ISSN 2063-5346

A HIGHLY EFFICIENT Q-LEARNING MODEL FOR NEUROLOGICAL DISEASE CLASSIFICATION

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Article History: Received: 02.07.2022 Revised: 15.07.2022 Accepted: 23.07.2022

ABSTRACT:

Classification of neurological diseases is a multidomain task, which involves parametric data collection, pre-processing, segmentation, feature extraction, feature selection, classification, and post processing. These tasks require highly efficient algorithms for an effective clinical system design. Due to saturation in data acquisition accuracy, initial steps of data collection, pre-processing, and segmentation are highly efficient, and have standard clinical operating performance. Most of the work in neurological disease classification is focussed on feature extraction, selection, classification & post processing, which is the directional area of this research. Electroencephalogram (EEG) is one of the most frequently used sensing devices for neurological classification, but its accuracy is limited by the number of leads used during data collection. In order to improve the accuracy of classification with limited number of EEG leads, this text proposes a Q-learning model that works on a reward mechanism. The proposed model is capable of augmented feature extraction, and variance-based feature selection with high efficiency of classification for Cerebral Aneurysm, Bell's Palsy, Amyotrophic Lateral Sclerosis (ALS), Acute Spinal Cord Injury, Brain Tumour, and Alzheimer's Disease (ALD). The proposed model is compared with various state-of-the-art methods, and it is observed that it outperforms them in terms of accuracy, precision, recall, fMeasure, and AUC performance. Furthermore, the proposed model is also observed to be scalable to a wide variety of diseases due to use of a highly efficient convolutional neural network (CNN) model which is based on the standard VGGNet architecture. Performance evaluation of the proposed model showcases that is has 98% accuracy, 93% precision, 90%, recall, and an AUC of 0.96 which makes it applicable for real-time clinical usage.

Keywords: Q-learning, EEG, classification, neurological, Cerebral Aneurysm, ALS, Spinal Cord Injury, Brain Tumour, ALD.

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DOI:10.48047/ecb/2023.12.7.360

Introduction

Handling of EEG signals is a multi-layered task, which includes plan and execution of signal handling calculations. These calculations incorporate but are not restricted to acquisition, separating, division, highlight extraction, selection, grouping, characterization and post-handling [1]. To plan a powerful EEG handling framework, the plan of these calculations ought to be exceptionally precise, and the yield of one calculation should be processable by the fell square. A General-purpose EEG handling framework can be seen from figure 1, wherein every one of the blocks and their interdependencies can be seen. From the figure it very well may be seen that the information EEG signal goes through the accompanying interior cycles to recognize any neurological infections.

In the initial stage, the EEG signal goes through expulsion, separating, band extraction and post sifting tasks. EEG signs can be defiled with power line impedance, direct current (DC) offset commotion, and so forth These commotion types should be separated utilizing channels like moving normal, wiener channel, and so forth After sifting, some extra exception groups may be appended to the EEG signal, which can be taken out utilizing a blend of limited motivation reaction (FIR) and endless drive reaction (IIR) channels. The yield of this square ought to be a commotion free EEG signal with high pinnacle signal-to-noise ratio (PSNR) execution.

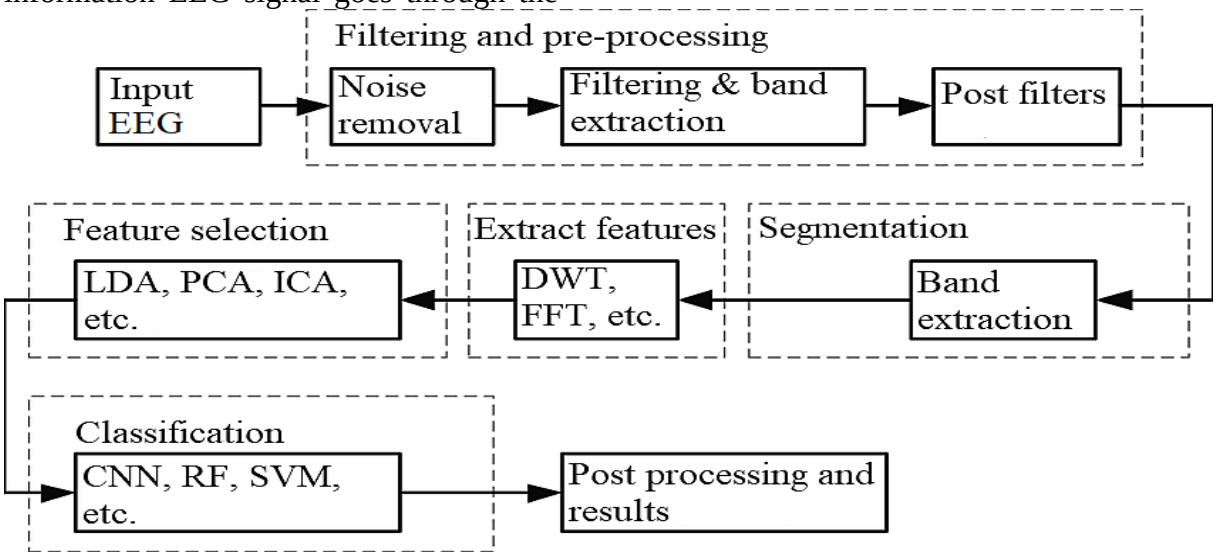

Figure 1. General-purpose EEG processing architecture

Once noise is taken out from the EEG signal, then, at that point, they are fragmented to get locales of interests. These locales of interest are assessed utilizing thresholding, windowing, and fix based handling strategies. Yield of this square ought to be diverse EEG waves that address interesting waveform shapes which can be utilized for powerful grouping. The fragmented locales are given to highlight extraction block, wherein highlights like discrete wavelet change highlights (DWT), quick Fourier change (FFT) highlights, and so forth are assessed. These provisions should have the option to depict the EEG waveform into mathematical parts with high proficiency, to such an extent that elements of same neurological sickness class are comparable, while elements of various neurological infection class are exceptionally variation from one another.

Element Selection: The separated provisions are given to an element determination block for eliminating excess or non-variation highlights from the set. These provisions are chosen utilizing calculations like autonomous part investigation (ICA), head part examination

(PCA), nearby discriminant examination (LDA), and so on The primary point of this square is to choose the elements separated by the component extraction block to get brief elements that are profoundly variation in nature. Utilization of this square enjoys 2-overlap benefits, which are decrease in characterization postponement, and improvement in arrangement precision. It is strongly prescribed to consolidate this square during EEG signal handling. Arrangement and Post handling: Selected components are sorted into neurological infections utilizing characterization calculations [2] like convolutional neural organizations (CNNs), repetitive neural organizations (RNNs), completely associated networks (FCNs), and so on The arrangement results are additionally broke down with the assistance of long-momentary memory (LSTM) and gated intermittent units (GRUs) to distinguish movement of the neurological sickness. The greater part of the examination in EEG signal handling is finished advancement of the characterization and post-handling blocks.

The following section portrays different calculations utilized for every one of these blocks, and assesses them based on execution and the sort of neurological sickness distinguished. This is trailed by a factual assessment of these calculations, and proposal of the Q-learning model which will help analysts researches to distinguish the best algorithmic blend for their given EEG handling application. At last, this text finishes up with certain fascinating perceptions about these calculations, and prescribes strategies to additionally work on their presentation.

1. Literature Review

A wide variety of algorithms are proposed for EEG classification, and each of them have a different area of application. For instance, the work in [1, 2, 3, 4] proposes fuzzy logic, Multiview convolutional neural networks (MVCNN), cross-day classification using transfer learning, and deep Gaussian Mixture hidden Markov model (DGMHMM) for classification of EEG signals. These models are observed to have high accuracy, and low delay for classification, and can be used for large scale EEG applications. Similarly, the models in [5, 6] use correlation EEG classification, and bidirectional gated recurrent unit (GRU) model for neurological disease detection. Both these models are showcased to have moderate levels of accuracy, with moderate delay, and thus are useful for medium scale EEG classification applications. The models discussed in [7] propose that deep learning with transfer learning can be used for effective EEG processing, and can be applied to a large variety of classification tasks. Moreover, the work proposed in [8, 9, 10, 11] aim at optimizing neurological disease classification via deep transfer learning, multilevel weighted feature fusion, imaging data for classification, and Hybrid Deep Feature Selection Method with effective CNN models for high speed and low complexity EEG classification.

Furthermore, deep transfer CNN models [12], sensor spatial configuration for EEG classification [13], Unified Novel Neural Network Approach [14], Bayesian Optimized Spectral Filters [15], and random forest [16] are proposed by researchers. These methods have good application specific performance, but lack in terms of large-scale EEG classification tasks. It is further recommended that these models must be combined for better classification performance, and can be used for solving complex stratification tasks. Based on this observation, a fused model that combines Q-learning with CNN is proposed in this text, and described in the next section.

2. Proposed highly efficient Q-learning model for neurological disease classification

The proposed Q-learning model collects EEG datasets from a large number of data

sources, and performs effective feature extraction & selection on them. The selected features are given to a Q-learning classification engine that utilizes CNN model for final disease detection. Thus, design of the proposed model is divided into 2 different parts, each of which are described in different sub-sections of this text. The proposed model is visualized using figure 2, wherein it is observed that after feature extraction & selection, a tagged database is created. This tagged database is used by the Q-learning model for final disease detection. Internal working of these blocks is described in different sub-sections of this text.

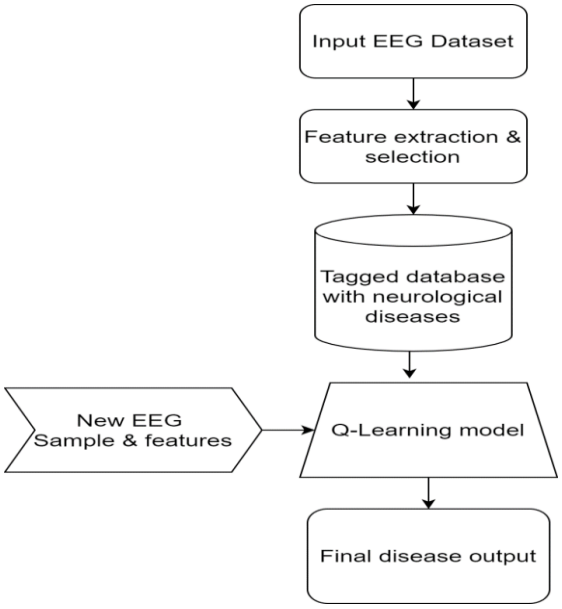

Figure 2. Block diagram of the proposed model

3.1. Feature extraction & selection using Genetic Algorithm

The input EEG data is given to a feature extraction module, wherein ensemble feature normalization is applied. In order to perform this task, a pool of discrete wavelet transform (DWT), discrete cosine transform (DCT), and discrete Fourier transform (DFT) features was evaluated. The Haar wavelet was used in order to estimate approximate entropy of EEG signals using equation 1,

$$DWT_i = \frac{EEG_i + EEG_{i+1}}{2} \ldots \quad (1)$$

While, DCT was evaluated using equation 2 as follows,

$$DCT_i = \frac{1}{\sqrt{2 * N}} * C_i * \sum_{j=1}^{N} EEG_i * \frac{cos\ cos\ (2 * j + 1)}{2 * N} \ldots \quad (2)$$

Where, C_i represents constant of DCT, and is estimated using equation 3,

$$C_i = \frac{1}{\sqrt{2}}, when\ EEG_i = 0, else\ 1 \ldots \quad (3)$$

Similarly, DFT is evaluated using equation 4,

$$DFT_i = \sum_{j=1}^{N-1} EEG_i * exp\ exp\ \left(-2 * \sqrt[2]{-1} * pi * j * \frac{n}{N}\right) \ldots \quad (4)$$

These features are combined using a singular feature vector, and the final feature vector is normalized using equation 5 as follows,

$$F_{norm_i} = \frac{F_i - (F)}{(F)\ - min\ (F)} \ldots \quad (5)$$

Where, F_i is the fused feature vector evaluated using equation 6, while F_{norm_i} is normalized feature vector in the range of 0 to 1, which allows the Q-learning model to estimate neurological diseases with good accuracy.

$$F_i = \cup\ \ DWT_i, DCT_i, DFT_i \ldots$$

Based on the normalized feature vector, a feature variance is evaluated using equation 7,

$$V_{avg}$$

$$= \sqrt{\frac{\sum_{a=1}^{m} \left(f_{norm_a} - \frac{\sum_{i=1}^{m} \sqrt{\frac{\sum_{j=1}^{n} \left(f_{norm_j} - \frac{\sum_{k=1}^{n} f_{norm_k}}{n}\right)^2}{n-1}}}{m}\right)^2}{m-1}} \ldots \quad (7)$$

Where, m, n represents features of one class, and features of other classes respectively. If the variance of any feature vector is lower than V_{avg} then that feature vector is discarded, while others are selected for final classification.

3.2. Classification using Q-learning

In order to classify the EEG samples using Q-learning, a reward function is evaluated. This reward function is represented using equation 8,

$$Q_{new} = Q_{old} + \partial * R + \emptyset * \left(Q_{old} - Q_{previous}\right) \ldots \quad (8)$$

Where, $Q_{new}, Q_{old}, \partial, R, \emptyset, and\ Q_{previous}$ represents new Q-value, old Q-value, learning rate, reward for current Q-value, discount rate, and all previous Q-values evaluated by the system. The initial Q-value is evaluated using equation 9, and represents difference between normalized input features, and the database features.

$$Q_{init} = F_{new} - F_{db} \ldots \quad (9)$$

The value of Q is evaluated until it is saturated for a given feature vector. Once saturated, then it is given to a standard VGGNet-16 architecture for classification. The VGGNet model is trained using normalized features, and evaluated using the saturated Q-learning features. Due to which, weighted classification is performed, and the model is able to obtain better recognition results. Architecture of the VGGNet-16 model is visualized in figure 3, wherein all the convolutional, max pooling, and dense layers are showcased. Based on this model, classification results were evaluated for multiple neurological diseases. The results of this classification can be observed from the next section of this text.

3. Result & Comparison

In order to evaluate the proposed model, the following datasets were used,

- EEG Lab List: https://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html
- Ming Wandering Dataset: https://drive.google.com/open?id=0B0LQHOLfcq-hMFlhOEFKUXFPTkE
- Psychophysics Dataset: ftp://www.sccn.ucsd.edu/pub/eeglab_data.set
- Temple University Dataset: https://www.isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml

All these sets were evaluated for [4], [6], [12], & the proposed model, and results for accuracy (A), precision (P), recall (R), and computational delay (D) were evaluated. Based on these results, it was observed that the proposed model outperforms the given models in terms of accuracy, precision, and recall, but requires larger delay when compared to some of these methods. Results for accuracy can be observed from table 1, wherein various EEG samples were used for evaluation, and Cerebral Aneurysm, Bell's Palsy, Amyotrophic Lateral Sclerosis (ALS), Acute Spinal Cord Injury, Brain Tumour, and Alzheimer's Disease (ALD) were classified.

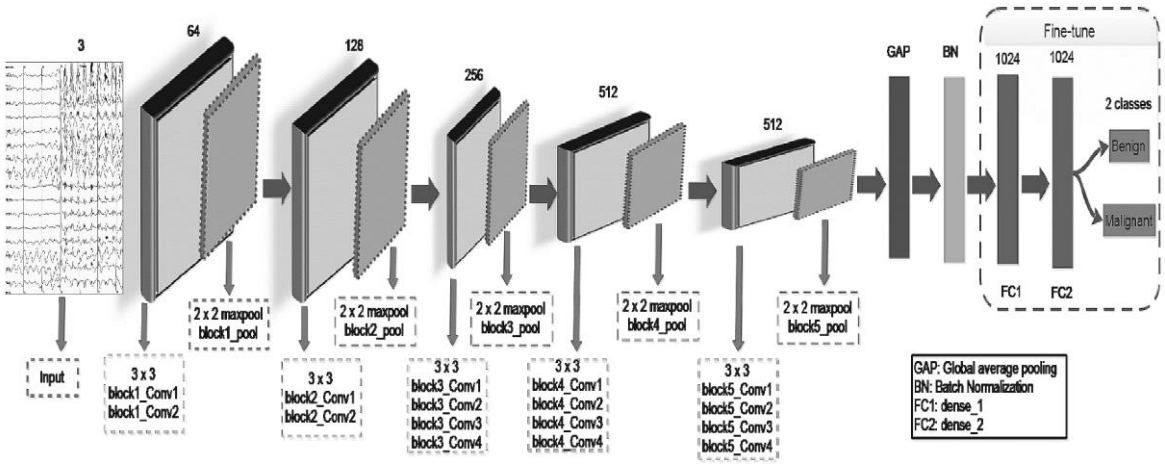

Figure 3. Architecture of the VGGNet-16 model

Table 1. Accuracy of different models

EEG Samples	**Acc. (%) [4]**	**Acc. (%) [6]**	**Acc. (%) [12]**	**Acc. (%) Proposed**
1000	86.50	75.60	83.13	90.83
2000	86.70	75.90	83.38	91.11
3000	88.20	76.30	84.36	92.17
4000	89.10	76.90	85.13	93.01
5000	89.30	77.30	85.44	93.35
8000	88.84	77.16	85.13	93.01
10000	89.31	77.48	85.53	93.45
12000	89.84	77.80	85.97	93.93
14000	90.17	78.10	86.29	94.28
16000	90.39	78.34	86.53	94.54
18000	90.61	78.56	86.75	94.78
20000	90.96	78.84	87.08	95.14
25000	91.30	79.11	87.39	95.48
30000	91.59	79.38	87.68	95.79
40000	91.88	79.63	87.96	96.10
50000	92.18	79.89	88.24	96.41
60000	92.50	80.16	88.54	96.74
70000	92.81	80.43	88.84	97.07
80000	93.11	80.70	89.13	97.39
90000	93.42	80.97	89.43	97.71
100000	93.73	81.24	89.73	98.04

From table 1 and figure 4, it is observed that the proposed model has at least 5% better accuracy than [4], 15% better accuracy than [6], and 8% better accuracy than [12] on different EEG sample sets. Similar performance was measured for precision, and can be observed from table 2 as follows,

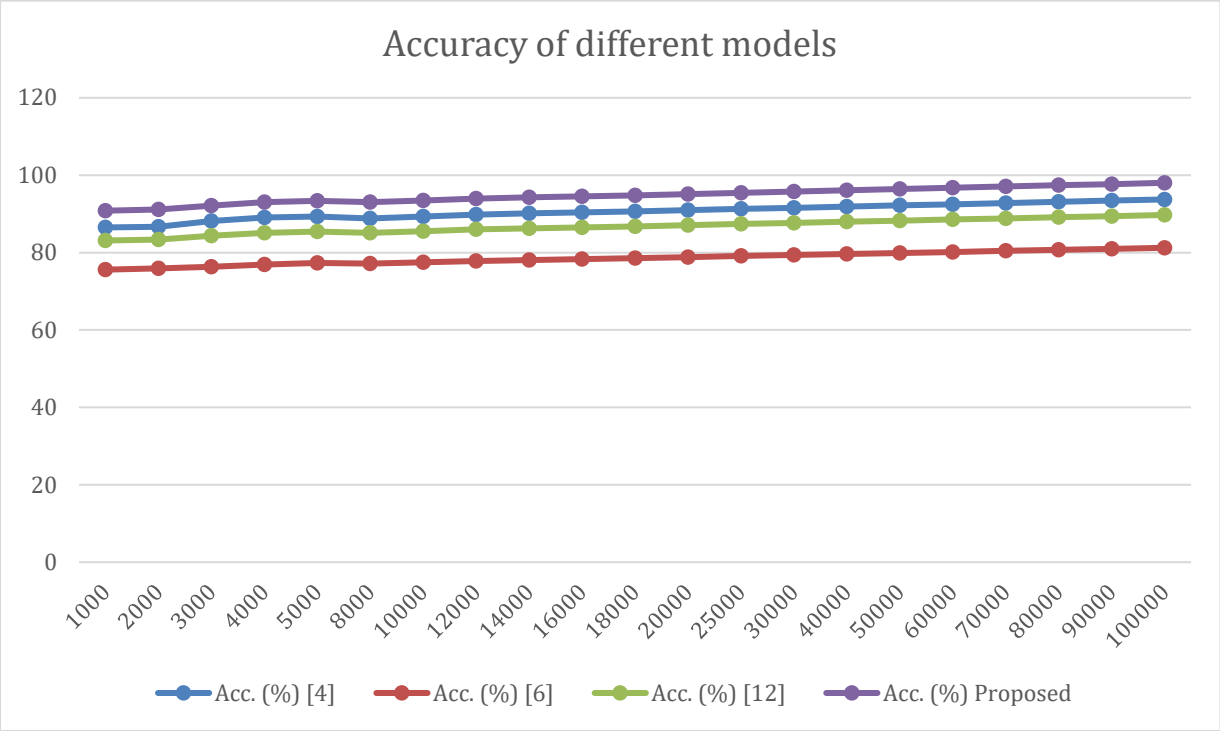

Figure 4 depicts accuracy of different models

Table 2. Precision of different models

EEG Samples	**Prec. (%) [4]**	**Prec. (%) [6]**	**Prec. (%) [12]**	**Prec. (%) Proposed**
1000	82.18	71.82	78.97	86.28
2000	82.37	72.11	79.22	86.55
3000	83.79	72.49	80.14	87.56
4000	84.65	73.06	80.87	88.36
5000	84.84	73.44	81.16	88.68
8000	84.40	73.31	80.87	88.36
10000	84.85	73.61	81.26	88.78
12000	85.35	73.91	81.67	89.23
14000	85.66	74.20	81.98	89.57
16000	85.87	74.43	82.20	89.81
18000	86.08	74.63	82.41	90.04
20000	86.42	74.89	82.72	90.38
25000	86.73	75.16	83.02	90.71
30000	87.01	75.41	83.29	91.00

40000	87.29	75.65	83.56	91.29
50000	87.57	75.90	83.83	91.59
60000	87.87	76.16	84.12	91.91
70000	88.17	76.41	84.40	92.21
80000	88.46	76.66	84.68	92.52
90000	88.75	76.92	84.96	92.82
100000	89.05	77.17	85.24	93.13

From table 2, it is observed that the proposed model has at least 4% better precision than [4], 14% better precision than [6], and 6% better precision than [12] on different EEG sample sets. Similar performance was measured for recall, and can be observed from table 3 as follows,

Table 3. Recall of different models

EEG Samples	**Rec. (%) [4]**	**Rec. (%) [6]**	**Rec. (%) [12]**	**Rec. (%) Proposed**
1000	84.34	73.71	81.05	88.55
2000	84.53	74.00	81.30	88.83
3000	86.00	74.39	82.25	89.87
4000	86.87	74.98	83.00	90.69
5000	87.07	75.37	83.30	91.01
8000	86.62	75.23	83.00	90.69
10000	87.08	75.54	83.40	91.12
12000	87.59	75.85	83.82	91.58
14000	87.92	76.15	84.14	91.93
16000	88.13	76.39	84.37	92.18
18000	88.34	76.59	84.58	92.41
20000	88.69	76.87	84.90	92.76
25000	89.02	77.13	85.20	93.09
30000	89.30	77.39	85.48	93.40
40000	89.58	77.64	85.76	93.70
50000	89.88	77.90	86.04	94.00
60000	90.19	78.16	86.33	94.32
70000	90.49	78.42	86.62	94.64
80000	90.79	78.68	86.91	94.95
90000	91.09	78.94	87.19	95.27
100000	91.39	79.20	87.48	95.58

From table 3, it is observed that the proposed model has at least 3% better recall than [4], 10% better recall than [6], and 4% better recall than [12] on different EEG sample sets. Similar performance was measured for average computational delay, and can be observed from table 4 as follows,

Table 4. Average computational delay for different models

EEG Samples	**Delay (s) [4]**	**Delay (s) [6]**	**Delay (s) [12]**	**Delay (s) Proposed**
1000	3.95	3.62	2.88	3.76
2000	3.94	3.60	2.87	3.75
3000	3.88	3.58	2.84	3.71
4000	3.84	3.56	2.81	3.68
5000	3.83	3.54	2.80	3.66
8000	3.85	3.54	2.81	3.68
10000	3.83	3.53	2.80	3.66
12000	3.81	3.52	2.78	3.64
14000	3.79	3.50	2.77	3.63
16000	3.78	3.49	2.77	3.62
18000	3.77	3.48	2.76	3.61
20000	3.76	3.47	2.75	3.59
25000	3.74	3.46	2.74	3.58
30000	3.73	3.45	2.73	3.57
40000	3.72	3.43	2.72	3.56
50000	3.71	3.42	2.71	3.55
60000	3.70	3.41	2.70	3.53
70000	3.68	3.40	2.69	3.52
80000	3.67	3.39	2.68	3.51
90000	3.66	3.38	2.68	3.50
100000	3.65	3.37	2.67	3.49

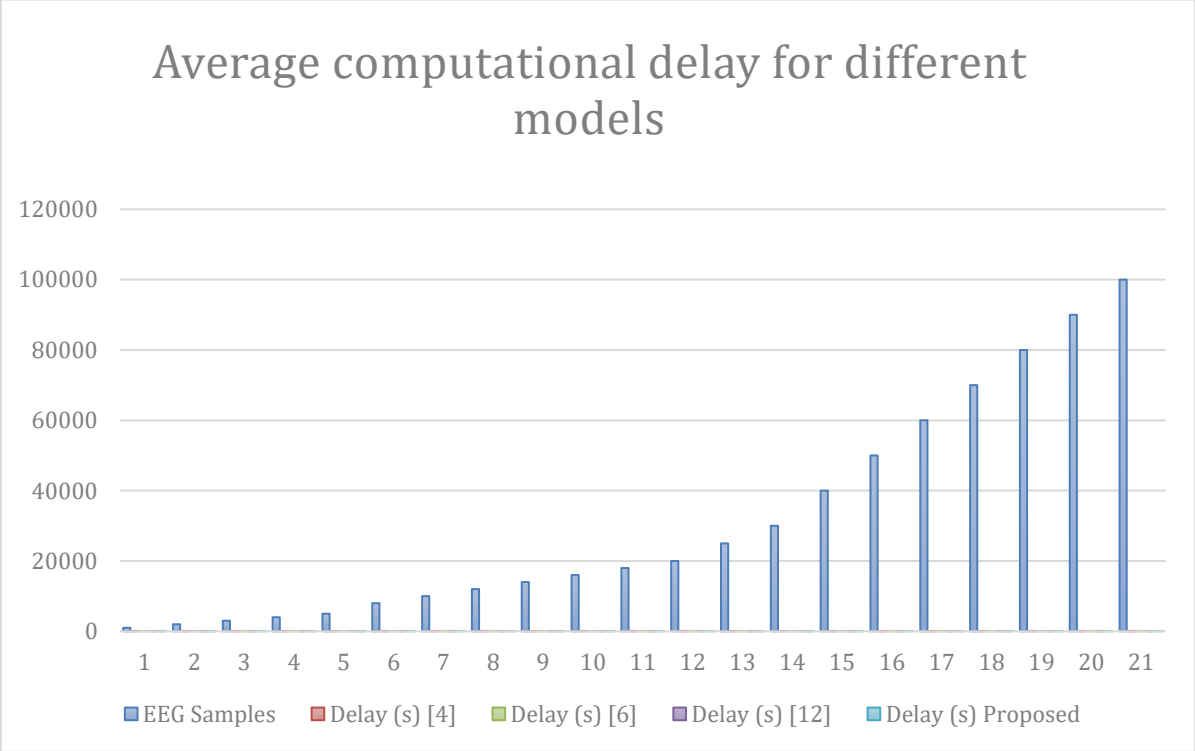

Figure 5 depicts Average computational delay for different models

From the delay comparison, it can be observed that the proposed model performs better than [4], and closely matches the delay performance of [6], while has higher delay than [12], thereby making it suitable for moderate to high-speed clinical applications.

4. Conclusion & future scope

From the result evaluation it is observed that the proposed model has 4% to 10% better accuracy than models proposed in [4], [6], and [12], while it has 3% to 8% better precision, and 3% to 6% better recall than these models. But the delay performance of the proposed model is only better than [4], while it is similar to [6], and the model has higher delay than [12], which makes it suitable for moderate to high-speed clinical deployments. Moreover, the model showcases 98% accuracy, which is higher than most the reviewed models, and has 93% precision & 95% recall, which makes it suitable for high precision neurological classification applications. The model's performance can be further improved via use of deep learning methods like recurrent neural networks (RNNs), and combination of long-short-term memory (LSTM) with gated recurrent unit (GRU) based models.

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