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ORIGINAL PAPER

Epileptic seizure detection using scalogram-based hybrid CNN model on EEG signals

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Abstract

Epilepsy is one of the most usual neurological diseases characterized by abnormal brain activity, resulting in seizures or strange behavior, sensations, and, in some cases, loss of consciousness. It is a persistent, non-communicable brain condition that can affect anyone at any age, nearly 50 million people globally, with about 80% of sufferers living in low- and middle-income countries. Electroencephalography (EEG) signals are largely used in epilepsy research to examine brain activity during seizures. The extraction of features and selection from EEG signals plays a major role in epileptic seizure detection. In traditional machine learning techniques, the hard-core feature extraction needs domain expertise, and this can be eliminated by deep learning. The benefits of deep learning techniques are they try to learn high-level features from the input signals in an incremental method. To meet the requirements of complicated feature engineering, deep learning techniques have received greater attention than conventional methods. A hybrid seizure detection-convolutional neural network and vector machine (SD-CNN and SVM) model is proposed for epileptic seizure detection with EEG signals. Transformation of signal to image is performed using continuous wavelet transform technique to generate scaleogram images and also SD-CNN works as a learnable feature extractor from the generated images and SVM works as a binary classifier. The experimental results extracted 94% with high quality of scaleogram images using hybrid SD-CNN and SVM model and removed the noise levels and time–frequency data from EEG signals.

Keywords Epilepsy · EEG · Scaleogram · CWT · SD-CNN · SVM

1 Introduction

EEG is a useful method for studying electrical activity to examine the functioning of human brain, particularly the dynamically occurring complex processes. Because of its high temporal resolution, tremendous flexibility, non-invasiveness, portability, ease of recording and low cost, it is widely used in clinical studies for identifying the abnormalities of the brain like dementia, epilepsy, etc. Epilepsy is a persistent, non-communicable brain condition that can affect anyone at any age. If epilepsy is correctly diagnosed and treated, up to 70% of persons with the condition could avoid seizures. Compared to the general population, epilepsy patients have a risk of dying before their time that is up to three times higher. However, epileptic seizure detection from the long-term EEG recordings which is a challenging task and also required expert clinicians [1–4]. Therefore, in this paper an attempt has been made to detect epileptic seizure using hybrid deep learning model.

Epileptic seizure detection using multichannel EEG signals is a complicated subject that has been extensively explored for many years. Different results have been obtained by researchers employing various traditional machine learning techniques such as K-nearest neighbors (KNNs) [5], support vector machines(SVMs), etc., for epileptic seizure detection [6]. In traditional machine learning (ML) techniques, temporal, spectral and time–frequency domain features [7–11] are required to achieve the most distinct characteristics among different classes, while preserving invariable characteristics within the same class for epileptic seizure identification. Traditional manual feature extraction is a laborious and time-consuming process; still there is need to develop significant algorithms for automated epileptic

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seizure detection which can be used in clinical purposes. Since 2016, significant research has been conducted in the subject of detecting epilepsy with deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs) [12], autoencoders (AEs), CNN-RNN and CNN-AE, etc. [13–17]. The hard-core feature extraction for epileptic seizure detection using machine learning techniques can be eliminated by deep learning. The benefits of deep learning techniques are they try to learn high-level features from the input signals in an incremental method [18].

When deep learning (DL) is concatenated with ML for classification, the model is defined as a hybrid model [19]. The hybrid models obtain features from the neural network's flatten layer and supplied them into a classification algorithm. With the help of these techniques, it has become much easier to find and diagnose different types of seizures, such as epileptic seizures. The main objective of this work is analysis of multichannel EEG signals to detect epileptic seizures using hybrid deep learning model and machine learning model, and it includes the following steps:

(i) The raw EEG signal's dataset for epileptic seizure are collected from Childrens Hospital Boston-Massachusetts Institute of Technology (CHBMIT) for different subjects.
(ii) Preprocessing of signals can be carried out by common average referencing and bandpass filter to remove SNR.
(iii) From the preprocessed EEG signals, scaleogram image generation using continuous wavelet transform (CWT).
(iv) SD-CNN is developed to learn the optimum features in scaleogram images.
(v) A hybrid SD-CNN and SVM is developed by extracting the features from the SD-CNN architecture and classification by SVM model for epilepsy seizure detection.
(vi) To evaluate the effectiveness of these techniques, different performance metrics are used.

In this research paper contributed with the study of Sect. 1 is the introduction about the SD-CNN with the scaleogram images, relevant study material discussed in Sect. 2 and Sect. 3 is the proposed methodology consists of dataset and preprocessing of EEG signals, comparison with the other methodologies of results and discussion in the Sect. 4 and summarizing with the Sect. 5.

1.1 Related works

The epileptic seizure detection from EEG is based on the long-term clinical recordings which needs high computational cost and time [20–25]. There are a very few databases related to epileptic seizures that are publicly available. Many studies in the literature used the Bonn dataset and a very few used CHBMIT dataset because of very long recordings [26–28]. Therefore, the CHBMIT dataset was used in this study. Recently, deep learning has gained popularity in medical image processing and biomedical signal processing areas. When dealing with vast amounts of data, it outperforms traditional methods in terms of pattern discovery and object recognition. Deep learning techniques, particularly the convolutional neural network (CNN) and recurrent neural networks (RNNs) are gradually adopted in the recent studies for seizure detection [29].

In [30], a study using hybrid CNN-SVM model for more accurate seizure prediction is proposed. The combination of CNN and SVM is found to provide an effective way for epileptic prediction. A support vector machine is a discriminative classifier described by a separating optimum hyperplane that is used to classify new data. Furthermore, employing edge computing services, the resulting model is made autonomous and demonstrated to be a valid seizure prediction approach. The findings may be useful in providing real-world support to epilepsy patients. Combination of CNNs with conventional feature extraction methods were investigated in [31]; they employed the empirical mode decomposition (EMD) for feature extraction, and a CNN to achieve improved accuracy in classification tasks [32, 33].

Based on relevant literature, the following points are listed below:

- Different deep learning structures are used for detection of epileptic seizure, but none of them has gained superior over the others. The ideal structure should be chosen carefully based on the dataset and problem characteristics, such as the need for real-time detection or minimal acceptable accuracy or even the use of pretrained models.
- There are numerous databases with various models available so it is hard to compare them because they were created using diverse datasets and models.
- Deep learning needs huge data to train and it is time-consuming for training so a robust model takes time to construct.
- The combination of CNN and SVM leverages the strengths of both techniques. CNNs excel at feature extraction and capture complex patterns in data, while SVMs are strong in binary classification tasks, making them a powerful duo for seizure prediction.
- False alarms can cause unnecessary stress for patients and may lead to inefficient resource allocation. By integrating CNN for feature extraction, the hybrid model may reduce false alarms by making the classification process more robust.
- The CNN-SVM hybrid model can provide a clear decision boundary, aiding medical professionals in understanding the model's predictions.

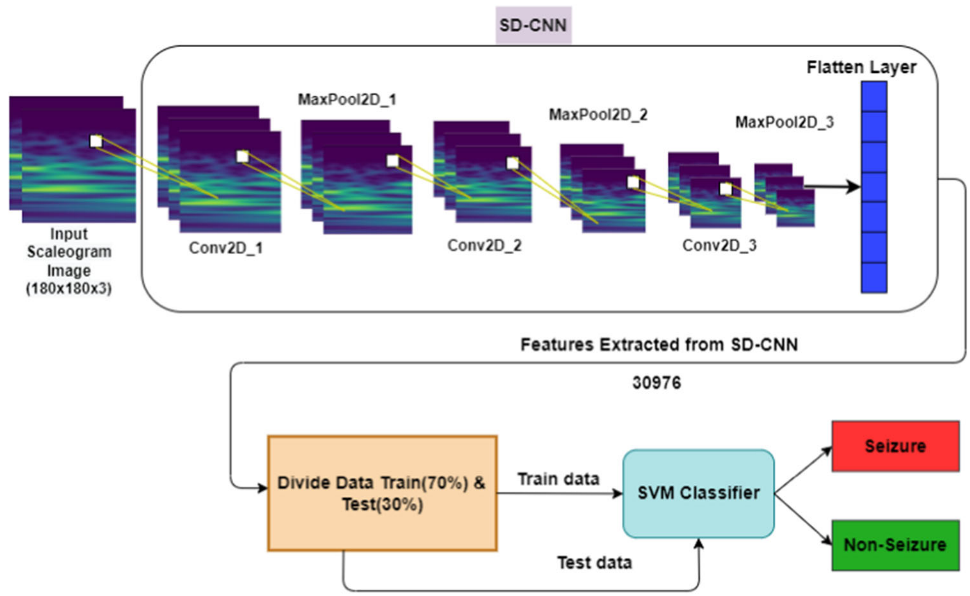

Fig. 1 The overall framework of the proposed hybrid SD-CNN and SVM model using scaleogram images for epileptic seizure detection

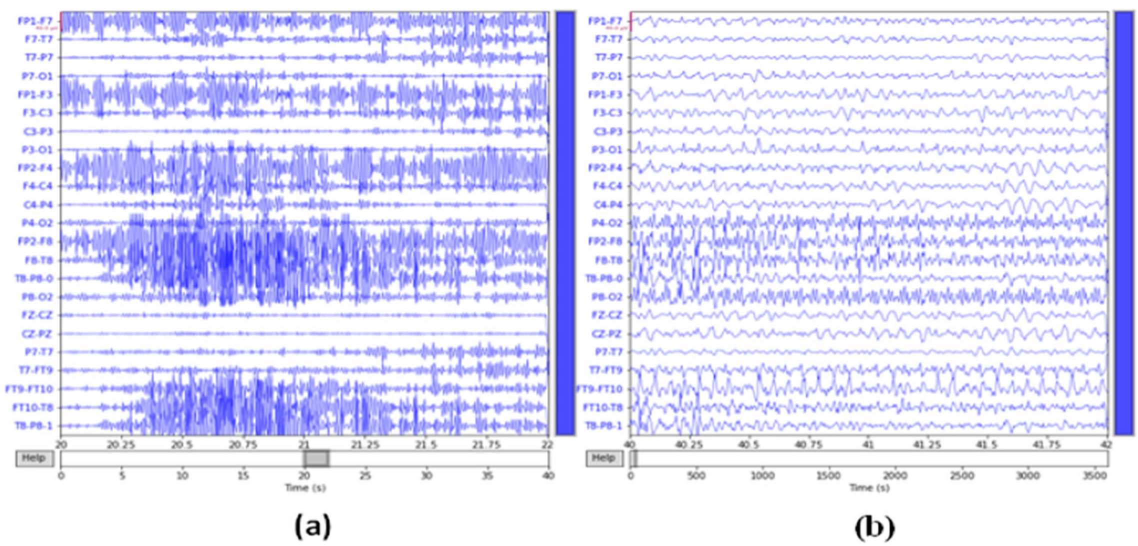

Fig. 2 Sample EEG recording of 23 channels for **a** seizure signal **b** non-seizure signal

2 Materials and methods

EEG signal analysis of seizure detection with proposed hybrid SD-CNN and SVM model is depicted in Fig. 1. For analysis of EEG signals with multichannels are split into fixed length epochs or segments. When c channels available and a segment has l samples, the input of a neural network for EEG processing is an array $X_i \in R^{c \times l}$. In this work, EEG signals of 23 channels are transformed into scaleogram images because it offers time–frequency analysis, which has to be proven an efficient way for analyzing.

In the proposed, a hybrid SD-CNN and SVM model in which SD-CNN comprises of convolution layers, pooling layers and fully connected layers for feature extraction. SVM classifier is used to classify the features from the SD-CNN model. To prepare input for the CNN, the multichannel EEG signal epochs are transformed into scaleogram images. The features for epileptic seizure detection are extracted from proposed SD-CNN model and SVM classifier using RBF kernel are trained with 70% of training dataset and 30% of testing dataset and is used for classifying seizure and non-seizure classes.

The scaleogram images are given to the input layer, which are transformed from the pre-processed EEG signals, and trained over SD-CNN for the number of epochs until it converges. The output layer of SD-CNN is replaced with the SVM classifier with a radial basis function (RBF) kernel. The hidden layer outputs are used by the SVM as a new feature vector, during training. The SVM classifier does the classification task and produces novel decisions based on the test images.

2.1 Data set

In this work, a publicly available CHBMIT [34] dataset is leveraged. The data were recorded at Children's Hospital Boston (CHB) in partnership with the Massachusetts Institute of Technology at a sample rate of 256 Hz (MIT). It is a scalp EEG dataset of epilepsy subjects (patients) using 10–20 international electrode placement system. Dataset consists of 22 subjects with 5 males of 3–22 years and 17 females of 1.5–19 years of age. The EEG records are stored in 'European Data Format' (.edf) format along with the annotations. Based on the annotations available in the dataset, data are labeled as seizure and non-seizure classes.

Eight subject's EEG records with seizure and non-seizure signals of 366 min duration were evaluated in this proposed work. It contains 23 channel EEG recordings for each subject who are advised to undergo routine EEG tests to diagnose epilepsy. Sample raw EEG signals for seizure and non-seizure are shown in Fig. 2, and x-axis represents time and y-axis represents number of channels.

2.2 Pre-processing

During the acquisition of EEG signals, noise is added that reduces the signal-to-noise ratio resulting in poor classification**.** Removing the noise from the input signals is a part of pre-processing**.** The pre-processing methods used to remove noise in this work are common average referencing and Butter worth band-pass filter. EEG signals comprise both low-frequency data with long time periods and high-frequency data with short time periods. Low signal-to-noise ratio and poor spatial resolution are problems with raw EEG data. Therefore, wavelet transform is also used in this work to perform multi-resolution analysis to recognize relevant frequency information at low frequencies along with time information at high frequencies.

2.3 Transformation of EEG signals to scaleogram image

EEG signals are converted into 2D scalogram images using continuous wavelet transform (CWT). Scaleogram represents the absolute value of a signal's continuous wavelet transform (CWT) as a function of time and frequency. The frequencies represent a signal's energy content in relation to time. It is well suited for non-stationary signals as it is a localized wavelet transform that reveals the frequency of the signal. The continuous wavelet transform (CWT) [35] uses mother wavelet functions. The process of construction of scaleogram from CWT is shown Fig. 3.

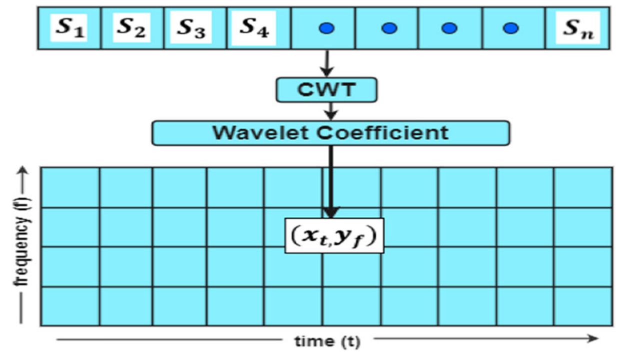

Fig. 3 Construction of scaleogram image from EEG signal

2.4 CWT (continuous wavelet transform)

To construct a scaleogram from a discrete EEG signal $x(n)$, a CWT ($\Psi(t)$) can be employed with various wavelet functions. Equation (1) represents CWT function which is convolution of input signal $x(t)$ with $\Psi(t)$ a scaled version.

$$X_{\text{cwt}}(a, b) = \int_{-\infty}^{\infty} x(t)\Psi^*_{a,b}(t)\mathrm{d}t \tag{1}$$

Here $X_{\text{cwt}}(a, b)$ of a signal $x(t)$ is CWT.

$\Psi^*_{a,b}(t)$ is a complex conjugate of scaled and shifted version of mother wavelet $\Psi(t)$.

a—scaling and b—shifting parameters.

$$X_{\text{cwt}}(a) = x(t) * \Psi^*_a(t) \tag{2}$$

$$X_{cwt}(f) = X(f) * \Psi_a * (f) \tag{3}$$

$X(f)$ represents Fourier transform of $x(t)$.

Equation (2) and Eq. (3) can be used in calculations of discrete signal to perform operations, such as multiplication, discrete wavelet function $\Psi(n)$ and convolution. Morlet wavelet, Gaussian, Gabor, etc. are generally used mother wavelet functions. In this work, Morlet wavelet function is used as mother wavelet because time–frequency localization features can be analyzed for non-stationary signals like EEG.

2.5 Morlet wavelet

Morlet wavelet denoted in Eqs. (4 and 5) controls the value of σ. The increase in raises the oscillation. Morlet wavelet function the convolution of Morlet wavelet with original signal is shown in Fig. 4, in which blue line indicates morlate

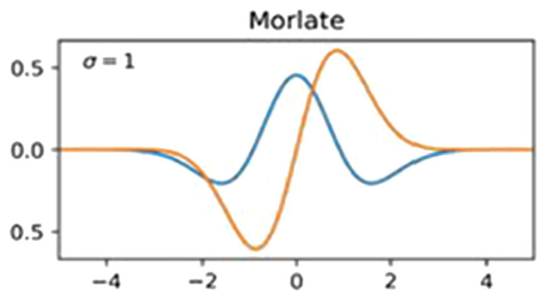

Fig. 4 Morlet Wavelet Function

mother wavelet and red line indicates original signal.

$$\Psi(t) = C_\sigma \pi^{-0.25} e^{-0.5t^2} (e^{j\sigma t} - K_\sigma) \tag{4}$$

$$\Psi(t) = C_\sigma \pi^{-0.25} \left(e^{-0.5(\sigma-\omega)^2} - K_\sigma e^{-0.5\omega^2} \right) \tag{5}$$

Here $C_\sigma = \left(1 + e^{-\sigma^2} - 2e^{-\frac{3}{4}\sigma^2}\right)^{-0.5}$, $K_\sigma = e^{-0.5\sigma^2}$, and $\omega = 2\pi f$.

In this work, scaleogram images are generated using CWT with a set of Morlet wavelet functions for all channels of each seizure and non-seizure segments. Sample of pre-processed EEG signal and their scaleogram image for seizure and non-seizure is shown in Figs. 5 and 6.

In Fig. 5a, plotting of pre-processed seizure signal for various channels and (b) represents scaleogram image for the plotted signal. *X*-axis represents time and *y*-axis represents amplitude. The seizure signal can be seen with high amplitude because of spike nature and same is reflected in the scaleogram image. Image contains high fluctuations in power as time progresses. The yellow shade in scaleogram images indicates the fluctuations in power which are very high in case of the seizure signal.

In Fig. 6a, plotting of pre-processed non-seizure signal for various channels and (b) represents scaleogram image of the plotted signal. The non-seizure signal can be seen with very low amplitude and fast waves as time progresses and same is reflected in the scaleogram image. Image contains constant power throughout the time period, and there is no abnormality. The yellow shade indicates that the power is constant without any fluctuations for the non-seizure signal.

2.6 Hybrid SD-CNN and SVM model

A hybrid SD-CNN and SVM model is proposed for epileptic seizure detection using multichannel EEG signals. In this hybrid model, SD-CNN works to extract hidden latent features from the scaleogram images and SVM works as a binary classifier. SD-CNN is a CNN that is trained on seizure and non-seizure scaleogram images for epileptic seizure detection. It is a multilayered deep supervised learning neural network that includes a trainable classifier and an automatic feature extractor. Feature extractor consists of feature map layers that performs convolutional filtering and down sampling to extract hidden latent features of the images and to reduce size of feature maps. Using a backpropagation technique, the feature extractor's classifier and weights discovered are trained.

Table 1 Parameters of SD-CNN for epileptic seizure detection

No. of training epochs	30
Batch size	32
Optimization	Adam, Adamax, RMSProp
Learning rate	0.001
Input shape	(180,180, 3)
No. of fully connected layers	3
No. of convolutional layers	3
No. of pooling layers	3
Activation function in convolutional layers	ReLU
Activation function in Output layer	Softmax

2.7 Feature extraction using SD-CNN

The SD-CNN model works on three layers: an input layer receives the scaleogram image, three 2D convolution (conv2D) layers used for feature extraction and fully connected layers that activate a particular neuron to classify seizure and non-seizure classes and is shown in Fig. 7.

The input layer of SD-CNN has a scaleogram image of size 180 × 180 × 3. Filter of 3 × 3 size is used in all three conv2D layers used to find hidden latent features from the input image. The first conv2D layer generates 16 feature maps by iteratively sliding 16 filters of size 3 × 3 over the input image. The ReLu activation function followed by convolution that outputs the input directly if it is positive, or outputs zero if it is negative. A 2 × 2 max pooling layer is applied to ReLu's output, reducing the feature maps to size 90 × 90 × 16.

In the second convolution layer, 32 filters applied to previous layer feature maps of same kernel size 3 × 3. To get down-sampled data, similar ReLu and max pooling operations are used and produced feature maps of size 45 × 45 × 32. Third convolution layer consists of 64 filters of kernel size 3 × 3 to perform the same operations, and again ReLu and max pooling are applied to produce a feature map of size 22 × 22 × 64 as output of the feature extraction process. The parameters of proposed SD-CNN model are illustrated in Table 1.

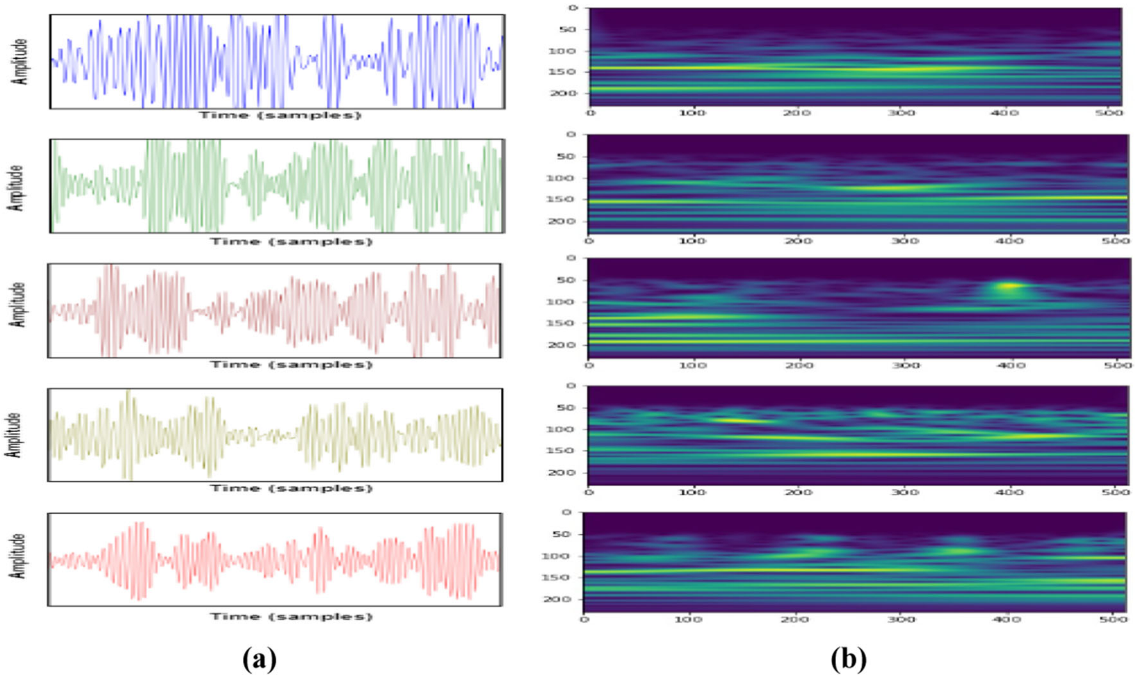

Fig. 5 **a** Sample seizure signal for different channels **b** scaleogram Images of the signal

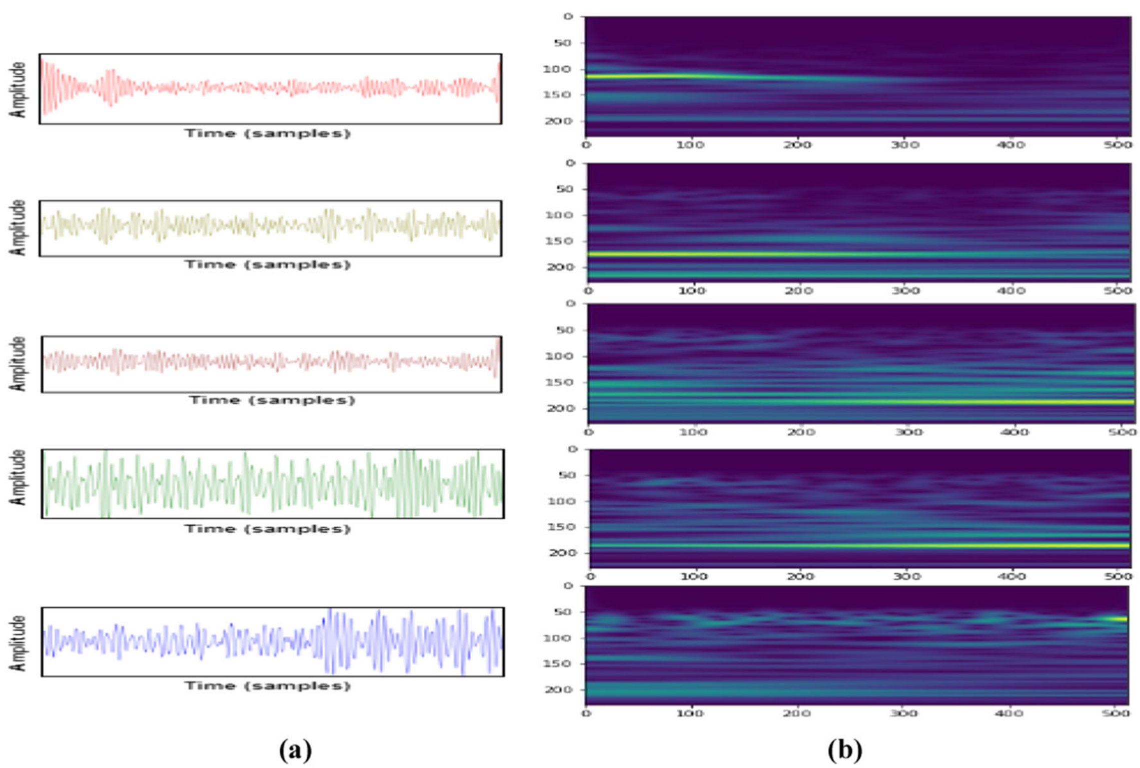

Fig. 6 **a** Sample non-seizure signal for different channels **b** scaleogram image of the signal

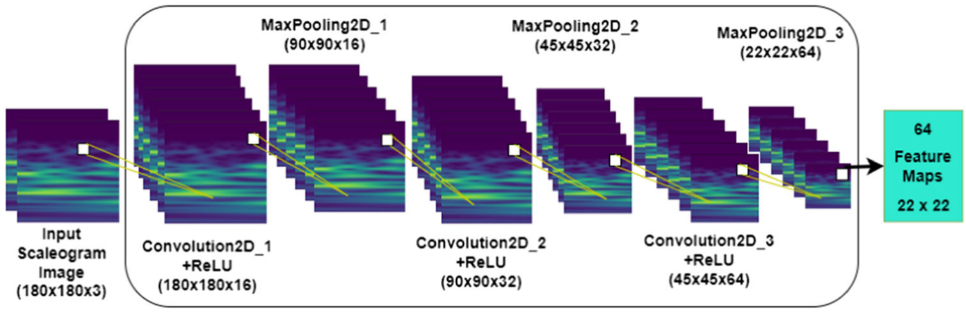

Fig. 7 Proposed SD-CNN Model for feature extraction

Extraction of these salient, high-quality features is a key step in the three-layer process that ensures reliable classification. The output of third convolution layer is flattened of 30,976 features and given as an input to the SVM Model.

2.8 Support vector machines (SVMs)

Two types of SVMs are linear and nonlinear SVM. If we are able to draw a decision boundary using slope and intercept for the data that is linearly separable, to find support vectors is called linear SVM. In general, we cannot classify data using linear boundaries since data may not be linear always. Nonlinear SVMs can always map the original feature space to a higher-dimensional feature space, in which training set is independent. To a high-dimensional space, a kernel function implicitly maps data. Significant kernels include linear, RBF (radial basis function) and Gaussian kernels, among others. Figure 9 represents SVM kernel trick.

In this work, the SVMs were trained using features extracted from SD-CNN, and it will make the label predictions with probabilities for binary classification to classify seizure and non-seizure classes.

2.9 Performance metrics

For assessing the performance and for comparative analysis of the deep learning model SD-CNN and hybrid model (SD-CNN and SVM), several performance metrics are used. Precision, Recall, F-Measure and Accuracy are employed in our proposed work, and they are represented in Eqs. (6, 7, 8, 9), respectively. Figure 8 shows the confusion matrix also known as a contingency table for seizure and non-seizure classes of epilepsy seizure detection (Fig. 9)**.**

For prediction, the elements of confusion matrix, i.e., true positive (TP) indicates correctly predicted seizure class, true negative (TN) indicates correctly predicted non-seizure class, false positive (FP) indicates incorrectly predicted non-seizure class, false negative (FN) incorrectly predicted seizure class values, are used to compare the labels of actual class and predicted class.

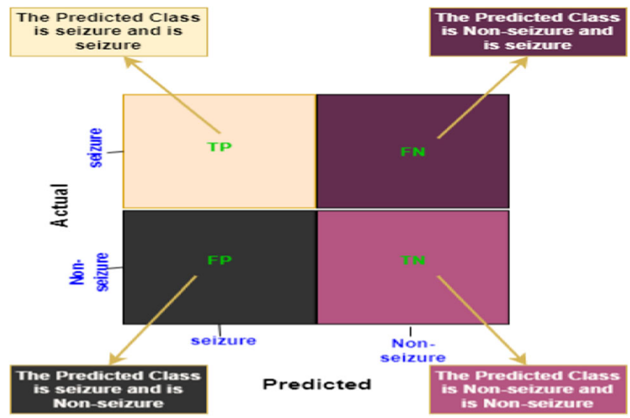

Fig. 8 Confusion matrix for seizure and non-seizure classification

Precision Precision is defined as the ratio of accurately predicted seizure class to all actual seizure and false seizure class in a binary classification problem.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{6}$$

Recall Recall is the ratio of accurately predicted seizure class to all actual seizure and false non-seizure class in a binary classification problem.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

F-Measure As Precision and Recall have a harmonic mean; it is necessary to tune the system for either Precision or Recall, as these factors have a greater impact on the end output.

$$F - \text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

The F-Measure is derived for seizure and non-seizure values in the same way as Precision and Recall are obtained for seizure and non-seizure classes.

Accuracy It is the most widely used metric for determining classification Accuracy. The ratio of correctly classified

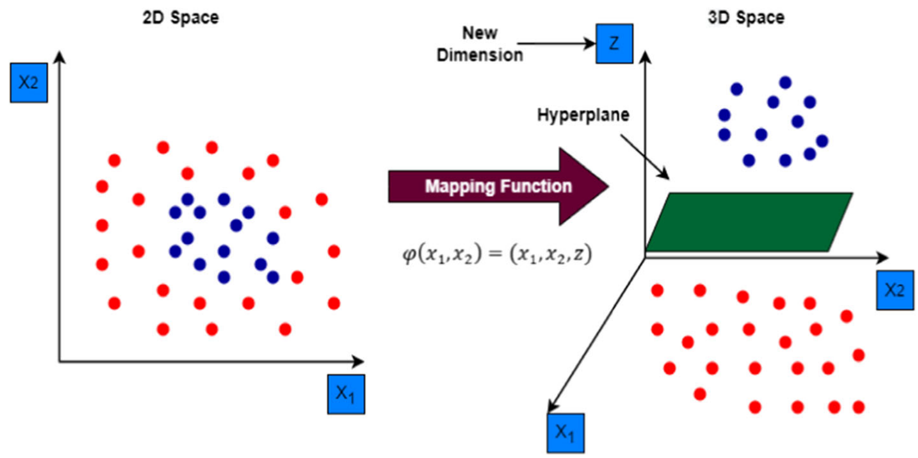

Fig. 9 SVM classifier proposed for seizure detection

classes to the total number of classes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (9)$$

3 Results and discussion

For epilepsy seizure detection, experiments are conducted using python programming language. EEG segmentation and noise removal are implemented using MNE (MEG & EEG) package, open-source toolbox for EEG and MEG signal processing, transformation of EEG signals to scaleogram are implemented using ssqueezepy package, CNN implementation was accomplished utilizing the Google Colab Pro environment, Keras 2.0 and Tensor flow 1.4.0.

Initially, the scalp EEG data were pre-processed by applying a common average referencing, fourth-order zerophase band-pass Butter worth filter between 1 and 45 Hz. The pre-processed EEG signal segmented into 2 s epochs for 23 channels, resulted in 239 seizure epochs for 182 min, 240 non-seizure epochs for 184 min.

Each 2 s epoch from all 23 channels of seizure and non-seizure signals is used to generate scaleogram image. Total number of 11,006 scalogram images from all the epochs. Among that 5520 images are non-seizure and 5486 images are seizure. Each scaleogram image size is 180 × 180 × 3. For training the SD-CNN model 70% of the total images are used and 30% are used for testing.

3.1 Hybrid SD-CNN and SVM Model for epileptic seizure detection

In the proposed hybrid SD-CNN and SVM model, the SD-CNN is used for feature extraction process, and fully connected layers are replaced with nonlinear support vector machines (SVM), which is used for classifying scaleogram images into seizure and non-seizure classes.

3.2 SD-CNN for epileptic seizure detection

In the proposed SD-CNN model, convolutional and pooling layers are used to train the model on a new scaleogram images. Adam, Adamax and RMSProp algorithms for optimization with a learning rate of 0.001 are used in this model. The number of training epochs was 30 and the batch size for each epoch was 32. The activation function in the hidden layer was ReLu, and Softmax was used in the last layer due to the binary classification problem.

Table 2 shows the confusion matrix and performance metrics of deep learning features acquired for analysis of EEG signals to detect seizure and non-seizure classes using SD-CNN and SVM model with different optimizers. The experiments carried out considering 70% of the scaleogram images for training and 30% are used for testing.

When analyzed with different optimizers for hybrid SD-CNN and SVM model, the experimental results show that Adam optimizer proved to achieve a highest accuracy of 94.48% when compared to others, due to exponentially weighted average of the gradients. Figure 10 shows the comparative analysis of SD-CNN and SVM with different optimizers for EEG signal analysis to classify seizure and non-seizure.

In Fig. 11, (a) shows plot of accuracy of the model over the training and testing data and (b) shows plot of loss of the model over the training and testing data. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 90–94% for Adam optimizer. The testing loss reaches its minimum only after 10 epochs. The training time of model is 12,000 ms.

In Fig. 12a shows plot of accuracy of the model over the training and testing data for RMSProp optimizer and (b)

Table 2 Performance metrics Hybrid SD-CNN and SVM model with different optimizers

Optimizer	Confusion Matrix			Performance Metrics (in %)			
		Seizure	Non-Seizure	Precision	Recall	F-Measure	Accuracy
Adam	Seizure	*94.10*	5.11	94.10	94.90	94.49	94.48
	Non-seizure	5.90	94.89	94.89	94.09	94.48	
RMSprop	Seizure	94.18	6.52	94.18	93.38	93.78	93.82
	Non-seizure	5.82	93.48	93.48	94.27	93.87	
Adamax	Seizure	88.25	7.28	88.25	93.07	90.60	90.37
	Non-seizure	11.75	92.72	92.72	87.69	90.14	

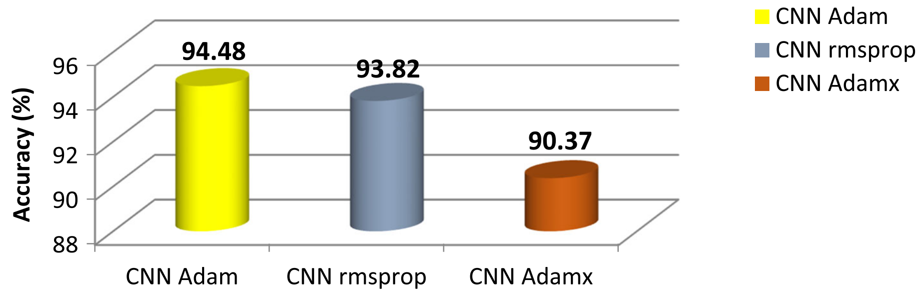

Fig. 10 Accuracy comparison of Adam, RMSProp and Adamax optimizers of Hybrid SD-CNN and SVM Model

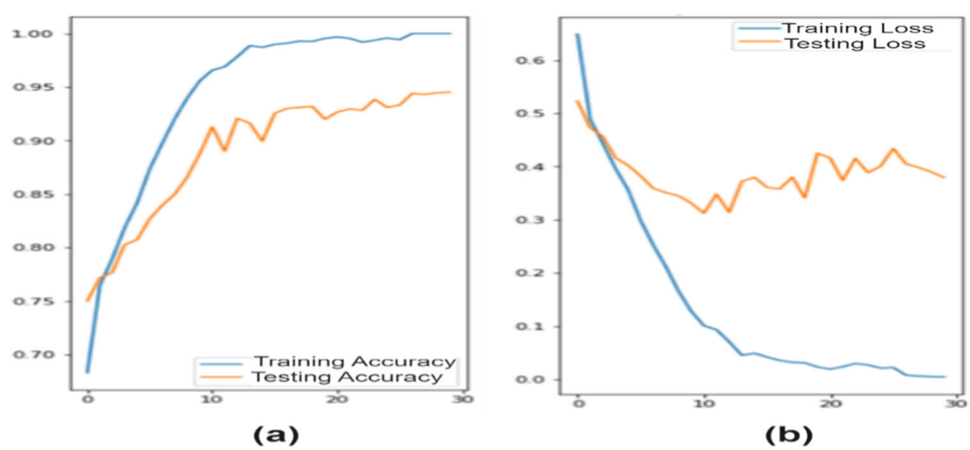

Fig. 11 SD-CNN & SVM with Adam Optimizer. **a** Training–Testing Accuracy and **b** Training–Testing loss

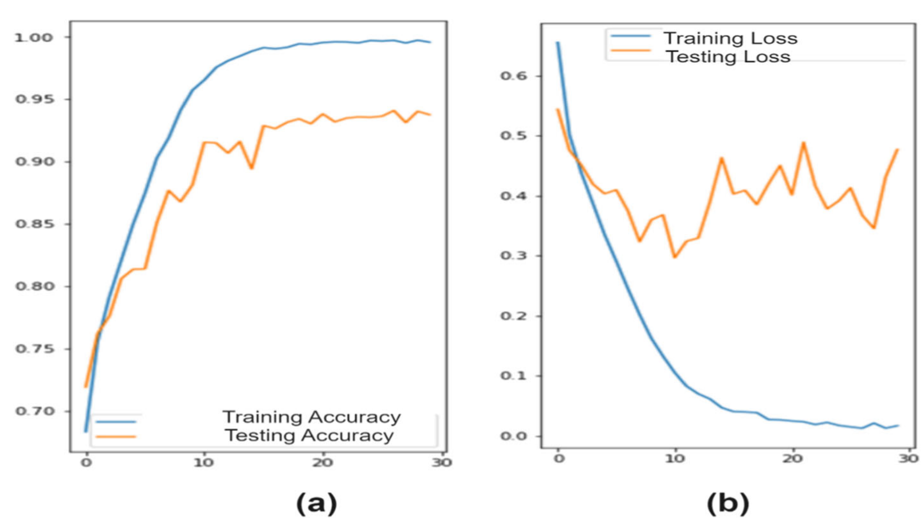

Fig. 12 SD-CNN and SVM with RMSProp Optimizer. **a** Training–Testing Accuracy and **b** Training–Testing loss

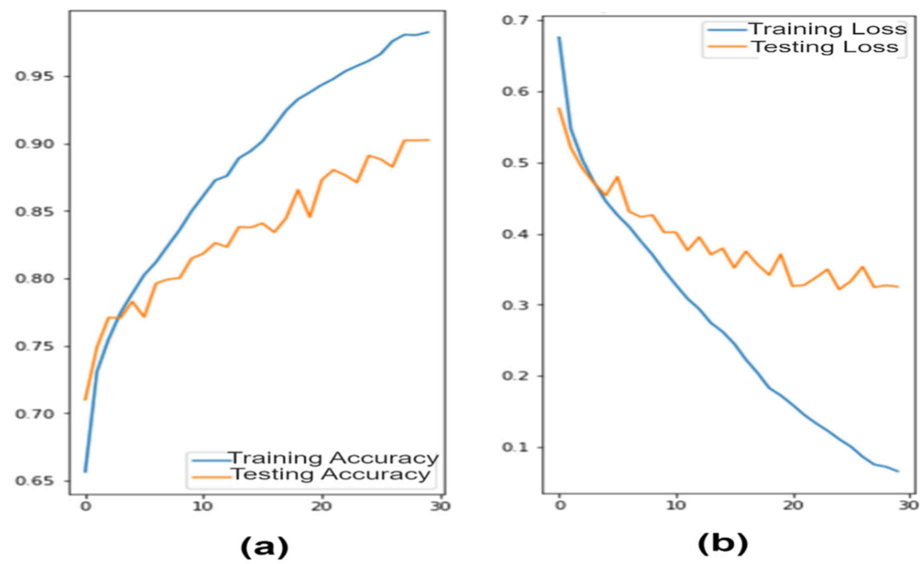

Fig. 13 SD-CNN and SVM with Adamax Optimizer. **a** Training–Testing Accuracy and **b** Training–Testing loss

Table 3 Comparative results obtained from baseline approaches and proposed approach on epileptic seizure detection in terms of Accuracy

Author	Methodology	Accuracy (in %)
Khan et al.	CNN	85.8
Acharya et al.	13-layer deep CNN structure	88.7
Proposed approach	Hybrid Model (SD-CNN and SVM)	94.48

shows plot of loss of the model over the training and testing data for RMSProp optimizer. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 90–93% for RMSProp optimizer. The testing loss reaches its minimum only after 25 epochs. The training time of model is 12,374.3 ms.

In Fig. 13a shows plot of accuracy of the model over the training and testing data for Adamax optimizer and (b) shows plot of loss of the model over the training and testing data for Adamax optimizer. The training accuracy increases linearly over time, until it reaches 100%, whereas the testing accuracy stalls at 85–90 for Adamax optimizer. The testing loss reaches its minimum only after 20 epochs. The training time of model is 12,374.3 milli seconds.

Table 3 compares the Accuracy values obtained using the proposed approach to those obtained using other approaches described in the literature using the CHBMIT dataset. The table shows that the proposed scaleogram-based hybrid CNN approach outperforms the results obtained by authors of various articles in the literature.

4 Conclusion

Because of the complexity of EEG data, effectively detecting epileptic seizures is difficult. This paper addressed some of the challenges of the traditional epileptic seizure detection methods using hybrid deep learning model. The proposed hybrid model was implemented using deep learning-based feature extraction and nonlinear SVM as a classifier, experimented on the CHBMIT dataset. From the experimental results, it is observed that the proposed model gives optimum result of 94.48% accuracy than that of existing models. For further improvements in EEG epileptic seizure detection signal-to-noise ratio can be improved with enhanced preprocessing steps. Due to lack of datasets for research related to EEG Muse like EEG devices can be used for data collection. Model performance can be improved by increasing the number of layers and hyper parameter tuning.

Authors contribution Each author contributed equally in each part.

Funding Authors have not disclosed any funding.

Data availability The CHBMIT scalp EEG signal dataset used for the research contains 22 subjects with 1 to 4 h duration for each subject. The file RECORDS contains a list of all 664.edf files included in this collection, and the file RECORDS-WITH-SEIZURES lists the 129 of those files that contain one or more seizures. In all, the onsets and ends of 182 seizures are annotated. It is available for download in the repository CHB-MIT scalp EEG Database v1.0.0 (physionet.org), and it is also cited [34].

Declarations

Conflict of interest The authors declare no Conflict of interest.

Ethical approval This article does not contain any studies with human participant and animals performed by author.

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