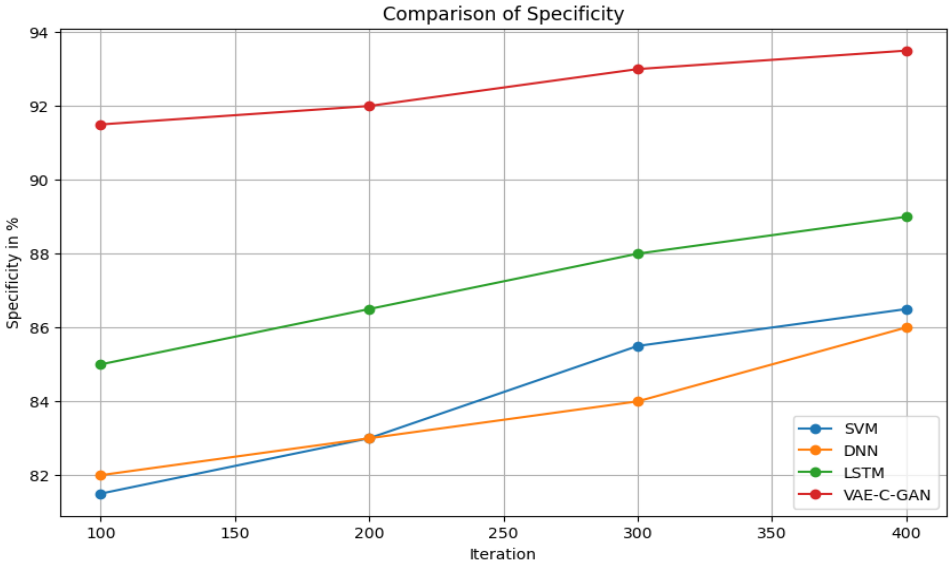

Fig 5. Comparison of Specificity.

VAE+C+GAN achieved the highest mean specificity (93.13%), indicating that it correctly identified TN most accurately among all models. VAE+C+GAN stands out as the top-performing model in mean specificity, closely followed by LSTM. SVM+DNN have slightly lower mean specificity values but still show reasonable performance. Specificity is an important metric, especially in medical applications like ED, where correctly identifying TN (healthy instances) is crucial. When selecting the best model, consider accuracy, specificity, and other relevant evaluation metrics depending on the specific requirements and priorities of the ED task. **Fig 5** and **Table 3** shows the comparison of specificity.

Mathews Co-Efficient Correlation (MCC)

MCC is the covariance between the actual and predicted binary classifications divided by the geometric mean of the total TP and TN products with the total predicted positives and negatives. It is calculated as EQU (16)

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{16}$$

where TP is the number of correctly identified epilepsy cases, TN is the number of correctly identified non-epilepsy cases, and FP is the number of non-epilepsy cases incorrectly identified as epilepsy cases by the model. FN is the number of epilepsy cases the model did not detect (missed). And the +1 indicates perfect prediction, 0 random prediction, and -1 complete disagreement between predictions and actual labels on the MCC scale. Because it considers both TP and TN rates and is less affected by class imbalances than accuracy, MCC is a good metric for evaluating a binary classification model, especially when the data is skewed. **Fig 6** and **Table 4** shows the comparison of MCC.

Table 4. Comparison of MCC

Iteration	SVM	DNN	LSTM	VAE+C+GAN
100	0.4765	0.5132	0.564	0.6786
200	0.4912	0.5342	0.5754	0.6843
300	0.5341	0.5431	0.5831	0.6984
400	0.5534	0.5562	0.5981	0.7134

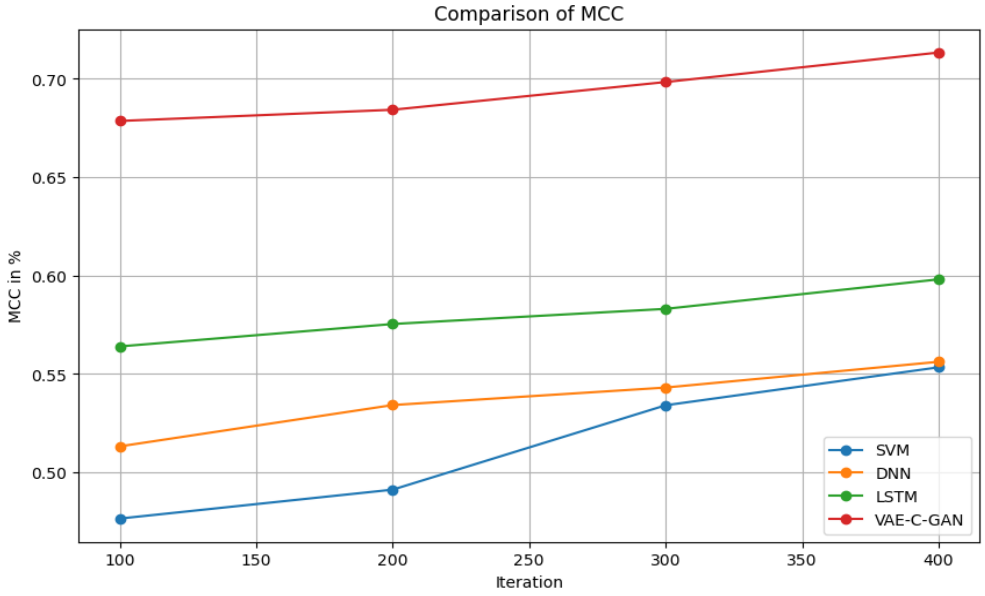

Fig 6. Comparison of MCC.

VAE+C+GAN achieved the highest mean metric value (0.6937), indicating better performance based on the specific metric. In this analysis, higher values of the performance metric are better. Based on the provided data, VAE+C+GAN demonstrates the best performance in terms of the specific metric used, followed by LSTM, DNN, and SVM, respectively.

V. CONCLUSION AND FUTURE WORK

Epilepsy, a chronic neurological disorder characterized by recurring convulsions, can be detected through EEG signals. EEG is widely used to confirm epilepsy cases, although there have been some instances where Epilepsy has been managed without EEG. The diagnosis of Epilepsy heavily relies on Feature Extraction (FE) and pattern classification. Accurate and efficient FE is crucial for reliable diagnosis; however, it often requires significant computational time, limiting the practical use of the sliding window strategy for continuous EEG diagnosis. To address this challenge, a novel reconstruction algorithm is proposed for a large, annotated dataset. This algorithm utilizes a Variational Auto-Encoder-based Generative Adversarial Network with the Cramer Distance (CD) and a Temporal-Spatial-Frequency (TSF) loss function. The proposed approach achieves an accuracy of 90.64%, demonstrating the effectiveness of VAE+C+GAN and outperforming existing techniques.

This approach can be expanded to handle significant signals with multiple channels in the future.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests

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