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Quadrature Response Spectra Deep Neural Based Behavioral Pattern Analytics for Epileptic Seizure Identification

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Abstract: The brain's Electroencephalogram (EEG) signals contain essential information about the brain and are widely used to support the analysis of epilepsy. By analyzing brain behavioral patterns, an accurate classification of different epileptic states can be made. The behavioral pattern analysis using EEG signals has become increasingly important in recent years. EEG signals are boisterous and non-linear, and it is a demanding mission to design accurate methods for classifying different epileptic states. In this work, a method called Quadrature Response Spectra-based Gaussian Kullback Deep Neural (QRS-GKDN) Behavioral Pattern Analytics for epileptic seizures is introduced. QRS-GKDN is divided into three processes. First, the EEG signals are preprocessed using the Quadrature Mirror Filter (QMF) and the Power Frequency Spectral (PFS) and Response Spectra (RS)-based Feature Extraction is applied for Behavioral Pattern Analytics. The QMF function is applied to the preprocessed EEG input signals. Then, relevant features for behavioral pattern analysis are extracted from the processed EEG signals using the PFS and RS function. Finally, Gaussian Kullback–Leibler Deep Neural Classification (GKDN) is implemented for epileptic seizure identification. Furthermore, the proposed method is analyzed and compared with dissimilar samples. The results of the Proposed method have superior prediction in a computationally efficient manner for identifying epileptic seizure based on the analyzed behavioral patterns with less error and validation time.

Keywords: Electroencephalography, behavioral pattern analytics, quadrature mirror filter, power frequency spectral, response spectra.

1. INTRODUCTION

The human brain plays an important role in controlling human behavior through motor stimuli and consists of trillions of neurons. Electroencephalography (EEG) signals are analyzed to understand cognitive behavior or patterns in brain signals. Pattern analysis techniques have been used extensively to differentiate neural activity associated with several perceptual or other cognitive states by analyzing EEG signals.

With the help of digital signal processing mechanisms and deep learning techniques, EEG signals can be analyzed to provide beneficial results for various applications, such as neurological disorder detection, brain- computer interface investigation, emotion recognition, etc. Deep learning techniques are therefore used in EEG signal analysis to extract features and classify brain states.

EEG is generally used in neural engineering, neuroscience and as a Brain-Computer Interface (BCI). Accurate classifications of EEG signals are essential for BCI. Motivated by the above facts, this work aims to investigate the classification time and error-based features of stimulated EEG signal analysis using a novel method called Quadrature Response Spectra-based Gaussian Kullback Deep Neural (QRS-GKDN) for Behavioral Pattern Analytics based on deep neural networks.

The structure of the paper is as follows. Section 2 reviews the literature works for EEG signal classification based on behavioral patterns. Section 3 explains the proposed QRS-GKDN method. The experimental setup and detailed discussion are provided in Section 4. Finally, the conclusion is presented in Section 5.

2. LITERATURE REVIEW

A hybrid deep learning-based seizure detection, XAI4EEG, was proposed in [1]. Deep learning was combined with area information by using the frequency band, the EEG leads position and their corresponding temporal individuality.

To assess cognitive abilities and improve the dual categorization of EEG signals, the Multi-scale High-density Convolutional Neural Network (MHCNN) classification method was proposed in [2]. Moreover, EEG frequency band features are extracted by multi-dimensional conditional mutual information. In addition, the coupling features were also converted into multispectral images. However, discriminative features were not preserved.

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The validation using dissimilar EEG signals was designed in [3]. Furthermore, a classifier was also used to distinguish between two stages. Despite the improvement in accuracy, the error factor was not focused. In [4], an iterative learning model was proposed with the purpose to speed up the entire process and reduce the error in the overall process.

In [5], spatial and temporal dependencies between time points and distinct channels were analyzed for accurate classification. Another automated method for emotion recognition using forest ensemble classifier was proposed in [6]. In this type of ensemble classifier, a tunable Q-wavelet transform was used, which in turn ensures accurate classification. In [7], a method for mental activity recognition using bidirectional Long Short-Term Memory (LSTM) neural networks was presented. With this type of bidirectional deep learning, accurate classification was ensured in addition to error detection. Several machine learning methods for EEG analysis with bioengineering applications are presented in [8]. In [9], [10] disease prediction based on EEG signals was discussed.

To achieve higher classification accuracy and less time consumption, the proposed QRS-GKDN is introduced for epileptic seizure identification.

The contributions of QRS-GKDN are listed below.

The QRS-GKDN method uses the Quadrature Mirror Filter (QMF) for preprocessing.

A Power Frequency Spectral (PFS) and RS-based Feature Extraction algorithm is used to extract relevant features in the frequency domain.

Gradient Kullback–Leibler divergence is applied to a Deep Neural Network to enable accurate classification of EEG signals via the sigmoid feature.

3. PROPOSED SYSTEM

In this section, the proposed models for the preprocessing of EEG signals and Epileptic Seizure Recognition dataset are explained. An EEG signal classification method called QRS-GKDN for Behavioral Pattern Analytics is presented.

Fig. 1 shows the QRS-GKDN diagram, (1) preprocessing of EEG signals, (2) Feature Extraction for behavioral pattern analysis, and (3) classification of epileptic states by Gaussian Kullback–Leibler Deep Neural Classification (GKDN). The QRS-GKDN architecture is shown in Fig. 1.

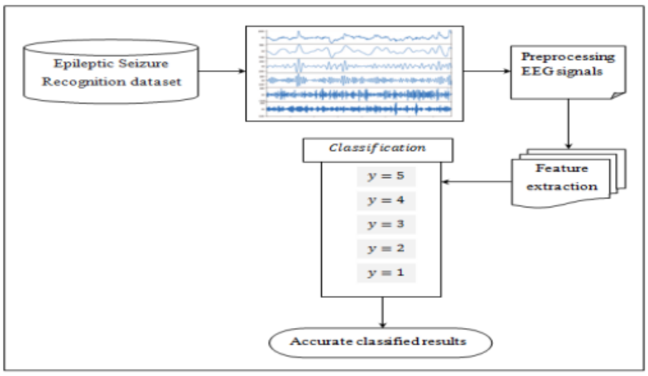

Fig. 1. Block diagram of QRS-GKDN.

A. *Epileptic Seizure Recognition dataset description*

The Epileptic Seizure Recognition dataset consists of 500 different files, each file representing a single subject or person. All data points represent EEG recording values. So in total we have *500* individuals, each of which has *4097* data points for a time interval of *23.5* s. Each of the *4097* data points has been divided into *23* chunks, with each chunk containing *178* data points in a *1* s time interval. Thus, the entire dataset has *23 x 500 = 11500* pieces of information in each row and each data set contains *178* data points for a time interval of *1* s in each column.

B. *Preprocessing EEG signals using QMF*

During recording, various types of artifacts, such as power line interference, muscle movements and the environment, are combined with the EEG signals. Fig. 2 shows the structure of the QMF-based preprocessing model.

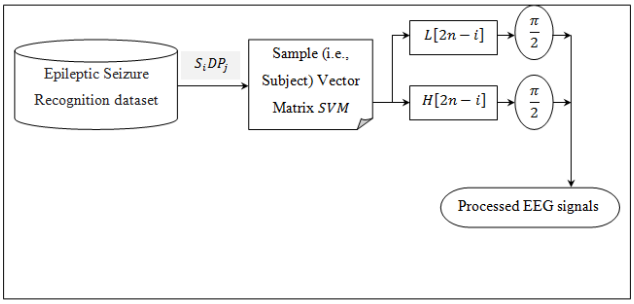

Fig. 2. Structure of QMF-based preprocessing model.

When inputting the dataset for Epileptic Seizure Recognition, the goal is to eliminate the noise and interference during the recording of the EEG signals. First, a sample vector matrix is formulated and the relevant data points are included in the simulation. Second, definite coefficients and indefinite coefficients are determined for each sample using the QMF function. Finally, the aggregated values form the processed (i.e., interference eliminated) EEG signals. Let us consider the samples S_i with their corresponding data points DP_j at a different point in time for *23.5* s. The input vector matrix *SVM* has been formulated.

$$SVM = \begin{bmatrix} S_1DP_1 & S_1DP_2 & \dots & S_1DP_n \\ S_2DP_1 & S_2DP_2 & \dots & S_2DP_n \\ \dots & \dots & \dots & \dots \\ S_mDP_1 & S_mDP_2 & \dots & S_mDP_n \end{bmatrix} \tag{1}$$

The above mathematical formulation (1) shows that the sample vector matrix *SVM* is divided in such a way that it accommodates *4097* data points in *23* chunks, with each chunk having *178* data points in *1* s, respectively. With the sample vector matrix *SVM*, the QMF function remains with the division of the total function into definite coefficients and indefinite coefficients, respectively. The QMF function is represented mathematically as follows.

$$y[n] = (SVM * L * H)[n] \tag{2}$$

In (2), *L* and *H* represent the definite coefficients and indefinite coefficients. The above function is called QMF because *SVMi(n)* is called the QMF of *SVMi(n)* when $SVM_i(n) = SVM_j(-n)$.

$$y_L[n] = \sum_{i=-\infty}^{\infty} SVM[i]L[2n-i] \quad (3)$$

$$y_H[n] = \sum_{i=-\infty}^{\infty} SVM[i]H[2n-i] \quad (4)$$

With the above coefficient results as in (3) and (4), the aggregated values are formulated as follows.

$$y_L = (SVM * L)\frac{\pi}{2} \quad (5)$$

$$y_H = (SVM * H)\frac{\pi}{2} \quad (6)$$

$$y[n] = y_L + y_H \quad (7)$$

With the aggregated values given in (5), (6) and (7), the input sample vector matrix is divided into two bands. The resulting definite and indefinite coefficients are reduced by a factor of $2\frac{\pi}{2}$, resulting in a signal that is free of interference from the original signal. In this way, the validation time can be considerably shortened by denoising the EEG signals.

C. *PFS and RS-based Feature Extraction for Behavioral Pattern Analytics*

In this work, the PFS, which is consistent with the RS, is used for Feature Extraction for denoised EEG signals. Fig. 3 shows the structure of the PFS and RS-based Feature Extraction for Behavioral Pattern Analytics.

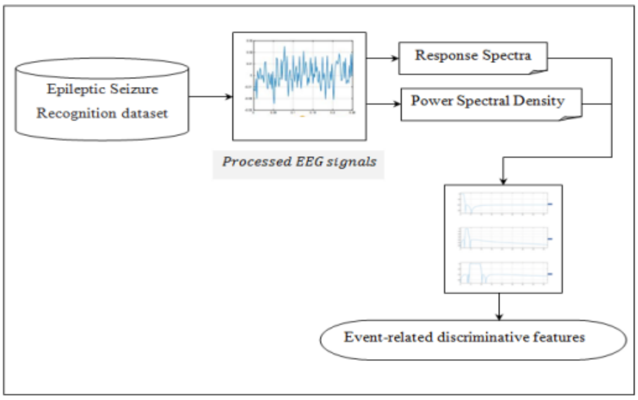

Fig. 3. Structure of PFS and RS-based Feature Extraction for Behavioral Pattern Analytics.

As shown in Fig. 3, the RS for determining the behavioral analytics is modeled with the denoised EEG signals as input. The RS function for the corresponding processed EEG signals is as follows.

$$y[n](T) = \begin{cases} y[n]_i\left[1+(af-1)\frac{T}{T_{P1}}\right], 0 \le T \le T_{P1} \\ af\ y[n]_i, \quad T_{P1} < T \le T_{P2} \\ af\ y[n]_i\left(\frac{T_{P2}}{T}\right)^{S_1}, \quad T_{P2} < T \le T_{P3} \\ af\ y[n]_i\left(\frac{T_{P2}}{T_{P3}}\right)^{S_1}\left(\frac{T_{P3}}{T}\right)^{S_2}, \quad T > T_{P3} \end{cases} \quad (8)$$

In (8), T_{P1}, T_{P2} and T_{P3} denote the three distinct behavioral patterns generated at different time intervals T using the amplification factor *af* with respect to the denoised EEG signals $y[n]_i$.

$$PFS = \lim_{T\to\infty}\frac{1}{T}\int_{t_0}^{t_n}|y[n](T)|^2 dt \quad (9)$$

From (9), the power frequency spectrum *PFS* is used for the denoised EEG signals and the RS.

D. *GKDN for epileptic seizure identification*

The PFS and RS-based Feature Extraction algorithm reduces dimensionality. The three distinct behavioral patterns (T_{P1}, T_{P2} and T_{P3}) are extracted. For the five classes $y = \{1, 2, 3, 4, 5\}$, five maximum individual patterns are simply focused on, which is why the features $3 \times 5 = 15$ are also extracted from both trials.

The input signal $PFS_n (n = 1, 2, 3\ldots)$ is transferred to the hidden layer in Fig. 3. On the other hand, the hidden layer performs the actual calculations. The corresponding EEG signal weight is measured as shown below.

$$\alpha_i = F\ \sum_{i=1}^{n} W_i PFS_i \quad (10)$$

From (10), it can be seen that W_i represents the connections weight and the neurons are represented as *n*. *15* input layers are used since the input features are *15*. Also, *2* hidden layers are used, which is expressed mathematically as follows.

$$Sim_{j|i} = \frac{exp\left[-\left(SPFS_i - SPFS_j\right)^2\right]/\ 2\sigma_i^2}{\sum_{i\neq k} exp[-(SPFS_i - SPFS_k)^2]/\ 2\sigma_j^2} \quad (11)$$

4. TESTING AND VALIDATION

The validations are performed with EEG signals from 5 distinct folders, each with *100* files, where each file denotes a single subject or person in Python. The input dataset was divided into two sets, namely the training set and the testing set. Most of the samples (*70*%) were used for training, and the least (*30*%) for testing.

A. *Validation time*

The validation time is measured as shown below.

$$VT = \sum_{i=1}^{n} S_i * Time\ [Validating\ samples] \quad (12)$$

In (12), *VT* stands for the validation time, S_i for sample subjects and the time required to validate the samples *Time [Validating samples]*. It is calculated in ms. Three different methods, QRS-GKDN, XAI4EEG [1] and MHCNN [2] are described in Table 1.

Fig. 4 shows the validation time results obtained with the three methods, QRS-GKDN, XAI4EEG [1] and MHCNN [2] for *10000* distinct samples each. The validation time with the QRS-GKDN method was reduced by *20*% compared to [1] and by *28*% compared to [2].

Table 1. Tabular representation of the validation time using three methods, QRS-GKDN, XAI4EEG [1] and MHCNN [2].

Samples	Validation time [ms]		
	QRS-GKDN	XAI4EEG	MHCNN
1000	250	380	410
2000	310	400	435
3000	335	425	490
4000	350	485	555
5000	425	565	625
6000	485	615	685
7000	535	690	735
8000	700	785	850
9000	755	835	955
10000	835	890	1035

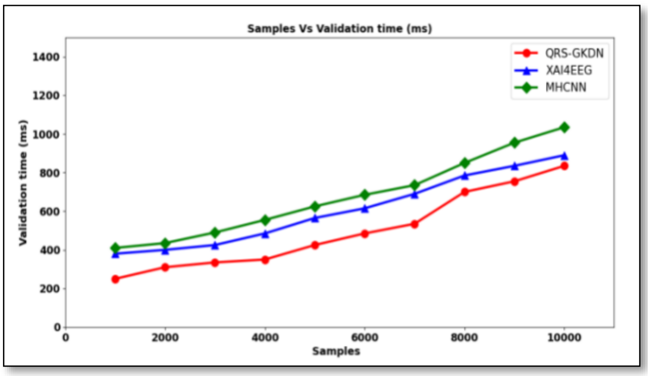

Fig. 4. Validation time results for distinct EEG samples.

B. *Performance analysis of the error rate*

The error rate *ER* was calculated as the percentage between the number of samples wrongly classified S_{WC} and the total samples S_i. This is expressed mathematically as shown below.

$$ER = \sum_{i=1}^{n} \frac{S_{WC}}{S_i} * 100 \tag{13}$$

From (13), the error rate *ER*, is based on the samples wrongly classified and the actual samples.

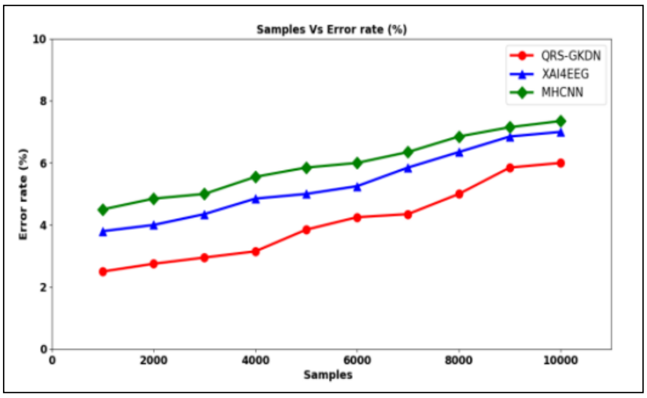

Fig. 5. Error rate results for distinct EEG samples.

The error rate with the corresponding samples is shown in Fig. 5. The x-axis represents samples between *1000* and *10000* and the y-axis represents the error rate. The error rate involved in epileptic seizure identification is up to *25%* lower than [1] and *33%* lower than [2].

C. *Classification accuracy*

The second parameter in the analysis of behavior patterns based on EEG signals is the accuracy of classification. In other words, classification accuracy refers to the percentage ratio of the number of accurate classifications. This is expressed mathematically as follows.

$$CA = \sum_{i=1}^{n} \frac{S_{AC}}{S_i} * 100 \tag{14}$$

From (14), it can be seen that the classification accuracy *CA* is evaluated based on the number of accurate classifications *AC*.

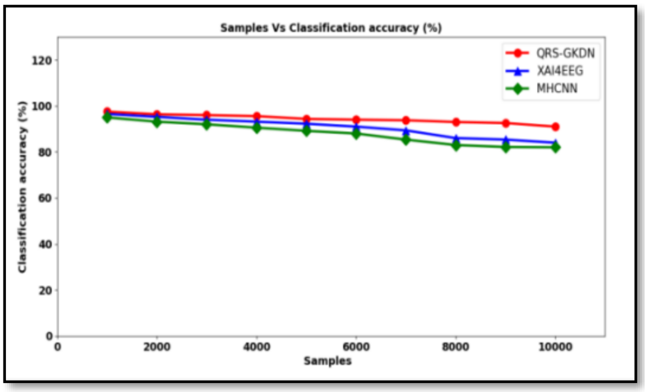

Fig. 6. Classification accuracy results for distinct EEG samples.

Fig. 6 shows the classification results obtained with the three methods QRS-GKDN, XAI4EEG [1] and MHCNN [2]. The classification accuracy is *4%* and *7%* higher with QRS-GKDN than with [1] and [2], respectively.

D. *Performance analysis of recall*

The recall is the ratio of the true positive results to the sum of the true positive results and the false negative results from the input data.

$$Recall = \left[\frac{TP}{FP+FN}\right] * 100 \tag{15}$$

From (15), sensitivity is measured based on true positive *TP*, false positive *FP*, and false negative *FN*.

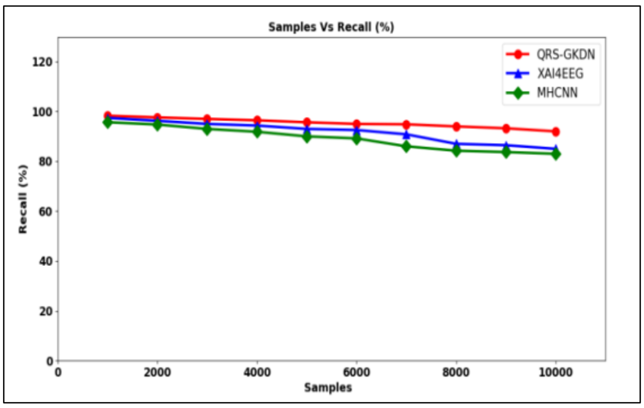

Fig. 7. Recall results for distinct EEG samples.

Fig. 7 explains the measure of recall considering different samples. From Fig. 7, it can be seen that the proposed QRS-GKDN method has better performance compared to the existing methods, namely XAI4EEG [1] and MHCNN [2]. The recall is improved by *4*% with QRS-GKDN compared to [1] and *7*% compared to [2].

5. Conclusion

In this paper, we proposed a novel behavioral pattern analysis QRS-GKDN for epileptic seizure identification from EEG signals. The QRS-GKDN method we developed for epileptic seizure identification accurately extracts relevant features for classification. The experimental result shows that the proposed behavioral patterns of EEG signals for epileptic seizure identification achieve greater improvement in terms of classification accuracy with minimum error rate and validation time.

Data availability statement

Available Based on Request. The datasets generated and/or analyzed during the current study are not publicly available due to the extension of the submitted research. They are available upon reasonable request to the corresponding author.

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