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Investigation of Optimal Components and Parameters of the Incremental PCA-based LSTM Network for Detection of EEG Epileptic Seizure Events

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ABSTRACT

Prediction of Epileptic seizures is highly imperative to improve the epileptic patient's life. Epileptic seizures occur due to brain cells excessive abnormal activity that leads to unprovoked seizures and may occur without prior notice. Therefore, preventive measure that monitor and alert the possible occurrence of the seizures is paramount. Commercial and clinical available epileptic seizure computer aided detection system that utilized deep learning algorithms suffers from many challenges. These challenges ranges from low accuracy and precision, sensitive to artifacts and noise, among others. To enhance and increase the accuracy and optimal performance of these networks, this paper endeavor to investigate various optimization algorithm to optimized the network components and parameters in the developed incremental Principal Components Analysis based Long Short-Term Memory (Inc-PCA-LSTM) network for the detection and classification of Electroencephalograph (EEG) epileptic seizure signals based on the big data scenario. The model proved to be effective in the characterization of seven seizure events. The Adam, Elu, Orthogonal, and L1/L2 performed better than their counterparts in optimization functions, activation functions, initialization functions, and regularisation techniques respectively. The accuracy values of 97.5%, 97.5%, 98.4%, and 98.5% was obtained for each of the mentioned core components receptively.

Keywords: EEG, Epileptic Seizure, PCA, LSTM, Deep Learning

INTRODUCTION

Neurological related studies have been widely investigated with Electroencephalography (EEG) that plays a vital role in diagnosis of brain diseases, functions, mental disorders and different kinds of treatments in medical and health care fields. The problem of extracting and understanding brain dynamics is complex however, EEG signals has been generally accepted and recognized as a leading approach in neurological related studies [1]. EEG signals are widely accepted and used for studies of neurological diseases, monitoring and treatment such as emotions recognition [2,3], measuring the depth of anesthesia [4], stroke-related disorders [5], depression [6], Parkinson's diseases [7], sleep-related disorders [8], brain death [9], and epileptic seizure [10]. It is also helpful for the treatment of abnormalities, behavioural disturbances (e.g., Autism), attention disorders, learning problems and language delay [11].

To measure the brain's electrical activity for diagnosis and analysis of normal and abnormal brain disorders, an electroencephalogram (EEG) signal is a one of the best options. This signal can be measured and recorded using electrodes from the surface of the scalp or intracranial (ECoG). One of the brain disorders that seriously affects the patient daily life activities is called Epileptic seizures [12]. This seizure causes a loss of conscious, jerking, and loss of memory which may occur at any time without notice [13,14]. Therefore, using automated aided techniques to predict it is occurrence is highly paramount.

The recent development and progress of the smart internet of medical things (IoMT) and recent launching of 5G networks has paved away for integration of recently machine learning and deep learning models for monitoring, analysis and diagnosis of epileptic seizures [15,16]. Conventional manual technique of interpretation of EEG signals is complex, time consuming, and prone to human biased even by the expert neurologist. However, the deep learning models that are recently investigated must be evaluated with the recent available big datasets for effective performance and validation [17,18]. Another important factor that determines the efficient performance of deep learning models is the investigation of core parameters and components to find the optimal values of these components for efficient utilization of the models. These optimal values are necessary for the integration of these models with low-cost, smart, wearable, and portable IoMT devices [19].

Several works have been proposed by researchers on the detection and classification of epileptic seizures. such as time-frequency techniques analysis [20], wavelet analysis [21], auto regressive spectral analysis [22], multivariate technique analysis among others [23]. Various promising results have been reported in literature on detection and classification of epileptic seizures, but till date the transition of these automated detection and prediction system into a commercial product and real-world application is limited due to some challenges encountered and limitations that need to be overcome in order to increase the accuracy and sensitivity of the detection system.

To increase the performance of epileptic detection system close to acceptable levels for real world applications, this paper leverages on the recent advances on machine learning and deep learning architectures coupled with recent big data resources to proposed and developed robust hybrid model known as incremental PCA-based LSTM network with optimized core parameters. The model is validated with the low-level learnable features proposed in [24] for effective characterization of different seizure classes as contained in TUH data corpus.

The contribution of this paper is to investigate the various core parameters and components of the developed deep learning network to optimized the network's performance by employing the optimal parameters that improve and enhance the detection and classification of scalp EEG epileptic seizure signals. The investigation is necessary due to the nature of the EEG epileptic data which is complex, multi-seizure big data. The most important components that determines the deep neural network performance investigated in this paper are optimization functions, activation functions, initialization functions, and regularisation techniques

RELATED WORKS

Researchers reported various works on the automated detection of epileptic seizure. The works reported includes those that investigated feature extraction techniques to characterized the EEG signals, and explore the embedded properties of the signals. These relevant and important features are then supplied to classifiers for distinguishing between normal and abnormal rhythms of EEG seizure signals. These techniques include traditional time and frequency domain features [25,26,27], Fourier transform spectral analysis [28], discrete and continuous wavelet transform [29], [30], [31], traditional statistical techniques and higher order statistical analysis [32], non-linear techniques such as various entropy parameters [33] among others. The unavailability of large dataset with many seizure classes limit the utilization of these techniques as most of the works validated their models on binary classification problems or on focal and non-focal epileptic seizures [34].

With the emergence of Temple University Hospital (TUH) recently, the investigation of multi-seizure detection and classification have been the focal point for many researchers. This is due to the huge number of clinical data with eight types of different epileptic seizures. Authors that employed TUH dataset in their work includes [35] which use CNN technique in classification of multi-seizure EEG signals with an average F1-score of 96.0%. Another work [36] developed Neural Memory Networks (NMN) in the detection of complex multi-classification dataset and obtained an average F1-score of 94.5%. Hybrid model based on CNN-LSTM networks was proposed to characterized various types of seizures in [37], [38], and [39]. A deep learning network based on CNN, RNN, and AE was used to develop a cloud-fog-integrated smart neurocare system to detect the presence of epileptic seizures [40]. The stacked neural network was also proposed to identify epileptic seizures using the Hilber transform and Variational Mode Decomposition for feature extraction [41].

As mentioned previously, many works proposed on epileptic seizure detection and classification utilized the classification in terms of ictal and non-ictal EEG signals, others employed datasets with low number of seizure events and short duration. Recently, some researchers started investigating the efficacy of the deep learning models with the TUH corpus. However, investigation the performance of deep learning models core parameters and components with big data approach is highly essential in order to integrate the developed models with smart IoMT devices. Therefore, this work is endeavor to contribute towards addressing the aforementioned issues.

MATERIALS AND METHODS

Dataset

TUH Corpus Description

TUH corpus was recently released by the Temple University Hospital to contribute and address the limitations of most of the existing publicly available dataset such as Bern and Bonn datasets. Currently, this dataset is the largest epileptic seizure repository in the world. It consists of 3,050 seizure events recorded from over 300 patients that are screened and carefully annotated by experts. The class distribution of seizures in the dataset is depicted in Table 1. [42] and [43] provides the details description of the dataset.

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Table 1: TUSZ 1.5.2 seizure type classes

Type of Seizures	Seizure Events	Duration (sec)	Patients
FNSZ	1836	121139	150
GNSZ	583	59717	81
CPSZ	367	36321	41
ABSZ	99	852	12
TNSZ	62	1204	3
TCSZ	48	5548	12
SPSZ	52	2146	3
MYSZ	3	1312	2

LSTM Structure with Incremental Principal Component Analysis

Inc-PCA

Due to low computational resources in the researchers' domain that can handle large datasets and features, dimensionality reduction must be proposed and deployed to reduce the dimension of the feature and make the memory more efficient. These techniques enable low-efficient memory, such as Nivida 1080ti with a memory of 8GB, to be deployed in executing advanced machine learning algorithms. This work employed a dimensionality reduction technique, a modified version of Principal Component Analysis (PCA) known as Incremental Principal Component Analysis (Inc-PCA). This technique is very effective and memory efficient than the conventional PCA technique.

To compute $y_1(n), y_2(n), \dots, y_k(n)$, known as the first k dominant principal components of PCA from the input, $x(n)$, can be described as:

$For\ n = 1, 2, \dots, do\ the\ following$:

(1) $x_1(n) = x(n)$.

(2) $For\ i = 1, 2, \dots, \min(k, n), do$:

$a)\ if\ i = n, initialize\ the\ i\ principal\ component\ as\ y_i(n) = x_i(n)$;

$b)\ otherwise\ compute$:

$$y_i(n) = \frac{n-1-p}{n} y_i(n-1) + \frac{1+p}{n} x_i(n) x_i^T(n) \frac{y_i(n-1)}{||y_i(n-1)||}, \quad (1)$$

$$x_{i+1}(n) = x_i(n) - x_i^T(n) \frac{y_i(n)}{||y_i(n)||} \frac{y_i(n)}{||y_i(n)||}, \quad (2)$$

where p is termed as the amnesic parameter. Typically, $p > 0$ and ranges from $[2,4]$. The eigenvector and eigenvalues are computed as:

$$e_i = \frac{y_i(n)}{||y_i(n)||}\ and\ \lambda_i = ||y_i(n)|| \quad (3)$$

The advantages of Inc-PCA is that; the large dataset can be used without loading the entire dataset into memory, has constant memory complexity proportional to the batch size, and changing the batch size in Inc-PCA enables more direct control of memory usage that shows it is dependent on the dimensionality of the input data features.

Inc-PCA-LSTM

In this work, we integrated the LSTM structure with Inc-PCA, known as Inc-PCA-LSTM, as shown in Figure 1. In this model, the features extracted from our proposed feature extraction methods developed using advanced time-frequency, entropy, energy, and statistics are fed to the input of the Inc-PCA layer to perform dimensionality reduction and spatial context analysis. Seizure detection is performed by one-layer LSTM

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when it receives the output of Inc-PCA. The product of the number of features per frame, the number of channels, and the number of frames of context represents the input to the Inc-PCA. Experiments show that the temporal context of 6 seconds shows promising results. Therefore, the Inc-PCA input vector is a dimension of 22 x 34 x 6 x 10 for the number of channels, features, second, and frames/second, respectively; this results in the total number of 432 elements. Inc-PCA has the number of 50 as batch size; at 10 frames/seconds, its output has 25 elements. For LSTM to learn long-term dependencies, a single hidden layer of 128 for both size and batch size is implemented along with cross-entropy and Adam as loss and optimization functions, respectively.

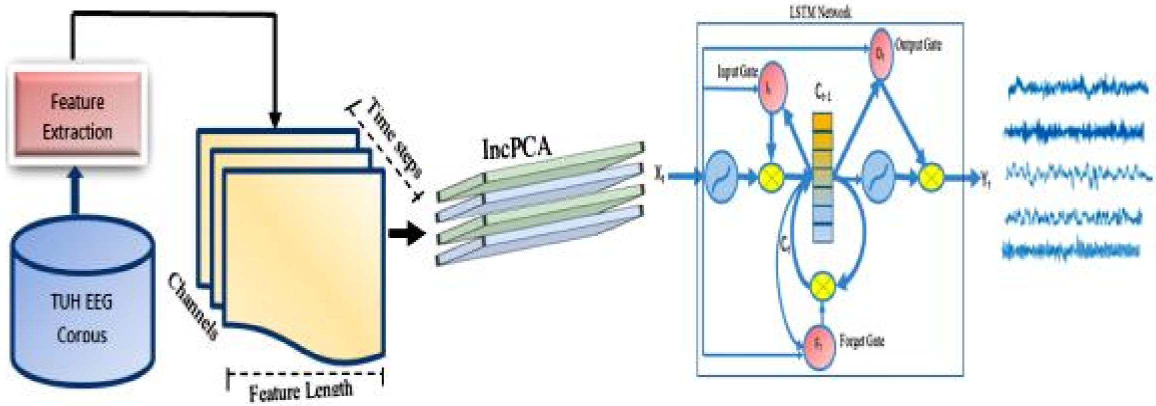

Figure 1: Inc-PCA-LSTM architecture for EEG epileptic seizures detection

RESULTS AND DISCUSSION

In this study, the Inc-PCA-LSTM is used for training and validation of TUH corpus database to detect and classified seven seizures events. The dataset was appropriately distributed for training and testing stage. We carried out the simulation using Tower workstation Think station P620, 16 GB NVIDIA Quadro® P2200 at State Key Laboratory of Hebei University of Technology, Tianjin, China. Python Tensorflow and Keras, Spyder 3.6 environment was used as a software for training and testing the deep learning model.

Performance Measures

The classification performance of the developed model is considered in terms of sensitivity, specificity, accuracy, precision, and F1-score. The used performance measures are defined as:

$$\text{Sensitiivity} = \frac{TP}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{TN}{\text{TN} + \text{FP}}$$

$$\text{Accuracy} = \frac{TP + TN}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

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

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$$\text{F1\_Score} = 2\frac{\text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

Where, (TP) is true-positive, (FP) false positive, (TN) is true negative, and (FN) is false-negative.

Core parameters and components optimization

Optimization Function

We have investigated the core parameters and components of the models experimentally to adjust the model's parameters as we observed that the choice of parameters for models' optimization proved to have an impact on the system's performance considerably. We investigate the impact of these parameters on various models developed in this work. However, we present the results of optimization techniques on the Inc-PCA_LSTM system. The optimization techniques considered and investigated in this work are Adagrad [44], Stochastic Gradient Descent (SGD) [45], Nadam [46], Adam [51], RMSprop [46], Adamax [45], and Adadelta [46].

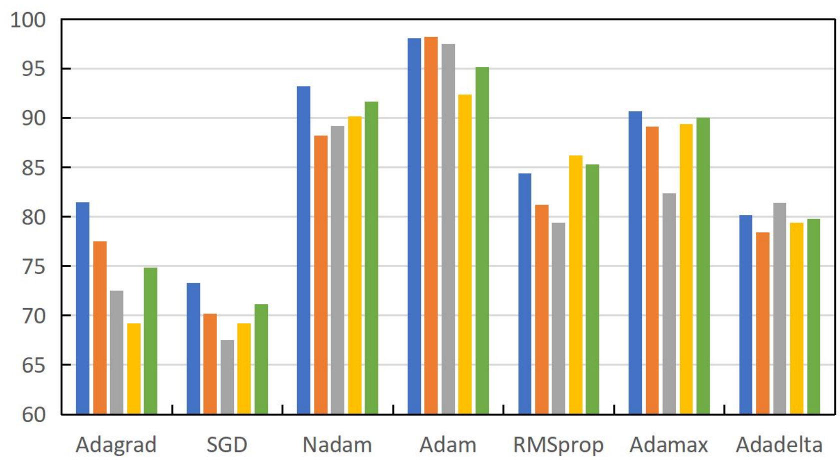

Figure 2: Impact of optimization techniques on the developed Inc-PCA-LSTM model

From the Figure 2, it is seen that Adam optimizer with an exponential decay rate of β1, β2, learning rate η, and fuzz factor of 0.9, 0.999, 0.0005, and $\epsilon = 10^{-8}$ respectively performed better than other optimization algorithms. We adopt the notation expressed in [45] for parameter selection. The optimization algorithm that shows comparable performance with Adam is Nadam. Combining the advantages of RMSProp, which works well in non-stationary settings, and that of Adagrad, which works well with sparse gradients, are the reasons for Adam's superior performance.

Activation Function

The next parameter investigated to optimize the proposed structure is the activation function. Different activation functions were selected, the Inc-PCA-LSTM model was evaluated, and the result is presented in Figure 3. The activation functions considered in this work are Sigmoid, ReLU, Linear, ELU, Tanh, and Softsign. From the Figure, ELU performed better than other activation functions with a 98.2%, 97.5%, 97.5%, 98.4%, 97.6%, and 98.3% sensitivity, specificity, accuracy, precision, false positive rate, and F1-score, respectively.

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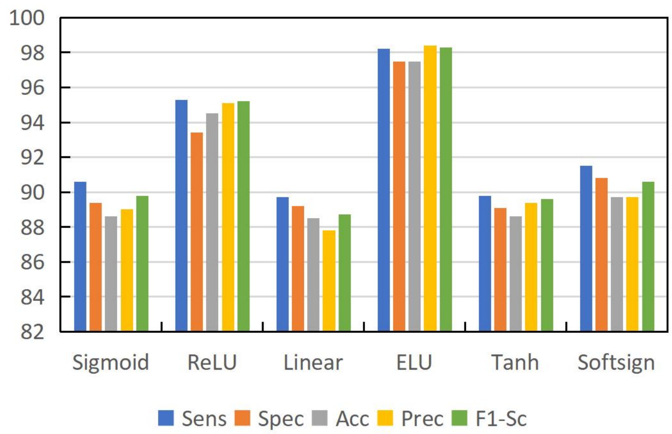

Figure 3: Impact of activation functions on the developed Inc-PCA-LSTM model

Initialization Functions

One difficulty in training the deep learning network is selecting a suitable initialization approach for the networks' parameters. Therefore, this work investigates the initialization approaches to optimize the Inc-PCA-LSTM structure. Figure 4, shows the performance of Inc-PCA-LSTM under various initialization methods. From the experiment conducted, we can deduce that in the Inc-PCA-LSTM structure, the initialization of weights is critical to convergence. For example, the convergence process could be entirely stalled by the initialization of tensor values to zero or one.

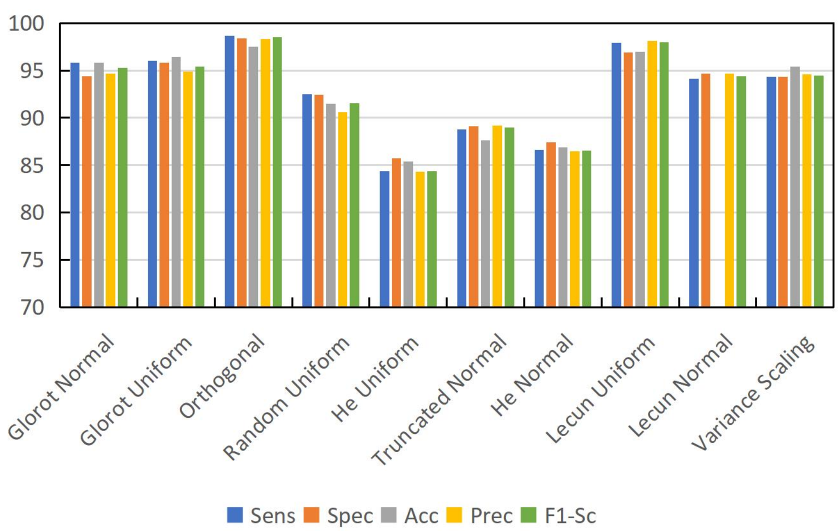

Figure 4: Impact of initialization functions on the developed Inc-PCA-LSTM model

We observed from the Figure that the orthogonal initialization achieved the best performance. Some of the reasons behind the best performance is that; the method is a simple but efficient method of overcoming exploding and vanishing gradients. This method chooses the random orthogonal matrix as a weight matrix. The random orthogonal matrix is a square matrix W for which $W^T W = I$. A matrix of random numbers from a normal distribution is decomposed using QR decomposition to obtain an orthogonal matrix. It has an eigenvalue of the absolute value of one and preserves the norm of a vector. This can be described as that; the resulting matrix does not vanish or explode even if we perform a repeated matrix multiplication no matter the number of times. Orthogonal matrices help the weight to learn different input features because rows and columns and orthogonal matrices are all orthonormal to one another. For example, in a CNN network, applying the orthogonal initialization of each layer results in a weight vector that is orthogonal to the weight vectors of the other channels in each channel.

Regularisation Techniques

Finally, we investigated the regularisation techniques to overcome the serious issue in deep learning networks with many parameters known as overfitting. The regularization methods investigated are L1, L2, L1/L2, dropout and zero-centered Gaussian noise. Figure 5 shows the performance of Inc-PCA-LSTM with various regularization approaches. From the Figure, the best regularization method that shows better performance is L1/L2 with accuracy, sensitivity, specificity, precision, false positive rate, and F1-score of 98.5%, 98.7%, 97.6%, 97.8%, and 98.2%, respectively.

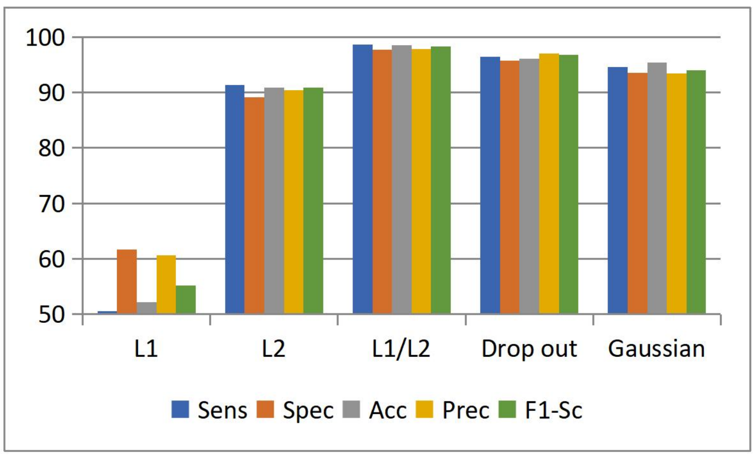

Figure 5: Impact of regularization techniques on the developed Inc-PCA-LSTM model

DISCUSSION

Deep learning algorithms are currently most widely investigated in the application of artificial intelligence to smart health care systems. Although for effective utilization of these models, the most important parameters and components of the model must be optimized and carefully selected in order to achieve the optimal performance. Some of the factors that must be considered in the selection of deep learning model include dimensionality reduction capability. This is due to the large amount of data supported by these models. Other factors include the optimization algorithms employed, activation functions, initialization functions, and regularisation techniques. This work focused on the development of the model with dimensionality reduction supported by Inc-PCA. Also, LSTM network was employed to learn a long-term dependencies of the big data TUH corpus.

Investigation the effects of the core components and deep learning model parameters on the developed hybrid model proved to be essential due to the complex nature of the TUH dataset. Among the most common optimization techniques investigated such as Adagrad, Stochastic Gradient Descent (SGD), Nadam, Adam, RMSprop, Adamax, and Adadelta. Adam optimization function performed optimally compared to others. In the case of activation functions, this work selected the most common functions such as Sigmoid, ReLU, Linear, ELU, Tanh, and Softsign. It was found that ELU activation provides a higher performance. To overcome the issue of exploding and varnishing gradients in deep leaning model, orthogonal initialization functions was found to be effective than other initialization functions considered in this work. Finally, to overcome the overfitting in the model, regularisation techniques such as L1, L2, L1/L2, dropout and zero-centered Gaussian noise were investigated. It was observed that L1/L2 performed better that it is counterpart functions.

CONCLUSION

This study investigates various most important components parameters that determine the performance of deep neural network to improve and enhance the efficacy of developed Inc-PCA-LSTM network. The model was developed to detect and characterized the scalp EEG epileptic signals using the complex, multi-seizure, and big data TUH corpus. The effect of Optimization functions, activation functions, initialization functions, and regularisation techniques on the deep learning model were investigated and the optimal parameter values were obtained. The model proved to be suitable for big data analysis due to it is dimensionality reduction capability that make it suitable for detection and classification of seven epileptic seizure events of big data TUH Corpus. Despite the performance improvement achieved in this work, future work should consider validating the optimal parameters in other deep learning networks.

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