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WCQMV : Design of A Wavelet Compression Based Quadratic Model for EEG Classification Using Multivariate Analysis

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ABSTRACT

Electroencephalogram (EEG) signals represent functioning of the brain, and assist in identification of multiple brain-related disorders including Epilepsy, Alzheimer's disease, emotional states, Parkinson's disease, strokes, etc. To design such models, a wide variety of machine learning & deep learning approaches are proposed by researchers. But these approaches use a black-box generic model for EEG classification, due to which their scalability is limited. To enhance this scalability, a novel feature augmented extraction model is proposed in this text. The model uses wavelet compression on input EEG data, and processes the compressed signal using a variance-based selection approach. Due to which, the model is capable of low-delay, and high accuracy classification for different brain-diseases. It evaluates wavelet-based features from input EEG data, and performs ensemble feature selection for improving feature variance. The wavelet features are able to convert input EEG data into different directional components, which assists in improving efficiency of feature representation & model training for different signal types. The proposed model uses a quadratic Neural Network (QNN) classification engine, and is capable of achieving an accuracy of 96.5% for different EEG classes. These classes include 3 types of Epilepsy, presence of Alzheimer's disease, & evaluation of brain strokes. Due to use of feature variance-based classification, the proposed WCQMV model outperforms existing feature selection & classification models by 4% in terms of accuracy when averaged over multiple datasets. Moreover, the proposed model also improves speed of classification by 4.9% when compared with these models, thus making it useful for high-speed EEG processing applications. This performance improvement is possible due to effective feature reduction, which assists in identification of different EEG signal types. The model was tested on various EEG datasets including, IEEE Port Epileptic dataset, and BNCI dataset for Alzheimer & brain strokes. It was observed that the proposed model was capable of high-performance classification on each dataset, thereby indicating high-scalability across multiple EEG applications.

Keywords: EEG, quadratic, variance, Neural, Network, ensemble, augmented, classification, features

I. INTRODUCTION

EEG classification is a multidomain task which involves design of design of data pre-processing, segmentation, feature extraction, feature reduction, classification & post-processing operations. To design a highly effective EEG classifier, Models for these operations must be developed with high-efficiency & reduced delays. An instance of such a classification model is described in figure 1, wherein classification of EEG for emotion recognition is observed [1]. The model captures EEG signals from headset-based interface, and pre-processes it using denoising & filtering techniques. The pre-processed signal is given to a feature-extraction model, wherein different angular features are extracted. These features represent time-domain interpretations of brain state, and thus can be used for categorization into different classes.

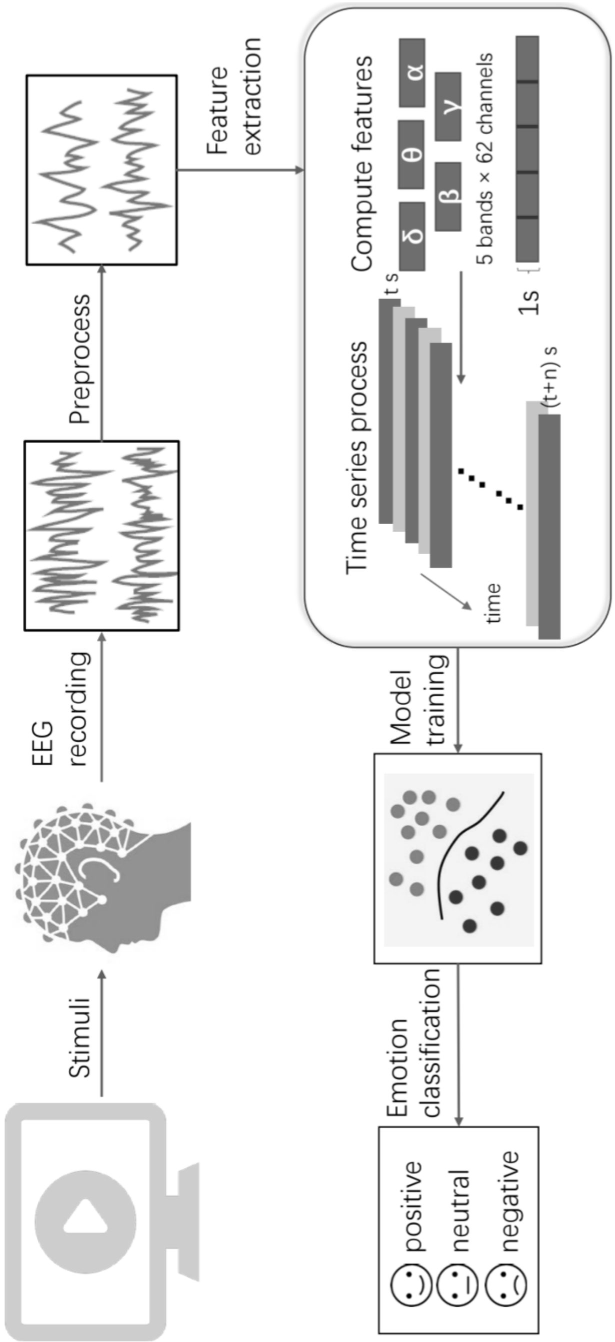

Figure 1. A typical brain emotion classification model using EEG signals

The extracted features are given to a classification model, which uses support vectors to identify positive, negative and neural emotion types. These emotions can be used by cascaded systems to identify application-specific information depending upon varying model designs. It can be observed that accuracy of these models is highly dependent on feature extraction, feature selection, and classification blocks. Design of these blocks along with performance characteristics from various state-of-the-art classification models is discussed in the next section of this text. Based on this discussion, it is observed that these approaches use a black-box model or are very generic, which limits their scalability in terms of delay & accuracy performance. To improve this performance, section 3 discusses design of the proposed augmented feature selection engine for EEG classification using multivariate analysis. Performance of this model is evaluated in section 4, and is compared with various state-of-the-art approaches. Finally, this text concludes with some interesting observations about the proposed model, and recommends methods to further improve its performance.

II. LITERATURE REVIEW

A wide variety of EEG classification models are proposed by researchers over the years, and each of them vary in terms of applicability, precision, recall, accuracy & delay performance. For instance, work in [2, 3, 4] discusses design of reduced instruction set (RISC)-V convolutional Neural Network (CNN) Coprocessor, combination of linear discriminant analysis (LDA), k-nearest neighbour (KNN), support vector machine (SVM), & artificial neural network (ANN) with common spatial pattern (CSP), and Transfer TSK Fuzzy Classifier (TTFC) for achieving better classification results. These models have good accuracy, but lack in terms of precision performance due to their application-specific classification characteristics. Extensions to this model are discussed in [5, 6], wherein Neuroglial Network Model (NNM), and low-intensity focused ultrasound stimulation (LIFUS) are used for multidomain EEG classifications. These models have good precision, but cannot be scaled for multiple applications due to high computational complexity. To improve scalability, work in [7] proposes design of Multiple frequency Multilayer brain Network (MFMBN) that assists in achieving higher accuracy and better scalability than previously proposed models. Similar models that utilize CNN with cross wavelet transform (XWT) [8], Local Binary Pattern Transition Histogram (LBP TH) [9], and Multivariate Scale Mixture Model (MSMM) [10] are proposed by researchers. These models utilize augmented feature extraction methods for improving overall classification performance during epilepsy detection.

Based on these feature extraction models work in [11, 12, 13] propose fusion of Hand-Crafted Deep Learning EEG model (HC DL), quadratic classifier with wavelet features, and Multiple scaled NN with Dilated Convolutions (MSNN DC) is discussed. These models perform large-scale feature extractions to represent input EEG waveforms via multiple spectrums for better classification performance. But these models showcase moderate accuracy performance, which can be improved via the work in [14, 15, 16], wherein hierarchical discriminative sparse representation classifier, time domain sequential features classification using long short-term memory (LSTM) neural network, and Deep Convolutional Neural Network (DCNN) are discussed. These models assist in augmentation of EEG features in order to improve classification accuracy for different clinical applications. Similar models are discussed in [17, 18], wherein Extended K Nearest Neighbours, and Joint blind source separation methods are proposed by researchers for better scalability performance. These models utilize low complexity feature extraction methods, but cannot be applied to large-scale EEG datasets. Thus, it can be observed that models that have high accuracy are not applicable for large scale deployments, while models that have high scalability cannot be used for highly accurate classification applications. To overcome these issues, next section proposes design of wavelet compression based quadratic model for EEG classification using multivariate analysis, that assists in high-efficiency and high scalability EEG classification for different clinical scenarios.

III. Proposed wavelet compression based quadratic model for EEG classification using multivariate analysis

Based on the literature review, it was observed that most of the recently proposed EEG classification models are general purpose in nature, which limits their scalability when applied to real-time classification applications. To improve this scalability, a novel wavelet compression based quadratic model for EEG classification using multivariate analysis model is discussed in this section. Overall flow of the proposed model is depicted in figure 2, wherein it is observed that input EEG data is initially compressed via a wavelet transform block. The compressed signal is given to a feature extraction block, which assists in extraction of spectral & spatial features. These features are processed via a Quadratic Neural Network (QNN) based classification model, which assists in obtaining final epilepsy classification. The input EEG waves are initially processed via a wavelet compression block, which assists in feature reduction. Extraction of wavelet components is evaluated via equation 1 & 2 as follows,

$$W_a = \frac{x_i + x_{i+1}}{2} \ldots (1)$$

$$W_d = \frac{x_i - x_{i+1}}{2} \ldots (2)$$

Where, $W_a, and\ W_d$ represents approximate & diagonal wavelet components, while $x_i\ and\ x_{i+1}$ represents current and next EEG signal value. Both these components are processed via a feature extraction layer, which assists in evaluation of statistical & spectral features. These features are evaluated via equations 3 to 13 as follows,

$$Mean = \sum_{i=1}^{N} \frac{c_i}{N} \ldots (3)$$

$$Max = Maximum\left(\bigcup_{i=1}^{N} c_i\right) \ldots (4)$$

$$Min = Minimum\left(\bigcup_{i=1}^{N} c_i\right) \ldots (5)$$

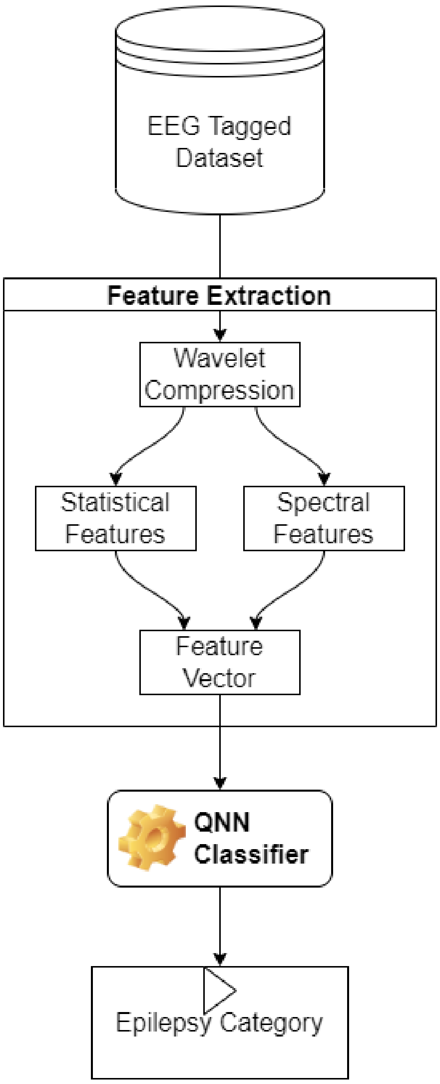

Figure 2. Overall flow of the proposed model

$$STD = \sqrt{\sum_{i=1}^{N} \frac{\left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)^2}{N}} \ldots (6)$$

$$Var = \sum_{i=1}^{N} \frac{\left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)^2}{N-1} \ldots (7)$$

$$CC = \frac{\sum_{i=1}^{N} \left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)}{\sqrt{\sum_{i=1}^{N} \left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)^2}} \ldots (8)$$

$$Cov = \frac{\sum_{i=1}^{N} \left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)}{N} \ldots (9)$$

$$Median = C\left[\frac{N}{2}\right], when\ N\ is\ even,$$

$$else\ \frac{\left[C\left[\frac{N-1}{2}\right] + C\left[\frac{N+1}{2}\right]\right]}{2}, when\ N\ is\ odd \ldots (10)$$

$$Kurtosis = \sum_{i=1}^{N} \frac{\left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)^4}{\left(c_i - \sum_{j=1}^{N} \frac{c_j}{N}\right)^2} * N \ldots (11)$$

$$Sum\ Square = \sum_{i=1}^{N} \frac{c_i^2}{N} \ldots (12)$$

$$ZCR = \sum_{i=1}^{N-1} |sgn(c_i)\ != sgn(c_{i+1})| \ldots (13)$$

Where, $Mean$ represents average value of signal, Max represents maximum value of signal, Min represents minimum value of signal, STD represents standard deviation value of signal, Var represents variance value of signal, CC represents correlation coefficient value of signal, Cov represents covariance value of signal, $Median$ represents Median value of signal, $Kurtosis$ represents kurtosis of signal, $Sum\ Square$ represents sum squared average value of signal, ZCR represents zero crossing rate value of signal, c_i represents instantaneous value of signal, and N represents total number of samples in the signal. All these features are evaluated for approximate & diagonal EEG components, and are combined to form a super feature vector. This feature vector is given to a quadratic Neural Network (QNN) model for final classification. Overall flow of the QNN model is depicted in figure 3, wherein multiple layers are connected via neuron connections to produce 3 different output classes.

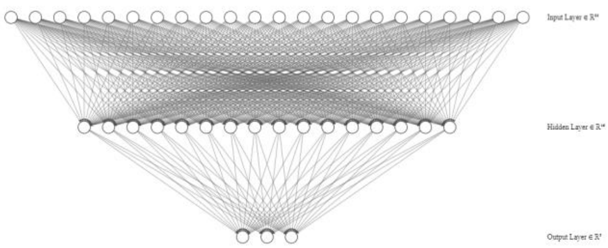

Figure 3. Overall flow of the QNN model

It can be observed that input layer consists of 22 different neurons, one for each extracted feature. These neurons are modified in multiples of 2, for achieving network sizes of 44, 66, and 132 input layer neurons. These neurons connected together to obtain 3 output classes, that include Normal, Interictal, and Ictal EEG types. The final class is evaluated by combining results from these classifiers via quadratic equation 14 as follows,

$$C_{out} = -\frac{1}{2}\left(x - \sum_{i=1}^{N} x_i\right)^T \sum_{j=1}^{N} (x_j - \sum_{l=1}^{N} x_l) + \log\left(\sum_{i=1}^{N} x_i\right) \ldots$$

Where, x, & N represents input feature vectors, and number of Neural Network configurations used to obtain the final classification result. Based on this equation, classification of input data into different epilepsy classes is performed. Results of this classification can be observed from the next section of this text.

IV. RESULT ANALYSIS AND COMPARISON

The proposed WCQMV model was tested on different EEG datasets for classification of input waveforms into Normal, Interictal, and Ictal EEG types. These waveforms were extracted from Seizure Prediction Project Freiburg, which can be accessed from https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database via open-source licensing for research purposes. The dataset consisted of 22 different EEG leads, and 200+ patients. A total of 2200 samples were extracted from this dataset, and divided into 70:30 ratio for training & validation respectively. Results were valuated in terms of accuracy, precision, recall & delay, and were compared with CSP [3], CNN XWT [8], and MSNN DC [13] for validation purposes. The results for accuracy can be observed from table 1 as follows,

Number of EEGs	**A (%) CSP [3]**	**A (%) CNN XWT [8]**	**A (%) MSNN DC [13]**	**A (%) WCQ MV**
100	75.60	77.50	76.29	80.49
200	79.40	80.30	78.65	83.63
300	81.20	81.55	79.83	85.12
400	81.90	82.65	81.09	86.19
500	83.40	84.50	82.74	87.95
600	85.60	85.75	83.73	89.50
700	85.90	86.05	84.02	89.82
800	86.20	86.35	84.47	90.18
900	86.50	87.29	85.47	90.97
1000	88.09	88.54	86.60	92.36
1200	88.99	89.45	87.48	93.31
1400	89.90	90.35	88.37	94.25
1600	90.80	91.26	89.25	95.20
1800	91.71	92.16	90.14	96.14
2000	92.62	93.07	91.02	97.09
2200	93.52	93.97	91.90	98.03

Table 1. Accuracy of different EEG classification models

Based on this evaluation, it can be observed that the proposed model is 4.5% accurate than CSP [3], 3.9% accurate than CNN XWT [8], and 6.8% accurate than MSNN DC [13] for different EEG signal types. The reason for this performance improvement in use of QNN, which assists in augmenting feature classification process. Similarly, precision performance of these models is tabulated in table 2 as follows,

Number of EEGs	**P (%) CSP [3]**	**P (%) CNN XWT [8]**	**P (%) MSNN DC [13]**	**P (%) WCQ MV**
100	72.90	73.23	74.66	76.70
200	76.05	75.69	77.27	79.84
300	77.50	76.85	78.55	81.31

400	78.36	77.97	79.65	82.27
500	79.95	79.64	81.28	83.95
600	81.60	80.71	82.49	85.55
700	81.88	80.99	82.78	85.85
800	82.17	81.34	83.17	86.18
900	82.76	82.27	84.02	86.86
1000	84.11	83.40	85.22	88.23
1200	84.97	84.25	86.09	89.14
1400	85.83	85.10	86.96	90.04
1600	86.70	85.96	87.83	90.95
1800	87.56	86.81	88.70	91.85
2000	88.42	87.66	89.58	92.75
2200	89.28	88.51	90.45	93.66

Table 2. Precision of different EEG classification models

Based on this evaluation, it can be observed that the proposed model is 4% precise than CSP [3], 5.2% precise than CNN XWT [8], and 3.1% precise than MSNN DC [13] for different EEG signal types. The reason for this performance improvement in use of QNN, which assists in augmenting feature classification process. Similarly, recall performance of these models is tabulated in table 3 as follows.

Number of EEGs	R (%) CSP [3]	R (%) CNN XWT [8]	R (%) MSNN DC [13]	R (%) WCQ MV
100	74.25	75.37	75.48	78.59
200	77.72	77.99	77.96	81.73
300	79.35	79.20	79.19	83.21
400	80.13	80.31	80.37	84.23
500	81.68	82.07	82.01	85.95
600	83.60	83.23	83.11	87.53
700	83.89	83.52	83.40	87.83
800	84.18	83.85	83.82	88.18
900	84.63	84.78	84.74	88.92
1000	86.10	85.97	85.91	90.30
1200	86.98	86.85	86.79	91.22
1400	87.87	87.73	87.67	92.15
1600	88.75	88.61	88.54	93.07
1800	89.63	89.49	89.42	94.00
2000	90.52	90.36	90.30	94.92
2200	91.40	91.24	91.17	95.85

Table 3. Recall of different EEG classification models

Based on this evaluation, it can be observed that the proposed model has 4.5% more recall than CSP [3], 4.6% more recall than CNN XWT [8], and 4.8% more recall than MSNN DC [13] for different EEG signal types. The reason for this performance improvement in use of QNN, which assists in augmenting feature classification process. Similarly, delay performance of these models is tabulated in table 4 as follows,

Number of EEGs	D (ms) CSP [3]	D (ms) CNN XWT [8]	D (ms) MSNN DC [13]	D (ms) WCQ MV
100	0.45	0.44	0.44	0.42
200	0.86	0.85	0.86	0.82
300	1.26	1.26	1.26	1.20
400	1.66	1.66	1.66	1.58
500	2.04	2.03	2.03	1.94
600	2.39	2.40	2.41	2.29
700	2.78	2.79	2.80	2.66
800	3.17	3.18	3.18	3.02
900	3.54	3.54	3.54	3.37
1000	3.87	3.88	3.88	3.69
1200	4.60	4.61	4.61	4.38
1400	5.31	5.32	5.32	5.06
1600	6.01	6.02	6.02	5.73
1800	6.69	6.71	6.71	6.38
2000	7.37	7.38	7.38	7.02
2200	8.02	8.04	8.04	7.65

Table 4. Delay of different EEG classification models

Based on this evaluation, it can be observed that the proposed model is 5.6% faster than CSP [3], 5.5% faster than CNN XWT [8], and 5.8% faster than MSNN DC [13] for different EEG signal types. The reason for this performance improvement in use of wavelet compression, which assists in augmenting feature selection process. Due to this performance improvement, the proposed model is capable of being deployed for a large number of real-time clinical applications.

V. CONCLUSION AND FUTURE SCOPE

The proposed EEG classification model uses a combination of wavelet compression with spatial & spectral features to train a QNN classifier. Due to use of spatial features, the proposed model is capable of achieving better accuracy, while due to use of spectral features the model is able to achieve better precision & recall performance under different EEG datasets. It is observed that the proposed model is able to achieve an average accuracy of 96.5% on different EEG datasets, which is 4.5% higher than CSP [3], 3.9% higher than CNN XWT [8], and 6.8% higher than MSNN DC [13], thereby making it useful for a wide variety of clinical EEG classification applications. Furthermore, the proposed model is observed to achieve a precision of 90.2% & recall of 91.6%, which is 4% better than CSP [3], 5.2% better than CNN XWT [8], and 3.1% better than MSNN DC [13] for different EEG class types. Due to which, the proposed model is applicable for a wide variety of clinical EEG classification applications. Moreover, due to use of wavelet features, the proposed model is capable of achieving faster classification results when compared with state-of-the-art approaches. Thus, making the proposed model useful for high-speed and high-performance classification applications. In future, researchers can integrate deep learning models like convolutional Neural Networks (CNNs), recurrent NNs (RNNs), and Q-learning for further enhancing accuracy & precision performance of the model. Furthermore, researchers can add a greater number of EEG based brain disease classes, which will assist in improving applicability of the system for a wide number of clinical scenarios.

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