Elliptical Seizure Classification from Electroencephalography Signals and 2-D Images: A Comprehensive Approach

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ABSTRACT - Epilepsy, a chronic neurological disorder that impacts countless individuals globally, is characterized by recurring seizures. Accurate and timely classification of different seizure types is crucial for effective medical intervention and patient care. By employing a deep learning approach, this project aims to enhance the accuracy and precision of seizure classification, which can significantly improve treatment strategies and outcomes for individuals with epilepsy. The project enhances the effectiveness of EEG signals, the primary diagnostic tool for epilepsy. In addition to analyzing EEG data, the project incorporates images derived from these signals, providing a multi-modal perspective that captures the diverse aspects of this condition. This groundbreaking project has the potential to greatly impact the management of epilepsy. By offering a more precise and all-encompassing method for classifying seizure types, it stands to dramatically enhance patient care and advance our comprehension of this intricate neurological condition.

KEYWORDS:* *Epilepsy, Seizure Classification, EEG Signals, CNN, LSTM, HVD, CWT

I. INTRODUCTION

Seizures, unpredictable bursts of electrical activity in the brain, are a pressing worry for countless people around the globe. These neurological occurrences can greatly impact a person's day-to-day, jeopardizing their safety, mental health, and general sense of wellness. Identifying and categorizing seizures accurately is essential in the realm of neurology, and has a direct impact on how patients are treated, their care, and their long-term outlook. The process of seizure classification involves the careful categorization of seizures into specific types, taking into consideration characteristics such as their clinical manifestations, EEG readings, and other diagnostic markers. This differentiation is crucial for healthcare professionals, as it allows for customized treatment plans, accurate prediction of recurrence probabilities, and overall improved patient care. Furthermore, seizure classification plays a vital role in the advancement of better therapies, ultimately leading to a better quality of life for those suffering from epilepsy. The significance of accurately classifying seizures goes beyond the medical field. In fact, individuals with epilepsy striving for independence heavily depend on the precise categorization of their seizures to make informed decisions about their way of life. Moreover, progress in seizure classification plays a crucial role in the creation of medical devices like neurostimulators and seizure detection systems, providing timely interventions and ensuring greater safety for those with epilepsy. Seizure classification is an essential link between the medical community, individuals living with epilepsy, and society as a whole. Its role is crucial in improving healthcare, ensuring safety, and enhancing the quality of life for people impacted by seizures.

Our primary goal is to design a powerful categorization outline from a cutting-edge methodology. Our focus will be on developing a system that is specifically adept at efficiently analyzing both EEG signals and images, resulting in precise identification of different categories of seizures. To accomplish this, we intend to employ variety of advanced methods namely the t-SNE (t-distributed Stochastic Neighbor Embedding), Long Short-Term Memory (LSTM), CWT – Continuous Wavelet Transform, HVD - Hilbert Vibration Decomposition, and CNN (Convolutional Neural Network). By combining these components, our objective is to create a flexible and high-accuracy model for accurately distinguishing between types of seizures. As we work towards our second goal, our aim is to maximize the effectiveness of our classification model by striving for the highest levels of accuracy, sensitivity, and specificity. This will require a meticulous process of fine-tuning model parameters, carefully selecting algorithms that best suit the task, and implementing strategies to tackle imbalanced datasets. Our third goal is to test and assess the efficacy of the classification model we have built. This involves evaluating its performance on various datasets that represent a wide range of patient populations and data sources. We will employ comprehensive assessment tools to fully grasp the model's advantages and disadvantages as well as its suitability for implementation in practical situations. Our fourth goal focuses on making seizure classification systems practical for use. To make it easily accessible and understandable to healthcare professionals, we are committed to developing an intuitive user interface.

Within the field of neurology, categorizing different forms of seizures is an important yet difficult undertaking. Epilepsy presents complex problems for medical practitioners due to its characteristic of repeated and unexpected episodes. Correct classification of seizure types is critical because it affects diagnosis, treatment decisions, and, in the end, patient outcomes. Our approach uses a cutting-edge deep learning technology to tackle this complex task by utilizing the analytical power of EEG data and supporting visuals. The goal of this novel method is to offer a comprehensive and sophisticated categorization of seizure types. It is impossible to overestimate the importance of Electroencephalography (EEG) signals in diagnosing and treating epilepsy as they record the electrical activity of the brain. However, a significant barrier to accurate categorization is the varied and subtle differences in EEG patterns throughout seizure types. Our proposal aims to overcome this difficulty by creating a thorough and precise categorization system. This methodology offers a sophisticated knowledge of seizure types that goes beyond traditional methods, which is intended to be beneficial to both medical professionals and people with epilepsy. This project has the potential to completely transform how epilepsy is identified and cured. When the intricacies of seizure type categorization are effectively tackled, patient outcomes can be significantly enhanced and overall quality of life can be raised. Our initiative intends to provide more efficient and individualized care for individuals affected by epilepsy by bridging the gap between the complex neurobiological subtleties of seizure types and the practical demands of healthcare practitioners. In summary, our deep learning-based research has the potential to completely transform the way that epilepsy is managed. It hopes to bring in a new age of precision medicine by utilizing its novel method to seizure type categorization and guaranteeing that people with epilepsy receive individualized and best-practice therapy for better health outcomes.

II. LITERATURE SURVEY

EEG signals, providing valuable insights into brain activity, are renowned for their sophistication and complexity. A highly advanced approach is utilized in the existing project to separate the EEG signals into various subcomponents, each representing a unique aspect of the signal. One of the noteworthy methods utilized in the decomposition process of the existing system is the Hilbert Vibration Decomposition (HVD). The existing project deals with HVD due to its ability to not only break down the EEG signals into their individual parts but also preserve critical phase information. The first three specific subcomponents are for further completion of the classification task due to its characteristics. The continuous wavelet transform technique translates the subcomponents into 2D images to provide a structured and spatial representation of the EEG data. In the existing project, classification is accomplished through a hybrid deep learning pipeline, which integrates two intelligent neural networks, which are CNN -Convolutional Neural Network and the LSTM -Long Short-Term Memory. This combination resulted in precise classification of EEG signals into various categories, including different types of seizures [3], [4], [5], [6]. Thus, the existing project deals with HVD to break down signals, identify significant, high-energy subcomponents, convert them into two-dimensional images, and employs a powerful fusion of CNN and LSTM to achieve precise classification of seizure types.

In the study by Saputro [1], they accurately differentiated seizures into three categories, including seizure-free, by utilizing a combination of Mel frequency cepstral coefficient, independent component analysis and Hjorth descriptor. Their approach, yielded an impressive accuracy of 91% by employing a SVM classifier. Similarly, Wijayanto [2] has proposed a unique technique using empirical mode decomposition paired with SVM classification to effectively distinguish into seizures of four categories achieving a classification accuracy of up to 95%. In another study by Kassahun, [3], utilized ontology to classify two types of seizures along with genetics, demonstrating a similar level of thoroughness in their methodology. Additionally, the success of these methods is heavily reliant on the meticulous selection of relevant hand-crafted features, posing significant challenges, especially in distinguishing small discrepancies between different types of seizures [4], [5], [6], [12]. In response to this obstacle, the implementation of a DL-based approach that eliminates the need for manual feature selection has shown promise [4],[5]. Moreover, in the realm of image-based classification, including biomedical signals, the efficacy of Deep Learning-based techniques has already been demonstrated [7], [8], [9], [10]. However, the effectiveness of using a Deep Learning method for specific uses heavily hinges on two crucial factors - the availability of a substantial and diverse dataset for automatic feature discovery [7], [8], [9], [12].

Several studies have explored DL-based pipelines for distinguishing between various types of seizures. For instance, Roy [13] have utilized a basic CNN and achieved 72.2% as an impressive F1-score in distinguishing eight distinct seizure types. However, these studies have not yet tackled the critical issue of developing an effective technique that generates images as input.

In a study by Sriraam and colleagues [6] expertly utilized four diverse CNN models - spanning from basic to advanced, including AlexNet, VGG19, VGG16 in order to effectively categorize eight distinct seizure types. Through the implementation of a vertically stacked 2D spectrogram of unprocessed input EEG data, their efforts resulted in astonishing accuracies of 84.06%, 81.14%, 79.71%, and 76.81%. Asif and colleagues [5] also exemplified innovation in their research by incorporating sophisticated techniques such as the saliency-encoded spectrogram. Additionally, they harnessed the powerful SeizureNet algorithm - a fusion of multiple CNN building blocks - to surpass their previous findings and achieve further significant enhancements.

Although their image generation mechanism is highly effective, it is worth considering that a Deep Learning (DL) pipeline comprised solely of convolutional neural network (CNN) blocks may not be the most optimal choice. While CNNs excel at extracting spatial features, temporal information is crucial for accurately detecting and differentiating between different types of seizures. To this end, Ahmedt et al. [13] utilized a stacked auto-encoder, RNN, CNN and recurrent CNN in their architecture in order classify eight seizure types, achieving an impressive weighted F1-score of 94.0%. Similarly, Liu et al. [4] followed a bilinear hybrid DL approach that utilized 2D depiction of the unfiltered input data for the classification of seizures into eight different types. They achieved their results through a fusion of a STFT—short-time Fourier transform and a deep learning architecture.

In their research, Emami et al. explored the effectiveness of using different durations of EEG components (ranging from 0.5s to 10s) in accurately classifying epileptic seizures [14]. Similarly, Gao and colleagues investigated the role of 4s frames in distinguishing between seizure episodes [9]. Additionally, Shankar examined the impact of dividing EEG signals into segments ranging from 5.9s and 10s to classify seizure activity and identify different seizure types [12], [15], [16] among other related studies. The new study uses the HVD approach on EEG fragments that were previously recovered from larger recordings, building on this earlier work. Furthermore, the 1D signals are decomposed and converted into 2D images for use in a deep learning-based classification approach. This innovative method shows promise in accurately identifying and categorizing epileptic seizures.

Emami and colleagues [14] captured 2D images by directly capturing snippets of EEG segments on specific durations. While Gao and colleagues [9] utilized power spectrum density energy diagrams to generate 2D images, the low-energy frequency accuracy of EEG may limit their efficiency. In contrast, Shankar and colleagues [12], [15], [16] introduced time series techniques such as gramian angular field and recurrence plot to construct 2D images for their deep learning-based seizure classification. However, these methods disregard the importance of spatial features.

Other techniques for generating 2D images includes using the TFR—Time and Frequency Representation for one dimensional input signals. This method is particularly effective as it retains the critical frequency and time data [11], [13], [17], [18]. Among the various TFR methods, the CWT has displayed a significant success in seizure analysis due to its ability to capture rapid frequency changes with high resolution [19]. As such, the current study utilizes TFR with CWT to transform 1D EEG signals into 2D images.

III. PROPOSED SYSTEM

Our groundbreaking system utilizes a cutting-edge methodology to analyze and interpret electroencephalogram (EEG) signals. Our primary goal is to uncover underlying patterns hidden within the data. To achieve this, we rely on the powerful Hilbert Vibration Decomposition (HVD) technique, which accurately deconstructs the EEG signals while preserving crucial phase details. To begin, our system applies HVD to break down the signals. Then, it identifies the subcomponents with the highest energy levels. These selected subcomponents are then further examined through CWT, which transforms the selected subcomponents into two-dimensional images. This process provides a deeper and more comprehensive analysis. Our approach predicated on a powerful hybrid deep learning pipeline that combines LSTM with CNN in an elegant way. This integration enables the simultaneous capture of the temporal as well as spatial properties present in the data collected from the EEG. Taking this all-encompassing approach improves our system's capability to identify complex patterns and correlations in the data. For dimensionality reduction, we include the t-SNE method to further optimize the system's performance. By optimizing the EEG data format, this innovation makes the analysis more streamlined and effective. All things considered, our methodology combines deep learning framework with sophisticated signal processing techniques to provide a solid foundation for deriving useful insights from EEG signals. The framework and working of the recommended system is depicted in Fig.1.

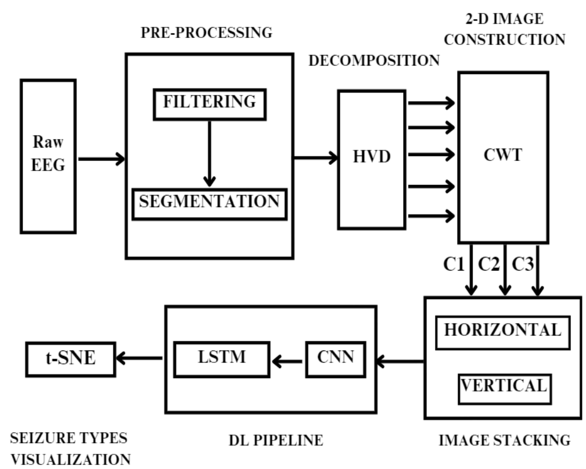


Fig. 1. System architecture of the recommended system

a. DATASET

The robust results were obtained by validating our experimental findings through the use of a prestigious epilepsy EEG dataset acquired from Temple University Hospital. The data set is of version TUH v1.5.2. This dataset is particularly notable as it encompasses EEG signals from five distinct seizure types, with varying sampling frequencies and montages, providing a diverse and all-encompassing collection of data for our analysis. Table. 1. shows the five kinds of seizure and its related durations. Notably, the distribution of EEG recordings across seizure types was uneven. To ensure the validity of our analysis, we specifically focused on 153 seizure sessions. This ensures that our findings are not skewed by an imbalance in data and provides a well-rounded representation of all five seizure types.

SEIZURE TYPE	DURATION (s)
Complex partial seizure (CPS)	1904.09
Focal non-specific seizure (FNS)	1829.19
Generalized non-specific seizure (GNS)	2060.84
Simple partial seizure (SPS)	1329.5
Tonic-clone seizure (TCS)	517.17
Seizure free (SF)	2000

Table. 1. Description of TUH v1.5.2 dataset

EEG data in dataset were recorded using the Av hardware setup. The data contains 250 Hz as sampling frequency and resolution of 16 bits. EEG signals from 23 common channels—each of which represents a particular electrode placement—are included in the collection. The channels used are: FP1-F7, F7-T7, T7-P7, P7-O1, FP1- F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8- 0, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8-1. These channels mentioned, corresponds to specific electrode placements on the scalp. These electrodes are strategically positioned to capture electrical impulses produced by the brain. Each channel represents the electrical responses between two designated electrode locations. This dataset's comprehensiveness and the careful selection of seizure episodes guarantee that our study is based on a representative and varied sample, which improves the validity and generalizability of our experimental results.

b. GOGLE COLABORATORY

Google Colaboratory, also referred to as Colab, is an exceptional cloud-based tool offered by Google that enables individuals to effectively utilize Python coding in a collaborative setting. It seamlessly integrates with Google Drive and grants access to top-notch computational capacities, such as GPU acceleration, eliminating the need for individual installations. Colab is especially valuable for tasks involving data analysis, machine learning, and deep learning, allowing users to collaborate and exchange ideas in real-time through shared Jupyter notebooks.

Google Colab is a valuable resource for both researchers and practitioners working on the seizure classification of EEG signals. Its powerful computational capabilities are easily accessible, allowing users to effectively implement machine learning models for the classification of electroencephalogram data. This is a crucial aspect in diagnosing and comprehending epileptic seizures. Additionally, Colab's available GPU resources significantly speed up the training process of advanced models, including neural networks, which are widely utilized for precise detection of seizure types. Furthermore, Colab's collaborative environment promotes knowledge sharing, making it a convenient platform for researchers to work together on enhancing and fine-tuning seizure classification algorithms using EEG signals.

Google Colab offers a robust and user-friendly platform for running sophisticated algorithms such as HVD, CWT, CNN, t-SNE and LSTM. With its seamless integration with Google Drive and access to GPU resources at no cost, individuals can efficaciously implement and execute complex algorithms on large datasets. Moreover, Colab's computational capabilities greatly improve the processing speed for tasks involving signal processing and time-frequency analysis, while the availability of GPU acceleration considerably speeds up the training process for deep learning models like CNN and LSTM.

c. PRE-PROCESSING

The first step in preparing the recorded EEG signals is to remove noise and artifacts [7], [8], [20], [21]. Our approach involved utilizing a Butterworth band-pass filter (Fifth order) with a frequency ranging from 0.5Hz to 50Hz [12], [24]. This carefully selected range greatly enhanced our ability to detect the intricate patterns present in epileptic seizures. The band pass filter played a pivotal role in our signal processing process, effectively removing irrelevant high frequencies and allowing us to focus solely on the vital frequency band [4], [5], [6], [11], [12]. We were able to isolate the distinctive features of epileptic seizure patterns with remarkable accuracy and precision by successfully removing unnecessary high frequencies from our filtering process [12], [24]. This crucial step enabled us to create a refined and concentrated dataset, laying the foundation for further analysis. In order to enable classification using deep learning, the produced signals were split into 10-second intervals that had a 50% overlap [14]. In order to preserve the data integrity and provide a continuous and comprehensive collection of samples for analysis, this segmentation approach was used. Because the overlapping segments capture possible transitions and changes within the data, they aid in a more detailed understanding of the temporal dynamics in the EEG signals [7], [8], [14]–[16]. The Hilbert Vibration Decomposition (HVD) method is utilized to enhance the accuracy of the segmented signals of EEG. Every segmented signal was subjected to HVD, enabling a thorough decomposition that maintains crucial phase information. By ensuring that the ensuing deep learning models are trained on high-quality, representative data, this stage helps to provide a more nuanced analysis and raises the system's accuracy and reliability in classifying epileptic episodes.

d. HVD- HILBERT VIBRATION DECOMPOSITION

The next step in our method is the complex decomposition of filtered electroencephalogram (EEG) data into many smaller components. HVD is a signal processing technique that is distinguished by its special qualities. It is the best decomposition method that can be used for variable data like EEG signal [25]. HVD varies the IA–instantaneous amplitude and IF–instantaneous frequency gradually. This procedure fulfils an important function by allowing researchers to separate and extract discrete elements or patterns from the EEG data. The analogy of breaking the signal down into its constituent parts is appropriate since it reflects the goal of obtaining a more complex understanding of the EEG signal's underlying structure. Filtering the IFs in each cycle, separates the slowly varying synchronous components. In addition to its ability to break down the signal, HVD is especially valuable because of its ability to maintain important phase information. This phase data is essential to the analysis since it provides information on the timing and alignment of different frequency components in the EEG signal. With HVD, our approach recognises the importance of preserving the temporal correlations and synchronisation of these components in addition to revealing their individual components. However, the HVD method is used under two main primary criteria: i) a minimum of one quasi-harmonic with many complete cycles is superposed to create the underlying signal and ii) the frequency and envelope of each vibrating components are distinct from one another.

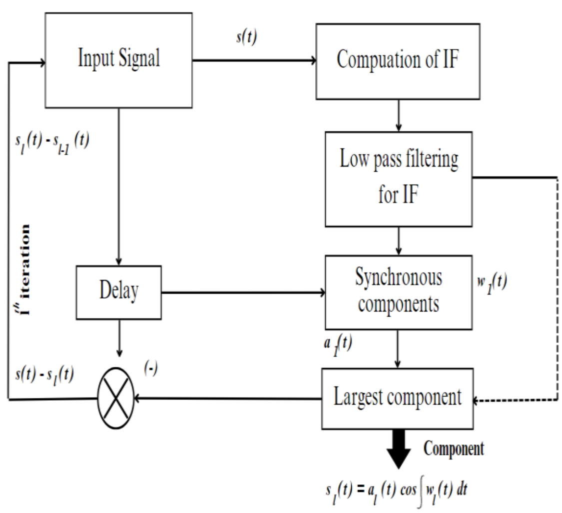


Fig. 2. Systematic working of HVD

The ECG signal does, in fact, meet these two main requirements since it exhibits many quasi-harmonic full-cycle components with varying IFs. Undoubtedly, it has already been effectively used to analyze EEG signals. The synchronous detection operation and IF estimate are carried out while the HVD is running. Because of the synchronous detection, it is finally possible to keep the elements with slight fluctuations in amplitude, are overpowered by other major elements. The IFs can be utilized to estimate it. As a result, both the IA as well as IF associated with an EEG are calculated first. Low-pass filter (LPF) with an extremely low threshold frequency is then used to filter the IF. The filtered IF and IA create the synchronous component. The biggest amplitude component is extracted from its source signal, followed by the utilization of the remaining portion in the further process. Fig. 2. illustrates the many phases of the HVD process.

A composite signal, $s(t)$, is defined by Equation (1). It consists of amplitude subcomponent $a(t)$, and l subcomponents of slowly varying frequencies:

$$\boldsymbol{s(t) = \sum_l a_l(t)\cos\left(\int \omega_l(t)\,dt\right)} \qquad (1)$$

Next, the IF may be estimated by utilizing the computational notation $A(t)$ of $s(t)$:

$$\boldsymbol{A(t) = s(t) + j\tilde{s}(t)} \qquad (2)$$

Using (3), we can assess the Cauchy principal value (P.V.) of the integral and $\tilde{s}(t)$ is represented as the Hilbert transform (HT) of $s(t)$.

$$\boldsymbol{\tilde{s}(t) = HT[s(t)] = \frac{1}{\Pi} P \cdot V \int_{-\infty}^{\infty} \frac{s(\tau)}{t-\tau} d\tau} \qquad (3)$$

Then, IF can be found using (4):

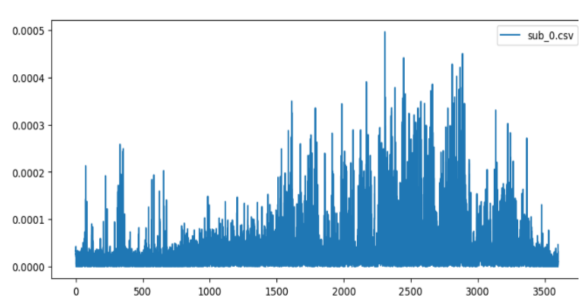
$$\boldsymbol{\omega(t) = \frac{d}{dt}\varphi(t) = \frac{d}{dt}\tan^{-1}\left(\frac{\tilde{s}(t)}{s(t)}\right)} \qquad (4)$$

where, respectively, $\omega(t)$ and $\varphi(t)$ stand for the instantaneous phase (IP) and the IF. Afterwards, synchronous demodulation has been used to identify the greatest envelope subcomponent. In fact, synchronous detection makes it possible to identify even minute changes in $s(t)$.

$$\begin{aligned} \boldsymbol{s_l =_r (t) = \frac{1}{2} a_l(t) \left[cos\left(\phi_l(t)\right) + cos\left(\int (\omega_l(t) + \omega_r (t)\, dt + \phi_l(t)\right)\right]} \\ \boldsymbol{\tilde{s}_l =_r (t) = \frac{1}{2} a_l(t) \left[sin\left(\phi_l(t)\right) - sin\left(\int \left(\omega_l(t) + \omega_r (t)\, dt + \phi_l(t)\right)\right)\right]} \end{aligned} \quad \textbf{(5)}$$

Using equation (5), one can now determine the HT phase ($\tilde{s}_l =_r (t)$ and in-phase $s_l =_r (t)$ in the r-referenc5e of the l^{th} component. In this case, the IF of the greatest factor in the r-reference is represented by $\omega_r (t)$, and the IP, IF, and IA from the l^{th} components are denoted by $\phi_l(t), \omega_l(t)$ and $a_l(t)$.

After that, the subcomponent with the highest energy, $s_1(t)$ was extracted from the original compositions, $s(t)$. The lower energy signal, $s_{l-1} = s_l(t) - s_1(t)$, can be broken down in the ensuing iterations. The energy of the decomposed subcomponents eventually decreases in order; that is, the energy of the first subcomponent is greater than that of the next, and so forth. As a result, the EEG signals were broken down into a number of smaller components, which were then taken into consideration for the creation of 2D images. In addition, of all the subcomponents that are deconstructed using HVD, the first three together maintain approximately 80 percent of the energy of the primary signal; for this reason, they have been given attention for additional processing. Fig. 3. depicts the plotting of all the five subcomponents (sub_0 to sub_4) obtained after performing HVD algorithm.



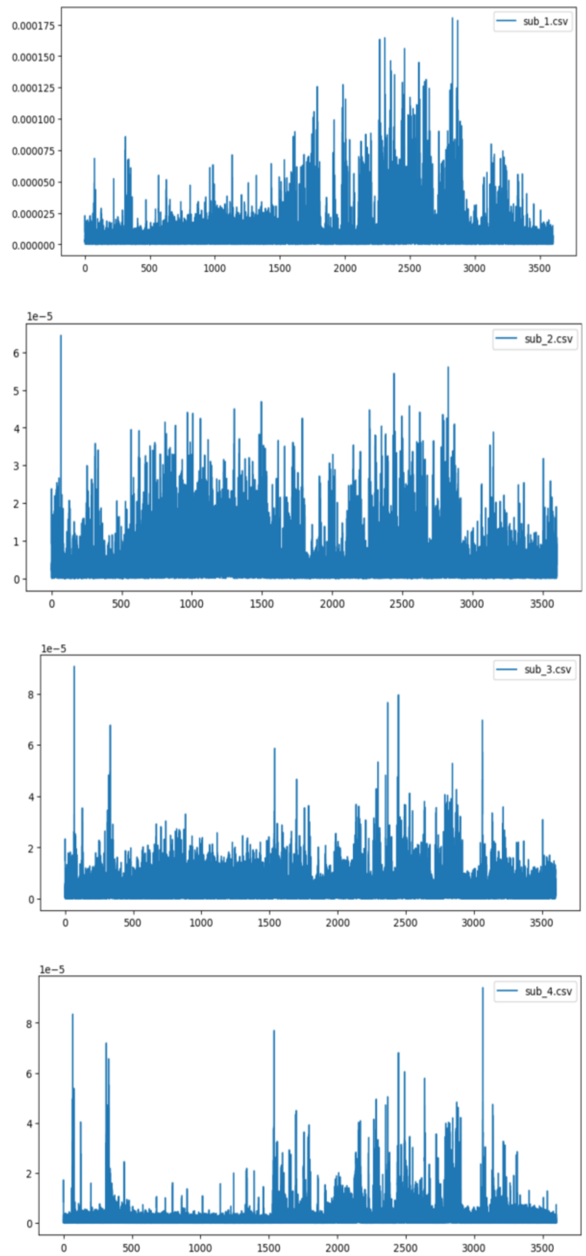


Fig. 3. HVD plotting of all subcomponents.

Additionally, to ensure that the subcomponents are appropriate, the correlation (C_c) between them and the main signal has been examined in Table. 2.

SUBCOMPONENTS	ENERGY (%)	C_c
C1	67.25	0.854
C2	11.35	0.386
C3	2.74	0.178
C4	0.715	0.120
C5	0.695	0.083

Table. 2. Correlation (C_c) and Energy percentage of all five subcomponents

e. 2D IMAGE GENERATION BY CWT

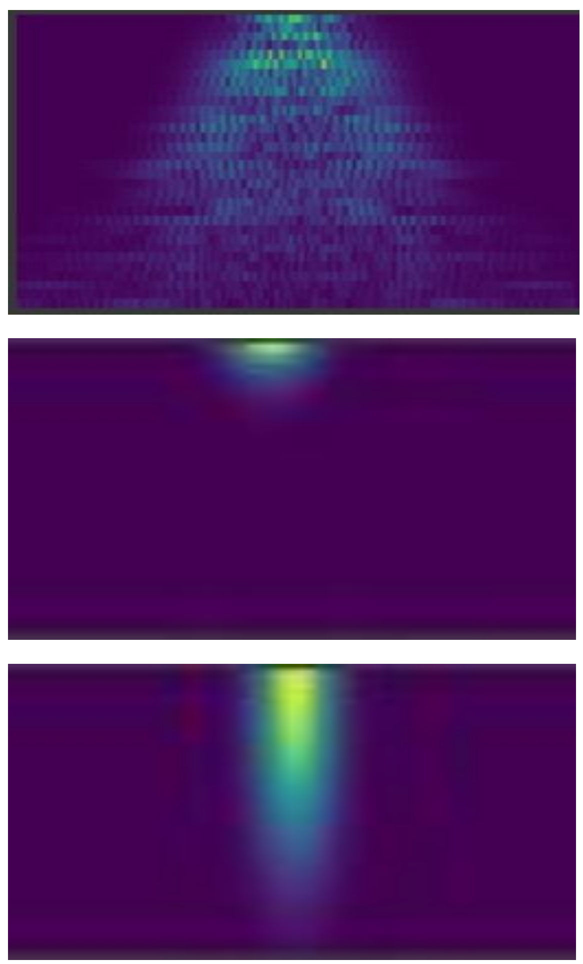
Upon identification of the three high-energy subcomponents via Hilbert Vibration Decomposition (HVD), the use of continuous wavelet transform (CWT) is a crucial step towards optimising them for deep learning analysis. The chosen subcomponents are transformed into 2D representations, which is useful for more efficient analysis and classification.

CWT helps in dividing input signal into parent wavelet. These are microscopic oscillations within an extremely small period [17], [18]. Excellent time and frequency translation is achieved by scaling and moving the parent wavelet across the period plane of the intended signals to form a time-frequency pattern [19]. It has been discovered that the CWT is incredibly effective and appropriate for modeling nonlinear and irregular signals, like EEG [7], [8], [17]–[19]. Mathematically the CWT of $x(t)$ signal can be determined by (6):

$$\boldsymbol{CWT_s(d,\Delta) = \frac{1}{\sqrt{d}}\int x(t)\,\psi\left(\frac{t-\Delta}{d}\right)dt} \qquad \textbf{(6)}$$

where the symbols ψ and $CWT(d,\Delta)$ stand for the base wavelet function and wavelet coefficient, respectively. Δ shifts the $\psi(t)$, and d contracts or dilates it. When d is less than 1, or contraction, $\psi(t)$ offers a high temporal resolution that is useful for measuring brief activities; when d is more than 1, or dilatation, $\psi(t)$ yields a high spectrum resolution [17]–[19]. The Morlet wavelet was used for this work because it is effective at evaluating complicated signals, such as EEGs [18], and it has shown respectable results in a number of EEG-based research [6], [13], [17]–[19]. It can accurately record short spike spines that alternate and repeat, together with a start and finish time [17]. Since t represents the sample instants, equation (7) provides a mathematical definition of the Morlet wavelet function.

$$\boldsymbol{\psi(t) = e^{-t^2/2}\ \cos(5t)} \qquad \textbf{(7)}$$



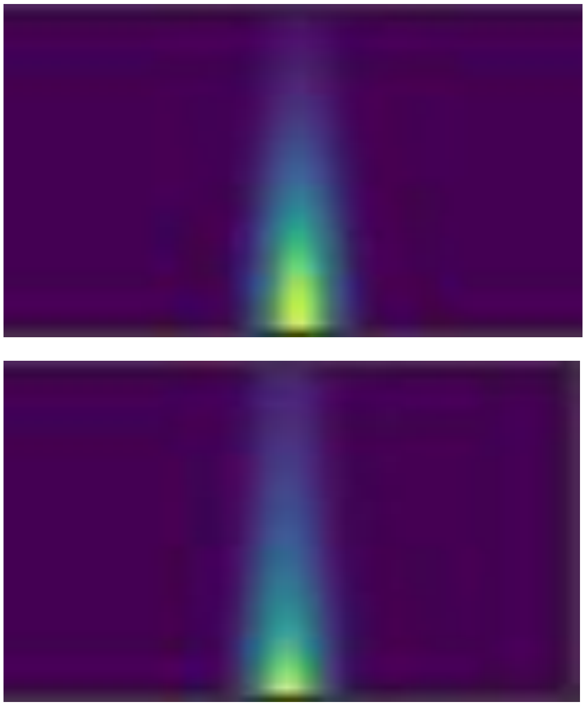


Fig. 4. CWT Image Generation for all subcomponents.

The Fig. 4. displays the 2 dimensional images of all five subcomponents. The complex information contained in the subcomponents and the analytical capability of deep learning are connected by the continuous wavelet transform. Deep learning models are presented with a structured format by graphically organising the data through the conversion of subcomponents into 2D representations. This conversion is important because it improves the data's fit for deep learning algorithms while preserving the critical information included in the subcomponents. Deep learning harnesses immense power in unraveling the intricate spatial ties, complex patterns, and unique attributes within EEG data. These subtle nuances may be obscured in the raw signal, but when transformed into 2D representations, they become clearer. The deep learning model's efficacy in processing this organized and enhanced data enables it to extract higher-level features, leading to a deeper comprehension of the underlying neural function. Essentially, the 20 continuous wavelet transform serves as a crucial precursor, paving the path for the deep learning model to expose hidden intricacies within the EEG data.

f. IMAGE STACKING

One of the most essential phases in using DL-based classifiers successfully is input data preparation [7], [8], [10], [22], [25]. The subcomponents are stacked in both vertically and horizontally to produce one image as displayed in Fig. 5. and Fig. 6. One image has been created by stacking the various images that each subcomponent generates in a horizontal and vertical manner. For uniformity, all photographs have been resized to 32 by 32. Ultimately, in order to determine the optimal image stacking technique, the hybrid Deep Learning pipeline receives the images obtained through stacking individually.

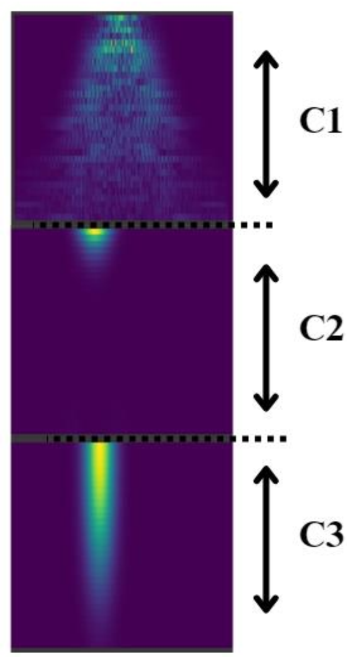


Fig. 5. Vertical Image stacking

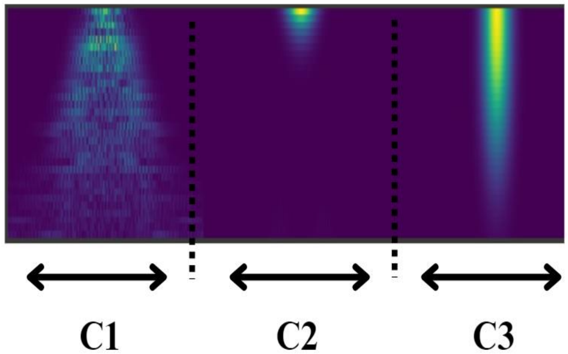


Fig. 6. Horizontal Image stacking

g. DEEP LEARNING PIPELINE

Two popular models—LSTM and CNN—make up the suggested hybrid DL pipeline. While the LSTM proficiently distinguishes time-related events, the CNN excels at extracting spatial features. This distinction can be crucial in the analysis of epileptic seizures [8], [22], [25]. The combination of the two models is highly effective in seizure analysis. Two combinations have been made out of them: parallel and serial. It has been discovered that the serial combination CNN followed by LSTM is more effective and have been used in this work. Additionally, 20% of the training samples were taken into account while validating the model training.

1. CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN's framework is designed to identify seizures by effectively extracting and processing spatial patterns in the frequency as well as time spectrum of the input data. Convolution, pooling, and batch normalization are the three hidden layers of CNN that automatically extract pertinent characteristics from the raw input data [9], [10], [12], [22], [25]. Convolutional layers are essential for filter-based input EEG picture scanning. The purpose of these filters is to recognise spatial patterns that point to seizure activity. Through convolving these filters over the input pictures, the network learns to identify important elements in the EEG signals' time-frequency domain. This makes it possible for the model to identify minute spatial correlations and patterns that might be signs of seizures. Pooling layers play a crucial role in reducing the size of data while preserving important features. This involves down sampling the output from convolutional layers, selecting relevant information and disregarding unnecessary details. This not only improves computational efficiency but also directs the network's attention towards the most significant aspects of the input. A labelled dataset is used to train the CNN, designating each EEG fragment as either a non-seizure or seizure condition. This process uses backpropagation, enabling the network to modify its filter and neuron weights. The inputs are convolutioned with a predefined kernel to extract structural information, which is then processed by an activation function which is non-linear. The result is calculated mathematically using (8):

$$\boldsymbol{C_p^m = f\left(\sum_{q=1}^{N_m-1} conv\ 2D\ \left(w_{q,p}^m,\ F_q^{m-1}\right) + b_p^m\right)} \tag{8}$$

Where $conv\ 2D$ represents the 2D convolution operation and C_p^m refers to the convolution output of the p^{th} node in the m^{th} stratum. The p^{th} node and the total nodes in the $(m-1)^{\text{th}}$ stratum are denoted by F_q^{m-1} and $N_m - 1$, respectively. The trainable kernel's weight is denoted by $w_{q,p}^m$. The convolution result was then followed by an activation that was non-linear $(f(y) = max(0,\ y))$. The normalization layer of the batch and the layer with the greatest pooling then receive the output from the convolution layer. By creating a smooth and recognizable collection of various unique features, maximum pooling stratum lowers the model's spatial size, feature variance, and complexity. [9], [12], [22]. Additionally, batch normalization helps reduce the problem of internal covariance shift [12], [14]–[16]. As a result, the CNN continually improves its ability to identify spatial patterns that indicate seizures. The CNN's fully connected layers offer the final categorization output. These layers use the high-level characteristics acquired from both the pooling layer and convolutional stratum in order to evaluate if input EEG segment is either from a seizure state or from a non-seizure state. Because of its extensive architecture, the CNN is an effective tool for automated seizure identification in neurological monitoring applications. It can learn and recognise spatial patterns in EEG signals on its own.

2. LONG SHORT-TERM MEMORY (LSTM)

LSTM is essential to seizure categorization models because they can store information across long sequences. Because of their unique architecture—which includes gating mechanisms and memory cells—LSTMs are able to recognise and comprehend complex patterns linked to seizures. During the learning process, the memory cells in long short-term memory (LSTMs) are educated to adjust their characteristics, such weights and biases [25]. To properly capture the temporal patterns that define seizures, this modification is essential. LSTMs employ the backpropagation through time (BPTT) technique to address the issue related to vanishing gradient. It is a prevalent difficulty in lengthy sequences, in contrast to conventional RNN. BPTT takes the full sequence into account when updating the weights, which helps LSTMs identify long-term dependencies from the input data that is sequential in nature. The handling of long-term dependence by LSTMs is very important when it comes to seizure identification. Since seizure patterns can span several time periods, the model must identify connections and dependencies over a long period of time.

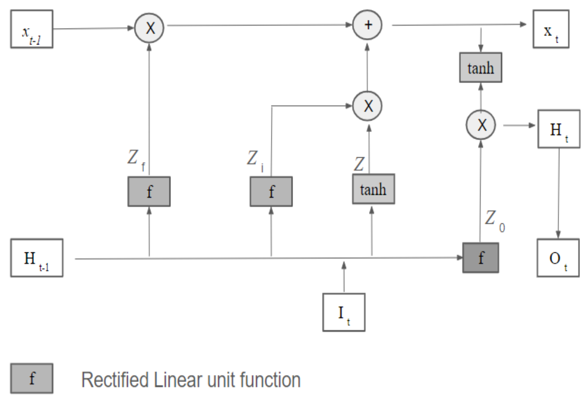


Fig. 7. The LSTM framework's internal working.

From the Fig. 7. The cell gate (*z*) in an LSTM is in charge of retaining information over time. The *zf* stands for the forget gate, *zi* is the input gate, and zo, which manages the amount of information in the cell that will be utilised to compute the output using the weight metrics, W. The *xt*, *Ht*, and *Ot* are three outputs that reflect cell state, hidden state, and current output, respectively, the xt-1, Ht-1, and It designate the cell state, prior hidden state, and current input.

In this case, LSTMs perform exceptionally well because they are able to capture the complex temporal dynamics related to seizures. The hidden states of the LSTM generate abstract representations of the input sequence. During classification, these concealed states provide an essential basis for differentiating between seizure and non-seizure states by encapsulating contextual information and learning properties. The LSTM is a reliable and efficient tool for modelling and classifying temporal patterns in EEG data. It is especially well-suited for the complex task of seizure identification because of its innate ability to retain and use information over extended sequences and resistance to the vanishing gradient problem.

h. T-DISTRIBUTION STOCHASTIC NEIGHBOR EMBEDDING (t-SNE)

One powerful method that is often used to make complicated data visualization easier is t-SNE. When high-dimensional features are difficult to grasp, this algorithm is very helpful. CNN extracts features extensively, however these features that are produced are frequently located in a space with a high number of dimensions, which makes it challenging to understand the patterns that they contain. This is exactly the situation in which t-SNE shines, providing a solution by mapping these complex properties onto a lower-dimensional space, usually in 2D or 3D. The efficacy of t-SNE is based on its capacity to maintain the correlations among data points while reducing dimensionality. In other words, data points which are closer to one each other will remain close in the lower-dimensional space. The maintenance of the relative positioning of data points, which indicates similarities or differences, is dependent upon the preservation of local structure, which is essential. t-SNE makes it easier to find unique clusters in the data by lowering dimensionality while maintaining local structure. Visualising and comprehending patterns or groupings that might be hidden in the higher-dimensional feature space is greatly aided by this. Through the identification of significant correlations and the discovery of clusters that may represent certain patterns or categories, researchers and practitioners can obtain understanding of the data's fundamental structure. t-SNE is an essential tool for improving interpretability and extracting insights from high-dimensional feature spaces. This helps to make complex datasets easier to grasp, particularly when it comes to CNN-derived features.

IV. RESULTS

The evaluation of the classification performance involved the computation of weighted F1-score, sensitivity, specificity, and accuracy. When all data sets are not proportionally available, the weighted F1-score becomes extremely essential [5], [7], [8]. Additionally, it offers a more precise evaluation of cases that were misclassified. Weighted F1-score, sensitivity, specificity, and accuracy have all been examined to assess the performance.

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(10)}$$

$$S_e = \frac{TP}{TP + FN} \quad \textbf{(11)}$$

$$S_p = \frac{TN}{TN + FP} \quad \textbf{(12)}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \quad \textbf{(13)}$$

where, FP is false positive and false negative is represented by FN. The genuine positive and negative is represented by TN and TP, respectively. Furthermore, an examination of the suggested model's robustness and methodical abilities has been conducted using the receiver operating characteristics (ROC) analysis [7], [8], [10], [19], [23].

The suggested approach achieved a variety of performance metrics, including Weighted F1-score, sensitivity, specificity, and accuracy, as demonstrated in Fig. 9. The horizontal axis displays multiple sets of input pictures, while the vertical axis represents the corresponding percentage of performance metrics.

The Table. 3.elucidates an analysis on similar works by comparing various factors.

WORKS	INPUT TO CLASSIFY		CLASSIFIER	ST	PM (%)	
	TYPES	IGM			Acc	F1
Liu et al.	2D IMAGES	STFT	CNN RNN HYBRID	8	- - -	95.5 95.8 97.4
Asif, et al.	IMAGES	SES	CNN	8	-	94
Sriraam, et al.	2D IMAGES	STFT	CNN	8	84.1	-
Ahmedt, et al.	EEG	FFT	P-NMN	7	-	94.5
Wijayanto, et al.	SF	-	SVM	4	95	-
Kassahun et al.	MD	-	GB-ML	2	-	77.8
Roy et al.	EEG	FFT	k-NN XGB CNN	8	- - -	90.1 86.6 72.2
Shankar el al.	2D IMAGES	GAF	CNN	5	84.2	84
This Work	2D IMAGES	HVD, CWT	CNN, LSTM	6	99.09	99.01

Table. 3. Analysis Table

The Fig. 8. Illustrates the t-SNE plotting using symbols of various colors which correspond to the numerous seizure types that have been identified.

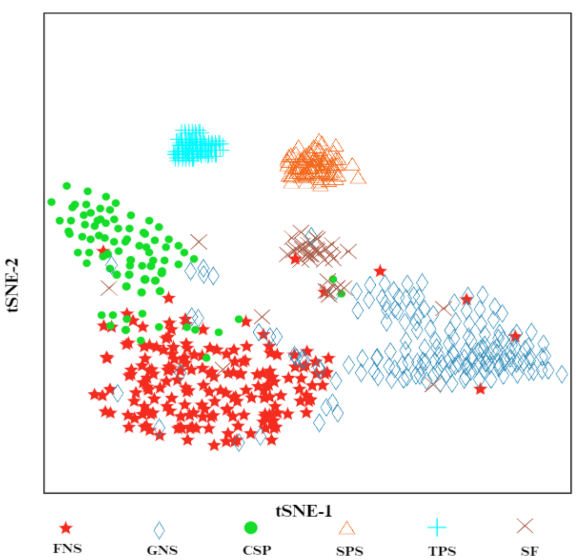


Fig. 8. t-SNE plotting for seizure types

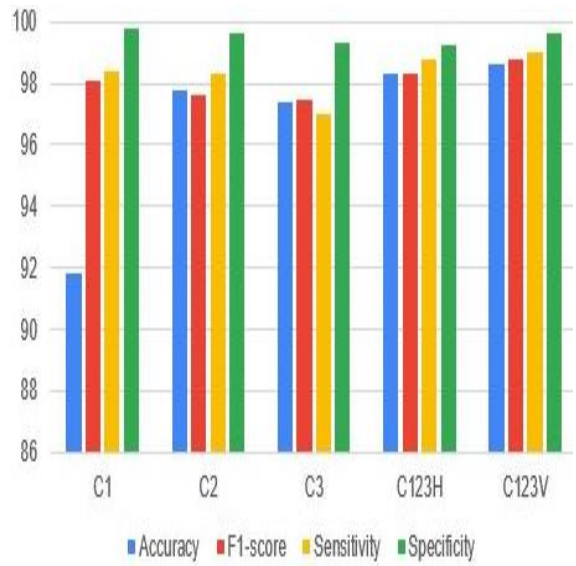


Fig. 9. Performance Metrics

V. CONCLUSION

The present work utilizes the Hilbert Vibration Decomposition (HVD) technique to carefully dissect electroencephalogram (EEG) segments into smaller constituents. In order to improve the analysis even further, the first three subcomponents that are produced from HVD are used to create 2D pictures using the CWT. CNN and LSTM networks are combined into a single representation for a hybrid Deep Learning (DL) pipeline, which allows for extensive feature extraction and categorization. Utilizing the Temple University EEG dataset (TUH), the experimental validation produces impressive outcomes. With an exceptional classification accuracy of 99.09%, the suggested technique gets a weighted F1-score of 99.01%. The application of t-SNE increases trust in feature extraction procedure's thoroughness even further. The suggested strategy outperforms existing methods in a comparative examination, exhibiting remarkable classification performance in EEG signal analysis. By using deep learning to improve and automate seizure type categorization, this study fills a major need in the medical industry. The ramifications are significant, resulting in improvements in patient care via early detection, individualized treatment plans, and a better understanding of seizure diseases. This research makes a substantial contribution to the area of neurology by successfully categorizing seizure types with such high accuracy. In addition to streamlining medical procedures, the hybrid DL pipeline's accurate and automatic categorization gives medical staff members insightful information that helps them provide patients with individualized treatment. In the end, this study might revolutionize the field of diagnosing and treating seizure disorders, highlighting the critical role that deep learning plays in improving medical practices.

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