ISSN 2063-5346

GSAMEN: DESIGN OF A GWO MODEL TO SELECTIVELY AUGMENT MULTIPLE LEAD EEG SIGNALS FOR PREDICTION OF NEUROLOGICAL DISEASES

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Article History: Received: 01.05.2022 **Revised:** 10.05.2022 **Accepted:** 19.05.2022

Abstract

Identification of Neurological diseases requires efficient analysis of multiple parameters that include clinical readings, electroencephalogram (EEG) signals, Computer Tomography (CT) scans, etc. To perform these tasks, researchers have proposed use of different machine learning models that can perform feature extraction, augmentation, selection, classification & post processing operations. EEG signals are observed to have better neurological disease classification performance then other features. But existing models that perform EEG classifications are either highly complex, or showcase limited accuracy performance due to the density of features presented by EEG signals. To overcome this limitation, a novel Grey Wolf Optimization (GWO) Model to Selectively Augment Multiple lead EEG signals for prediction of Neurological diseases is discussed in this text. These disorders include Epilepsy, Seizures, Amyotrophic Lateral Sclerosis, Alzheimer's Disease, Dementia, and Parkinson's Disease, which are commonly observed in most patients. The proposed model initially uses a combination of multiple lead EEGs, and extracts Mel Frequency Cepstral Components (MFCCs) from these signals. These MFCC values are given to a GWO based classifier parameter selection model, that uses a combination of Naïve Bayes (NB), 1D CNN, and SVM based classifiers. These classifiers are combined to form a novel ensemble deep learning classification model, that is capable of high-accuracy, and low-error classification operations. The GWO Model defines a novel fitness metric that combines accuracy, precision, and recall values, which assists in improving classifier parameter selection efficiency. Performance of this model was compared with various state-of-the-art models, and it was observed that the proposed model showcases 5.4% better accuracy, 3.5% better recall, and 4.5% better precision, which makes it useful for clinical deployments.

Keywords: EEG, Neurological, Diseases, Augmentation, Features, MFCC, CNN, SVM, NB, GWO, Selection, Features

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DOI: 10.31838/ecb/2023.12.6.305

Introduction

Classifying EEG signals for identification of different neurological diseases requires development of multiple models that can pre-process, filter noise, extract useful segments, optimize feature representation, deploy classifiers, and augments their responses via post-processing operations. Such models are multidomain in nature, and require validation on large-scale datasets. A typical model that can process EEG signals, and classify them into multiple neurological categories [1] can be observed from figure 1, wherein Discrete Wavelet Transform (DWT) along with sub-band relative entropies are evaluated for feature representation of raw EEG signals. These features are normalized via equation 1, where input signal and its maximum values are used as follows,

$$N_s(t) = \frac{S(t)}{Max\big(S(t)\big)} \dots (1)$$

Where, N_s & S represents normalized signal and original signal values, while $Max(S)$ represents it maximum amplitude levels. These features are classified via a set of linear & machine learning classification models, which assists in identification of different neurological conditions.

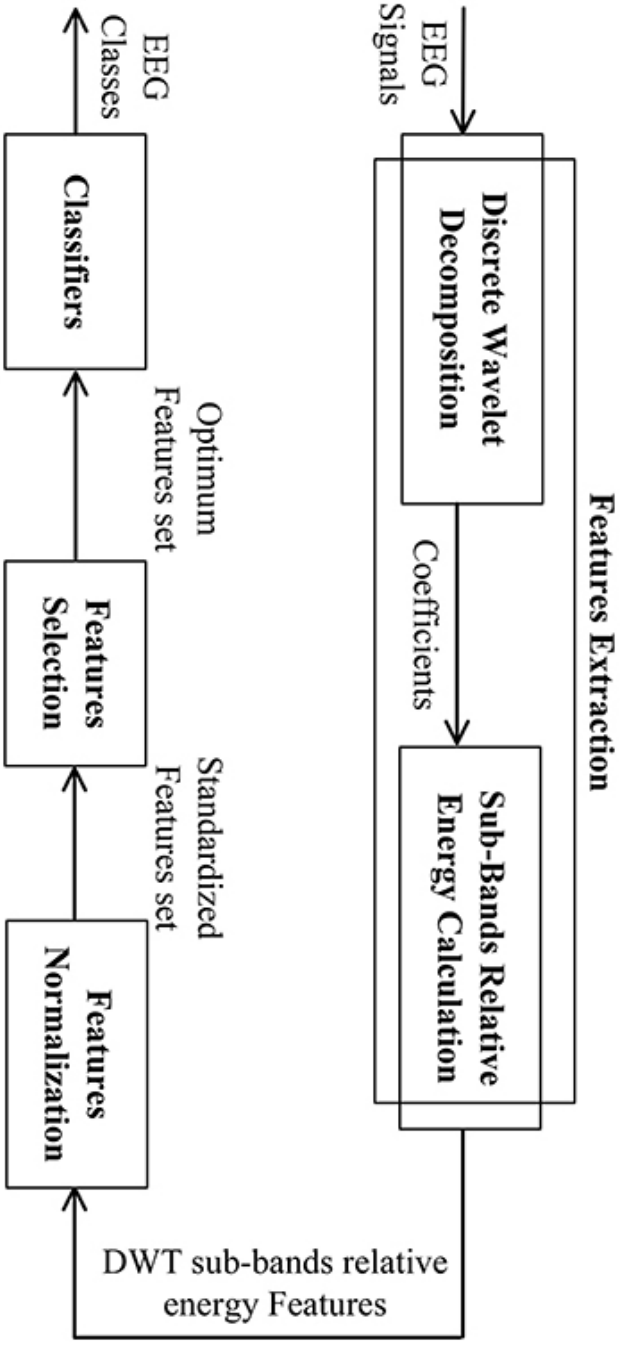

Figure 1. Design of a typical EEG classification model

Similar classification models [2, 3, 4] along with their contextual nuances, application-specific advantages, deployment-specific limitations, and functional future research scopes are discussed in the next section of this text. Based on this discussion it was observed that these models are either highly complex, or showcase limited accuracy performance due to low feature density levels. To overcome this issue, section 3 discusses design of a novel

Grey Wolf Optimization (GWO) Model that performs classifier parameter selection for multiple lead EEG signals. These signals are used to classify disorders including Epilepsy, Seizures, Amyotrophic Lateral Sclerosis, Alzheimer's Disease, Dementia, and Parkinson's Disease, which are commonly observed in most patients. The proposed model was evaluated in section 4, wherein its accuracy, precision, and recall performance was compared with different state-of-the-art methods. This study finishes with extensive observations on the proposed model and suggestions for enhancing its performance in a range of application scenarios.

1. Literature Review

Classifying EEG signals is a 1D signal processing task, thus large variety of models are proposed to categorize these signals into different categories. For instance, work in [5, 6] propose use of Support vector machine (SVM) with cross validations, and Deep Convolutional Neural Network (DCNN) that assist in efficient binary classification under different EEG datasets. But these models have lower scalability, which can be improved via use of Joint EEG-Development Inference (JEDI) [7] that combines multiple EEG sets, and classifies them via context-specific models. The JEDI Model serves as an interface towards improving classification performance for large scale sets. Based on this model, work in [8, 9, 10] proposes use of BioCNN, Network-Based Takagi-Sugeno-Kang (NB TSK), and Taylor-Fourier EEG-band energy (TFEBE) features with SVM, that assists in identification of large-scale EEG feature sets for efficient classification performance. But these models have higher complexity, thus cannot be used for high-speed applications. To overcome this limitation, work in [11, 12, 13] propose use of Synchronization Patterns, one-dimensional convolutional variational autoencoder (1D CVAE), and Model Agnostic Meta-Learning (MAML), which assists in reducing feature complexity under multiple disease types. These models showcase higher accuracy, and lower delay, thus can be applied for real time application scenarios.

Models that use Long Short-Term Memory (LSTM) [14], channel selection with CNN [15], Fourier transform (DFT) with Adaptive Chirp Mode Decomposition (ACMD) [16], multi-view Takagi-Sugeno-Kang Fuzzy CNN (MV-TSK-FCNN) [17], Resource-Efficient Oblique Trees [18], and Power Spectral Density Difference (PSDD) [19] are also discussed by researchers for high-efficiency operations. These models aim at improving feature density levels via estimation of highly variant feature sets under large-scale classification scenarios. These models are further extended in [20, 21, 22] via use of Decision Tree (DT), SVMs, and Fourier-Bessel series expansion domain empirical wavelet transform (FBSE-EWT) filters that are used with sparse autoencoder based support vector machine (SAE-SVM), for low complexity and high efficiency classification operations. These models transform input EEG signals and extract dense feature sets in order to optimize it real-time performance. Similar models are proposed in [23, 24, 25, 26], wherein Recurrent Neural Networks (RNN), Deep Convolutional LSTM (DC-LSTM), Parkinson's disease CNN (PDCNNet), and Multiple Output Gaussian process (MOGP) that enables better feature extraction & selection capabilities under multiple EEG datasets. But these models are either highly complex, or are capable of achieving limited accuracy performance for multiple neurological disorders. This is due to the density of features presented by EEG signals. To overcome these issues, next section proposes design of a novel Grey Wolf Optimization (GWO) Model that Selectively Augments Multiple lead EEG signals for prediction of Neurological diseases. The proposed model was also evaluated on multiple datasets, and compared with various state-of-the-art methods for real-time performance estimation under different scenarios.

2. Proposed GWO Model to Selectively Augment Multiple lead EEG signals for prediction of Neurological diseases

Based on the literature survey, it was observed that existing EEG classification models are either highly complex, or

are capable of achieving limited accuracy performance for multiple neurological disorders. This is due to the density of features presented by EEG signals.

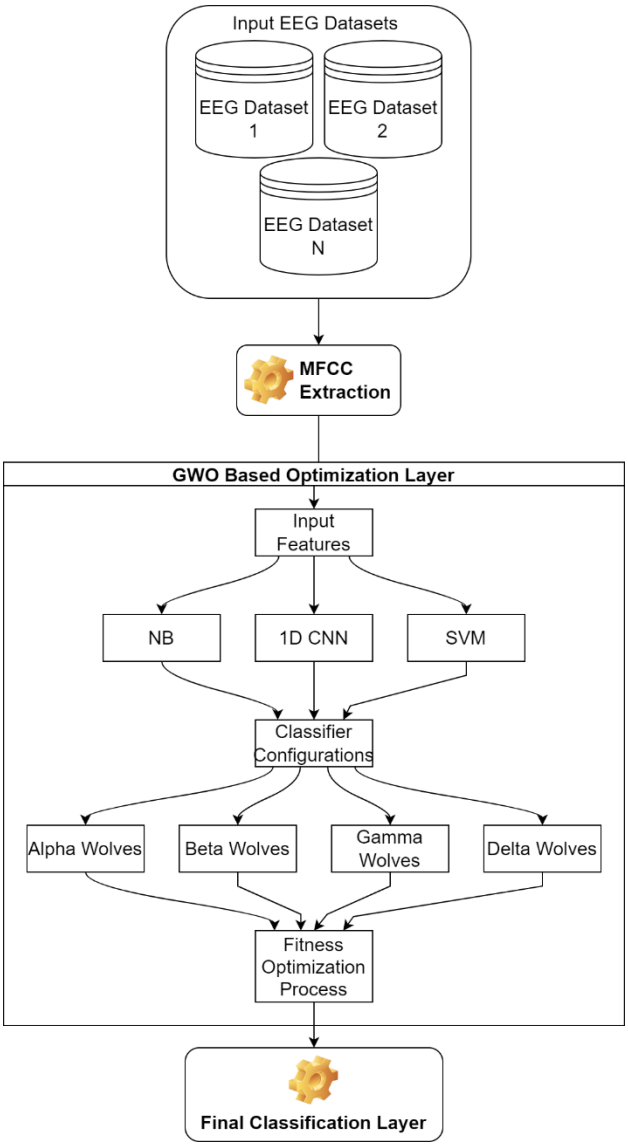

Figure 2. Overall flow of the proposed model

To overcome these issues, this section proposes design of a novel Grey Wolf Optimization (GWO) Model that Selectively Augments Multiple lead EEG signals for prediction of Neurological diseases. Flow of the proposed model is depicted in figure 2, wherein it can be observed that the model initially uses a combination of multiple lead EEGs, and extracts Mel Frequency Cepstral Components (MFCCs) from these signals. A GWO-based classifier parameter selection model that combines Naive Bayes (NB), 1D CNN, and SVM-based classifiers is activated via these MFCC values. A unique ensemble deep learning classification model that can perform high-accuracy and low-error classification tasks is created by combining several classifiers. In order to increase the effectiveness of classifier parameter selection, the GWO Model provides a unique fitness measure that combines accuracy, precision, and recall values under different use cases.

The proposed model initially processes all EEG signals via MFCC feature extraction techniques, which assists in identification of cepstral components. These components are evaluated via equation 2, where normalized form of input EEG signals are used for multispectral analysis.

$$MFCC_i = \sum_{m=1}^{N} log\ log \left[\sum_{i=0}^{N-1} [N_{s_i}]^2 * \left| \frac{i - f(h-1)}{f(h) - f(h-1)} \right|_{h \in (-1,1)} \right] * cos\ cos \left[i * \left(m - \frac{1}{2} \right) * \frac{pi}{N} \right] \quad \ldots (2)$$

Where, N_s represents normalized EEG signal while f represents frequency components of filter banks, and M represents number of MFCCs extracted by the model via augmentation process. These MFCCs are processed via a combination of different classification models, which are controlled by the GWO Model, that works via the following process,

- Setup the GWO Model via initialization of following parameters,
  - Total quantity of wolves used during optimization phase (N_w)
  - Maximum iterations that can be used to obtain the optimized solution sets (N_i)
  - Rate at which the wolves learn (L_r)
  - Minimum & Maximum values of Smoothing factor for Naïve Bayes (Min_{SF}, Max_{SF})
  - Minimum & Maximum values for error tolerance for SVM (Min_e, Max_e)

- Minimum & Maximum values for CNN Hyperparameters (Min_h, Max_h)

- Before iterating the model, setup all wolves to be 'Delta Wolves'
- Go to each iteration, and scan all wolves via the following process,
  - Check if wolf is not marked as 'Delta Wolf', then skip it and go to the next wolf in sequence
  - Else, generate new wolf configuration via equation 3, 4, and 5 as follows,

$$NB(SF) = STOCH(Min_{SF}, Max_{SF}) \dots (3)$$

$$SVM(E) = STOCH(Min_e, Max_e) \dots (4)$$

$$CNN(H_i) = STOCH\left(Min_{h_i}, Max_{h_i}\right) \dots (5)$$

Where, $STOCH$ represents a Markovian Stochastic process for generation of number sets, while $NB(SF), SVM(E), and\ CNN(H_i)$ represents smoothing factor value of NB, error tolerance for SVM, and i^{th} hyperparameter for CNN respectively.

  - Based on these parameters, MFCCs are classified into 1 of N neurological classes, and wolf fitness is evaluated via equation 5,

$$f_w = \frac{1}{N_s}\sum_{i=1}^{N_s} A(NB)_i + A(SVM)_i + A(CNN)_i + P(NB)_i + P(SVM)_i + P(CNN)_i + R(NB)_i + R(SVM)_i + R(CNN)_i \dots (5)$$

Where, A, P & R represents accuracy, precision, & recall levels for different classifiers.

  - This fitness is evaluated for different wolves, and at the end of each iteration, a fitness threshold is evaluated via equation 6,

$$f_{th} = \frac{L_w}{N_w} * \sum_{i=1}^{N_w} f_{w_i} \dots (6)$$

- At the end of every iteration, change marking of the wolf via the following process,
  - If $f_w > 2 * f_{th}$, then mark it as 'Alpha Wolf'
  - Else, if $f_w > f_{th}$, then mark it as 'Beta Wolf'
  - Else, if $f_w < 2 * f_{th}$, then mark it as 'Delta Wolf'
  - Else, mark the wolf as 'Gamma Wolf'
- Repeat this process for all iterations, and identify 'Alpha Wolves' each of the iterations

At the end of final iteration, select 'Alpha Wolf', and use its classifier configurations to classify input EEG signals into multiple neurological classes. Performance of this model was evaluated on multiple datasets, and compared with different state-of-the-art methods in the next section of this text.

3. Result & Comparison

The EEG classification model uses a combination of MFCC with GWO for estimation of classifier configurations to estimate different neurological classes. The model was evaluated in terms of classification accuracy (A), precision of classification (P), classification recall (R), and classification delay (D) performance levels. The model was compared with 1D CVAE [12], MV TSK FCNN [17], and DC LSTM [25], which will assist in validation of its performance under different classification scenarios. These scenarios include Epilepsy, Seizures, Amyotrophic Lateral Sclerosis, Alzheimer's Disease, Dementia, and Parkinson's Diseases, which were taken from TU (https://isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml), UCI (https://archive.ics.uci.edu/ml/datasets/eeg+database), & Google Toolbox (https://ieee-dataport.org/documents/eeg-signal-dataset), which were combined to form a large set of EEG signals. A total of 100k EEG records were aggregated, out of which 60% were used for training while other 40% were used for testing & validation purposes. Based on this strategy, classification accuracy (A) was evaluated and tabulated w.r.t. Testing & Validation EEGs (TVE) in table 1 as follows,

TVE (1000s records)	**A (%) 1D CVAE [12]**	**A (%) MV TSK FCNN [17]**	**A (%) DC LSTM [25]**	**A (%) QMWT**
8	80.81	81.59	79.94	85.03
12	82.36	82.99	81.24	86.52
16	83.62	84.12	82.29	87.73
24	84.62	85.03	83.14	88.70
28	85.44	85.79	83.88	89.51

32	86.15	86.54	84.63	90.29
36	86.92	87.38	85.48	91.15
40	87.84	88.32	86.40	92.13
44	88.81	89.28	87.33	93.13
48	89.76	90.21	88.23	94.10
52	90.66	91.11	89.10	95.04
56	91.62	92.05	90.01	95.94
60	92.66	93.03	90.96	96.73
64	93.77	94.07	91.95	97.35
68	94.79	95.04	92.89	98.26
72	95.76	95.99	93.79	99.29

Table 1. Comparison of accuracy for different models

Based on the evaluation in table 1, figure 3, it can be observed that the proposed model is capable of achieving 3.5% higher accuracy than 1D CVAE [12], 3.2% higher accuracy than MV TSK FCNN [17], and 5.5% higher accuracy than DC LSTM [25], under different neurological classification scenarios. The reason for this enhancement is use of GWO with ensemble classification process.

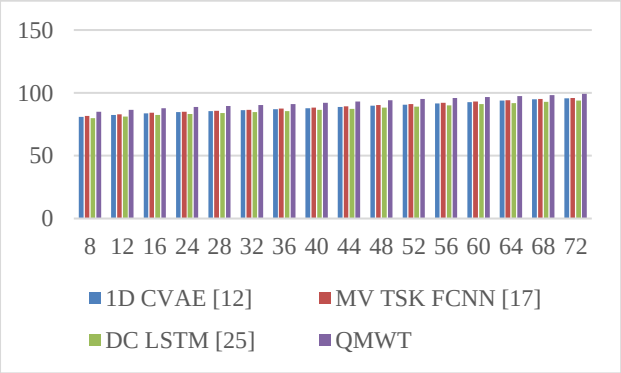

Figure 3. Comparison of accuracy for different models

Similar performance was evaluated for precision levels, and can be observed from table 2 as follows,

TVE	**P (%) 1D CVAE [12]**	**P (%) MV TSK FCNN [17]**	**P (%) DC LSTM [25]**	**P (%) QMWT**
8	77.33	76.92	78.55	81.18
12	78.74	78.21	79.89	82.63
16	79.88	79.24	80.96	83.80
24	80.79	80.08	81.83	84.74
28	81.54	80.80	82.57	85.53
32	82.24	81.51	83.30	86.26
36	83.00	82.31	84.11	87.08
40	83.89	83.20	85.01	88.01
44	84.80	84.10	85.93	88.96
48	85.70	84.97	86.82	89.90
52	86.56	85.82	87.69	90.80
56	87.46	86.70	88.59	91.74
60	88.42	87.62	89.54	92.75
64	89.45	88.59	90.54	93.81
68	90.40	89.50	91.47	94.80
72	91.31	90.37	92.37	95.75

Table 2. Comparison of precision for different models

Based on the evaluation in table 2, figure 4, it can be observed that the proposed model is capable of achieving 2.5% higher precision than 1D CVAE [12], 4.5% higher precision than MV TSK FCNN [17], and 3.5% higher precision than DC LSTM [25], under different neurological classification scenarios. The reason for this enhancement is use of continuous parameter optimization based on GWO with ensemble classification process.

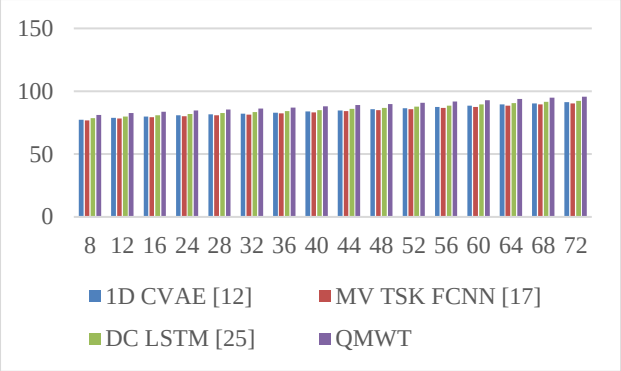

Figure 4. Comparison of precision for different models

Similar performance was evaluated for recall levels, and can be observed from table 3 as follows,

TVE	R (%) 1D CVAE [12]	R (%) MV TSK FCNN [17]	R (%) DC LSTM [25]	R (%) QMWT
8	79.07	79.25	79.24	83.10
12	80.55	80.59	80.56	84.57
16	81.74	81.68	81.62	85.76
24	82.70	82.56	82.48	86.72
28	83.49	83.30	83.23	87.52
32	84.20	84.03	83.96	88.28
36	84.96	84.85	84.79	89.11
40	85.87	85.77	85.71	90.07
44	86.80	86.70	86.63	91.05
48	87.73	87.59	87.53	92.00
52	88.61	88.46	88.40	92.92
56	89.54	89.37	89.30	93.89
60	90.53	90.32	90.25	94.91
64	91.60	91.33	91.25	95.99
68	92.59	92.27	92.18	97.00
72	93.53	93.18	93.08	97.97

Table 3. Comparison of recall for different models

Based on the evaluation in table 3, figure 5, it can be observed that the proposed model is capable of achieving 2.5% higher precision than 1D CVAE [12], 4.5% higher precision than MV TSK FCNN [17], and 3.5% higher precision than DC LSTM [25], under different neurological classification scenarios. The reason for this enhancement is use of continuous parameter optimization based on GWO with ensemble classification process.

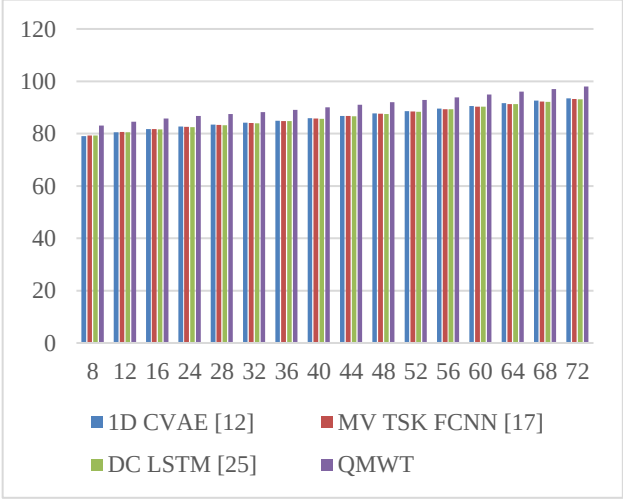

Figure 5. Comparison of recall for different models

Similar performance was evaluated for computational delay levels, and can be observed from table 4 as follows,

TVE	D (ms) 1D CVAE [12]	D (ms) MV TSK FCNN [17]	D (ms) DC LSTM [25]	D (ms) QMWT
8	1.44	1.44	1.44	1.37
12	1.83	1.83	1.83	1.74
16	2.20	2.21	2.21	2.10
24	2.58	2.58	2.59	2.46

28	2.95	2.96	2.96	2.81
32	3.35	3.35	3.36	3.19
36	3.80	3.80	3.81	3.62
40	4.33	4.34	4.34	4.12
44	4.95	4.95	4.95	4.71
48	5.61	5.62	5.62	5.35
52	6.30	6.31	6.31	6.00
56	6.91	6.93	6.93	6.59
60	7.44	7.46	7.46	7.09
64	7.87	7.89	7.89	7.50
68	8.29	8.30	8.30	7.90
72	8.73	8.75	8.74	8.32

Table 4. Comparison of delay for different models

Based on the evaluation in table 4, figure 6, it can be observed that the proposed model is capable of achieving 4.5% lower delay than 1D CVAE [12], 4.3% lower delay than MV TSK FCNN [17], and 4.5% lower delay than DC LSTM [25], under different neurological classification scenarios. The reason for this enhancement is use of continuous parameter optimization based on GWO with ensemble classification process.

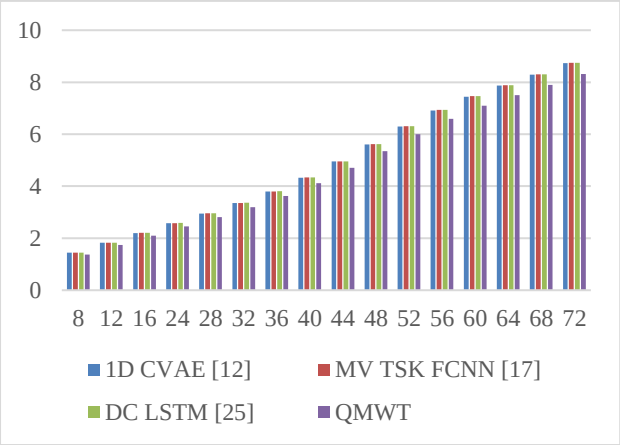

Figure 7. Comparison of delay for different models

Due to these optimizations, the proposed model is capable of low-error, high-speed, high precision, and better recall performance, which makes it useful for a wide variety of clinical applications.

4. Conclusion & future scope

The proposed model initially extracts a large set of MFCC features, which are classified via use of a parameter tuning GWO model for different neurological diseases. The proposed model uses a combination of Naïve Bayes, 1D CNN, and Support Vector Machines (SVMs) in order to optimize its internal classification performance. This performance was evaluated for Epilepsy, Seizures, Amyotrophic Lateral Sclerosis, Alzheimer's Disease, Dementia, and Parkinson's Disease types. Based on this evaluation, it was observed that the proposed model is capable of achieving 3.5% higher accuracy than 1D CVAE [12], 3.2% higher accuracy than MV TSK FCNN [17], and 5.5% higher accuracy than DC LSTM [25], it was also observed that the proposed model showcased 2.5% higher precision than 1D CVAE [12], 4.5% higher precision than MV TSK FCNN [17], and 3.5% higher precision than DC LSTM [25], under different neurological classification scenarios. The reason for this enhancement is use of continuous parameter optimization based on GWO with ensemble classification process. Similar performance was observed for recall & delay measures, which makes the model highly scalable for a wide variety of real-time applications. In future, the model must be validated for other large-scale datasets, and can be extended via use of multiple bioinspired computing models via parameter fusion process. Moreover, the model's performance can also be improved via integration of multiple deep learning models, that will assist in high-density feature extraction & classification under different use cases.

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