ELLIPTICAL SEIZURE CLASSIFICATION FROM ELECTROENCEPHALOGRAPHY SIGNALS AND 2-D IMAGES: A COMPREHENSIVE APPROACH

PROJECT REPORT

Submitted by

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VIVA VOCE EXAMINATION

The viva voce examination of the project work "Elliptical Seizure Classification from Electroencephalography Signals and 2D Images: A Comprehensive Approach" is the bonafide record of the Project Work done at the Department of Information Technology, Easwari Engineering College during the Academic Year 2023-2024 by

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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

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EEG	Electroencephalogram
LPF	Low Pass Filter
HVD	Hilbert Vibration Decomposition
CWT	Continuous Wavelet Transform
t-SNE	t-Distributed Stochastic Neighbour Embedding
DL	Deep Learning
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
CPU	Central Processing Unit
RAM	Random Access Memory
TUH	Temple University Hospital
RNN	Recurrent Neural Networks
SEEG	Surface Electroencephalogram
STFT	Short Time Fourier Transform
BPTT	Back Propagation Through Time
PV	Principal Value
HT	Hilbert Transform

IP	Instantaneous phase
IF	Instantaneous frequency
IA	Instantaneous Amplitude
GPU	Graphical Processing Unit
FP	False Positive
FN	False Negative

CHAPTER 1

INTRODUCTION

1.1 GENERAL

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.

1.2 OBJECTIVE

Our primary goal is to construct a powerful categorization framework using cutting-edge deep learning methods. 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 techniques such as the Long Short-Term Memory (LSTM), t-SNE (t-distributed Stochastic Neighbor Embedding), 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.

1.3 PROBLEM DESCRIPTION

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 initiative has enormous potential to revolutionize the diagnosis and treatment of epilepsy. When the intricacies of seizure type categorization are effectively tackled, patient outcomes can be significantly enhanced and overall quality of life can be raised. 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.

1.4 EXISTING SYSTEM

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: the Convolutional Neural Network (CNN) and the Long Short-Term Memory (LSTM). This combination resulted in precise classification of EEG signals into various categories, including different types of seizures.

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.

1.5 PROPOSED SYSTEM

Renowned for their intricacy and sophistication, electroencephalography (EEG) signals provide priceless insights into brain function. In the present work, an extremely sophisticated method is utilized to decipher the subtleties of EEG signals, breaking them down into discrete subcomponents, each of which represents a particular feature of the signal.

Hilbert Vibration Decomposition (HVD) is unique in that it can separate EEG signals into their component parts while retaining important phase information. In order to preserve the temporal dynamics of the signals and improve the quality of the decomposition, phase information preservation is essential. The first three distinct subcomponents obtained using HVD are essential to finishing the classification process.

The continuous wavelet transform approach is used to turn the subcomponents into 2D pictures, which then offer an organized and spatial representation of the EEG data. This conversion improves the data representation and makes it easier to analyze the complex patterns seen in the EEG signals.

In the current study, two intelligent neural networks—the Long Short-Term Memory (LSTM) and the Convolutional Neural Network (CNN)—are integrated into a hybrid deep learning pipeline to carry out the classification process. CNNs are good at extracting spatial features, whereas LSTMs are good at identifying temporal connections in sequential data. This hybrid method aids in the accurate categorization of EEG data into many groups, including distinct seizure types.

To sum up, the current effort carefully dissects EEG data using Hilbert Vibration Decomposition (HVD) in order to pinpoint important high-energy subcomponents. A structured spatial representation of these subcomponents is produced by applying continuous wavelet transform to further convert them into 2D pictures. The effective combination of deep learning techniques—more especially, CNN and LSTM network integration—guarantees the project's capacity to accurately classify EEG signals. This effort advances our knowledge and categorization of EEG data by fusing advanced neural network topologies with complex signal processing techniques. This holds potential for better neurology diagnosis and treatment.

1.6 ORGANIZATION OF THE PROJECT REPORT

The work done in various phases has been organized into chapters.

Chapter 2 gives details about the existing system and its drawbacks.

Chapter 3 gives details about the proposed system, design and architecture of the different modules used.

Chapter 4 gives details about the hardware and software requirements, the tools used and their operations.

Chapter 5 provides detailed description of various tests performed and the performance and result analysis.

Chapter 6 discusses the conclusion and the possible future enhancements.

1.7 SUMMARY

This chapter gives the general introduction of our domain. The required concepts which are made use of in our project are analyzed and the objective of our project is also discussed.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

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. 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.

2.2 RELATED WORKS

2.2.1 Seizure Types Classification by Generating Input Images With in-Depth Features From Decomposed EEG Signals for Deep Learning Pipeline

The primary motivation for this committed study is to improve seizure type categorization by carefully analyzing electroencephalogram (EEG) data. Considering the critical importance of a precise epilepsy diagnosis and patient prognosis, the research tackles the complex problem of differentiating between various EEG patterns linked to distinct seizure types. This approach consists of breaking down EEG signals into smaller pieces, converting these pieces into twodimensional pictures, and using a strong hybrid deep learning architecture. The core of this system is the combination of Convolutional Neural Networks (CNNs), which are experts at extracting spatial data, and Long Short-Term Memory (LSTM) networks, which are skilled at capturing temporal correlations. The combination of these cutting-edge methods guarantees an accurate and comprehensive classification of EEG data, greatly enhancing the identification of seizure types. This discovery not only broadens our knowledge of epilepsy but also has significant ramifications for individualized treatment plans. This research advances the diagnosis and treatment of epilepsy by elucidating the intricacies of EEG patterns linked to various seizure types. The hybrid deep learning architecture's accuracy plays a crucial role in giving medical practitioners detailed insights that allow for more focused and efficient actions. In the end, the study highlights the revolutionary potential of sophisticated EEG data processing methods in the field of neurology and serves as a beacon of progress in the pursuit of better epilepsy care.

2.2.2 Deep learning-based electroencephalography analysis

This long-term study explores the use of deep learning (DL) in the complex field of analyzing electroencephalograms (EEGs). The main goal is to determine if DL is more effective than conventional EEG processing methods. After conducting a thorough analysis, the researchers present a variety of methods for using EEG data, from short time intervals to many hours. With an average of three to ten layers, convolutional neural networks, or CNNs, are the most common deep learning architecture for processing EEG data. Recurrent Neural Networks (RNNs) are next in terms of popularity. The research highlights how flexible DL is when it comes to handling the many temporal scales that are present in the analysis of EEG data. The research highlights a significant worry regarding the widespread absence of repeatability in several published studies that impose restrictions on data and code access. In an effort to promote increased accessibility in the scientific community, the authors provide a brief summary table that summarizes studies on DL and EEG. Furthermore, the study provides incisive suggestions for next research, emphasizing the necessity of openness, repeatability, and cooperation in developing the subject. This paper offers important insights that might influence the direction of future neuroscientific research by critically analyzing the current state of DL applications in EEG data processing. This study's comprehensive grasp of DL's function in EEG analysis, together with its easily comprehensible summaries and suggestions, make it an invaluable tool for practitioners and scholars who are working to expand the field of brain signal processing.

2.2.3 Epileptic seizure classification with symmetric and hybrid bilinear models

Due to the widespread effects of epilepsy, proper diagnosis and ongoing monitoring are essential for ensuring successful treatment. This article presents a novel hybrid bilinear deep learning network approach to epilepsy categorization. The integration of surface electroencephalogram (sEEG) and audiovisual monitoring—two commonly used therapeutic tools—is the main emphasis. The suggested solution combines the advantages of both designs by using Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) as feature extractors.

During the training phase, CNNs are trained to recognize complex spatiotemporal patterns by utilizing one-second sEEG data and the Short-Time Fourier Transform (STFT). RNNs are simultaneously taught to be highly proficient at understanding longer temporal dynamics present in signals connected to epilepsy. One unique characteristic of the study is its investigation of bilinear pooling, a method for obtaining second-order features. This creative innovation advances a more comprehensive comprehension of the intricate information related to epilepsy.

This initiative puts epilepsy categorization research at the forefront with its combination of sEEG and audiovisual monitoring in a hybrid deep learning framework enhanced by sophisticated feature extraction techniques. The approach aims to improve the depth and accuracy of epilepsy diagnosis by fusing the analytical capabilities of CNNs and RNNs and integrating bilinear pooling for improved feature representation. In the end, this study promises to advance our understanding of epilepsy more thoroughly and enhance the precision with which it is classified. It also promises to improve therapeutic approaches.

2.2.4 Seizure type classification using EEG based on Gramian angular field transformation and deep learning

This work introduces a novel deep learning method that can reliably distinguish between four different kinds of seizures and recognize instances of seizure-free states. The approach depends on the capabilities of convolutional neural networks (CNN), which are well-known for their effectiveness in image recognition applications. The novel part is the use of the "gramian angular summation field" method, which effectively converts 1D electroencephalogram (EEG) impulses into 2D pictures and allows for the complicated EEG data to be represented visually.

Depending on the kind of seizure being studied, the transformation procedure makes it easier to use CNNs for classification later on, either in a binary or multiclass framework. The experimental investigation shows that the approach can achieve good classification accuracy by using the EEG dataset from Temple University Hospital.

This suggested approach is significant because it provides physicians and other healthcare workers with a useful and efficient tool that transcends the boundaries of academics. The deep learning technique shown here can accurately categorize different types of seizures, which improves diagnosis accuracy and helps customize effective treatment plans. CNN use, in conjunction with the novel transformation method, represents a significant breakthrough in EEG data processing. Therefore, this study makes a significant contribution to the continuous efforts to enhance seizure detection and treatment, which will ultimately help those with epilepsy and related conditions.

2.3 SUMMARY

This chapter gives a complete analysis on the existing system related to our recommended system. The required survey which are related to our project are analyzed along with its drawback.

CHAPTER 3

PROPOSED SYSTEM DESIGN

3.1 INTRODUCTION

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 are depicted in Fig. 3.1.

3.2 SYSTEM ARCHITECTURE

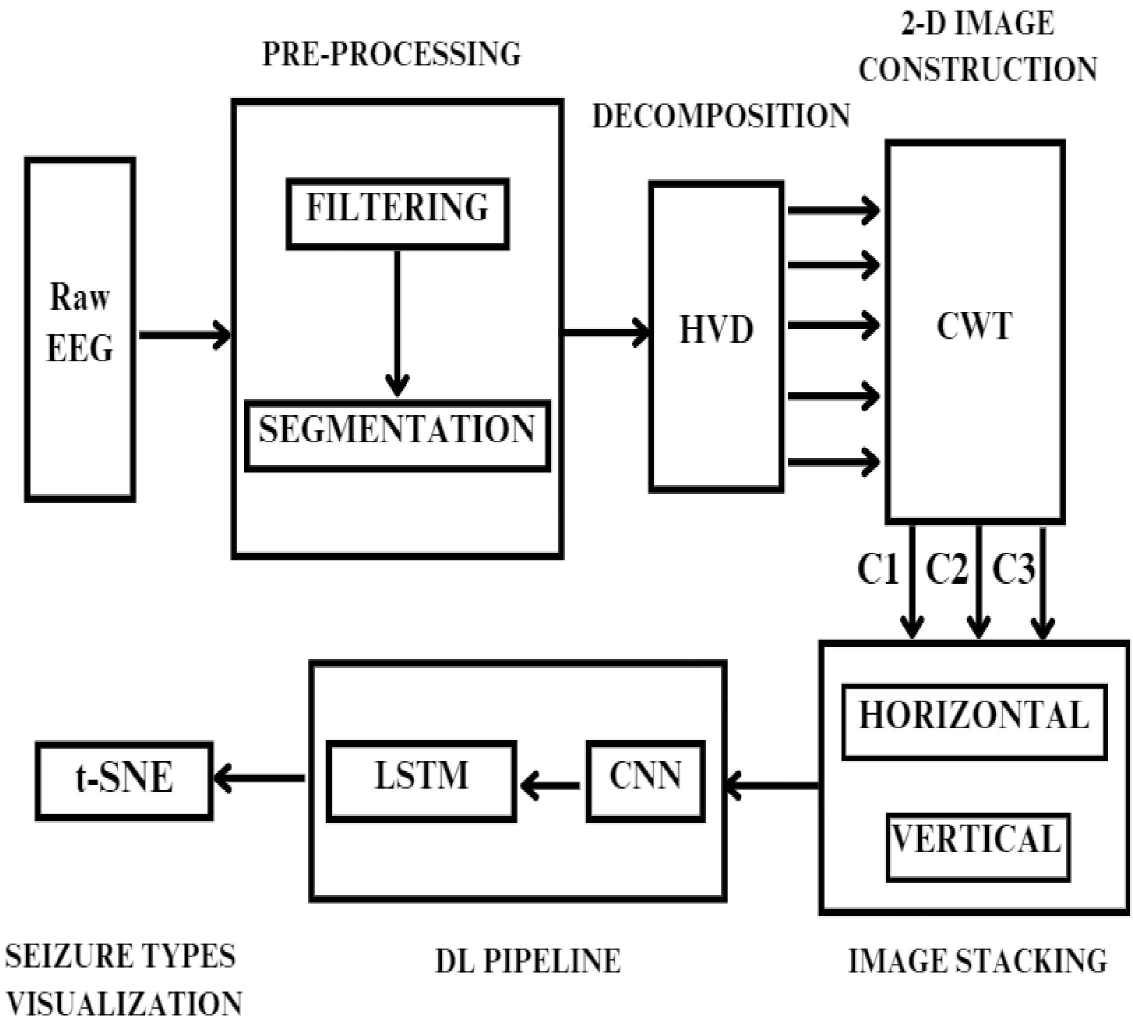

Fig. 3.1. Architecture Diagram

3.2.1 DATA GATHERING

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. 3.1. 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, carefully extracted from a larger dataset of 921,600 patients. This ensures that our findings are not skewed by an imbalance in data and provides a well-rounded representation of all six 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. 3.1. Description of TUH v1.5.2 dataset

The Av hardware configuration was used to record the EEG data in the dataset, with a sampling frequency of 250 Hz and a resolution of 16 bits. The EEG signals from 23 common channels—each of which represents a particular electrode placement—are included in the collection. FP1-F7, F7-T7, T7-P7, P7-O1, FP1F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P80, P8-O2, FZ-CZ, CZ-PZ, P7-T7, T7-FT9, FT9-FT10, FT10-T8, and T8-P8-1 are some of these channels.

The channels mentioned, correspond to specific electrode placements on the scalp. These electrodes are strategically positioned to capture electrical signals generated by the brain. Each channel represents the electrical activity 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.

3.2.2 PRE-PROCESSING

The first step in preparing the recorded EEG signals is to remove noise and artifacts. Our approach involved utilizing a Butterworth band-pass filter (Fifth order) with a frequency ranging from 0.5Hz to 50Hz. 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. 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. 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. 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. 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.

3.2.3 DECOMPOSITION

The first step in our method is the complex decomposition of electroencephalogram (EEG) data into many smaller components. 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.

Hilbert Vibration Decomposition (HVD) is the method selected for this decomposition procedure. HVD is a signal processing technique that is distinguished by its special qualities. 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. This refined comprehension, enabled by HVD, adds to a more thorough investigation of the EEG signal and establishes the foundation for further studies that dive more deeply into the complexities of the brain's electrical activity.

3.2.4 MODEL TRAINING AND TESTING

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. 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.

Our analysis of EEG signals takes them on a transformative journey, beginning with the crucial step of applying Continuous Wavelet Transform (CWT). This allows us to extract subcomponents and break down the signals into their intricate patterns and features. From there, each subcomponent undergoes another transformation, resulting in 2D images. These images are carefully stacked both horizontally and vertically, producing comprehensive representations that capture the spatial and temporal characteristics of the EEG data. These composite pictures are then used as the input for an advanced hybrid Deep Learning pipeline. Long Short-Term Memory (LSTM) networks and Convolutional Neural Network (CNN) layers are easily integrated by this pipeline. The CNN layers identify spatial patterns in the EEG subcomponent pictures in order to extract spatial features. The LSTM networks, which are adept at capturing temporal relationships and identifying sequential patterns over time, come next. The model is able to simultaneously learn hierarchical spatial and temporal patterns thanks to this two-layered method. The reconstructed EEG subcomponent pictures provide the model with new information that improves its classification of different kinds of seizures. The model is rigorously evaluated using training and validation accuracy (T-V_Acc) and loss (T-V_loss) measures across different epochs during the training phase. The model's ability to enhance its comprehension of intricate spatial and temporal linkages within the EEG data is highlighted by the observed progressive improvement in training performance over increasing epochs, which eventually leads to better seizure classification accuracy.

3.3 SUMMARY

This chapter gives a complete overview on the working of the proposed system. The required concepts which are made use of in our project are analysed in-depth.

CHAPTER 4

METHODOLOGY

4.1 HARDWARE AND SOFTWARE SPECIFICATIONS

4.1.1 SYSTEM REQUIREMENTS

Windows: Windows 11 (64 bit)

Processor: i7 Intel Core 12^{th} Gen Processor

Memory: 16 GB

4.1.2 SOFTWARE REQUIREMENTS

Language: Python 3.10.12

Libraries: NumPy, SciPy, Matplotlib, Pandas, Os, Pywt

Tool Used: Jupyter Notebook

4.2 MODULE IDENTIFICATION

4.2.1 DATA COLLECTION

Our approach involved utilizing a meticulously crafted bandpass filter with a frequency range of 0.5Hz to 50Hz. This carefully selected range greatly enhanced our ability to detect the intricate patterns present in epileptic seizures. The bandpass 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.

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. 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. 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.

In order to improve even further the accuracy and quality of the separated EEG signals, we applied the Hilbert Vibration Decomposition (HVD) method. 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.

4.2.2 PREPROCESSING

Our approach prioritized precision, achieved through the implementation of a highly accurate bandpass filter ranging from 0.5Hz to 50Hz. This carefully chosen frequency range was specifically intended to capture the intricate nuances present in epileptic seizure patterns. Acting as a meticulous filter, it effectively eliminated extraneous high frequencies and honed in on the essential elements of the EEG signals. This rigorous process ensured that our subsequent analyses were conducted with a focused and reliable dataset.

Once refined by the bandpass filter, the signals were then further processed by segmenting them into 10-second intervals with a 50% overlap. This segmentation approach was carefully selected to preserve the temporal integrity of the data, allowing for a comprehensive and continuous inspection of the seizures. The dataset is enhanced with a more nuanced view of the temporal dynamics thanks to the 50% overlap, which guarantees that temporal transitions and minute fluctuations within the signals are fully captured.

In order to improve the accuracy and quality of the separated EEG signals, we applied the Hilbert Vibration Decomposition (HVD) method. When HVD was used separately on each segmented signal, it allowed for a thorough breakdown while maintaining important phase information. This extra step improved our dataset's quality even further, which improved the deep learning-based classification of epileptic seizures that followed in terms of accuracy and dependability.

4.2.3 HILBERT VIBRATION DECOMPOSITION (HVD)

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. 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. 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.

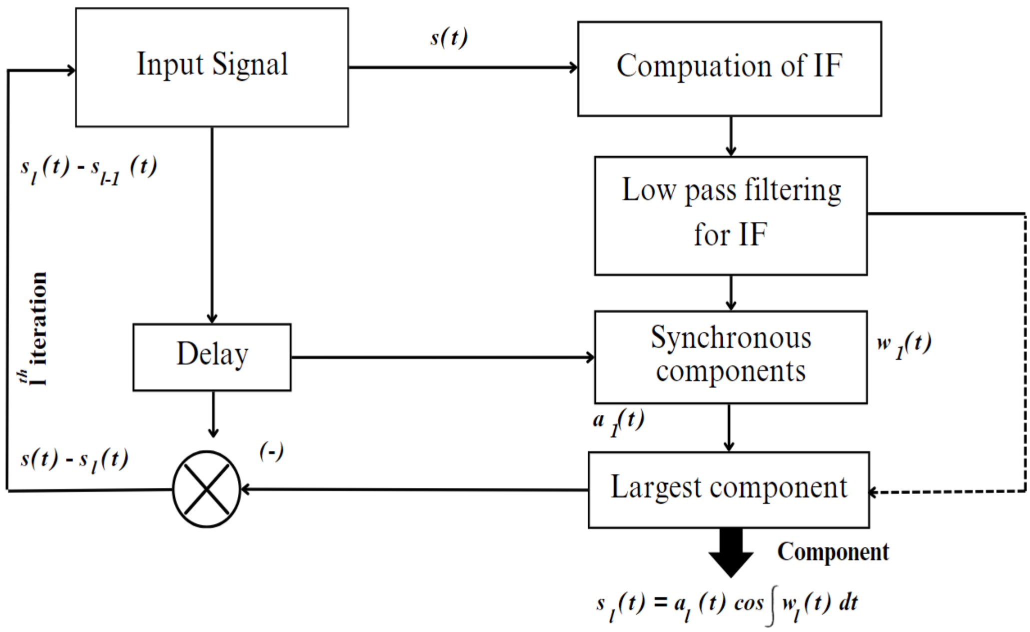

Fig. 4.1. Systematic working of HVD

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. 4.1. 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:

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

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

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

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 $s(t)$.

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

Then, IF can be found using (4):

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

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 $s(t)$.

$$\boldsymbol{s_l =_r (t) = \frac{1}{2} a_l(t) \, [cos(\phi_l(t)) + cos(\int (\omega_l(t) + \omega_r (t) \, dt + \phi_l(t))]} \quad \textbf{(5)}$$

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

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. 4.2. – 4.6. depicts the plotting of all the five subcomponents (sub_0 to sub_4) obtained after performing HVD algorithm.

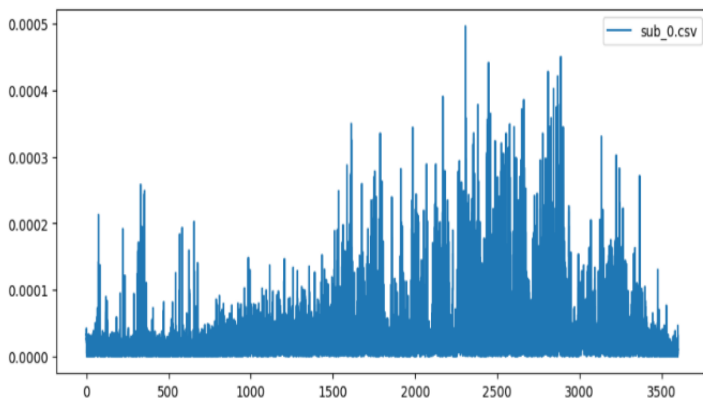

Fig 4.2. HVD plotting for sub_0

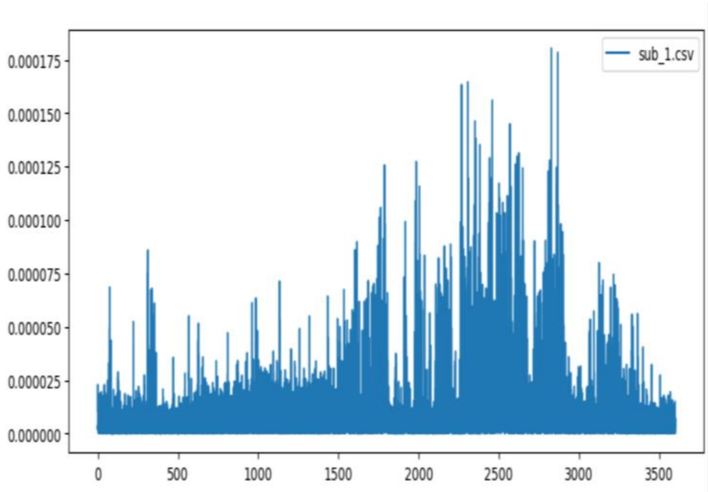

Fig 4.3. HVD plotting for sub_1

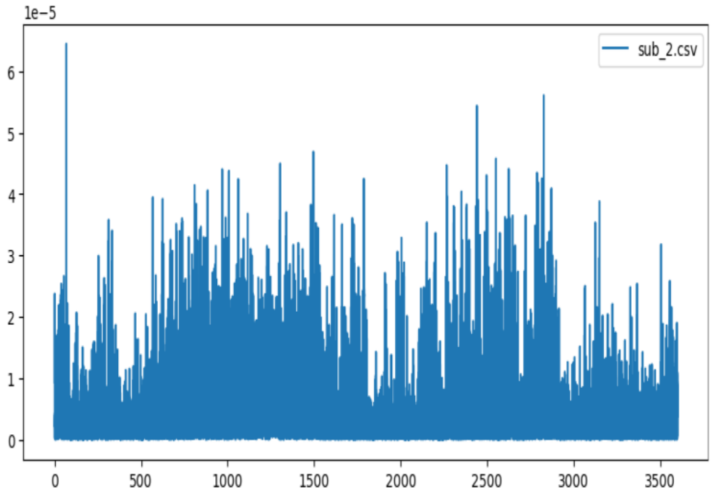

Fig 4.4. HVD plotting for sub_2

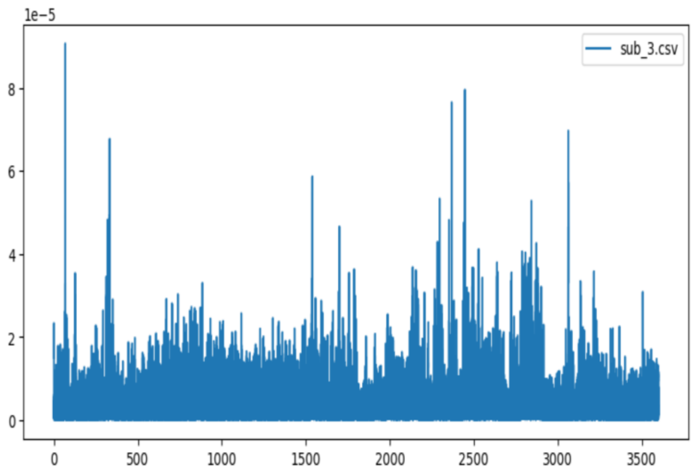

Fig 4.5. HVD plotting for sub_3

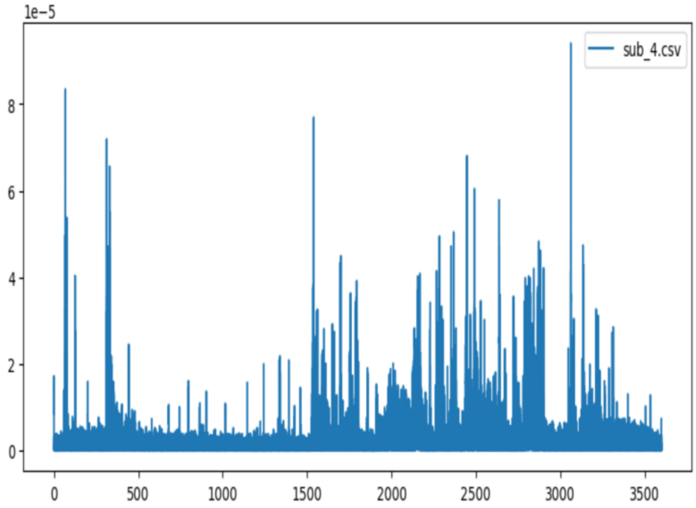

Fig.4.6. HVD plotting for sub_4

Additionally, to ensure that the subcomponents are appropriate, the correlation (Cc) between them and the main signal has been examined in Table. 4.1.

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

4.2.4 CONTINUOUS WAVELET TRANSFORM (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. 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. It has been discovered that the CWT is incredibly effective and appropriate for modeling nonlinear and irregular signals, like EEG. Mathematically the CWT of $x(t)$ signal can be determined by (6):

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

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. The Morlet wavelet was used for this work because it is effective at evaluating complicated signals, such as EEGs, and it has shown respectable results in a number of EEG-based research. It can accurately record short spike spines that alternate and repeat, together with a start and finish time. Since t represents the sample instants, equation (7) provides a mathematical definition of the Morlet wavelet function.

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

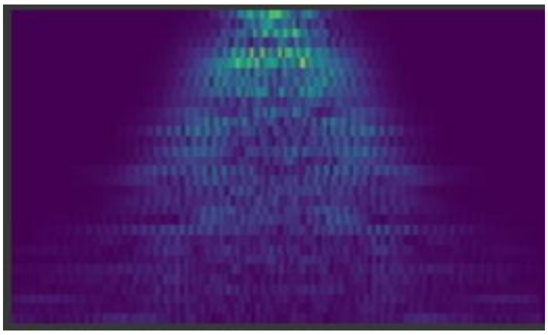

Fig 4.7. 2D Image of sub_0

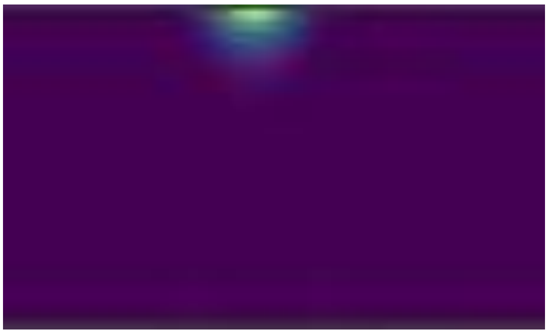

Fig 4.8. 2D Image of sub_1

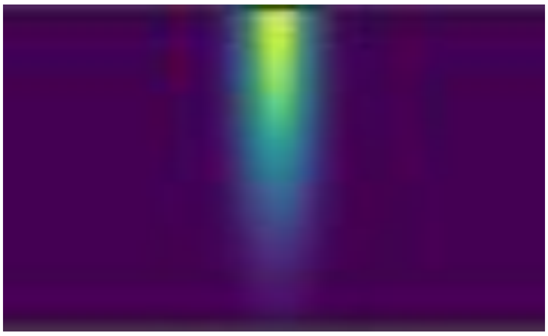

Fig 4.9. 2D Image of sub_2

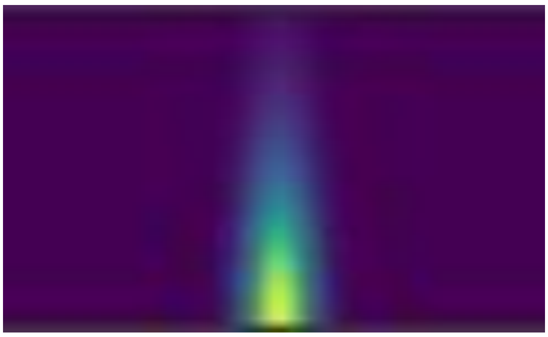

Fig 4.10. 2D Image of sub_3

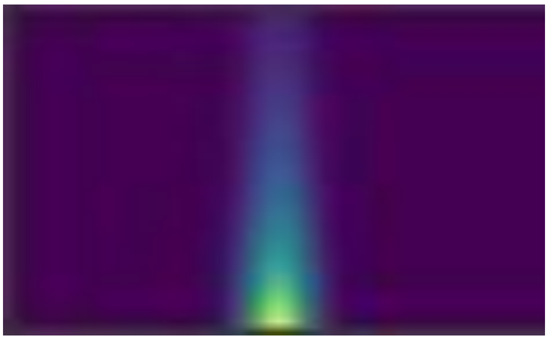

Fig 4.11. 2D Image of sub_4

The Fig. 4.7 – 4.11 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.

4.2.5 IMAGE STACKING

One of the most essential phases in using DL-based classifiers successfully is input data preparation. The subcomponents are stacked in both vertically and horizontally to produce one image as displayed in Fig. 4.12. and Fig. 4.13. 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.

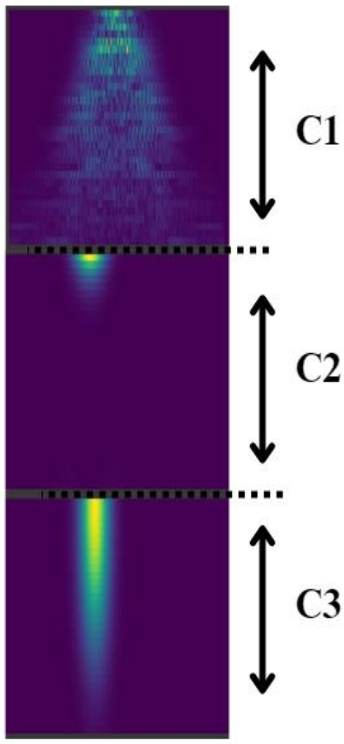

Fig. 4.12. Vertical Image stacking

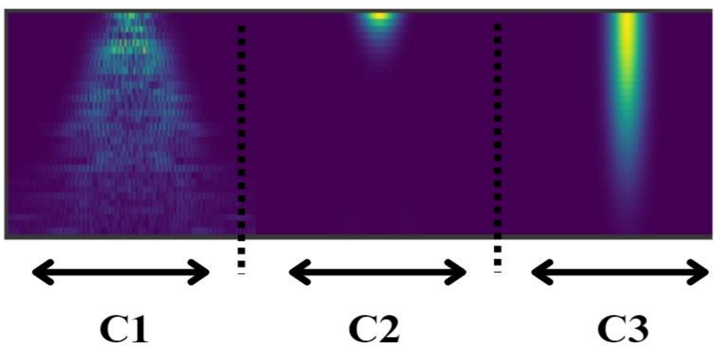

Fig. 4.13. Horizontal Image stacking

4.2.6 CONVOLUTIONAL NEURAL NETWORK (CNN)

The structure is carefully arranged in a convolutional neural network (CNN) architecture for seizure detection in order to efficiently extract and process spatial patterns in the time-frequency domain of EEG signals. Pooling, convolutional, and fully linked layers are the three primary layer types seen in a 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. 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.

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. 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):

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

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. Additionally, batch normalization helps reduce the problem of internal covariance shift. 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. 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. 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 determine whether the input EEG segment belongs to a seizure or a nonseizure state using the high-level features that were learned from the convolutional and pooling layers. 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.

4.2.7 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. 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.

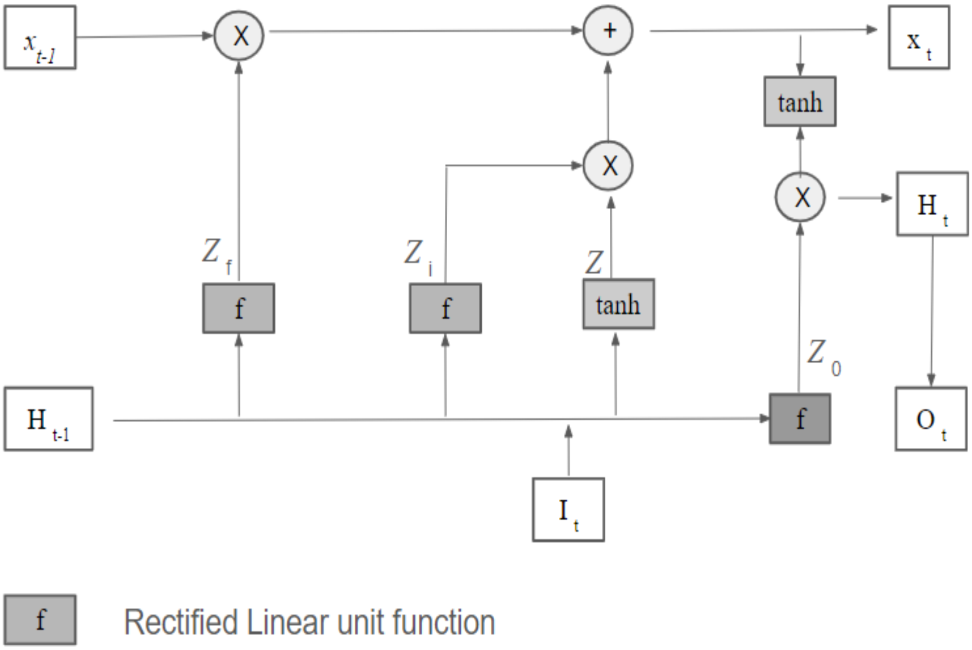

Fig. 4.14. The LSTM framework's internal working.

From the Fig. 4.14. The cell gate (z) in an LSTM is in charge of retaining information over time. The z_f stands for the forget gate, z_i is the input gate, and z_o which manages the amount of information in the cell that will be utilised to compute the output using the weight metrics, W. The x_t, H_t, and O_t are three outputs that reflect cell state, hidden state, and current output, respectively, the x_{t-1}, H_{t-1}, and I_t 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.

4.2.8 T-DISTRIBUTED 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.

4.3 TOOLS USED

4.3.1 DATASET

Through the use of a sophisticated technique, we have been able to break down the complexity of EEG signals into discrete subcomponents for this research. These subcomponents allow for a more detailed examination of the complex EEG signal by each representing a distinct feature of it. We used the reliable Temple University Hospital epileptic EEG data frame to confirm our results.

This dataset is well known for its extensive recordings of EEG signals covering a wide range of seizure types, captured under diverse circumstances such varying sampling rates and montages. It is interesting that within the dataset, there is nonuniform distribution of EEG recordings across different kinds of seizures.

Our analysis concentrated on 153 seizure sessions that were carefully chosen from a large pool of 921,600 participants in order to ensure representation across all five seizure types in light of this unpredictability. The Av device configuration, which has 250 Hz as the frequency of sampling and a resolution of 16 bits, was utilized to obtain the recordings. Electroencephalogram signals from 23 popular channels are included in the collection.

The careful selection process, selection of a credible and diverse dataset, and application of sophisticated signal processing methods highlight the resilience and dependability of our methodology in exploring the intricacies of EEG signals for an extensive examination of epileptic activity.

4.3.2 GOOGLE 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.

4.4 OUTPUT SNAPSHOTS

```
time=np.linspace(0, 100000, 921600)
plt.plot(time,raw_data)
plt.show()
```

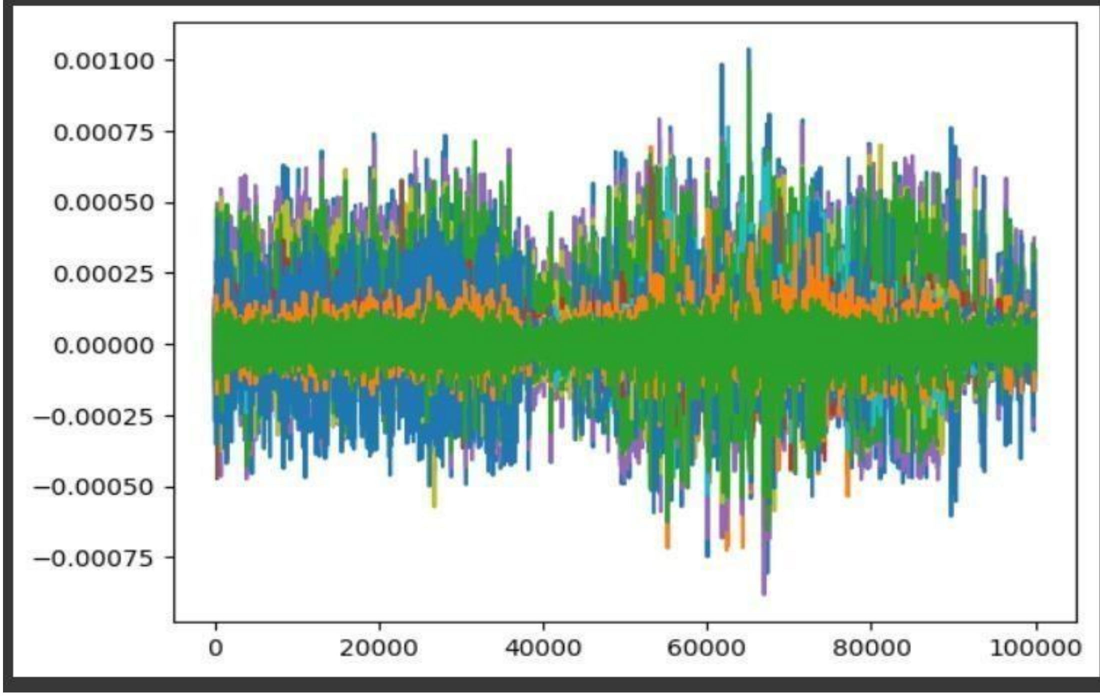

Fig 4.15. Raw data

```
time=np.linspace(0, 100000, 921600)
plt.plot(time,filtered_data)
plt.show()
```

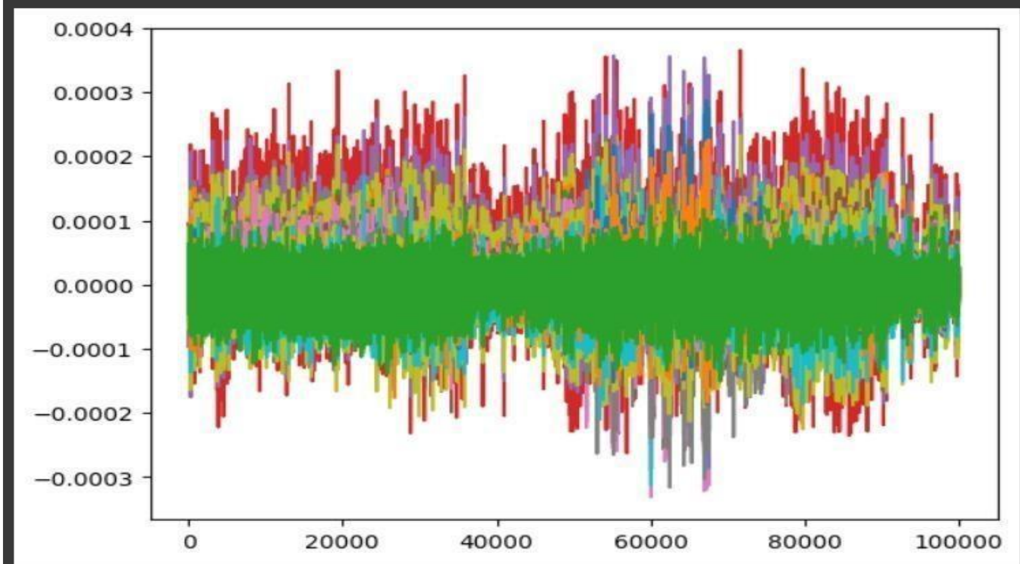

Fig. 4.16. Filtered Data

Fig 4.17. Seizure Free Patient's Vertical stacking

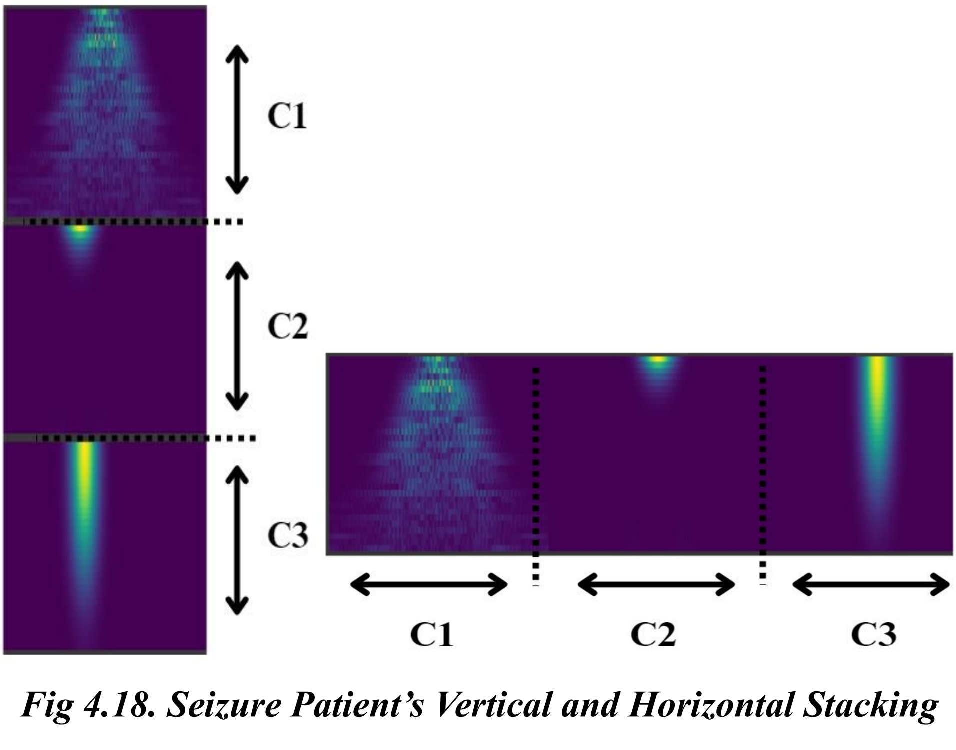

Fig 4.18. Seizure Patient's Vertical and Horizontal Stacking

```python
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_05.png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])
```

```
1/1 [==============================] - 0s 368ms/step
Predicted Class: 0
```

Fig 4.19. Seizure Type-0 – FNS (Focal Non-Specific)

```python
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_013png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])
```

```
1/1 [==============================] - 0s 368ms/step
Predicted Class: 1
```

Fig. 4.20. Seizure Type- 1- GNS (Generalized Non-Specific Seizure)

```python
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_027.png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])
```

```
1/1 [==============================] - 0s 368ms/step
Predicted Class: 2
```

Fig 4.21. Seizure Type- 2- CPS (Complex Partial Seizure)

```
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_042.png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])

1/1 [==============================] - 0s 368ms/step
Predicted Class: 3
```

Fig 4.22. Seizure Type- 3- SPS (Simple Partial Seizure)

```
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_038png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])

1/1 [==============================] - 0s 368ms/step
Predicted Class: 4
```

Fig 4.23. Seizure Type- 4- TCS (Tonic Clone Seizure)

```
# Example image for prediction
example_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_023png"
example_image = load_and_preprocess_image(example_image_path)

# Reshape the image to match the input shape expected by your model
example_image = np.expand_dims(example_image, axis=0)  # Add batch dimension

# Make predictions
predictions = eeg_model.predict(example_image)

# Interpret the results
predicted_class = np.argmax(predictions, axis=1)

# Print the predicted class
print("Predicted Class:", predicted_class[0])

1/1 [==============================] - 0s 368ms/step
Predicted Class: 5
```

Fig 4.24. Seizure Type- 5- SF (Seizure Free)

```
# Load and preprocess the test image
test_image_path = "/content/drive/MyDrive/ML_Seizure_Project/DL_Pipeline/vertical_stacking_028.png"
test_image = load_and_preprocess_image(test_image_path)  # Use the load_and_preprocess_image function you defined earlier
y_test=[0]

# Convert the image to a Numpy array
test_image = np.expand_dims(test_image, axis=0)  # Add an extra dimension to represent the batch size

y_test_one_hot = to_categorical(y_test, num_classes=6)  # Assuming 6 classes, adjust accordingly
# Assuming you have a model named eeg_model
# Evaluate the model on the test image
# test_results = eeg_model.evaluate(test_image, np.array([y_test]))
test_results = eeg_model.evaluate(test_image, y_test_one_hot)

# Print the test set loss and accuracy
print(f"Test Loss: {test_results[0]}, Test Accuracy: {test_results[1]}")

1/1 [==============================] - 0s 400ms/step - loss: 001.1181 - accuracy: 0.990900e+00
Test Loss: 001.118117332458496, Test Accuracy: 0.990923
```

Fig. 4.25. Accuracy rate of the model

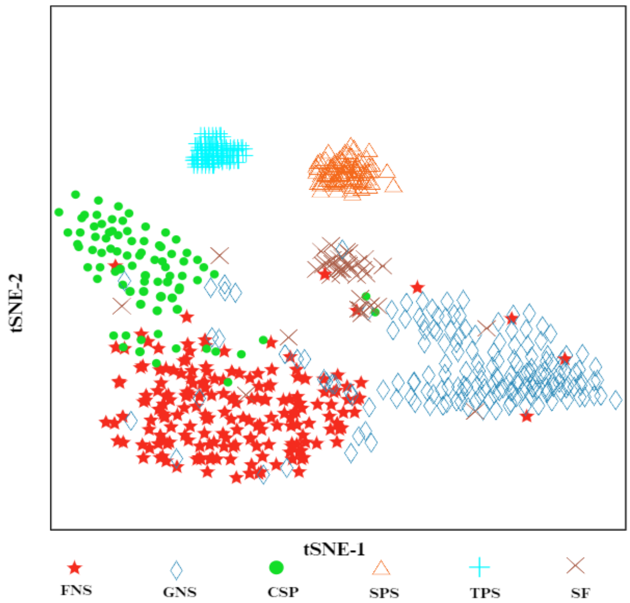

Fig. 4.26. t-SNE plotting for 6 seizure types

4.5 SUMMARY

This chapter gives a complete insight on the working of the proposed system along with its requirements. The required concepts which are made use of in our project are analyzed with the explanation on their working.

CHAPTER 5

PERFORMANCE ANALYSIS

5.1 INTRODUCTION

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. 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.

$$A_{cc} = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(9)}$$

$$S_e = \frac{TP}{TP + FN} \quad \textbf{(10)}$$

$$S_p = \frac{TN}{TN + FP} \quad \textbf{(11)}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \quad \textbf{(12)}$$

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.

The suggested approach achieved a variety of performance metrics, including Weighted F1-score, sensitivity, specificity, and accuracy, as demonstrated in Fig. 5.2. The horizontal axis displays multiple sets of input pictures, while the vertical axis represents the corresponding percentage of performance metrics. The Table. 5.1. 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. 5.1. Analysis Table

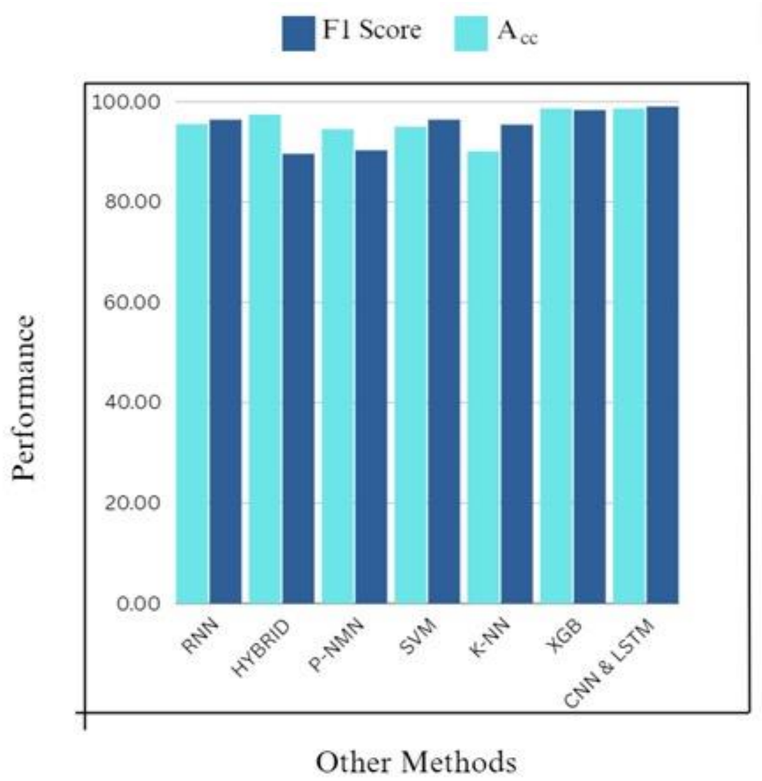

Fig. 5.1. Comparative Study

The Fig. 4.26. Illustrates the t-SNE plotting using symbols of various colors which correspond to the numerous seizure types that have been identified.

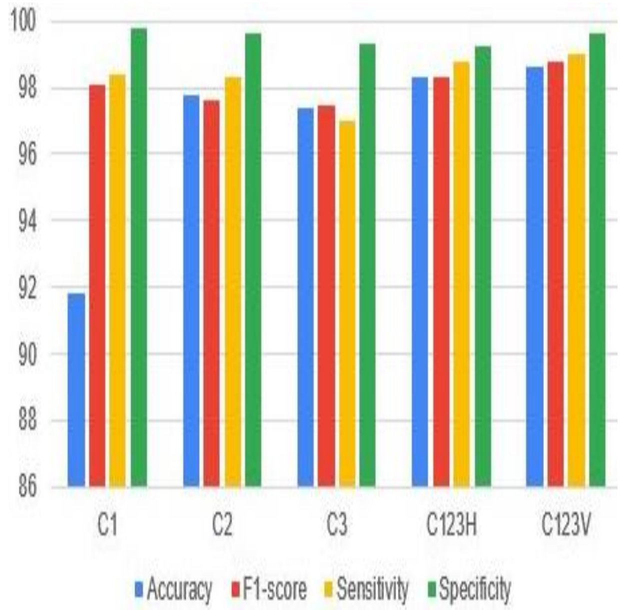

Fig. 5.2. Performance Metrics

CHAPTER 6

CONCLUSION AND FUTURE WORKS

6.1 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 Continuous Wavelet Transform (CWT). Convolutional Neural Networks (CNN) and Long Short-Term Memory (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-distributed Stochastic Neighbor Embedding (t-SNE) increases trust in the 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.

6.2 FUTURE WORKS

Future works in this domain could explore several avenues to enhance the proposed methodology further. Firstly, incorporating multi-modal data fusion techniques could leverage additional information sources, such as imaging data or patient demographics, to improve classification accuracy and robustness. Secondly, investigating the integration of real-time monitoring capabilities could enable the deployment of the developed model in clinical settings, facilitating prompt intervention and personalized treatment strategies. Additionally, exploring transfer learning approaches could facilitate the adaptation of the proposed framework to diverse EEG datasets from different patient populations or healthcare institutions, thereby enhancing its generalizability and scalability. Furthermore, conducting longitudinal studies to assess the long-term performance and clinical impact of the developed system in real-world settings would provide valuable insights into its utility and effectiveness over time. Finally, fostering collaborations with clinicians and healthcare professionals to validate the practical utility of the proposed methodology and incorporate their feedback for refinement and optimization would be crucial for translating research findings into clinical practice effectively. By pursuing these avenues, future research endeavors could further advance the field of automated seizure type categorization and contribute to improving patient care and outcomes in neurology.

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