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ROBUST DEEP LEARNING APPROACH FOR PREDICTING EPILEPTIC SEIZURE PATTERNS ENABLING MULTI STATE EEG CLASSIFICATION AND IMPROVED PATIENT MONITORING SYSTEMS

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Abstract

Epileptic seizure refers to a transient, uncontrolled electrical brain disturbance that alters behaviour, movements, or consciousness. Epileptic seizure detection from Electroencephalogram (EEG) records can facilitate the monitoring of patients and prompt intervention but may be challenged by multi-state EEG patterns and noisy signals. To overcome this problem, this manuscript proposes a robust deep learning approach for predicting epileptic seizure patterns enabling multi state EEG classification and improved patient monitoring systems (PES-EEG-PMS-SMCNN) is proposed. The input data is gathered from NeuroVista Trial Data. After that, data is pre-processed using Fuzzy-Enhanced Kalman Filter (FEKF) is used for data resizing, and data normalizing. The pre-processed data are then fed into the feature extraction phase, where the Refined Linear Chirplet Transform (RLCT) extracts the time domain features like Mean, standard deviation, variance, kurtosis, and skewness. The extracted features are given to Self-Modulating Convolutional Neural Networks (SMCNN), which is employed to predict epileptic seizure and classify EEG signals into Interictal, Pre-Ictal, Ictal, and Post-Ictal phases for improved patient monitoring. The proposed method was implemented in Python, and its performance was measured based on various metrics including, accuracy, precision, recall, F1- score as well as confusion matrix. The developed PES-EEG-PMS-SMCNN model yielded accuracy, precision, recall, and F1-score of 98.3%,97.5%, 97.7% and 98.2%, respectively. Results were compared with traditional STC-EEG-XGBoost model for a multi-class automatic seizure detection, and DES-EEG-LSTM pattern on the epileptic EEG dataset as well other automatic epilepsy classification methods showing that this approach outperformed all of them. System utilizing EEG signals and ML techniques (STC-EEG-XGBoost), detection of epileptic seizure in EEG signals utilizing ML techniques and DL approaches (DES-EEG-LSTM) and automatic epilepsy seizure classification using EEG signals depending upon the CNN-LSTM model (ESC-EEG-CNN), respectively.

Keywords: Electroencephalogram, Epileptic seizure patterns, Fuzzy-enhanced Kalman filter, Refined linear chirplet transform, Self-modulating convolutional neural network, Neurovista trial data.

1. Introduction

Based on the WHO; Approximately 50 million individuals worldwide are living with epilepsy, a common neurological disorder. Epilepsy is a neurological condition characterised by seizures, which are episodes of abnormal and excessive discharges from the brain that causes an attack [1]. Seizures may manifest in various forms, including momentary loss of consciousness, convulsions, or brief lapses [2]. Although epilepsy can develop at any stage of life, it is most identified during childhood and in older adults and is often connected to an inherited trend, traumatic brain injury, tumour, neurodevelopmental disorders, and cerebrovascular pathology [3]. Usually, seizures are classed as either focal or generalised.

Depending on the state of consciousness, focal seizures can be simple or complicated and happen within a particular area of the brain. Generalized seizures affect the greater part of the brain and constitute motor and non-motor forms including clonic, tonic clonic, absence, tonic, atonic, or myoclonic seizures [4]. Accurate characterization and classification of seizure types are critical because therapy and drug use is based on the type of seizure. The electroencephalogram (EEG) is an established method of detection and classification of seizures because it measures by recording the brain's electrical signals using electrodes attached to the scalp. The EEG presents essential temporal and spatial information essential for understanding unusual patterns of brain activity [5]. However, with the expanded availability of EEG monitoring and traditional diagnostic methods, there remain challenges.

EEG signals are highly nonlinear and non-stationary, and consequently extracting meaningful patterns is difficult [6]. Inter-patient variability and unpredictable seizure initiation create further complications for detection. Human interpretation/detection requires many hours of experience and training, is subject to human error, and often is not able to detect subtle and/or highly ambiguous pre-seizure indicators. Further, limited annotation of EEG datasets and high dimensionality of EEG signals complicate automatic seizure classification [7]. Recent advancements in ML and DL provide possible solutions. Deep learning (DL) based methods can automatically capture intricate spatial and temporal features from EEG data, but can also provide multi-state classification, early prediction, and real-time patient monitoring. Such systems aid clinicians in timely intervention, minimize seizure-associated risks, and enhance patient outcomes and thus are a key tool in contemporary epilepsy management.

2. Literature Review

Literature summarizes several research studies on deep learning-based prediction of epileptic seizure patterns facilitating multi state EEG classification employing various methods. This section summarizes some of the latest studies.

Abirami, et al. [8] have described an automated model for identifying epileptic seizure types with EEG signals. Seizures of patients were studied from the Temple University Hospital dataset. The EEG signals were pre-processed, and time, frequency, as well as time-frequency domain features were obtained. Relevant features were determined based on statistical tests and the XGBoost algorithm. Binary and multiclass models were constructed, and it was found that EEG band powers 11–13 Hz, 27–29 Hz, IMF band power 19–21 Hz, and delta band (1–4 Hz) were the most discriminative. The method was however, hampered by its reliance on one dataset, which impacts its generalizability to other patient groups.

Kunekar et al. [9] have discussed the automatic epileptic seizure detection utilizing ML and DL methods. They emphasized that before DL; feature extraction was based on handcrafted features by traditional ML, which had restricted performance. With DL, both feature extraction and classification were automatically processed, achieving better accuracy in the diagnosis of epilepsy. The UCI-Epileptic dataset was utilized for both training and validation purposes, and several ML and DL methodologies were compared. LSTM was employed to determine the best method. The study was, however, biased by its use of a single dataset, potentially limiting generalizability to heterogeneous patient populations.

Vinutha et al. [10] designed an automated method to classify focal and nonfocal EEG signals from patients with epilepsy. They used Inception-ResNet v2 architecture in conjunction and a Deep Adagrad-optimized LSTM network. Inception and ResNet layers were utilized to extract features from EEG signals and then the CNN was integrated with the Adagrad-LSTM layer for training and classification. The method was designed to minimize the dependency on labour-intensive manual inspection by medical professionals. The technique, though, had the limitation of being applied to a unique dataset, which can influence its validity for different patient groups or EEG recording settings.

Kode et al. [11] have examined automated recognition of epileptic seizures with the assist of ML and DL methods on EEG signals. They aimed at classifying time-series EEG data through ML classifiers like XGBoost, TabNet, and Random Forest, in addition to a One-Dimensional-CNN. The UCI EEG dataset was pre-processed and utilized for training as well as evaluation. The model of 1D-CNN performed better compared to other strategies based on accuracy, sensitivity, as well as precision. Still, the study was restricted by being based on one dataset, which limits the applicability of the findings to larger populations or other EEG recording setups.

Sahoo et al. [12] have investigated seizure prediction in epilepsy employing memory-based learning methods like transfer learning and recurrent neural networks (RNNs). They targeted classifying temporal lobe epilepsy from pre-processed EEG signals to model temporal dependencies within sequential data. Some of the deep learning architectures were tested, and GoogLeNet offered to be the finest among the models. To improve model flexibility and avoid forgetting, Elastic Weight Consolidation (EWC) was used in conjunction with a customized learning rate scheduler. However, the method had a limitation of using a particular dataset, which limits the model generalizability to other patient groups or EEG recording conditions.

Shawly, and Alsheikhy [13] have suggested an automated deep learning method for epilepsy prediction based on EEG signals. To enhance feature extraction, they integrated a Novel Attention Module (NAM) into a CNN, computed features using the Fourier Transform, and reduced dimensionality using Principal Component Analysis (PCA). To improve learning, the Adam optimiser was utilised to optimise stochastic gradient descent. It was trained and tested on several publicly accessible EEG datasets with excellent generalization. The method was, however, restricted by its computational complexity and dependence on certain preprocessing procedures, which limit applicability across different clinical environments.

Abtahi et al. [14] have investigated the prediction of epileptic seizures using electrocardiogram (ECG) signals through the combination of traditional Heart Rate Variability (HRV) and Lorenz features, and multifractality features for the first time. They found that multifractality features in combination with traditional features produced better prediction performance than HRV and Lorenz features. Features were interpreted for importance with an SHapley Additive explanations (SHAP) to evaluate patterns predicted by which enabled to show that multifractality features were useful patterns that traditional features could not detect.

The generic evaluation of current studies shows that while numerous automated and deep learning-based techniques have been planned for epileptic seizure detection and classification utilizing EEG signals, most methods are limited by their reliance on specific datasets, computational complexity, preprocessing requirements, or by focusing on non-EEG signals that do not capture all neurological aspects of seizures, collectively restricting their generalizability and applicability across diverse patient populations and recording conditions. Numerous academics are addressing this issue with various technologies in the literature, including CNN, LSTM, and Extreme Gradient Boosting (XGBoost).

Even though XGBoost works well for feature selection and structured data, it is not very good at handling sequential or time-series data, like EEG signals, and it mostly depends on hand-crafted features. LSTM networks excel at capturing temporal dependences in sequential data, but they demand substantial volumes of training data, involve high computational costs, and are prone to overfitting or vanishing gradient issues for very long sequences. CNN are powerful for spatial feature extraction and pattern recognition but exhibit limited ability to model temporal dependencies, demand careful preprocessing and tuning, and become computationally exclusive for high-dimensional data. These problems and drawbacks have motivated this research project.

The primary objective of this study is to design a robust DL technique for predicting epileptic seizure patterns and classifying multi-state EEG signals, addressing challenges in accurate seizure detection and enhancing patient monitoring systems for improved healthcare outcomes.

In order to overcome the drawbacks of existing seizure detection techniques, the work introduces the PES-EEG-PMS-SMCNN approach to enhance accurate prediction and multi-state categorizations of epileptic seizures. FEKF is employed to enhance EEG signal quality and normalize data, RLCT is utilized to extract meaningful temporal features, and SMCNN is applied to model complex spatial-temporal patterns in EEG signals; this approach enables high-precision classification of Interictal, Pre-Ictal, Ictal, and Post-Ictal phases. It facilitates better patient monitoring through capturing nuanced EEG dynamics variations, enabling timely intervention, and facilitating better clinical decision-making. Its capacity to dynamically and strongly analyse multi-state EEG patterns is a big leap in automated seizure detection and real-time neurological monitoring.

Major contributions of this paper include.

- A new deep learning paradigm, PES-EEG-PMS-SMCNN, is designed to enhance prediction patterns for epileptic seizure, as well as multi-state EEG classification to propel patient monitoring.

- The FEKF is intended to provide sophisticated sizing and normalization of data to ensure only the highest quality data is fed into the next analysis step.
- The RLCT utilized sophisticated time domain features such as mean, standard deviation, variance, kurtosis, and skewness, in order to increase the quality of seizure classification features.
- A personalized SMCNN is used to classify EEG signals into multi-states, interictal, pre-ictal, ictal, and post-ictal stages, with increased accuracy of seizure prediction and accuracy in patient monitoring.
- The PES-EEG-PMS-SMCNN approach demonstrated superiority over classic models such as STC-EEG-XGBoost, DESS-EEG-LSTM, and ESC-EEG-CNN, with its precision, recall, accuracy, and F1-Score demonstrating usefulness for seizure classification.
- The method is trained as well as tested on NeuroVista Trial Dataset, comprising real-world EEG recordings, making it practical to use in systems for monitoring patients.

Remaining manuscripts arranged as below: section 2 depicts the planned methodology, section 3 explains the outcomes and discussions, section 4 outlines the conclusion.

3. Proposed Methodology

In this part, a robust deep learning approach for predicting epileptic seizure patterns enabling multi state EEG classification and improved patient monitoring systems (PES-EEG-PMS-SMCNN) is proposed. The system initiates with the NeuroVista trial data, which is pre-processed via a FEKF for data normalization and resizing. Feature extraction using the RLCT is then used to extract time-domain features like mean, standard deviation, variance, kurtosis, and skewness.

The processed data is subsequently fed to a SMCNN for prediction and classification with the intent of predicting epileptic seizures. The block diagram of proposed PES-EEG-PMS-SMCNN approach is illustrated in Fig. 1.

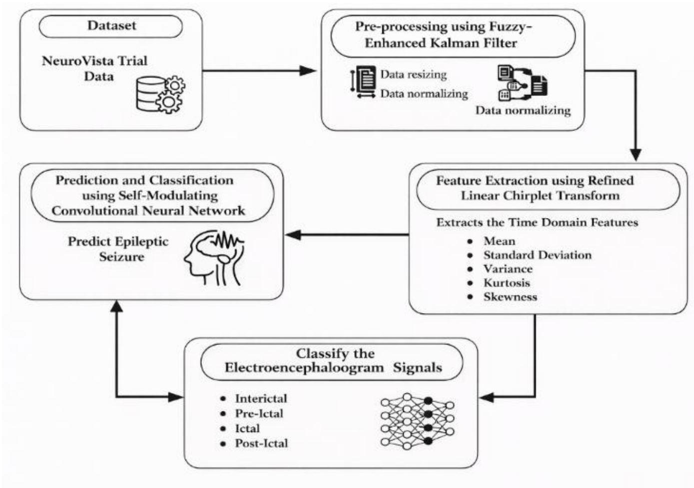

Fig. 1. Block diagram of the proposed PES-EEG-PMS-SMCNN.

3.1. Data acquisition

Firstly, input data is taken via NeuroVista Trial Data [15]. The NeuroVista Trial Data consists of a large body of long-term intracranial electroencephalography (iEEG) recordings in 15 patients, covering periods between 6 months to 3 years. The NeuroVista dataset comprises long-term 400 Hz intracranial EEG recordings from 15 drug-resistant focal epilepsy patients, collected via an implantable multi-channel seizure advisory system, with clinically annotated seizure stages in large-scale continuous data.

The database contains seizure (ictal) data, and non-seizure (interictal and preictal) labelled respectively, to enable exploration of the mechanisms of seizure development, as well as helping with designs of prediction algorithms. The subsequent data segments consist of 10-minute ensembles, with interictal segments beginning on the hour, and preictal segments beginning at 30 minutes after the hour facilitating recognition of brain states. A dataset like this can be used as a tool for seizure prediction research, epilepsy dynamics.

3.2. Pre-processing utilizing fuzzy-enhanced Kalman filter (FEKF)

This section deals with pre-processing using an FEKF [16]. EEG signals were adaptively denoised using FEKF with fuzzy-optimized covariance, followed by normalization and imputation. Data were segmented into 10-s windows and scaled (0–1) for robust feature extraction. FEKF extends the Kalman Filter by adaptively updating noise covariance using fuzzy logic. By tuning parameters based on innovation error, it better handles non-stationary EEG signals. This adaptive filtering improves denoising, stability, and robustness before feature extraction. The FEKF applies to data resizing and data normalizing.

The FEKF is all but perfect for predicting epileptic heralding seizure patterns because it combines the advantages of the conventional Kalman Filter's adaptive estimation, with fuzzy logic being able to accommodate uncertainty. This allows for more robust and precise multi-state EEG classification, even in the presence of noisy and sometimes incomplete EEG signals, as one would typically find in clinical situations. The main aims of FEKF based systems aim to both provide real-time seizure detection, increase seizure onset prediction accuracy, and permit the continuous monitoring of patients, allowing timely intervention, reduced injuries from seizures, and ultimately, improve the quality of life of epilepsy patients. The FEKF relies on raw EEG signals that, often, contain noise and sampled at irregular intervals. Precise data is given in Eq. (1).

$$e_k = x_k - \hat{x}_{k|k} = \begin{bmatrix} e_{1,k} \\ . \\ . \\ e_{n,k} \end{bmatrix} \tag{1}$$

The state estimate $\hat{x}_{k|k}$represents the current filtered value of the network data. The error between the actual statex_k and the estimated state$\hat{x}_{k|k}$;$e_k$is the dissimilarity between the actual and assessed state at iteration$k$ is represented, and $x_k$denotes the true state of the network, while $\hat{x}_{k|k}$represents the current estimate and $e_{n,k}$denotes the normalized data. FEKF resizes the EEG data by interpolating or down sampling it to a uniform length suitable for neural network input, while retaining key signal features. This matrix $P_k$helps to assess the reliability of the current estimate by indicating the variability of the system using Eq. (2).

$$P_k = x_k - \hat{x}_{k|k} \tag{2}$$

The cost function is then minimized by adjusting the Kalman gainG_k. Kalman filter update layer refines the state estimation and error covariance matrices using the adjusted parameters for improved filtering accuracy. After resizing, the filtered EEG data is normalized to ensure consistent scale across all channels and segments. The cost function $J_k$minimizes the error by reducing the distinguish between the true as well as predictable states, ensuring a more accurate and noise-free estimate using Eq. (3),

$$\min_{G_k} J_k = \min_{G_k}(E(e_{1,k}^2)+\ldots+E(e_{n,k}^2)) \tag{3}$$

In this equation, $E(e_{1,k}^2)$represents the expected value of the squared error for each component at iteration$k$ and the goal is to minimize this total error to improve the accuracy. Lastly, the FEKF technique was utilized for missing values imputation, data cleaning, and noise reduction in the input data. Subsequently, pre-processed data are input to feature extraction.

3.3. Feature extraction using refined linear chirplet transform (RLCT)

The feature extraction utilizing the RLCT method is discussed in this segment [17]. RLCT is used to extract the time domain features including Mean, standard deviation, variance, kurtosis, and skewness. The RLCT provides tremendous benefits in epileptic seizure pattern prediction due to the higher-resolution time frequency investigation of EEG signals, which is quintessential in revealing the non-stationary and intricate dynamics of brain activity. Its adaptable frequency change tracking allows enhanced detection of subtle pre-seizure changes through multiple EEG states and, as a result, is likely to have enhanced multi-state classification accuracy. This enhanced resolution and granularity allow earlier and more reliable seizure prediction, leading interventional or caregiving alert systems and advanced patient-care systems, allowing for all might positively affect seizure management, reduce accident risk, potentially impacting quality of life, for patients with epilepsy and seizures. The RLCT begins by converting the EEG signal to a time-frequency domain via a chirplet-based conversion. This is given in Eq. (4).

$$\alpha_{k,j}^{lb} = -\frac{\pi}{2} + \frac{\pi}{N+1}, \qquad \alpha_{k,j}^{ub} = \frac{\pi}{2} - \frac{\pi}{N+1}(j = 1,2,\ldots,J) \tag{4}$$

When, start calculating the iteration from$k = 1$; Nimplies the number of local searches in the iteration; $\pi$is the angle range. The initial interval of α(rotation angle) is given as $\alpha_{k,j}^{ub}(k = 1)$at all-time instant $t_j$is denoted by $(j = 1,2,\ldots,J)$, where the lower limit $\alpha_{k,j}^{lb}$ and upper limit $\alpha_{k,j}^{ub}$ are respectively. After obtaining the time-frequency representation, RLCT isolates localized segments of the EEG signal corresponding to specific chirplet components are stated in Eq. (5).

$$\alpha_{k,j,n} = \alpha_{k,j}^{ub} + \frac{n}{N-1}\left(\alpha_{k,j}^{ub} - \alpha_{k,j}^{lb}\right)(n = 0,1,2,\ldots,N-1) \tag{5}$$

here, linear chirplet transform is applied to calculate the illustration $S_{k,j,i,n}\left(= S\left(t_j, w_i, \alpha_{k,j,n}\right)\right)$ consistent to every rotation angle $\alpha_{k,j,n}$, N represent the number of candidate rotation angles per iteration. Beyond basic statistics, RLCT also calculates higher-order moments such as kurtosis and skewness for each chirplet segment is expressed in Eq. (6).

$$N_{RLCT} = N + (K-1)(N-1) = KN - K + 1 \tag{6}$$

There are N times of the linear chirplet transform used in the main iteration$(k = 1)$ in the RLCT-Method, and $N - 1$in each iteration thereafter $(k = 2,3,\ldots,K)$. Finally, RLCT has obtained the time domain features such as Mean, standard deviation, variance, kurtosis, and skewness. Subsequently, the extracted features are provided to the classification stage.

3.4. Prediction and classification using self-modulating convolutional neural networks (SMCNN)

This section revolves around the SMCNN [18]. SMCNN was trained with an 80:20 balanced split using Adam (0.0001) and categorical cross-entropy for 100 epochs (batch size 128). Early stopping and dropout mitigated overfitting, and the best model was selected by validation F1-score on a GPU-based Python platform. The SMCNN technique is implemented to predict seizures in patients with epilepsy, and to categorize EEG data into the respective states of Interictal, Pre-Ictal, Ictal, and Post-Ictal phases to provide an accurate method to monitor the patient. For clarity and clinical interpretability, the definitions of Interictal, Pre-Ictal, Ictal, and Post-Ictal states are formally introduced here. Interictal denotes the baseline between seizures, Pre-Ictal marks the period preceding a seizure with subtle EEG changes, Ictal represents active seizure activity, and Post-Ictal reflects recovery toward baseline.

SMCNN's provide useful advantages in predicting patterns of seizure because they utilize the incoming EEG signals to adjust their convolutional filters dynamically over time and perform a better job of feature extraction across states of the brain. SMCNN employs self-modulation to adapt intermediate feature maps using contextual EEG information. Unlike static CNNs, it applies adaptive scaling to emphasize seizure-related patterns and suppress noise. This enables effective multi-scale temporal–spatial feature learning and reduces overfitting, enhancing robustness and cross-patient generalization in multi-state EEG classification.

This flexibility improves multi-state EEG classification, so that subtle patterns prior to seizure are detected better and with less false-positives. The opportunities for SMCNN's in this context, are to display accurate and indistinguishable seizure prediction in real-time, to provide intervention at an appropriate time, and to clinically monitor patients over a continuous timeframe. Furthermore, the model self-modulation capabilities, allows the SMCNN to optimally obtain the spatial and temporal dependencies that are present in the EEG data more efficiently than existing methods.

In effect, utilizing these methods contributes towards patient safety and personalized treatment, and also towards improved clinical decision-making. The SMCNN begins by receiving pre-processed EEG features extracted through the RLCT, including mean, variance, standard deviation, skewness, and kurtosis is expressed in given Eq. (7),

$$m_{next}^{c} = \gamma_c(y\lambda)\frac{m_{pre}^{c} - \mu_c}{\sigma_c} + \beta_c(y^{\lambda}) \tag{7}$$

Where, m_{next}^{c} signifies the feature after self-modulation, γ_c and β_c represented as self-modulation parameters, $y\&\lambda$ represent spectral of the brain tissue, σ_c denotes the mean and standard deviation of channel c, m_{pre}^{c} is the pre-modulation feature from the CNN, y^{λ} is the agronomic context vectors and μ_c is represent the modulation functions. In the convolutional layers, SMCNN applies multiple convolutional filters to the modulated feature maps to extract hierarchical patterns are expressed in given Eq. (8),

$$A_c = \frac{1}{du}\sum_k^d \sum_l^u g_{pre}^{c}(k,l) \tag{8}$$

where A_c denotes average activation of channel c, g_{pre}^{c} represent the pre-modulation feature value at pixel channel c, k represents the severity level of detected abnormalities, du is the height as well as width of the feature map and l denotes the spatial indices. The extracted feature maps are flattened and approved through fully linked layers, where the network predicts the probability of each seizure phase are expressed in given Eq. (9),

$$\sigma_c = \sqrt{\frac{1}{du}\sum_k^d \sum_l^u (g_{pre}^{c}(k,l) - \mu_c)^2 + \delta} \tag{9}$$

where, σ_c denotes the standard deviation of channel c, μ_c represent the time dependent function, K represent the time dependent function, and δ represent small constant to avoid division by zero. Finally, the SMCNN has predicted epileptic seizure and classify EEG signals into Interictal, Pre-Ictal, Ictal, and Post-Ictal phases for improved patient monitoring.

Table 1 lists the SMCNN hyperparameters: a learning rate of 0.0001 for stable weight updates, a batch size of 128 for efficient training, and 100 epochs to allow sufficient learning over the dataset. To handle inter-patient variability, the model combines FEKF adaptive denoising, channel-wise normalization, and RLCT statistical features to reduce individual sensitivity. The multi-scale self-modulated CNN further enhances generalised seizure pattern learning, improving cross-patient robustness.

Table 1. Hyper parameters of SMCNN.

Parameter	Value
Learning Rate	0.0001
Batch Size	128
Epoch	100

4. Results and Discussion

The experimental results of the proposed PES-EEG-PMS-SMCNN are presented in the segment. The model was implemented in Python and tested. Several performance criteria are evaluated. To prevent biased estimates due to temporal correlation, EEG signals were segmented into fixed windows before dataset splitting to avoid data leakage. An 80:20 balanced split across all seizure states was applied. This approach minimizes correlation bias and ensures realistic model generalization. The results of proposed PES-EEG-PMS-SMCNN technique are related to those of existing techniques STC-EEG-XGBoost [8], DES-EEG-LSTM [9] and ESC-EEG-CNN [10].

4.1. Performance metrics

Various evaluation metrics are employed to analyse and validate the system's effectiveness. The confusion matrix serves as the basis for computing key performance indicators. These include accuracy, precision, recall, and F1-score.

4.1.1. Accuracy

Equation (10) is employed to compute the accuracy value

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FN+FP)} \tag{10}$$

here, TP implies True Positive; TNindicates True Negative; FP shows False Positive and FNrepresents False Negative.

4.1.2. Precision

The precision is determined by Eq. (11). This value can be either positive or negative based on the class for which it is measured.

$$Precision = \frac{TP}{(TP+FP)} \tag{11}$$

4.1.3. Recall

Recall is a measure that regulates how many accurate forecasts were produced among all the positive forecasts. The following Eq. (12) is used to measure it.

$$Recall = \frac{TP}{(TP+FN)} \tag{12}$$

4.1.4. F1 - Score

Equation (13) formulates the F-score

$$F1Score = \frac{TP}{\left(TP+\frac{1}{2}[FP+FN]\right)} \tag{13}$$

4.2. Performance analysis

The experimental outcomes of PES-EEG-PMS-SMCNN technique are shown in Figs. 2-9. The proposed PES-EEG-PMS-SMCNN method is related to existing STC-EEG-XGBoost, DES-EEG-LSTM and ESC-EEG-CNN models. Figure 2 shows that the model's training as well as validation accuracy both improve steadily over 50 epochs, indicating effective learning. The training accuracy rises consistently, peaking at 98% near epoch 45, while the validation accuracy also increases, with some fluctuations, reaching 96% by the end.

The two metrics remain closely aligned, with training accuracy slightly higher than validation, proposing minimal overfitting. After 50 epochs, the model has a training accuracy 97.5% and validation accuracy 96%. These performances ensure the strong ability of the model in well-classifying epileptic seizure patterns for secure multi-state EEG classification and improved patient observation.

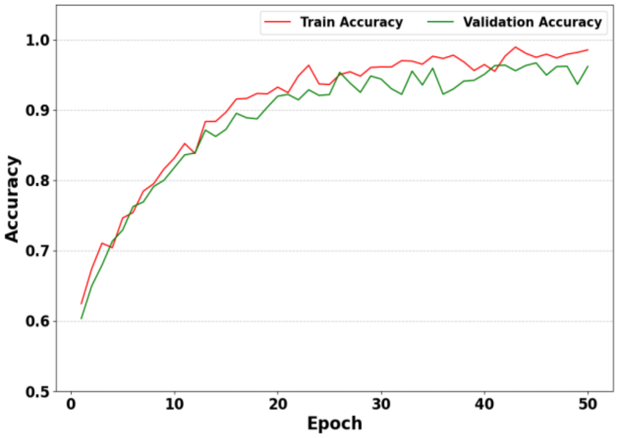

Fig. 2. Performance analysis of training as well as validation accuracy.

Figure 3 shows that both the model's training loss as well as validation loss reduce linearly over 50 epochs, which indicates good learning and generalization. Training loss reduces continuously; reaching 0.05 at the end and validation loss does the same, reaching 0.07 at the end. The proximity of both loss curves with minimal divergence indicates that the model is doing well with little overfitting. The low terminal values of the losses demonstrate high confidence in the model's outputs.

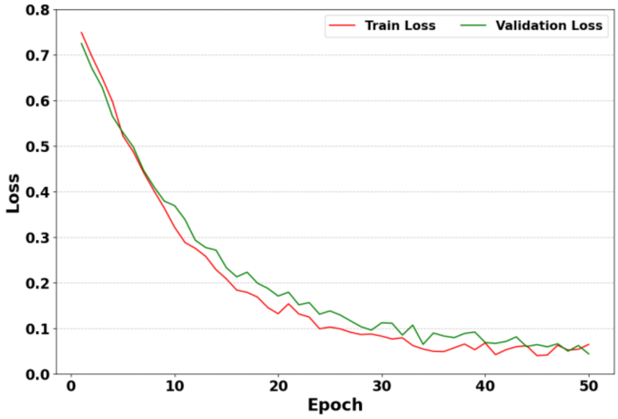

Fig. 3. Performance analysis of training as well as validation loss.

Figure 4 is the comparison of the recall percentages of four models on four classes of epilepsy-related EEG states: Interictal, Pre-Ictal, Ictal, and Post-Ictal. The models used are STC-EEG-XGBoost, DES-EEG-LSTM, ESC-EEG-CNN, and the proposed PES-EEG-PMS-SMCNN. The proposed PES-EEG-PMS-SMCNN model performs better than any other model in recall in all four classes. It attains a recall of 96.7% for Interictal, 97.5% for Pre-Ictal states, 97.1% for the Ictal state, and 96.1% for the Post-Ictal state. Conversely, the STC-EEG-XGBoost model has recall rates of 80.4% for Interictal, 73% for Pre-Ictal states, reducing to 84.3% for Ictal and 76% for Post-Ictal. The DES-EEG-LSTM and ESC-EEG-CNN also have lower recall, particularly in the Ictal and Post-Ictal states. The high and consistent recall of the proposed model proves it to be effective in identifying correctly positive instances of every EEG state, which is crucial for successful multi-state epileptic seizure identification and improved patient observation.

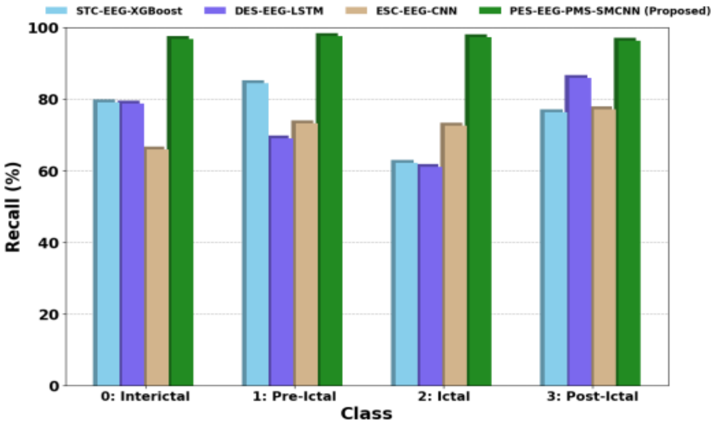

Fig. 4. Analysis of recall.

Figure 5 shows the F1-scores of some machine learning models in predicting four epileptic seizure states: Interictal (0), Pre-ictal (1), Ictal (2), and Post-ictal (3). The PES-EEG-PMS-SMCNN model consistently attains the highest F1-scores for all classes, showing better capacity to effectively determine each seizure state. With regard to accuracy, the model attains 96.4% in Pre-Ictal and 97% in Ictal stages, surpassing the current models, which register accuracy values such as 86.8% and 81.5%, and precision values such as 69.2% and 86.3%, respectively. These results point to the performance of PES-EEG-PMS-SMCNN in classifying multi-state EEG data, leading to improved seizure prediction and improved patient monitoring systems for better clinical decision-making.

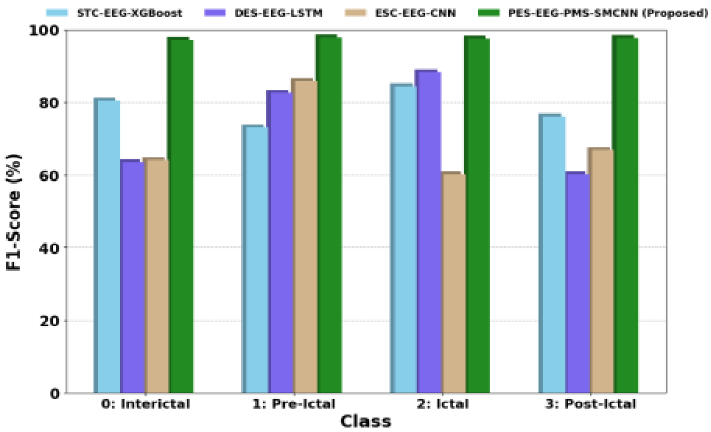

Fig. 5. Performance analysis of F1-score.

Figure 6 comparing the actual and predicted counts for four classes (0, 1, 2, and 3) in a multi-state EEG classification model for epileptic seizure patterns. The model performs very well, as the predicted counts closely match the actual counts across all classes, especially for Class 0 and Class 2, where both actual and predicted counts exceed 6000. For the smaller classes, Class 1 and Class 3, with counts below 500, the estimated values also align nearly with the actual counts. The strong correspondence across all classes demonstrates the model's high accuracy in classifying EEG signals and distinguishing between different states, supporting more effective patient monitoring.

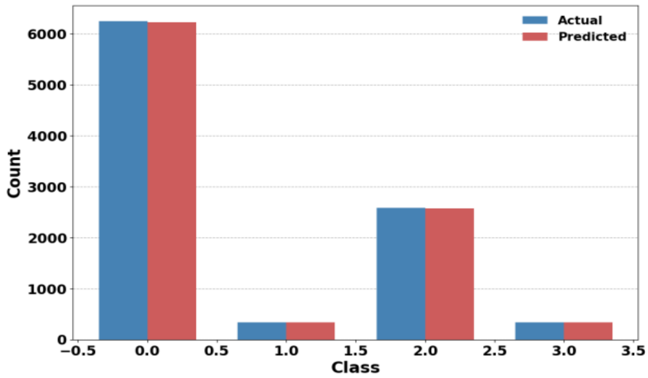

Fig. 6. Comparison of actual vs. predicted labels.

Figure 7 presents an EEG signal in the time domain. The signal exhibits fluctuations ranging from -300 to 220, showing periods of both high and low amplitude. Around time sample 10, a positive peak of 220 is observed, followed by a negative trough of -200 near time sample 75, and a sharp negative trough of -280 at time sample 100. These variations in amplitude and frequency are characteristic of normal EEG activity. Monitoring such patterns is crucial for identifying transitions to ictal states, supporting multi-state EEG classification and enhanced patient monitoring.

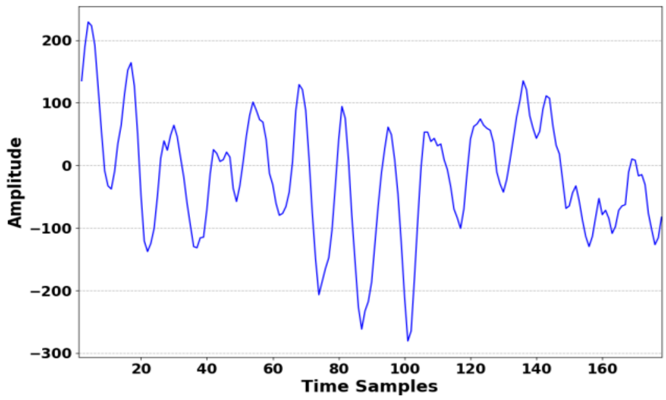

Fig. 7. EEG time domain signals.

The spectrogram in Fig. 8 illustrates EEG data, representing the frequency content of brain activity over time. Colour intensity reflects the power or amplitude of the signal at each frequency and time point. The spectrogram reveals a notable increase in signal power within the theta (4–8 Hz) and alpha (8–13 Hz) frequency bands, peaking between 0.4 and 0.6 seconds. The maximum power is observed around 10–12 Hz at 0.55 seconds. This localized increase in theta and alpha power may indicate a specific brain state or serve as a precursor to an epileptic seizure. Such distinctive patterns are essential for developing multi-state EEG classification models and enhancing patient monitoring by supporting early detection of seizure events.

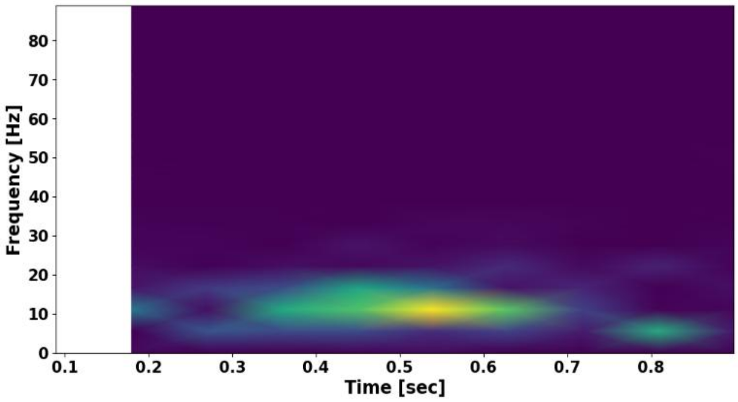

Fig. 8. EEG spectrogram.

Figure 9 presents a confusion matrix for the proposed PES-EEG-PMS-SMCNN model predicting epileptic seizure patterns across four states: 0: Interictal, 1: Pre-Ictal, 2: Ictal, and 3: Post-Ictal. Rows correspond to true labels, and columns tally to estimated labels, with the numbers indicating counts of correct and incorrect predictions. The model performs very well in classifying Interictal and Ictal states, with 6229 and 2571 correct predictions, respectively, shown on the main diagonal. It also shows reasonable accuracy for the Post-Ictal state, with 337 correct predictions. The model's performance is lower for the Pre-Ictal state, correctly identifying 335 instances while misclassifying 2 as Post-Ictal. Overall, the findings indicate that the PES-EEG-PMS-SMCNN model achieves strong classification performance for the major seizure phases, supporting effective patient monitoring.

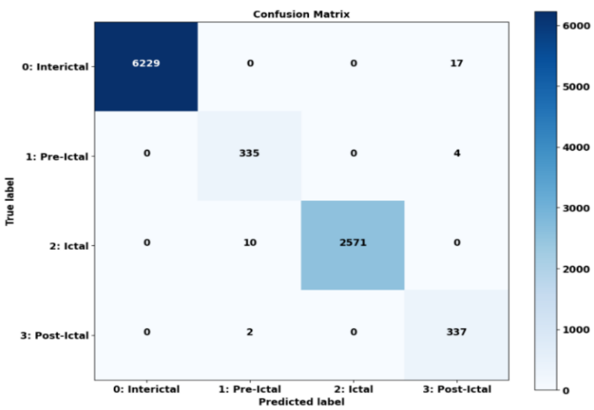

Fig. 9. Confusion matrix for NeuroVista trial data.

Table 2 compares the performance of the proposed PES-EEG-PMS-SMCNN model with existing methods STC-EEG-XGBoost, DES-EEG-LSTM, and ESC-EEG-CNN in predicting epileptic seizure patterns. The evaluated model outperforms other models in all states and demonstrates specific performance improvements in accuracy, including 98.1% for Pre-Ictal states and 98.3% for Ictal states. The model also achieved higher precision than existing models with 96.4% Pre-Ictal and 97% Ictal, relative to existing model accuracy values (862% and 81.5%) and precision values (69.2% and 86.3%). These results indicate the capabilities of PES-EEG-PMS-SMCNN in accurately classifying multi-state EEG data and ultimately improving seizure prediction and monitoring systems for patients for improved clinical decision-making.

Table 2. Comparison of Performance metrics with proposed and existing methods.

Performance metrics	Classification	PES-EEG-PMS-SMCNN (Proposed)	STC-EEG-XGBoost	DES-EEG-LSTM	ESC-EEG-CNN
Accuracy (%)	Interictal	96.6	66.4	77.5	80.5
	Pre-Ictal	98.1	86.8	75.7	78.8
	Ictal	98.3	66.9	81.5	75.9
	Post-Ictal	96.1	87.4	77.5	71.2
Precision (%)	Interictal	96	64.6	69.8	70.6
	Pre-Ictal	96.4	69.2	87.5	79.8
	Ictal	97	86.3	86.2	85.3
	Post-Ictal	98.2	88.6	84.9	60.7

5. Discussion

EEG-based seizure prediction follows two paradigms: raw end-to-end deep learning and feature-based learning. While raw CNNs/transformers model complex patterns, they require large datasets and are noise sensitive. The proposed PES-EEG-PMS-SMCNN uses FEKF-enhanced signals and RLCT features for compact, stable, and generalizable classification, achieving a balanced trade-off between robustness and representation power. The proposed PES-EEG-PMS-SMCNN method considerably outperforms current seizure detection systems by offering precise, multi-state EEG classification, which is essential for enhancing patient monitoring systems. FEKF data pre-processing, and RLCT feature extraction, provide enough robustness to be tolerant of noisy signals, and derive meaningful features from EEG data. The SMCNN model classified the EEG signals encompasses the most significant steps of the epileptic seizures, therefore can predict accurately, provide early interventions.

Overall, the PES-EEG-PMS-SMCNN model performs robustly in multi-state EEG classifications with results in detecting epileptic seizures with a training accuracy of 97.5% and a validation accuracy of 96% with little to no overfitting. The model improved in recall and F1-score for Interictal, Pre-Ictal, Ictal and Post-Ictal states, with recall values of 96.7, 97.5, 97.1 and 96.1, and F1-scores of 97.2, 97.7, 97.5, and 97.6 respectively. In relation to the other techniques, STC-EEG-

XGBoost, DES-EEG-LSTM and ESC-EEG-CNN, PES-EEG-PMS-SMCNN had comparable measures of accuracies and precision, most notable as it obtained an accuracy of 98.1 with respect to the Pre-Ictal and 98.3 with the Ictal states.

This model obtained a total accuracy of 97.5, with precision of 97, recall of 97.5, and F1-score of 97.7. Transformer and CNN–ViT model [19] emphasize attention without adaptive signal modelling, while graph-based approaches [20] are often dataset-specific, and many CNN–RNN hybrids [21] focus on binary tasks. In contrast, the proposed method performs four-class seizure state classification, achieving 98.3% accuracy with strong precision, recall, and F1-scores, offering a robust and clinically scalable framework.

Overall, the model exhibits promising potential for helping regional health authorities with epilepsy seizure detection and patient monitoring systems, and overall, the results are demonstrating an important contribution of the model to epilepsy detection and monitoring systems.

6. Conclusion

In this section, a robust DL approach for predicting epileptic seizure patterns enabling multi state EEG classification and improved patient monitoring systems (PES-EEG-PMS-SMCNN) is successfully implemented. The proposed ES-EEG-PMS-SMCNN is implemented in python. The proposed methodology ES-EEG-PMS-SMCNN is used to predict the epileptic seizure.

The method shows significant improvements in accuracy, recall, precision, f1-Score and confusion matrix across different evaluation metrics, the presentation of PES-EEG-PMS-SMCNN also performed better than STC-EEG-XGBoost, DES-EEG-LSTM and ESC-EEG-CNN with performance measures like 98.3 % accuracy, 98.2 precision, 97.5 recall, and 97.7 F1-score in multi-state of EEG classification for the detection of epileptic seizure. The results indicate that the PES-EEG-PMS-SMCNN model is more effective in detecting all four seizure states Interictal, Pre-Ictal, Ictal, and Post-Ictal achieving outstandingly high recall rates of 96.7%, 97.5%, 97.1%, and 96.1%, respectively.

This study also shows limitations of the proposed process are reliance on large and complex datasets EEG data sets that may not always be available. Future works should investigate methods for incorporating generalization with multi-modal data to improve transfer learning, adapting for different data that can be used very much as the EEG data is for monitoring patient specific use models with the models developed, reducing processing time and complexity.

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