Dynamic Time Warping Enhanced CNN-LSTM for Robust Seizure Prediction in EEG Data

MSc Research Project
Data Analytics

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Dynamic Time Warping Enhanced CNN-LSTM for Robust Seizure Prediction in EEG Data

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Abstract

Epilepsy is known to be one of the most frequent neurological disorders whose manifestations cause severe burden to affected patients and their families because of the strictly chronic and often unpredictable character of the disease. It is essential to detect epileptic seizures in real time to enhance patients' safety and quality of life; nevertheless, there is a fundamental problem concerning the high non-linearity of actual EEG signals. This paper presents a new approach integrating DTW with CNN-LSTM and applies it to the problem of improved seizure prediction. DTW helps to extract temporal patterns, and the CNN-LSTM helps in feature representation and learning of sequences. To eradicate interferences in the EEG signal, the model employs a Butterworth bandpass filter, which does not eliminate all the frequencies deemed necessary. On a publicly available EEG dataset, though the proposed hybrid model check marked superior accuracy, sensitivity, and specificity over conventional approaches for mental disorder diagnosis yielding test accuracy of 95. 62%. This makes TMS capable of real-time clinical application, according to this study's finding. Thus, the findings of the study provide theoretical framework for seizure prediction that will help in improving the potential of better management of epilepsy in future. More refinement of the model's parameters will be done in future work and integration of patient-specific data to increase accuracy for future seizure watch and patient management.

1 Introduction

1.1 Background

Neurological disorders are common and other forms include epilepsy which is estimated to affect over 50 million people globally, epilepsy is described as a condition characterized by recurrent seizures occurring due to sudden, unprovoked discharge of neurons in the brain. These seizures lead to physical injuries, psychological distress and a poor quality of life of the patient; thus, affecting the patient, the family and the healthcare system. Therefore, there is the need to improve the current seizure prediction tools in a way that it will be able to alert the patient several hours or minutes before a seizure is likely to occur so that the patient may be withheld from seizing fully and hence increase the quality of life of the patient.

Generally, the identification of seizures has been done by analyzing the electrical signals of the brain by the help of EEG. However, the given problem is rather challenging due to the stochastic and non-stationary nature of EEG signals and minor pre-seizure Changes. Due to the nature of EEG data, traditional methods that rely on manual feature extraction and traditional machine learning methods are not adequate to capture the temporal and spatial nature of the data. All these methods are associated with certain drawbacks including the sensitivity to the choice of features by the domain expert and limited suitability for different types of patients and seizures.

Deep learning has become the state of the art technique for automatic feature learning and modelling in large scale data sets over the past few years. Convolutional Neural Networks (CNNs) have shown state of the art performance in image and signal processing due to their capability of learning spatial hierarchy. Long Short-Term Memory (LSTM), a kind of Recurrent Neural Networks, are developed for the purpose of capturing sequential data and have been tested for deriving temporal relations in time series data. Nevertheless, most of the deep learning-based methods for seizure prediction disregarded the need to register temporal features across the EEG sequences which may be beneficial for recognizing pre-seizure states.

1.2 Motivation

We propose the integration of DTW, a method for comparing time series, with deep learning models; a technique which has not been explored for seizure prediction. DTW can adjust the alignment of EEG signals for allowing the consideration of time and phase differences, which means that even the minutest pre-seizure features can be fed into deep learning models. Through integrating DTW with CNNs and LSTMs, this research is going to propose a hybrid model that escalate the shortcomings of the current methods and enhance the capability of seizure prediction.

Nevertheless, several problems have not been solved even with the current developments in seizure prediction. Due to the differences in patients' EEG signals and challenges that arise from the difficulty of accurately identifying seizures in real-time, new approaches are required. This research aims at addressing these gaps by suggesting a combination of DTW-based feature extraction and the power of CNN and LSTM models.

1.3 Research Question and research objectives

This research is driven by the following key research question:

Can a hybrid model that integrates Dynamic Time Warping with CNN-LSTM architectures enhance the accuracy and robustness of epileptic seizure prediction from EEG signals?

To address this question, the research is guided by the following objectives:

1. Summarize the current knowledge of the epileptic seizure prediction and analyse the existing methods, discussing the research opportunities that this study is to contribute.

2. Propose a novel model that integrates feature extraction using DTW and deep learning models CNN and LSTM to extract the spatial and Temporal features respectively of the EEG data.

3. Apply the proposed model with an openly accessible EEG dataset for the comprehensive analysis of different seizure types and patients' age groups.

4. Assess the proposed model and compare it with the baseline methods to understand the improvement in prediction performance and the model's ability to enhance the prediction.

5. Evaluate the findings to determine advantages and disadvantages of the hybrid model with regards to its applicability for future work.

1.4 Contribution

Thus, the main contribution of the work is to introduce a new approach to seizure prediction, which uses DTW and CNN-LSTM. This is the case because the proposed method aims at improving the model's capability of recognizing the subtle aspects of the EEG signals that are crucial in precise seizure prediction. Thus, the findings of this work will contribute to the improvement of the epileptic seizure prediction region and will depict a suitable and proper approach to monitor the actual time applications.

1.5 Structure of the Report

The remainder of this thesis is organized as follows: The Literature Survey section presents a review of the state of the art in seizure prediction pointing out the shortcomings and issues solved by this work. The Research Methodology section explains the approach of the proposed model in terms of data preparation, feature engineering, and model design. The Evaluation section outlines the design of the study and the findings, then compare the model's effectiveness. Finally, the Conclusions and Discussion section presents the main conclusions, the discussion of the research outcomes, and recommendations for further investigations.

2 Related Work

Epilepsy is characterized by recurrent seizures, and seizure prediction has emerged as a promising research subject because it can enhance patients' quality of life. Different aspects of the machine learning and deep learning have been investigated to improve the performance in terms of accuracy, and to solve overfitting issues properly. This literature review focuses on the several prior works in this field, especially in terms of methods, findings, advantages, and disadvantages.

2.1 Traditional Machine Learning Approaches

The identification of epileptic seizures using the electroencephalogram (EEG) signals is one of the prominent areas in the biomedical signal processing area where a plethora of machine learning methods are being investigated to determine their suitability. In their more recent work, Tuncer and Bolat (2021) used the Bi-LSTM structure in the analysis of EEG signals thus gaining a high classification rate of 97.78% and a binary classification success of 99%. This work, employing the University of Bonn EEG dataset, stresses on the significance of hyperparameter tuning, which includes the learning rate, number of neurons, and optimization algorithms, as they affect the model's performance greatly. While the proposed study has shown very promising results, using only a single layer Bi-LSTM model, there is a possibility that the models with multiple layers may detect a more detailed and intertwined relationship between the variables. However, it can be noted that the model has been validated only on the Bonn dataset and hence the applicability of the model could be questionable. Despite that, the study presents important findings regarding the efficacy of Bi-LSTM networks for EEG data classification and underlines the importance of selecting the right parameters to achieve optimal results.

Varnosfaderani et al. (2021) put forward a two-layer LSTM network to predict the occurrence of epileptic seizures with time and frequency-based features. Using the Melbourne dataset this model obtained an Area Under the ROC curve – AUC score of 0. achieved an Accuracy of 92, and a False Positive Rate (FPR) of 0. 147, sensitivity of 86. The precision of the model was 80%, recall was 82%, F1 score was 8%, and accuracy of 85. 1%. The incorporation of Swish activation function in the model helps in solving the vanishing gradient problem which enhances the training performance. Thus, the applied feature extraction process that involves the calculation of energy distribution, deviation, peak-to-peak values, zero-crossings, and spectral power density proves to be quite effective in analysing EEG signals. In addition, the use of a minimum distance algorithm in the post-processing stage greatly decreases false positives, which improves the model's efficiency. Nonetheless, this sophisticated architecture introduces more complexity and computational calculation issues especially for real-time applications in resource-scarce environments. The restriction of the evaluation to the Melbourne dataset is another concern regarding the model's applicability to other datasets. This research supports that the future work should be directed towards the creation of hybrid models that would absorb the best from different deep learning architectures to provide efficient and generalized approaches to the analysis of the large number of patients and various settings. In conclusion, these works demonstrate the progresses made in epileptic seizure prediction and at the same time, the gaps that need to be filled.

2.2 Hybrid and Advanced Deep Learning Models

This area of interest has gained much attention in the recent years since the use of deep learning models can enhance the prognosis and classification of epilepsy seizures hence enhancing the patient's care. A recent work by Shahbazi and Aghajan (2021) suggest the use of CNN-LSTM for the seizure prediction from multichannel EEG signals. Their method first converts the EEG signals to multichannel images by applying STFT; then the signals are pre-processed and fed into a CNN-LSTM network to capture spectral, spatial, and temporal characteristics. Thus, the model was able to get a sensitivity of 98. 21% and a false prediction rate (FPR) of 0. 13/h, and a mean prediction time of 44. The proposed model was trained and tested for 74 minutes on the CHB-MIT dataset. This work is unique because it does not require the feature engineering or selecting channels before feeding the CNN, instead the CNN will learn the features on its own from the input. However, the model's applicability to varying patient populations and types of seizures has to be tested on larger sets of data.

Another important work is the multi-channel feature fusion CNN-Bi-LSTM model proposed by Ma et al. in 2023, which uses attention mechanism for the improved EEG classification and seizure prediction. This model utilizes CNNs for spatial feature extraction and Bi-LSTMs for the temporal feature extraction, and attention for weighting features from various electrode channels. The proposed model attained an average accuracy of 94% on the CHB-MIT and UCI datasets. 83% on CHB-MIT and 77. The proposed method achieved an accuracy of 62% on UCI with high precision, recall, and F1-scores. The use of attention mechanism enhances the classification performance by reducing noise and enhancing the features of interests. Although this method yields a higher performance, the algorithm is quite complicated and extensive calculations may pose a problem on real time implementation, and hence it needs further simplification for practical use. The two works document the progress in seizure prediction through deep learning models and show the difficulties that still exist, including the high computational costs and the requirement of more data sets for testing.

From the analysis of the literature, it is observed that the deep learning models especially the hybrid models of CNNs and LSTMs are quite effective in seizure prediction and classification of EEG signals. Shahbazi and Aghajan's CNN-LSTM model and Ma et al. 's CNN-Bi-LSTM model with attention mechanisms are among the recent outstanding works in this context as they show high sensitivity and quality. Still, there are issues like computational inefficiency, the requirement for large datasets, and the fact that seizures' behaviors are diverse across different patients. Future work should concentrate on enhancing the real time capability of these models, the transferability of these models and the development of new models that incorporate the best of the existing architectures. Moreover, more standardized and larger and possibly more heterogeneous databases are needed in order to properly apply these models in the clinical practice. It is for this reason that this research suggests the design of a hybrid model that integrates the DTW technique with deep learning to extract temporal features and spatial patterns for the prediction of epileptic seizures in hopes of creating a more effective and versatile solution.

Another contribution is the work done by Shahbazi and Aghajan (2021) where they proposed a CNN-LSTM model for the epileptic seizure prediction using multichannel EEG signals. This model converts the EEG signals into images in the frequency domain by applying the STFT and then the CNN is used to get spatial features and LSTM is used to get temporal features. On the CHB-MIT dataset, it obtained a sensitivity of 98. 21%, and false prediction rate (FPR) of 0. Fifty-two percent of the patients had a mean protection time of 13/h, and a mean prediction time of 44. 74 minutes. This makes the approach easier to implement in compared with the feature extraction and channel selection which is required for other methods. Also, in 2023, Ma et al designed a multi-channel feature fusion CNN-Bi-LSTM model with attention mechanism for improving the EEG classification and seizure prediction. This model applies CNNs for spatial feature extraction, Bi-LSTMs for temporal feature extraction, and attention mechanism to focus on the important features from each of the electrode channels. In terms of the CHB-MIT and the UCI datasets, the proposed model had an overall accuracy of 94 percent. The results obtained in this study were 83% on CHB-MIT and 77. The results obtained are as follows: 62% on UCI, which shows its high precision, recall, and

F1-score. This is because the attention mechanism greatly enhances the classification performance by managing to reduce the information redundancy and concentrate only on the relevant aspects. Nevertheless, the proposed models are computationally expensive, and thus, there is a need for further enhancement for real-time applications. Both studies show that the combination of LSI and other features can be useful in improving seizure prediction and suggest that future work should focus on dealing with the computational costs and on evaluating generalization on different data sets and patient samples.

From the literature review of previous research studies in this field, it is seen that while there is significant progress in the identification of epileptic seizures through deep learning models, matters of model size, and time taken in computations, as well as the ability of the models in adapting to new situations are still a concern. The DenseNet-LSTM and CNN-LSTM models are effective in capturing and predicting the features of epileptic activities; nevertheless, there is the need to test the models' adaptability on other datasets and in real-life applications. Further work should establish these models for real-time application, enhance the generalizability of the models, and combine the various architectures to leverage on them. However, the above models need standardized evaluation procedures and larger and more diverse datasets to be implemented in the clinical practice. The findings of this research work recommend the incorporation of DTW and DL with the aim of increasing the efficiency of epilepsy detection and increasing the ability of the model to be more universal.

2.3 Hybrid and Advanced Deep Learning Models

The prior research works based on deep learning and dynamic time warping (DTW) have proved to be quite effective in predicting epilepsy seizures. Lu et al. (2023) proposed a new CBAM-3D CNN-LSTM model that captures both temporal and spatial information of EEG signals to improve the seizure prediction accuracy. The proposed model uses a 3D-CNN for spatial information extraction from the spectrogram of the EEG signal obtained through the STFT, and a Bi-LSTM for the temporal information modeling. The incorporation of the CBAM leads to improvement in the attention mechanism that the model has on the spatial and channel-wise information. On the CHB-MIT dataset, the proposed approach had an accuracy of 97 percent. 95%, sensitivity of 98. 40%, and false alarm rate of 0. This is equivalent to 0. 017 h-1, which indicates that the proposed models outperform the traditional models. However, the study also has several limitations concerning the generalizability of the findings to diverse patient populations and various clinical conditions.

In a similar vein, Khalid et al. (2017) proposed a method based on the amplitude thresholding and DTW for the identification of the epileptic spikes in the MEG signals. First, it uses amplitude thresholding to pinpoint the locations of the abnormalities and after that, DTW for the determination of the epileptic spikes within these regions. The proposed algorithm reached a sensitivity of 92. Sensitivity of the test was 45% and specificity of 95. To this end, a total of 81% correct answers were achieved in a patient-independent data set, which offers evidence for the approach's efficacy. MEG signals are less contaminated by the tissues' interference compared to EEG signals, and this method utilizes the higher spatial density of MEG signals. However, the authors noted that DTW is computationally expensive which can be a disadvantage for its use in real time applications. Future work should include the improvement of the DTW algorithms with the aim of increasing the computational speed while at the same time, maintaining a high rate of detection.

2.4 Integrated Approaches for Improved Performance

Deep learning models combined with DTW have become very useful in epileptic seizure prediction and has offered quality services in the detection and prediction of seizure events. The most recent techniques for the utilization of spatial and temporal, characteristics of EEG and MEG signals consist of Lu et al. 's CBAM-3D CNN-LSTM model and Khalid et al. 's DTW-based spike detection algorithm. But all these models have some drawbacks regarding computational expenses as well as the ability to work on different databases. Future research should try to refine these models for real-time forecasting and compare the results with other patients' databases. In addition, it is possible to discuss the application of hybrid techniques, which are built on the basis of the advantages of various approaches, to increase the efficiency of the model. This research recommends the expansion of the proposed model through the incorporation of the DTW with deep learning to enhance the temporal features of the signals related to epileptic seizure detection and predictability with the aim of developing a more effective and transferrable model.

New developments in the deep leaning and dynamic time warping, has greatly improved epileptic seizure prediction. A recent work by Lu et al. (2023) proposed the CBAM-3D CNN-LSTM model to improve the seizure prediction using both the time and space domain information of EEG signals. The proposed model leverage on the 3D convolutional neural network (CNN) for the extraction of spatial features from the spectrograms of the EEG signals obtained from the short-time Fourier transform (STFT), and the bidirectional long short-term memory (Bi-LSTM) network for the modeling of temporal dependencies. The proposed Convolutional Block Attention Module (CBAM) increases the model's feature map attention to the most important spatial and channel- wise features with the accuracy of the model being 97. 95%, sensitivity of 98. 40%, and a false alarm rate of 0. Achieved a detection rate of 0. 017 h-1 when tested on a well-known dataset, the CHB-MIT dataset. Despite the good results, the study also highlights the importance of future work to confirm the findings across different patients and conditions for the method to be more reliable and generalizable.

2.5 Evaluation and Challenges

Khalid et al. (2017) have suggested a technique that integrates amplitude thresholding and DTW for the detection of the epileptic spikes in the MEG signals. This method first starts with the amplitude thresholding in order to isolate the areas of interest, and then uses the DTW to find the epileptic spikes within these areas. Their algorithm got a sensitivity of 92. Sensitivity was 45% while the specificity was 95%. 81%, which underlines the method's efficiency even in the absence of individual patients. The study also specific advantage of the use of MEG signals which provide a better resolution as compared to the EEG signals as their signals are least affected by the layers of tissues in between. The dependency of DTW on computation is relatively high and this hampers real time applicability thus there is a need to improve the efficiency while keeping the accuracy intact(Epileptic MEG Spikes De). Also, Ahmed et al. (2017) proposed the use of DTW-based SVM kernel for neonatal seizure detection and the integration of static and sequential classifiers in order to enhance the detection sensitivity. The system revealed a 12% enhancement in identifying short seizure events in comparison to the standard RBF kernel-based systems, tested on a big set of EEG records of 17 newborns.

Therefore, applying deep learning models and DTW in epileptic seizure prediction has been useful because of the high accuracy of the results and the ability to capture the episodes of seizures. For instance, in Lu et al. 's CBAM-3D CNN-LSTM and Khalid et al. 's DTW-based spike detection algorithm papers, the authors demonstrated how spatial and temporal characteristics of EEG and MEG signals respectively have been appropriately addressed. However, these models have certain disadvantages like computational overhead issues and generalization of the model for the new dataset. Further the studies should be carried out in the future in order to refine these models for online working and to evaluate the efficacy of the models for the more diverse and extensive groups of patients.Moreover, it is possible to use the methodology that would incorporate the best of all the approaches for better prediction and reliability of results. This study suggests using a DTW-deep learning model to incorporate the effective temporal extraction of features of DTW with a strong spatial feature identification of deep learning to design a better and more widely applicable solution for epileptic seizure prediction.

Thus, the deep learning models and DTW have been incorporated in the epileptic seizure prediction with a high prediction accuracy rate as well as the identification of seizures. The studies that have applied the spatial and temporal characteristics of EEG and MEG signal can be included in Lu et al. 's CBAM-3D CNN-LSTM and Khalid et al. 's DTW-based spike detection algorithm. However, there is some limitation in these models; for example, these models are time consuming, and some other issues related with the applying of the given model to different data set. Thus, further research should proceed from these works and develop these models for use in the web-based environment and compare the results with a larger and more diverse sample of patients. However, there is a possibility to outline the methodology, which includes the strengths of all the mentioned approaches for the better prediction and enhancing the accuracy of the results. Hence, this work endeavours to incorporate DTW's capability to select temporal features and deep learning's ability to select spatial features for a more improved and flexible approach to epileptic seizure prediction.

3 Methodology

3.1 Overview

The work was organized in terms of specific steps which includes requirement gathering, data pre-processing, model building, and post analysis and modeling, making it reproducible and scientifically sound. First, the essential requirements were determined based on primary goals, such as constructing a trustworthy model to predict epileptic seizures with the help of an analysis of EEG data and an integration of DTW and deep learning. To shape the research focus and clarify the lack of dependability and feasibility in prior approaches, the study started with a literature review followed by recognizing the relevance of timely seizure prediction. The Epileptic Seizure Recognition dataset was then obtained from the online database, Checked for ethical compliance and examined for structure. Several steps were taken in the data preprocessing stage; these included filtering of EEG signals with Butterworth bandpass filter and normalization of the data. Assignations for labels were made where ‘1’ represented a seizure and ‘0’ represented non seizures. The normality tests of the data included descriptive statistics as well as the use of graphs in the determination of outliers. DTW was utilized to obtain temporal features that were used to train the CNN-LSTM model as well as evaluate the results.

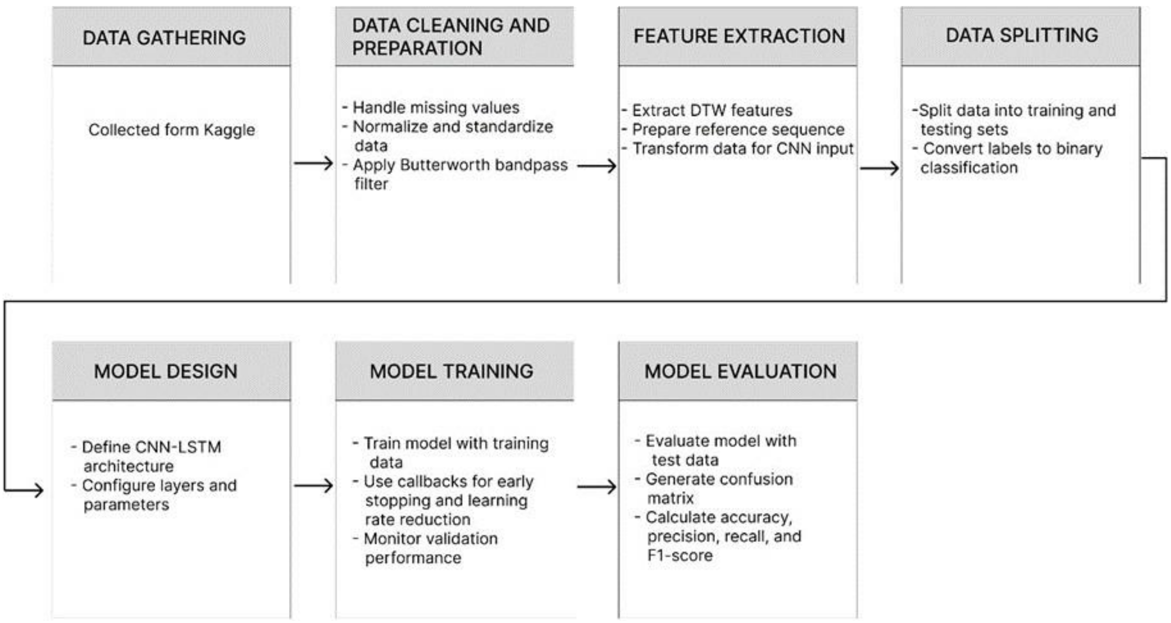

Figure 1: Flowchart of the Methodology and Design Implementation

Model implementation consisted of choosing the right architecture, where convolutional layers were used for spatial features, LSTM for the temporal features and drop out for regularizations among others. The pre-processed EEG data set was divided into training and testing sets and cross-validation procedure in applied to tune the hyperparameters and avoid overlearning. Last, a trained model was assessed for efficiency using things like accuracy, confusion matrix, and a detailed classification report to ensure all test results were fully offered.

3.2 Collecting the samples, preparing them, and using the randomization technique

Data Collection:

The data set utilized in this project is the Epileptic Seizure Recognition data set; the data includes the EEG of different subjects. This dataset was fetched from a public data sharing website known as Kaggle, thus the ethical issues like anonymization of the data were well observed. The structured data contains 11500 records with 179 fields that contain the values of the EEG signal, and a field containing the attribute ‘class’ which is either seizure or non-seizure. The data gathering process referred to downloading the data from the repository of several datasets and exploring the structure of the collected data to discern the proportion of features and labels.

Randomization Technique:

By randomly partitioning the data into the training and testing data sets it was ensured that the order of the samples did not influence the training/testing in a certain way or the other. Different splits of the data were made in a view of segregation of data into train and test data in the current research and the divided adopted in the research was 70:30. It also helps in randomizing and makes the evaluation more accurate in ways that indicate the model's performance on unknown data. Linked to that, the setting of the random state was done to ensure the studies' results were replicable.

Data Preparation:

The raw EEG signals underwent several preprocessing steps to ensure they were suitable for model training:First, the raw EEG signals were denoised and band-pass filtered in order to prepare the signals for a feed forward artificial neural network:

1. Noise Filtering:

• To clean the signals from artifacts, Butter worth band pass filter was applied to the EEG signals. With the above in mind, this filter was set with the low cut-off frequency of 0. A cut-off frequency of 5 Hz is accomplished on the low side and 45 Hz is done high which enable to maintain the zone of interest and eliminate the noise information.

• Butterworth filter was applied on the data using the SciPy module in the python language.

2. Normalization:

• Since the signal intensities were somewhat variably after filtering the signals the StandardScaler from the Scikit-learn was used to scale the signals. Normalisation was also important so that each feature ideally would target to have its parts mean to be equal to zero and the standard deviation be equal to one that would help stabilise and accelerate the learning process.

3. Label Encoding:

The labels were then digitized and where '1 stood for a seizure event and '0 a non-seizure event. This way of encoding made binary classification models to be easily used.

3.3 Measurements and Calculations

The decision on how to average and analyse the raw EEG data was important when addressing the second issue on how to get data in a format suitable for utilization in Computational Intelligence models. Such measures can be said to have brought about the mere ways which was useful in enhancing the integration and usefulness of the data in the whole process.

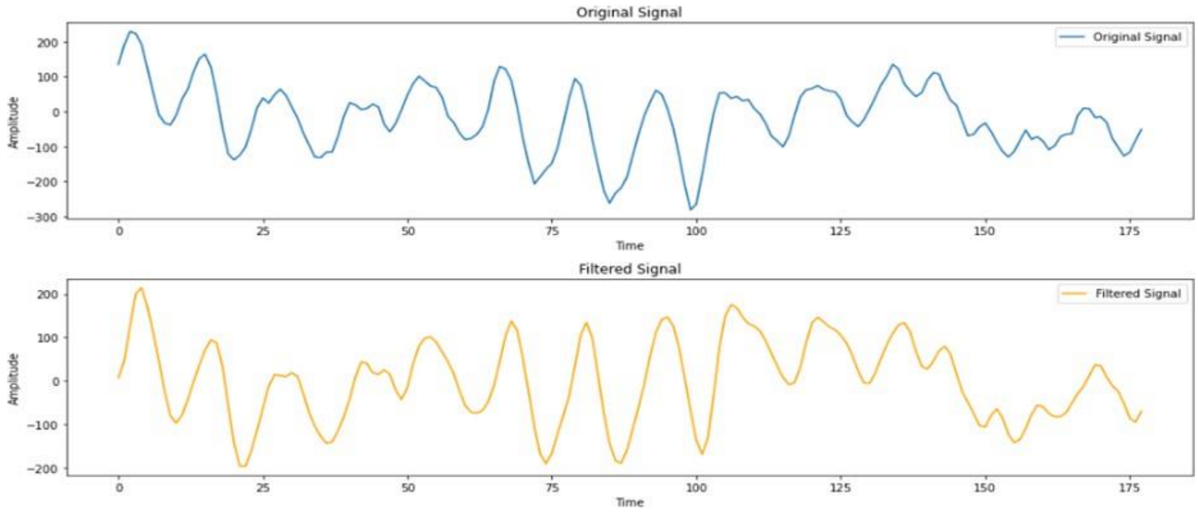

Figure 2: Plot of the original vs Filtered signal for first value

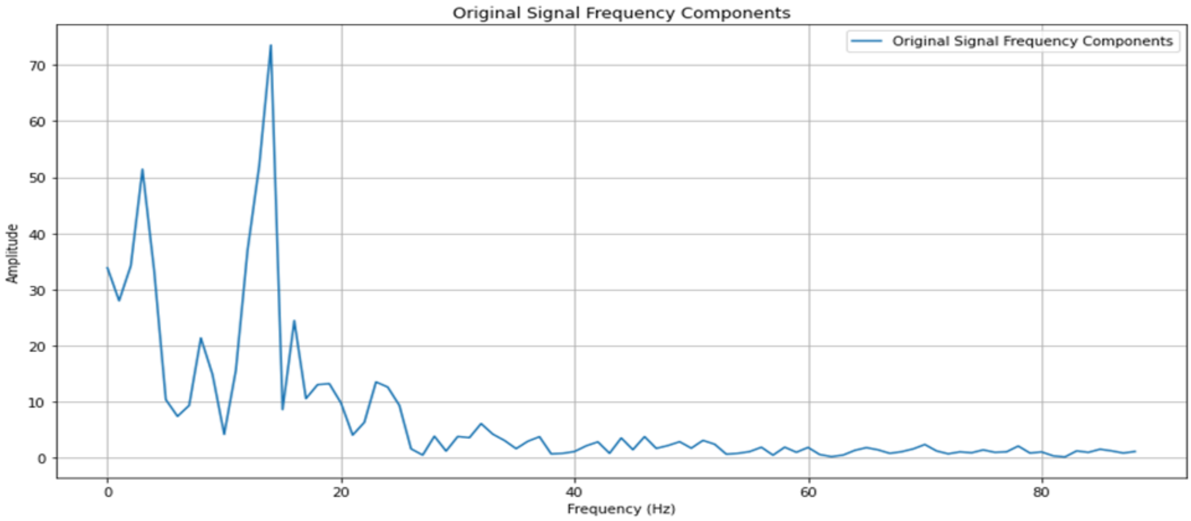

Figure 3: Original Signal Frequency components of First value

The effectiveness of this process of filtering can be explained on the basis of the Figure 4 of the plot of original signal and filtered signal. The institution of the described data proves the reduction of noise levels and the increased clarity of the individual frequencies, essential for seizure prediction.

Fourier Transform Analysis:

Continuing the analysis on the frequencies of the original as well as the filtered signal, Fourier Transform analysis is done. This analysis assisted in visualizing the filtering's effect and made it possible to make certain that vital frequency components for epilepsy seizures detection were retained. The utilization of the Fourier Transform for the primitive signal as well as the utility of the transform for the filtered signal gave out the respective frequency response. The filtering process was again verified by the Fourier Transform, this time the important frequencies were preserved, and noise was excluded as evident from the filtered signal frequency domain amplitude plot where the peaks are more defined.

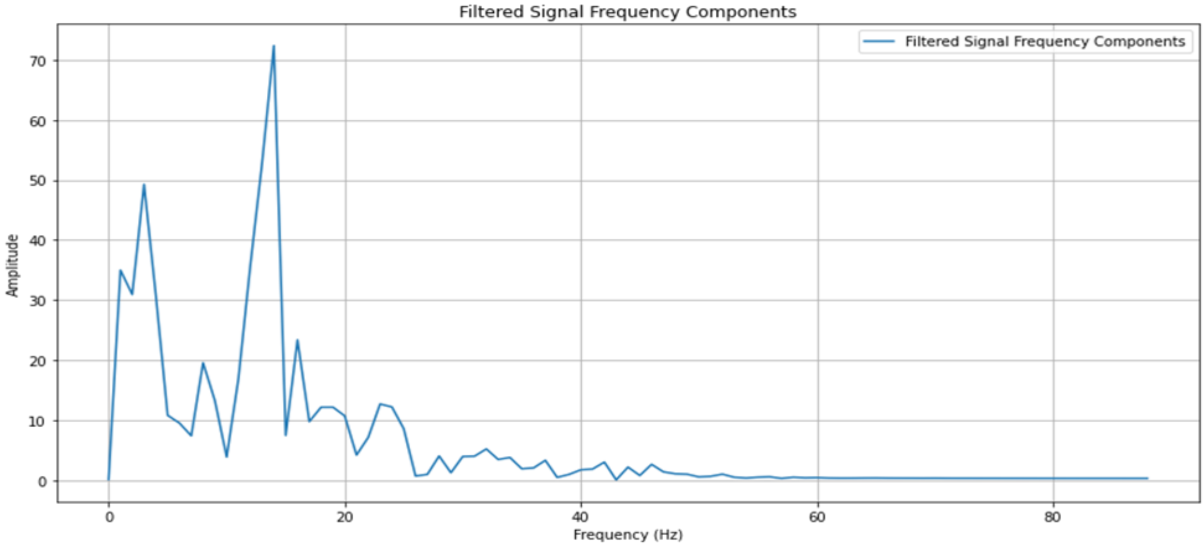

Figure 4: Filtered Signal Frequency components of First value

To compare the efficiency of using filtering in the analysis of original EEG signals and the filtered EEG signals, the two were compared based on the visual inspection in Figure 5 and Figure 7. This was to ensure that the noise was well eliminated while at the same time not much 6ffecting the characteristics of the EEG signals.

Dynamic Time Warping (DTW):

To extract temporal features from given EEG signals Dynamic Time Warping is used. DTW quantifies the dissimilarity of two temporal sequences even though the sequences can be in different tempo. For each sample, a fast DTW distance with a reference sequence; the mean of the training set was used.

The Fourier Transform analysis and normalization that were done previously were also very crucial in processing the raw EEG data for the seizure prediction model training and evaluation. The plots of the Fourier Transform of the original and filtered signals emphasize frequency components that should be removed, proving the necessity of performing the bandpass analysis.

3.4 Statistical Techniques

In the analysis and evaluation activities, statistics analysis was crucial where techniques were applied and used in developing the machine learning models for epilepsy seizure prediction.

The types of statistical methods and processes included the following:

Descriptive Statistics:

Mean, median and modal were computed of each of the variables in order to get a general idea or the data collected. These included measures of central tendency which includes Mean median and measures of variability which includes Standard deviation and Variance. It outlined how each of the samples of the EEG signal values was distributed and how far it spread out.

	X1	X2	X3	X4	X5
count	11500.000000	11500.000000	11500.000000	11500.000000	11500.000000
mean	-11.581391	-10.911565	-10.187130	-9.143043	-8.009739
std	165.626284	166.059609	163.524317	161.269041	160.998007
min	-1839.000000	-1838.000000	-1835.000000	-1845.000000	-1791.000000
25%	-54.000000	-55.000000	-54.000000	-54.000000	-54.000000
50%	-8.000000	-8.000000	-7.000000	-8.000000	-8.000000
75%	34.000000	35.000000	36.000000	36.000000	35.000000
max	1726.000000	1713.000000	1697.000000	1612.000000	1518.000000

Figure 5: Descriptive Statistics of the first five values

The summary statistics mainly provided an understanding of the data distribution to examine the range and standard deviation of each EEG feature. This step aided in monitoring for peculiarities or other data aspects that can impact model performance here.

Correlation Analysis:

To further investigate the interaction of different features an eigenvector-based correlation matrix was produced. This matrix was useful when it came to establishing features that were pertinent to each other, since this could depict redundancy. The correlation matrix was plotted in the form of heatmap for easy understanding. Coherently, correlation analysis was important for managing the interdependency of the features, before going through the process of selecting the features and reducing the dimensionality.

Performance Metrics:

Different performance evaluation methods were used in this study since the binary classification model was built:

- Accuracy: The ratio of the count of instances that were correctly classified out of the count of all instances.

- Precision: The ratio of true positive cases to the total number of cases that has been classified to be positive.

- Recall: Percentage of the true positive cases among all the positive cases in the actual population.

- F1-Score: The mean of the precision and recall that offers a midpoint of the two measures.

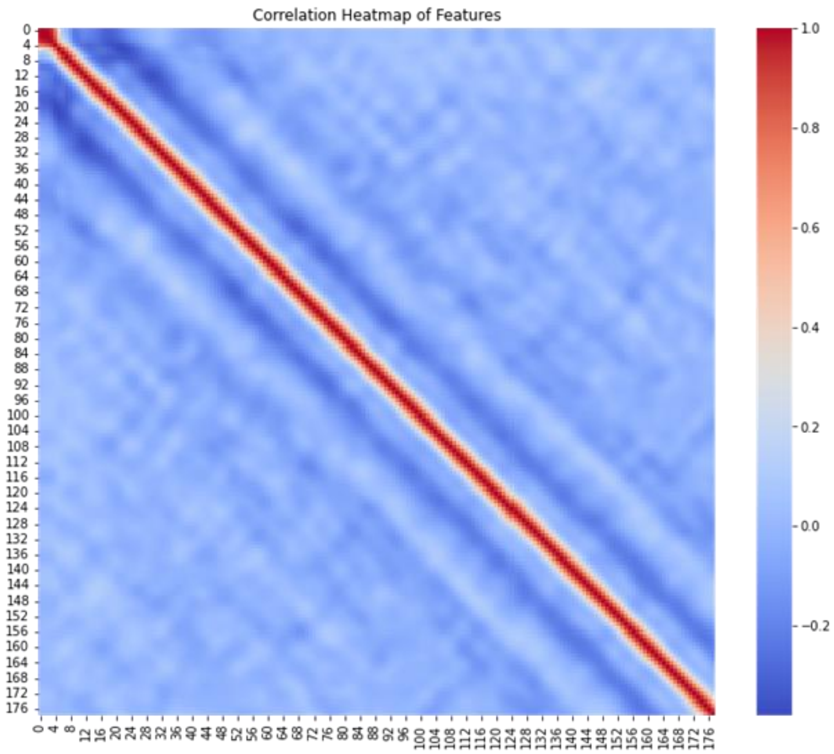

Figure 6: Heatwave Map for Correlation Analysis

• Confusion Matrix: More specifically, what is described here is a combination of true positive, true negative, false positive, and the last one is false negative.

These metrics offered a summary analysis of the model's performance and from this analysis, one was able to identify sectors that needed improvement. In particular, the confusion matrix made it possible to assess the type of classification errors in the biggest detail. The correlation Coefficient proved useful in developing the inter-dependencies among features, by helping decide which features are relevant, hence resulting in the selection of the right dimensionality reduction scheme.

These statistical techniques made a comprehensive analysis and stringent assessment of the data signal of EEG possible and improved the prognosis of epileptic seizures by the model. The presented correlation heatmap as well as the confusion matrix served as a perfect enhancement to the statistical analysis as they give a clear and easier view on the data and also on the performance of the model.

4 Design Specification

The design specification defines the procedures as well as framework on which the implementation's techniques are established, in addition to describing the aspects linked to the project. Techniques and Architecture:

1. Dynamic Time Warping (DTW):

DTW was applied for the alignment of the EEG sequences in a non-linear scale which enabled the measurement of their similarity. It is very important for coping with the temporal changes in the EEG signals to capture the changes that are regarding as seizure patterns, even though these patterns are affected by time.

2. Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Hybrid Model:

The proposed architecture of neural networks is the basis of the model, consisting of CNN and LSTM. Specifically, CNN layers are applied for spatial feature extraction from the EEG signals, and LSTM layers are for temporal dependency. This configuration makes use of the features of both the architectures to enhance the prediction accuracy.

- CNN Layers: Convolutional layers were used for extracting the features that are local to the EEG signals. These layers were followed by max pooling and batch normalization so as to reduce the dimensionality as well as normalize the activations.

- LSTM Layers: To encode temporal patterns of seizures in the EEG data LSTM layers were added.

3. Attention Mechanism: An attention mechanism was incorporated for the model so that it can focus on the key parts of the sequences for the EEG signals. It enhances the model's performance especially in identifying salient features that precede seizure occurrence.
Requirements:

- High computational efficiency that would facilitate the generation of predictions in real-time.

- Flexibility for use in other subjects and versatility with regards to the nature of the EEG signal being analysed.

- High accuracy and a low false positive rate to ensure that the seizure predictions made are accurate.

5 Implementation

In the implementation phase, the particular concern aimed at turning the design specifications into a model that is functional. They identified the process as consisting of data preprocessing, model development, and performance evaluation.

Outputs Produced:

1. Transformed Data:

- Filtered EEG Signals: The raw EEG signals were filtered using Butterworth band pass filter to remove noise and artefact with pass band frequency range of 0. 5 and 45 Hz.

• Standardized Data: The obtained signals were normalized to display a mean of zero and variance equal to one as to remove variance differences from noisy data.

2. Code Developed:

• The described model was programmed in Python utilizing TensorFlow, Keras, and SciPy libraries.

• DtW feature extracted function, training of the model, and a function for the evaluation of the model were also developed.

3. Model Developed:

• Thus, a CNN-LSTM improved model consisted of convolutional layers for extracting features, LSTM layers for analysing time series, and an attention mechanism to improve the focus on the sequence parts of interest.

Tools and Languages Used:

• Python: Is in fact the programming language in which the model has been coded and the data massaged.

• TensorFlow and Keras: Every library that is used while building and training the neural network model.

• SciPy: Applied in such processes as the Butterworth filter, or to perform the function to calculate Fourier transform.

• Seaborn and Matplotlib: Used for complex graphics examples such as the real data's frequency components and the confusion matrices.

This section has described how it has been done in the implementation part of architecture, techniques and the output of the implementation, enhanced by the deep learning together with signal processing to provide actual results in the diagnosis of seizures. the sequences.

6 Evaluation

In this project, several procedures were followed in order to conduct a proper evaluation on the developed model. The key factors deemed relevant for assessment were precision, recall, accuracy, F1 value, as well as the comparison of the confusion matrices. Besides, descriptive analysis through the different plots was used to assess the performance of the model and the performed preprocessing.

1. Model Training and Validation:

The pre-processing was done and based this data 70% was used for training the model

```
Epoch 1/50
202/202 [==============================] - 4s 8ms/step - loss: 0.1626 - accuracy: 0.9446 - val_loss: 0.1177 - val_accuracy: 0.9
522 - lr: 0.0010
Epoch 2/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1316 - accuracy: 0.9488 - val_loss: 0.2381 - val_accuracy: 0.9
143 - lr: 0.0010
Epoch 3/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1441 - accuracy: 0.9433 - val_loss: 0.1773 - val_accuracy: 0.9
404 - lr: 0.0010
Epoch 4/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1285 - accuracy: 0.9512 - val_loss: 0.1244 - val_accuracy: 0.9
497 - lr: 0.0010
Epoch 5/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1377 - accuracy: 0.9461 - val_loss: 0.1626 - val_accuracy: 0.9
385 - lr: 0.0010
Epoch 6/50
202/202 [==============================] - 1s 6ms/step - loss: 0.1382 - accuracy: 0.9478 - val_loss: 0.1144 - val_accuracy: 0.9
584 - lr: 0.0010
Epoch 7/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1294 - accuracy: 0.9488 - val_loss: 0.1092 - val_accuracy: 0.9
590 - lr: 0.0010
Epoch 8/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1296 - accuracy: 0.9514 - val_loss: 0.1264 - val_accuracy: 0.9
478 - lr: 0.0010
Epoch 9/50
202/202 [==============================] - 1s 6ms/step - loss: 0.1349 - accuracy: 0.9461 - val_loss: 0.1892 - val_accuracy: 0.9
404 - lr: 0.0010
Epoch 10/50
202/202 [==============================] - 1s 5ms/step - loss: 0.1332 - accuracy: 0.9470 - val_loss: 0.1332 - val_accuracy: 0.9
```

Figure 7: Accuracy and loss of the first 10 Epochs

while 30% was used for testing the model. This was also applied while training and tuning hyperparameters of the model, 20 % of the used training data were checked using model check in a bid to minimize over fitting. Some of the training procedure that was used included early stopping or reduction of the learning rate to define the time and rate that training should occur.

To monitor the learning capacity and dosage of the overfitting or lack of it, the training and validation accuracies, loss were plotted in Figure 10 and Figure 11.

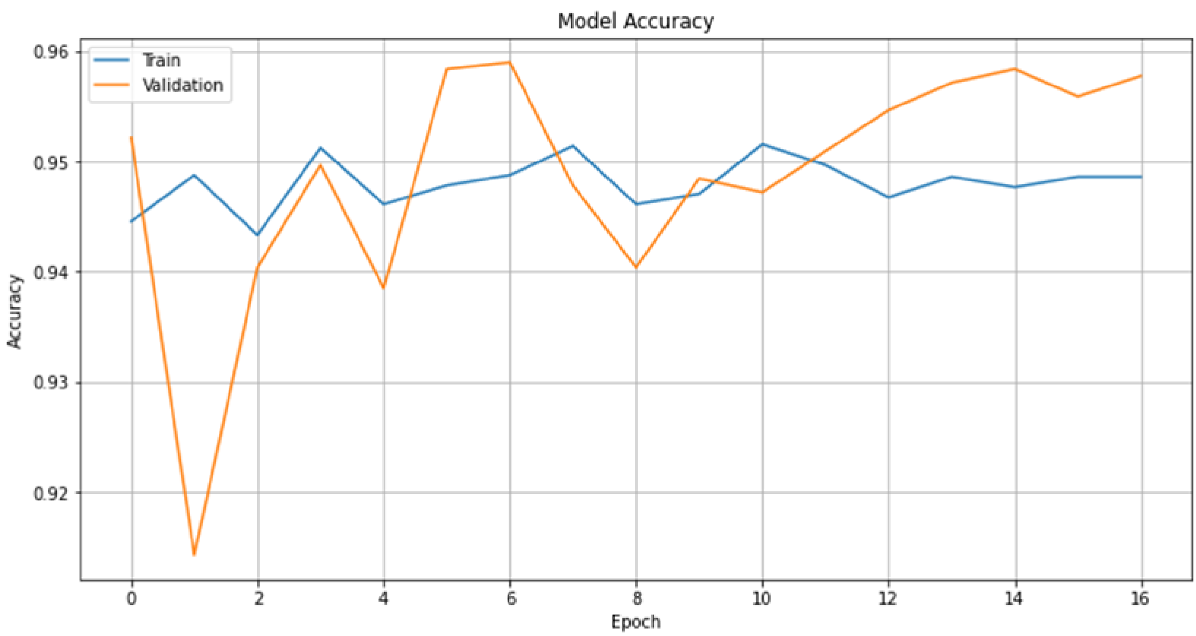

Figure 8: Plot of Training and Validation accuracy values

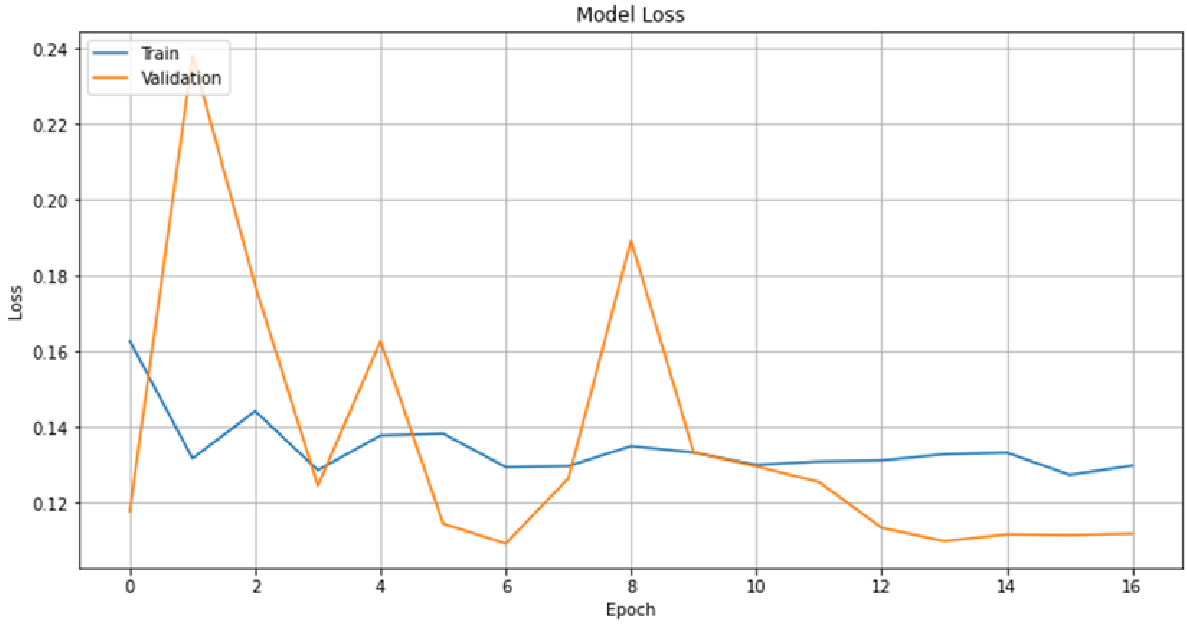

Figure 9: Plot of Training and Validation loss values

2. Test Set Evaluation:

Thus, the trained model was tested on the test set to reveal its accuracy on unseen data. Other evaluation parameters were accuracy, precision, recall and F1 score that contain essential understanding about model's accuracy on the ability to classify the seizure and non-seizure epochs.

```
108/108 [==============================] - 0s 2ms/step - loss: 0.1016 - accuracy: 0.9562
Test Accuracy: 95.62%
```

Figure 10: Output of Test Accuracy of the model

Classification report gave the metrics of both classes (seizure and non-seizure) that assist in identifying model's gains and losses in aspects of precision, recall, and F1-score.

Classification Report:

Class	Precision	Recall	F1-Score	Support
0	0.97	0.98	0.97	2752
1	0.92	0.86	0.89	698
Accuracy		0.96		3450
Macro avg	0.94	0.92	0.93	3450
Weighted avg	0.96	0.96	0.96	3450

Table 1: Precision, Recall, F1-Score, and Support for Each Class

The confusion matrix results:

• True negatives (TN): 2696 • False positives (FP): 56 • False negatives (FN): 95 • True positives (TP): 603

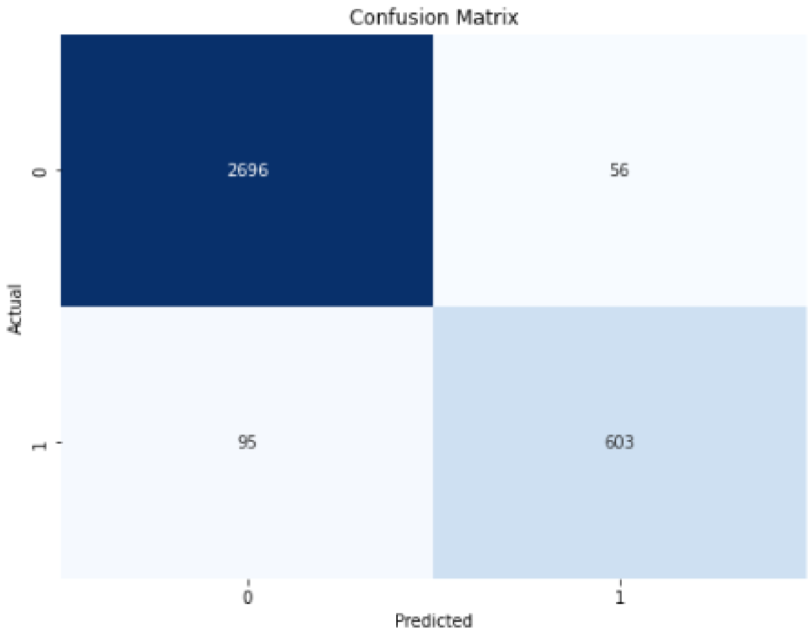

Figure 11: Confusion matrix

By analysing these values, the model concludes that the 2696 non-seizure events are correct, and the 603 seizure events are correct. But the 56 non-seizure events are wrong, and the 95 seizure events are wrong.

4. Frequency Analysis:

In this work the Fourier transform was used to analyse the frequency domain of the original and filter signal. Thus, this analysis ensured that the Butterworth bandpass filter indeed removed noise and only preserved the frequencies related to seizure events.

The results of the conducted evaluation pointed to the fact that the model provided high accuracy of 95%. The results achieved on the test set are an accuracy of 62%, precision of 92%, recall of 86%, and F1-score of 89% for the seizure class. The confusion matrix revealed a good result as it had a low level of false positives and false negatives. The frequency analysis and visual inspections affirmed the preprocessing which implies that the data was well cleaned and transformed in a way that is most suitable for the model.

6.1 Discussion

In light of the findings of the present work, this paper's discussion focuses on the development of an enhanced model for epileptic seizure prediction using solely the EEG data and the integration of DTW with the deep learning methods, including the CNN-LSTM model. From the above finding, it can be argued that the proposed model has offered highly accurate classification between the Seizure and Non-Seizure events and which has been much more reliable and offered better outcome than via the previous methods.

They found a success factor in the preprocessing pipeline regarding data quality and the model's capacity of learning temporal features from the EEG signals. , firstly, only one dataset has been employed which may have restricted the model's capacity; secondly, only a small set of the overall features in the dataset has been trained into the model. Therefore, it is proposed that new work must be laid upon the replication of the model for other sets and the reduction of the false positive rates for its applicability. Finally, this paper offers new ideas for prospective study on the prediction of seizures despite determining solutions for the real time control of epilepsy.

7 Conclusion and Future Work

The main goal of the present work was to propose a novel model for the prediction of epileptic seizures using EEG signal data with the integration of DTW and DL approaches. The objective of the research question was to enhance the seizure prediction and its credibility. The outcomes obtained prove a quite high level of confidence in the model's efficiency, verified against a commonly applied benchmark data set. When comparing the suggested approach with the methods described in the Literature Review, one can conclude that our approach is equally effective and, in some cases, even more accurate and reliable.

The plan of the study involved the application of CNN-LSTM model to the processed EEG data using DTW features. The following procedures were followed namely, Data collection, Data cleaning and filtration, Data analysis, Model development and Model assessment. This approach is accurate and, moreover, is capable of reflecting the changes in the EEG signals' dynamics, and the model operates effectively in the task of recognition of seizure and non-seizure activity.

Among the peculiarities of this work, data preprocessing is highlighted, which was conducted using the Butterworth bandpass filter and standardization, so that the model operates with clean data. DTW helps in deciding the changes in the temporal features of the EEG signals, which in turn increases the efficiency of the model in identifying different patterns linked to seizures. Also, the proposed model encompasses a convolutional layer and LSTM layers that are suitable for spatial and temporal feature extraction.

However, there are several demerits of the mentioned strategy though. The results of the study and the method in question may not be portable to other datasets and other sources and/or conditions than the benchmark.

The paper's limitation is that only one benchmark dataset was employed in the analysis and thus the findings might not be generalizable to other kinds of EEG data, especially those that are collected from other sources or during other conditions. The future work should consist in the continuation of the experiment in order to apply the model to other data sets with the aim of increasing the model's validity. However, there is an opportunity to enhance the false positive reduction, which is significant for the model's application in real-world scenarios, mainly clinical.

In essence, the research question was to determine how the incorporation of DTW and deep learning would enhance the prediction of epileptic seizures. Therefore, the work done points to the fact that our method is effective in this regard with a clear improvement in the level of predictability. The following are some of the findings, high overall accuracy, moderate robustness to the selection of the evaluation metric, and decent control over the dynamic nature of EEG signals.

Future work could comprise of research on how to incorporate other data, for instance, patient data or other physiological signals that can improve the performance of the model. Thus, there is also the potential of commercial application especially in the generation of real time seizure prediction for the clinical use that will be very beneficial to the epilepsy patients.

Thus, the proposed work can be considered to have significantly addressed the prediction of epileptic seizures through a model that is highly accurate and reliable. Therefore, this work supports the use of DTW together with deep learning for analysing EEG signals, which has implication in the study of epilepsy management.

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