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QMWT: Design of an Improved EEG Classification Model via Q-Learning Based Processing of Multispectral Wave Traits

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Abstract

Electroencephalogram (EEG) signals represent various wave patterns that assist in identification of normal & abnormal brain activities. These wave patterns consist of alpha waves, which indicate relaxation phases, beta waves, that indicate normal brain rhythms & can be disturbed due to cortical & other damages, delta waves, which are dominant in infants during sleep, & theta waves, which represent irregular metabolic & hydrocephalus activities in adults. A combination of these waves is capable of representing multiple brain conditions for both adolescents & adults. Various models have been proposed by researchers to analyze these signals, and most of them work on single or bi-domain features, which limits their classification performance. Most of these models are also static, and do not incorporate continuous feedback & incremental processes. Due to which their precision & recall performance is either constant or reduces w.r.t. newer evaluations. To overcome these limitations, this text proposes design of a novel EEG classification model that uses Q-Learning for classification of multispectral feature sets. The model extracts Mel Frequency Cepstral Coefficients (MFCC), and iVector features from raw EEG data, which assists in multispectral representation of these signals. The extracted features are classified via Q-Learning based Recurrent Neural Network (RNN) classifier, that combines Gated Recurrent Unit (GRU), and Long-Short-Term Memory (LSTM) based feature sets. Due to extraction of MFCC, the GRU & LSTM Models are able to identify power spectral variation, cepstral variations, spectrogram patterns, DCT (Discrete Cosine Transform) variations, etc. While, due to iVector, entropy variations are recognized and processed for better accuracy levels. Thus, both LSTM & GRU Models assist in augmenting extracted features, which improves feature variance for better classification performance. Results of these classifications are feedback into the training set via a correlation-based analysis layer, that assists in continuously improving precision & recall performance for different evaluations. Due to incorporation of this layer, the model is capable of improving precision by 8.5%, recall by 8.3%, and accuracy by 4.9% when compared with various state-of-the-art models. It was also observed that this performance incrementally improves w.r.t. number of evaluations, which assists in deploying the model for real-time applications.

Keywords: EEG, iVector, MFCC, Q-Learning, LSTM, GRU, RNN, Incremental, Continuous.

1. Introduction

Designing EEG classification models is a multidomain task involving data pre-processing, filtering, segmentation, feature extraction, feature selection, classification, and post-processing. The components of a typical EEG classification model [1] are depicted in figure 1: denoising, continuous wavelet transform (CWT) with statistical feature extraction, principal component analysis (PCA), data normalization, and Support Vector Machine (SVM) for classification. These models function by extracting single-domain or bi-domain feature sets from input EEG signals, thereby limiting their feature representation and classification capabilities. Other models that utilize multidomain features lack continuous learning mechanisms, limiting their classification performance in real-time. For improved EEG classification performance, it is therefore recommended that multidomain features and incremental learning be incorporated for different use cases.

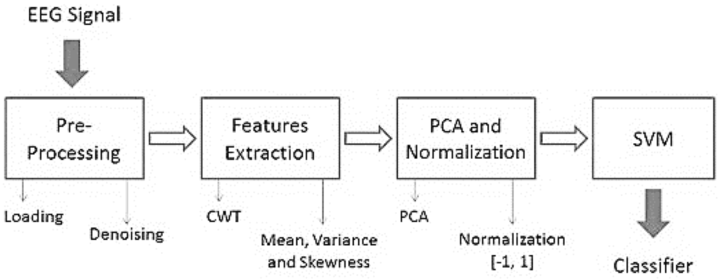

Figure 1. A typical EEG classification model

Researchers propose various models for performing these tasks. The following section discusses a brief overview of these models [2, 3, 4] along with their context-specific nuances, application-specific benefits, function limitations, and suggested future scopes. On the basis of this discussion, it was determined that the performance of existing models decreases relative to the number of EEG disease types. This constrains the scalability of these models, thereby reducing their real-time deployment capabilities. Section 3 discusses the design of a novel EEG classification model using Q-Learning-based processing of Multispectral Wave Traits to circumvent this limitation. The model employs a combination of MFCC and iVector for feature extraction and LSTM and GRU for feature augmentation process integration. The classification of augmented features via a combination of Q Learning-based RNN models improves precision and recall under multiple EEG disease types. In section 4, this performance is evaluated and compared to various state-of-the-art methods. This text concludes with some context-specific observations about the proposed model, as well as recommendations for improving its performance in clinical and real-time scenarios using advanced processing techniques.

2. Literature Review

Models that classify EEG signals employ a variety of Machine Learning Methods (MLMs) with varying internal operating and performance characteristics. Support Vector Neural Network (SVNN) and semi-skipping Layered Gated Unit (SLGU), which facilitate the extraction of highly dense feature sets for efficient classification applications, are proposed in [5, 6]. However, the complexity of these models restricts their application to small and medium-sized scenarios. To enhance this performance, [7] proposes the use of Sensor Spatial Configuration, which optimizes sensing devices for improved feature representation across classes. The model processes data at the source level, reducing complexity and improving classification performance. Extensions to this model are discussed in [8, 9, 10], which propose the use of Multiscale High-Density Convolutional Neural Network (MHD CNN), Sparse Spectro-Temporal Decomposition Model (SSDM) with CNN, and linear classification techniques, which aid in identifying class-specific patterns for various EEG types. Multiple scenarios are applicable to these models, but they cannot be scaled to larger class sets. To enhance this performance, [11, 12, 13] propose the use of high duration EEG samples, a Channel-Fused Dense Convolutional Network (CFD CNN), and interval type-2 fuzzy sets, which aid in separating input datasets into class-level features that can be classified using fully connected neural network structures.

Researchers have also proposed models employing Continuous wavelet transform (CWT) [14], hierarchical discriminative sparse representation classification model [15], Graph Signal Processing (GSP) [16], task-related common spatial patterns (TCSP) [17], and Deep Shared Multi-Scale Inception Network (DSMSIN) [18], which aid in enhancing feature variance levels. This is accomplished by estimating low-complexity Eigen operators, which can be applied to multispectral datasets containing multiple internal classes. Expansions of these methods are discussed in [19, 20], which proposes the use of Sliding Singular Spectrum in conjunction with independent component analysis and linear classification in order to address complexity issues with existing classifiers. Work in [21, 22, 23] proposes the use of spatiotemporal-filtering-based channel selection (STECS) and hierarchical neural networks (HNN) that perform feature-level augmentation for improved classification performance with real-time clinical inputs. Similar models are discussed in [24, 25], which propose the use of Tensor-Based Recovery and bionic Whale Optimization Models (WOM) for the design of low-error, high-accuracy classifiers that are applicable to a variety of use cases. However, the single or bi-domain characteristics of these models limit their performance when tested against large datasets. Continuous feedback and incremental learning processes are missing from the majority of these models. In comparison to more modern techniques, their precision and recall performance are either stable or declining due to these issues. In order to circumvent these limitations, the following section proposes the creation of a novel classification model based on Q-Learning that can manage multispectral feature sets. Additionally, the model was evaluated based on various clinical metrics and compared to existing models to validate its performance in various clinical scenarios.

Proposed improved EEG classification model via Q-Learning based processing of Multispectral Wave Traits

According to the literature review, it can be seen that current models for classifying EEG data only use single or bi-domain characteristics, which restricts how well they perform when tested against big datasets. The majority of these models lack continuous feedback and incremental procedures and are static as well.

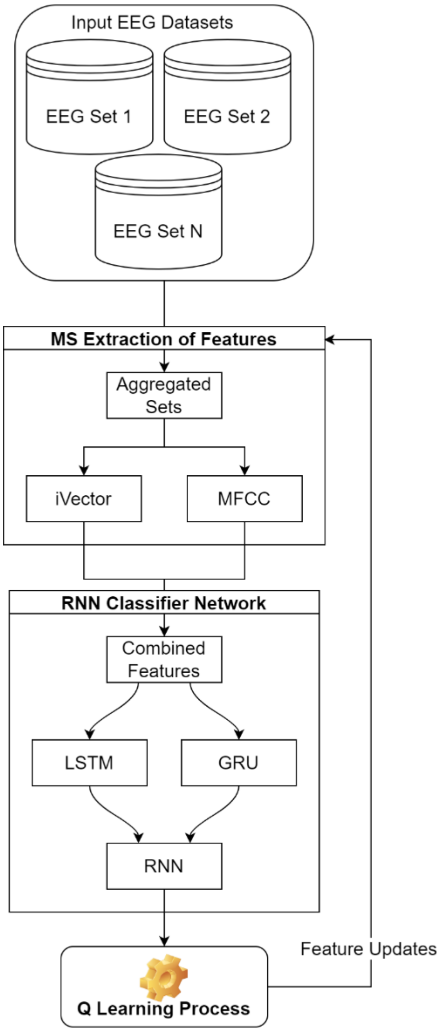

Figure 2. Overall flow of the Q-Learning based classification process

These problems cause their precision & recall performance to be either stable or to decline in relation to more recent evaluations. This section suggests creating a novel Q-Learning-based classification model that can handle multispectral feature sets in order to get over these constraints. The model's workflow is shown in Figure 2, where it can be seen that it extracts iVector features and Mel Frequency Cepstral Coefficients (MFCC) from the raw EEG data to help describe these signals in multispectral domains. Gated Recurrent Unit (GRU) and Long-Short-Term Memory (LSTM) based feature sets are combined in a Q-Learning based Recurrent Neural Network (RNN) classifier to classify the extracted features. The GRU & LSTM Models can recognize power spectrum variation, cepstral variation, spectrogram patterns, DCT (Discrete Cosine Transform) variations, etc. thanks to the extraction of MFCC. While entropy variations are identified and processed for greater accuracy levels due to iVector. In order to increase feature variance and classification performance, both LSTM and GRU Models help to augment extracted features.

As observed from figure 2, the model initially extracts MFCC & iVector feature vectors, which assists in efficient representation of EEG signals. The MFCC feature vectors are evaluated via equation 1 as follows,

$$MFCC_i = \sum_{m=1}^{M} \log[T_a(m)] * \cos\left[i * \left(m - \frac{1}{2}\right) * \frac{pi}{M}\right] \dots (1)$$

Where, T_a represents a triangular filter function, and is evaluated via equation 2, while M represents number of MFCCs extracted during the process.

$$T_a = \sum_{i=0}^{N-1} \left[Norm_{a_i}\right]^2 * \left|\frac{i - f(h-1)}{f(h) - f(h-1)}\right|_{h \in (-1,1)} \dots (2)$$

Where, f represents frequency of input signals, while $Norm_a$ is the normalized input signal, that is evaluated via equation 3,

$$Norm_a = \frac{\left(C_a - \sum_{i=1}^{M} \frac{C_{a_i}}{M}\right) * (M-1)}{\sqrt{\sum_{j=1}^{M} \left(C_{a_j} - \sum_{i=1}^{M} \frac{C_{a_i}}{M}\right)^2}} \dots (3)$$

Where, C_a represents Mel Frequency Cepstrum, and is evaluated via equation 4,

$$C_a = ifft\left[\log\left(fft\left[4 * f_s * log_{10}\left(1 + \frac{Q_a}{f_s}\right)\right]\right)\right] \dots (4)$$

Where, Q_a represents quantized input signal, and is evaluated directly from EEG signals via equation 5,

$$Q_a = \frac{EEG - \min(EEG)}{\max(EEG) - \min(EEG)} \dots (5)$$

These MFCC vectors are combined with iVector features which are evaluated via equation 6,

$$iVector_i = MAX\left(\bigcup_{j=1}^{M} EEG_j\right) + \begin{bmatrix} (1,1)_{var} & \cdots & (1,n)_{var} \\ \vdots & \ddots & \vdots \\ (n,1)_{var} & \cdots & (n,n)_{var} \end{bmatrix} * EEG_i \dots (6)$$

Where, $M \, and \, EEG$ represents number of MFCCs, and raw EEG input signal, while $(x,y)_{var}$ represents relative variance levels, which are estimated via equation 7 as follows,

$$(x,y)_{var} = \frac{\exp\left(\frac{x^2}{2}\right)}{2 * pi * var(x) * var(y)} \ldots (7)$$

While, $var(x)$ indicates variance of input signal, and is evaluated via equation 8 as follows,

$$var(x) = \frac{1}{M-1} * \sum_{i=1}^{M} \left(x_i - \sum_{j=1}^{N} \frac{x_j}{M} \right)^2 \ldots (8)$$

These feature vectors are further augmented via use of a hybrid LSTM & GRU based feature processing model, which is depicted in figure 3, and uses a combination of different feature sets.

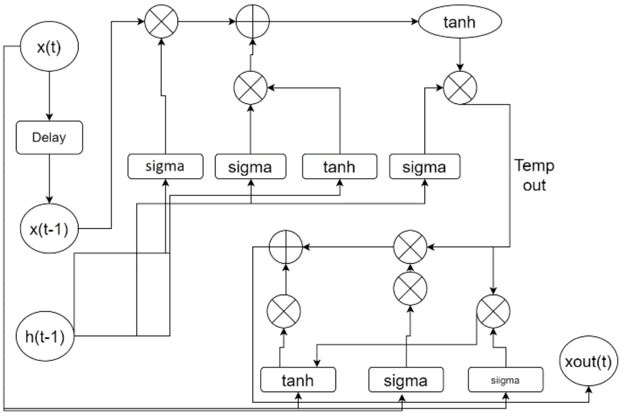

Figure 3. Fused LSTM & GRU Model for Augmentation of MFCC & iVector features

The model processes combined MFCC & iVectors x, and uses internal kernel inputs h, for generation of an augmented feature vector $xout$, that can be used for high-efficiency classification process. A delayed version of these input features and underlying kernel function are combined for performing these tasks. The model generates an initialization & functional feature vector via equations 9, and 10 as follows,

$$i = var\left(x_{in} * U^i + h_{t-1} * W^i\right) \ldots (9)$$

$$f = var(x_{in} * U^f + h_{t-1} * W^f) \ldots (10)$$

These vectors along with the output feature vector evaluated via equation 11, is used to generate an initial convolutional vector via equation 12 as follows,

$$o = var(x_{in} * U^o + h_{t-1} * W^o) \ldots (11)$$

$$C_t' = tanh(x_{in} * U^g + h_{t-1} * W^g) \ldots (12)$$

Using these features, a temporary output feature vector & an output kernel feature vector is evaluated via equation 13 & 14,

$$T_{out} = var(f_t * x_{in}(t-1) + i * C_t') \dots (13)$$

$$h_{out} = \tanh(T_{out}) * o \dots (14)$$

In these equations, U, W represents cosntants used by LSTM, and are tuned via RNN using a hyperparameter tuning process. Outputs of this model are processed via a GRU based feature augmentation process, that works via equations 15, 16, 17 & 18 as follows,

$$z = var(W_z * [h_{out} * \ T_{out}]) \dots (15)$$

$$r = var(W_r * [h_{out} * \ T_{out}]) \dots (16)$$

$$h_t' = tanh(W * [r * h_{out} * \ T_{out}]) \dots (17)$$

$$xout = (1 - z) * h_t' + z * h_{out} \dots (18)$$

Where, W represents GRU constants, which are tuned similar to constants of LSTM via hyperparameter tuning process. The combined features are classified via a Recurrent Neural Network (RNN), that uses purely linear activation function, and a series of feature-specific weights that are continuously optimized via a Q-Learning based optimization process. The output class is evaluated by the model via equation 19 as follows,

$$C_{out} = purelin\left(\sum_{i=1}^{N} xout_i * W_i\right) \dots (19)$$

Where, W_i represents a feature specific weight that is evaluated via Q-Learning for accuracy optimization purposes. This weight is estimated on a per-feature level, and is termed as ‘Q-Learning Reward’ level, which is evaluated via equation 20,

$$W_i = \frac{Var(New) - Var(Old)}{L_r} - r * Max\big(Var(New)\big) + Var(Old) \dots (20)$$

Where, $Var(New)$ & $Var(Old)$ represents new & old values of variance, that were estimated via modifying internal feature vectors, while L_r & r represents learning rate & discount factors, that are decided by Q-Learning designers for optimum accuracy performance. This performance was evaluated in terms of accuracy, precision & recall measures, and compared with other models in the next section of this text, where it was evaluated for different EEG datasets under multiple disease types.

Result evaluation & comparison

The proposed model uses a combination of MFCC & iVector for multispectral feature analysis, which was followed by an augmentation model that uses LSTM & GRU for efficient representation of these extracted feature sets. Resulting features were classified via use of a Recurrent Neural Network (RNN) model, which was continuously tuned via Q-Learning based optimization process. The model was evaluated in terms of accuracy (A), precision (P), recall (R), and delay (D) performance, and compared with MHD CNN [8], CFD CNN [8], and DSM SIN [18], which will assist in validation of its performance under different use cases. These use cases were taken from SEED Dataset (https://bcmi.sjtu.edu.cn/~seed/seed.html), BCI Challenge Dataset (https://www.kaggle.com/c/inria-bci-challenge), and University of Leicester EEG Dataset https://le.ac.uk/engineering/research/), which are available with Open-Source licenses. These datasets were combined to form a total of 300k EEG records, which were segregated into 70:30 split, where 210k records were used to train the model, while 90k records were used to test & validate the model under different use cases.

Based on the representation in figure 4, it can be observed that the proposed model showcased 2.5% better accuracy than MHD CNN [8], 1.9% better accuracy than CFD CNN [8], and 4.5% better accuracy than DSM SIN [18], under multiple EEG classification scenarios. The reason for this accuracy enhancement is use of high-efficiency feature representation models, that assist in continuous performance optimization with minimum overheads.

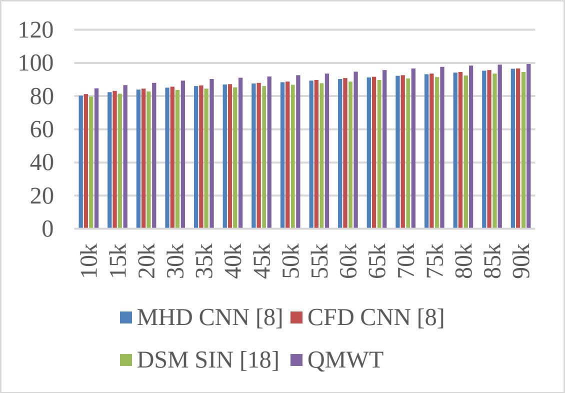

Figure 4. Classification accuracy for different models under different test case scenarios

Based on the representation in figure 5, it can be observed that the proposed model showcased 3.9% better precision than MHD CNN [8], 4.5% better precision than CFD CNN [8], and 3.5% better precision than DSM SIN [18], under multiple EEG classification scenarios. The reason for this precision enhancement is use of high-efficiency feature representation models along with Q-Learning & RNN, that assist in continuous performance optimization with minimum overheads.

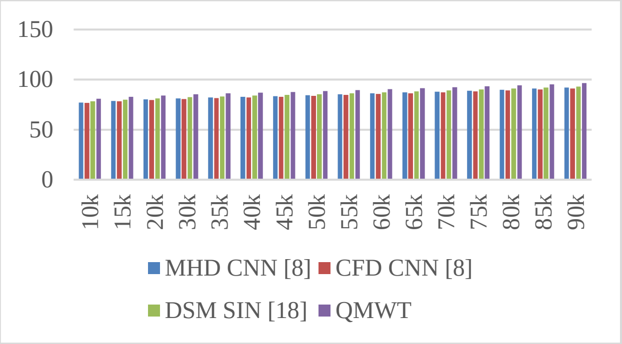

Figure 5. Precision of different EEG classification models

Based on representation in figure 6, it can be observed that the proposed model showcased 4.5% better recall than MHD CNN [8], 4.9% better recall than CFD CNN [8], and 4.8% better recall than DSM SIN [18], under multiple EEG classification scenarios. The reason for this recall enhancement is use of LSTM & GRU models along with Q-Learning & RNN, that assist in continuous performance optimization with minimum overheads.

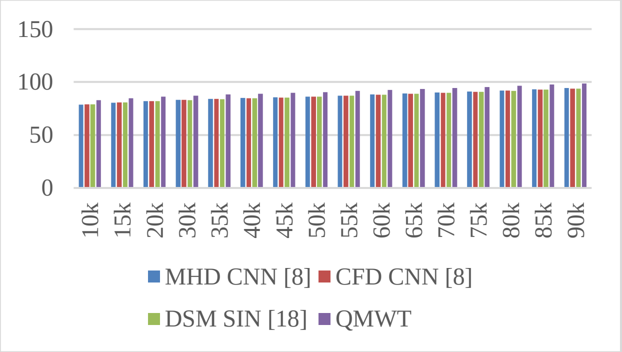

Figure 6. Recall of different EEG classification models

Based on representation in figure 7, it can be observed that the proposed model showcased 5% faster performance than MHD CNN [8], CFD CNN [8], and DSM SIN [18], under multiple EEG classification scenarios. The reason for this speed enhancement is use of simplistic feature extraction models, that assist in continuous performance optimization with minimum overheads.

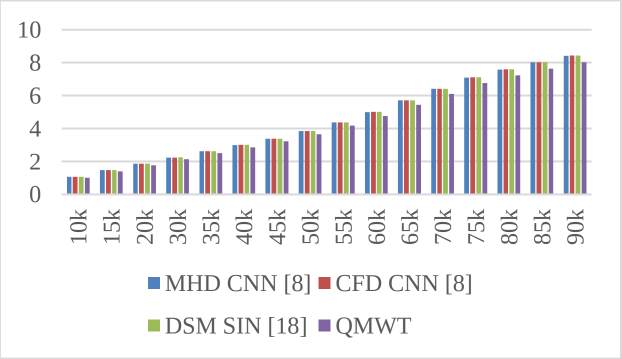

Figure 7. Delay of different EEG classification models

Due to these performance enhancements, the proposed model is capable of high accuracy, better precision, good recall, and better speed classifications when compared with other models. Thus, the proposed model is useful for real-time clinical applications, that require better performance for multiple EEG disease types with multisource signals under clinical scenarios.

Conclusion

The proposed model processes raw EEG signals, and converts them into multispectral features via use of MFCC & iVector feature sets. These feature sets are augmented via use of GRU & LSTM Models that assist in convolutional operations for improving feature variance levels under different use cases. The augmented features are classified via use of RNN Models, and Q-Learning based optimizations, that allow the model to process & categorize signals that represents multiple EEG classes. As a result of this combination, the proposed model is capable of achieving 2.5% better accuracy than MHD CNN [8], 1.9% better accuracy than CFD CNN [8], and 4.5% better accuracy than DSM SIN [18], while it also showcased 3.9% better precision than MHD CNN [8], 4.5% better precision than CFD CNN [8], and 3.5% better precision than DSM SIN [18], in terms of recall it was capable of achieving 4.5% better recall than MHD CNN [8], 4.9% better recall than CFD CNN [8], and 4.8% better recall than DSM SIN [18] under different datasets & classes. The model was also capable of delivering 5% faster performance than MHD CNN [8], CFD CNN [8], and DSM SIN [18], under multiple EEG classification scenarios, which is due to use of LSTM & GRU models along with Q-Learning & RNN, that assist in continuous performance optimization with minimum overheads.

Future Scope

In future, the proposed model must be validated on larger datasets, and can be enhanced via use of Convolutional Neural Networks (CNNs), Masked Recurrent NN (MRNN), and other Machine Learning Models (MLMs), which can assist in performing high-density feature extraction operations. Moreover, researchers can also fuse multiple bioinspired models, which will further improve classification performance under real-time clinical use cases.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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