How to Cite:
Kala, S., Mishra, P. K., & Dubey, S. P. (2022). Design of an improved soft computing model for EEG classification using MFCC and quad classifier. *International Journal of Health Sciences*, *6*(S4), 9888–9903. https://doi.org/10.53730/ijhs.v6nS4.10819

Design of an improved soft computing model for EEG classification using MFCC and quad classifier

Shawetangi Kala
Rungta College of Engineering & Technology Bhilai, CG, India
Corresponding author email: shawetangikala@gmail.com

Dr. Pankaj Kumar Mishra
Rungta College of Engineering & Technology Bhilai, CG, India
Email: pankaj.mishra@rungta.ac.in

Dr. S. P. Dubey
Vice-Chancellor, The ICFAI University, Raipur, CG, India
Email: spdubeyfee@gmail.com

***Abstract*---**Electroencephalography (EEG) signals are a combination of complex pattern sequences,that are periodic in nature. These pattern sequences include a gamma waves that indicates deep thinking behaviour, a beta wave sequence that indicates busy and active mind status, an alpha wave segment which indicates reflective and restful behaviour, a theta wave which is an indicative of drowsiness, and a delta wave which indicates sleeping & dreaming conditions. Features like frequency changes, amplitude changes, pattern changes, etc. are used to identify chronic, ischemic and other diseases related to the brain. In order to classify these wave patterns into brain diseases like epilepsy, a series of high complexity signal processing operations are needed to be executed in tandem. These operations include signal pre-processing, feature extraction, feature selection, classification into epileptic & non-epileptic seizure and post-processing. A large variety of algorithms are developed by researchers for each of these operations. Performance of these algorithms varies largely w.r.t. the number of leads used for EEG capture, filtering efficiency, feature extraction & selection efficiency, and classifier efficiency. Thus, it becomes ambiguous for researchers and system designers to select the best possible algorithm set for their application. the proposed AMVAFEx model uses Multiple Neural Networks for definite EEG grouping. Because of which, the model is fit for accomplishing better exactness, higher accuracy, preferable review over different methodologies. This exhibition was tried on various EEG datasets

Manuscript submitted: 27 April 2022, Manuscript revised: 18 June 2022, Accepted for publication: 9 July 2022

for order of info waveforms into multiple epileptic kinds. The dataset comprises of 15 distinct EEG drives, which were utilized to gather information of 500 unique patients. For this assessment, all out 5000 unique sections wereseparated from this dataset, and were partitioned into 60:40 proportion for preparing and testing individually. Results were assessed regarding exactness, accuracy, review and deferral, and were contrasted for approval purposes.

***Keywords*---**design improved, soft computing model, EEG classification, MFCC, quad classifier.

Introduction

Electroencephalogram (EEG) signals address working of the cerebrum, and aid ID of various mind related messes including Epilepsy, Alzheimer's sickness, passionate states, Parkinson's infection, strokes, and so on. To configuration such models, a wide assortment of AI and profound learning approaches are proposed by analysts. However, these methodologies utilize a black-box nonexclusive model for EEG order, because of which their adaptability is restricted. To improve this adaptability, an original expanded highlight extraction model that consolidates Mel Frequency Cepstral Coefficients (MFCC) with iVector is proposed in this text. Because of this mix, the model is able to do low-deferral, and high exactness order for various mind illnesses. It assesses wavelet- based highlights from input EEG information, and performs troupe include choice for further developing component difference. The wavelet highlights can change over input EEG information into various directional parts, which helps with further developing effectiveness of component portrayal and model preparation for various sign sorts. The proposed model purposes a quadratic characterization motor, and is equipped for accomplishing an exactness of 96.5% for various EEG classes. These classes incorporate 3 kinds of Epilepsy, presence of Alzheimer's sickness, and assessment of mind strokes. Because of purpose of component fluctuation based arrangement, the proposed AFSMVA model outflanks existing element determination and characterization models by 4% with regards to exactness when found the middle value of over different datasets. In addition, the proposed model additionally further develops speed of order by 8.9% when contrasted and these models, subsequently making it valuable for rapid EEG handling applications. This exhibition improvement is conceivable because of successful component decrease, which aids ID of various EEG signal sorts. The model was tried on different EEG datasets including, IEEE Port Epileptic dataset, and BNCI dataset for Alzheimer and cerebrum strokes. It was seen that the proposed model was prepared to do superior execution arrangement on each dataset, accordingly demonstrating high-adaptability across different EEG applications. Proficient plan of EEG arrangement models includes plan of plan of sign sifting, district of interest (RoI) extraction, highlight portrayal, highlight determination, delineation and post-handling activities. A profoundly successful EEG order model requires plan of these models with low computational deferral, and high effectiveness of grouping. A common EEG arrangement model is pictured in figure 13, wherein transformation of EEG information into various feelings is portrayed. In this model, EEG information is caught from ongoing headsets, and pre-handled to diminish impact of clamor and other outside and inward unsettling influences. In the wake of sifting, different worldly highlights are removed from it, which incorporates rakish, spatial, and recurrence based include vector.

These highlights address time-space understandings of flow cerebrum state, and can be utilized for definition into various mind sickness or mind state classes.

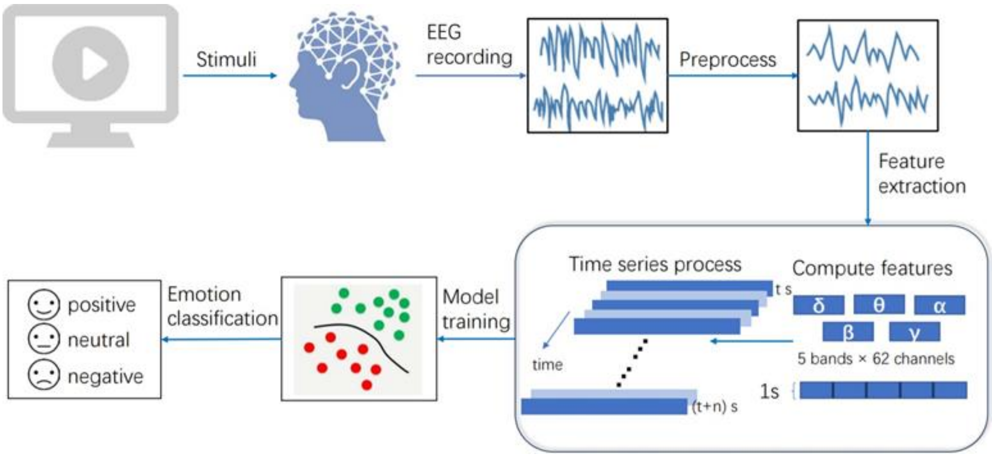

Figure 1. A general-purpose EEG classification model

In this framework, a help vector machine (SVM) model is utilized for order of removed highlights into various inclination types. These feelings can be used by outer frameworks for ID of client conduct, and consequently aid psychometric investigation. It very well may be seen that precision of these models is exceptionally subject to highlight extraction, include choice, and characterization blocks. Plan of these squares alongside execution attributes from different cutting edge characterization models is examined in the following segment of this text. In light of this conversation, it is seen that these methodologies utilize a black-box model or are extremely conventional, which restricts their adaptability regarding delay and precision execution. To work on this presentation, area 3 talks about plan of the proposed expanded include choice motor for EEG arrangement utilizing multivariate examination. Execution of this model is assessed in area 4, and is contrasted and different best in class draws near. At last, this text finishes up for certain intriguing perceptions about the proposed model, and prescribes techniques to additionally work onits exhibition.

Literature Review

A wide collection of EEG portrayal models is proposed by researchers all through the long haul, and all of them vary similar to congruity, exactness, survey, accuracy and concede execution. For instance, work in [2, 3, 4] analyzes plan of reduced direction set (RISC)- V convolutional Neural Network (CNN) Coprocessor, blend of direct discriminant examination (LDA), k Nearest Neighbor(KNN), support vector machine (SVM), and counterfeit brain organization (ANN) with ordinary spatial model (CSP), and Transfer TSK Fuzzy Classifier (TTFC) for achieving better portrayal results. These models have incredible precision, yet need terms of exactness execution due to their application-unequivocal portrayal characteristics. Developments to this model are discussed in [5, 6], wherein Neuroglial Network Model (NNM), and low-force trotted ultrasound energy (LIFUS) are used for multidomain EEG groupings. These models have extraordinary exactness, yet can't be scaled for a long while on account of high computational multifaceted design. To additionally foster flexibility, work in [7] proposes plan of Multiple repeat Multilayer Neural Network (MFMBN) that assists with achieving higher accuracy and favored versatility over as of late proposed models. Equivalent models that utilization CNN with cross wavelet change (XWT) [8], Local Binary Pattern Transition Histogram (LBP TH) [9], and Multivariate Scale Mixture Model (MSMM) [10] are proposed by researchers. These models utilize expanded component extraction techniques for additional growing for the most part portrayal execution during epilepsy disclosure.

Taking into account these component extraction models work in [11, 12, 13] propose mix 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 colossal degree incorporate extractions to address input EEG waveforms through various reaches for better gathering execution. However, these models display moderate precision execution, which can be improved through the work in [14, 15, 16], wherein moderate discriminative insufficient depiction classifier, time region progressive components request using long transient memory (LSTM) brain association, and Deep Convolutional Neural Network (DCNN) are inspected. These models help increment of EEG features to additionally foster request precision for different clinical applications. Equivalent models are discussed in [17, 18], wherein Extended K Nearest Neighbors, and Joint outwardly impeded source division systems are proposed by researchers for better adaptability execution. These models utilize low multifaceted nature feature extraction systems, yet can't be applied to gigantic extension EEG datasets. Thusly, it might be seen that models that have high precision are not pertinent for colossal degree game plans, while models that have high flexibility can't be used for significantly exact portrayal applications. To overcome these issues, next region proposes plan of wavelet pressure based quadratic model for EEG request using multivariate examination, that helps high-capability and high versatility EEG portrayal for different clinical circumstances.

Proposed Design of an Improved Soft Computing Model for EEG Classification

From the survey it tends to be seen that a wide assortment of AI models were proposed for EEG arrangement, and every one of these models are sent for a specific sort of cerebrum infection. Because of which their presentation for broadly useful arrangement is restricted, while models with higher adaptability execution have second rate accuracy, review, and exactness execution. To conquer this downside, an increased component extraction motor with quadratic classifier is proposed in this part, which can be applied for a wide assortment of order applications. By and large progression of the proposed model is portrayed in figure 14, wherein its inside working can be envisioned. It very well may be seen that input EEG signals are at first compacted by means of wavelet pressure, and afterward handled through MFCC and iVector based blocks. These squares aid extraction of multispectral highlights, which aid better portrayal of info signals. These elements are handled through a difference augmentation layer,that helps with accomplishing canny class- based include choices. The chose highlights are grouped utilizing a quadratic classifier, which is developed of Multiple Neural Networks, and helps with accomplishing last EEG delineation into various infection types.

From the model, it very well may be seen that input EEG waves are at first handled through a wavelet pressure block, which aids highlight decrease. Extraction of wavelet parts is assessed by means of condition 1 and 2 as follows,

$$EEG_{a_i} = \frac{x_i + x_{i+1}}{2} \dots (1)$$

$$EEG_{d_i} = \frac{x_i - x_{i+1}}{2} \dots (2)$$

Where, , and addresses rough EEG and detail EEG parts separated by the Haar wavelet change, while and addresses current EEG and next EEG test values extricated from the information EEG signals.

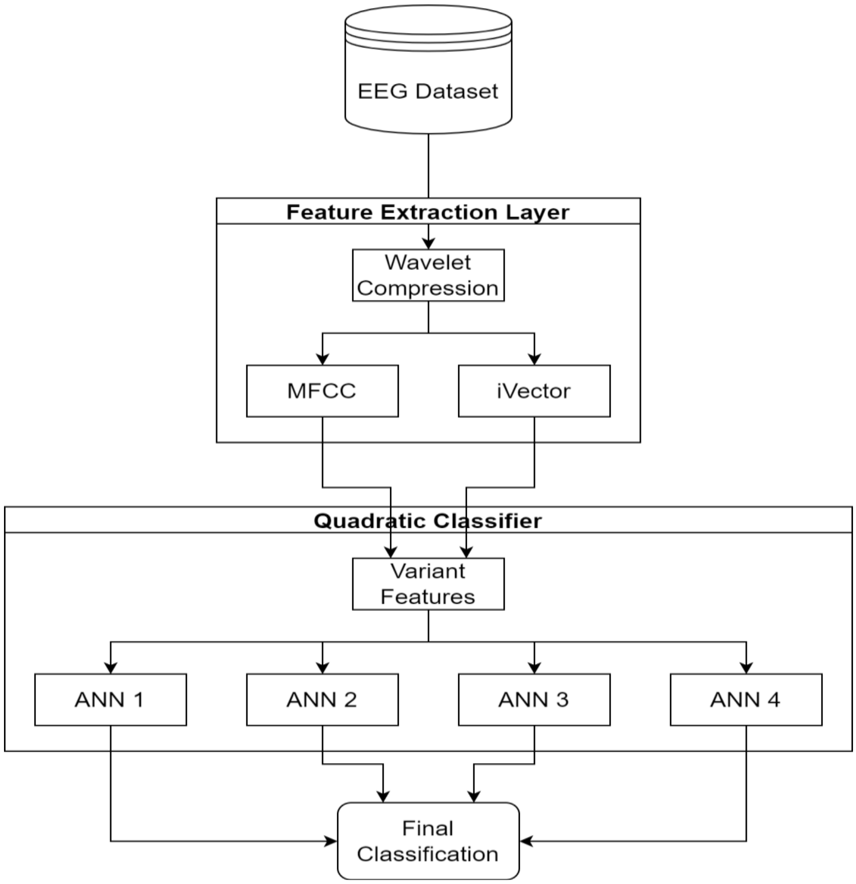

Figure 2. Overall flow of the proposed model

The detail part is disposed of, while estimated part is utilized for highlight extraction. The motivation behind this cycle is to decrease aspects of EEG signals, while holding its entropy state for various sign levels. These surmised parts lessen aspects of information EEG signal significantly, which aids quicker grouping, and better element portrayals. To address these parts into highlights, Mel Frequency Cepstral Coefficients (MFCCs) are separated, which aids recurrence space portrayal of information signals. To play out this undertaking, at first Fourier change of estimated parts is separated through condition 3,

$$F_{approx_i} = \sum_{j=0}^{N-1} EEG_{a_j} * \left[\cos\left(\frac{2 * pi * i * j}{N}\right) - \sqrt{-1} * \sin\left(\frac{2 * pi * i * j}{N}\right)\right] \dots (3)$$

Where, N addresses absolute number of removed examples, and $i \in (0, N-1)$. These coefficients are handled further to assess MFCC for ghostly examination through condition 4,

$$MFCC_l = \sum_{i=1}^{n} \log(S_i) * \cos\left(\frac{pi}{n} * l * (i - 0.5)\right) \dots (4)$$

Where, $l \in (1, n)$, n addresses absolute number of MFCC parts to be extricated, S addresses Mel power range coefficients, and are assessed through condition 5,

$$S_i = \frac{\sum_{j=1}^{N} F_{approx_j} * w_i}{N} \dots (5)$$

Here, i addresses MFCC part number, w_i addresses MFCC part's weight. This weight is chosen in light of recurrence and scale worth of each information signal and can be adjusted according to demonstrate necessities. A sum of 20 distinct MFCC parts were removed, and joined straightly to frame a MFCC highlight vector. This vector was joined with exceptionally productive iVector highlights. The iVectors were assessed through condition 6 as follows,

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

Where, N, F_{approx} addresses number of data sources, and Fourier change of that contribution, while $(x, y)_{var}$ addresses difference between Fourier parts x and y, which was assessed through condition 7 as follows,

$$(x, y)_{var} = \exp\left(\frac{x^2}{2}\right) * [2 * pi * var(y) * var(x)]^{-1} \dots (7)$$

Where, $var(x)$ is difference of info x, and is utilized for consistency approval between inputs. This fluctuation is assessed by means of condition 8,

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

In light of these personalities, input EEG signal is addressed into highlight vectors, which can be utilized for conclusive grouping and examination. Perception of MFCC and iVector parts can be seen in figure 3 (a), and 3 (b) separately, where a similar EEG signal was utilized for assessment of component vectors.

These elements are joined to frame a combined component vector, which contains different element redundancies. To decrease these redundancies, a novel between class fluctuation edge is assessed between these highlights. This change is assessed by means of condition 9, wherein between class data is used for assessment of definite difference.

$$V_{th} = \sqrt{\frac{\sum_{a=1}^{m}\left(FV_a - \frac{\sum_{i=1}^{m}\sqrt{\frac{\sum_{j=1}^{n}\left(FV_j - \frac{\sum_{k=1}^{n} FV_k}{n}\right)^2}{n-1}}}{m}\right)^2}{m-1}} \dots (9)$$

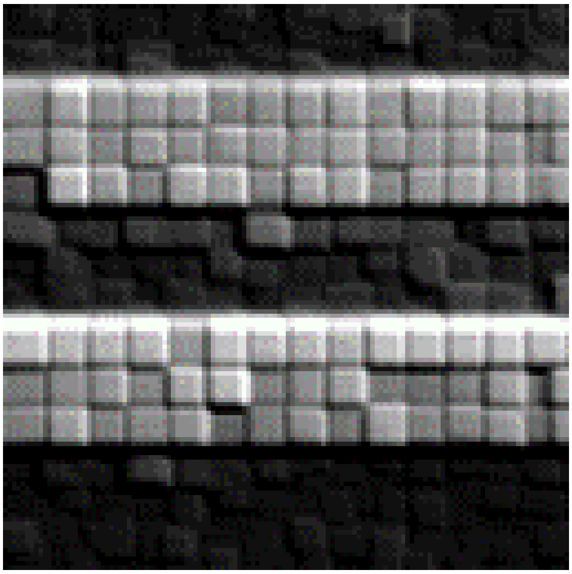

Fig. 3 (a) MFCC of EEG signal

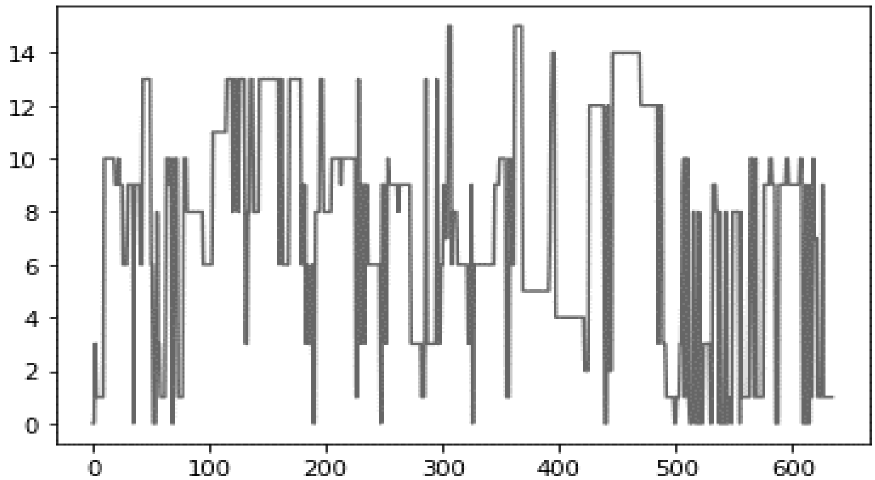

Fig. 3 (b) iVector of the same signal

Where, m addresses absolute number of elements in current class, n addresses complete number of highlights in different classes, FV addresses include vector an incentive for the given arrangement of elements. Highlights that have change lower than V_{th} are disposed of, while others are utilized for plan of Multiple Neural Network classifier. Change of elements is assessed by means of condition 10 as follows,

$$var(F) = \sum_{i=1}^{N} \frac{\left(F_i - \sum_{j=1}^{N} \frac{F_j}{N}\right)^2}{N-1} \dots (10)$$

Where, F and N addresses highlight vector worth, and complete number of elements present in the component vector individually. The highlights are given to the proposed classifier that involves a Quadratic Neural Network with expanding Neurons for proficient EEG order. In general progression of one NN model is portrayed in figure 16, wherein numerous layers are associated through neuron associations with produce different result classes.

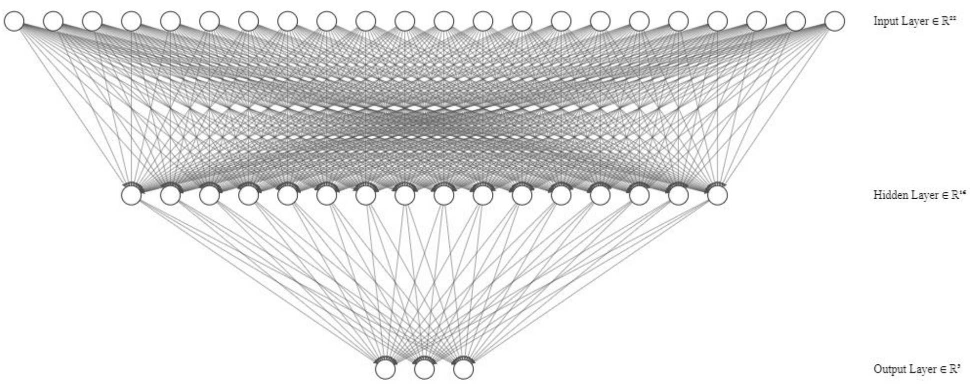

Figure 4. Overall flow of one NN model

Each NN model purposes exceptionally variation highlights for definite order. The consolidated QNN model purposes $n, 2*n, 3*n, \& 4*n$ number of Neurons in the last classifier plan. Here, n addresses complete number of elements extricated by means of difference-based determination. Result of each NN is controlled through condition 30, wherein include vectors, and their logarithmic reaches are utilized to deliver the result class.

$$C_{out} = -\frac{1}{2} * \sum_{j=1}^{N} (VBF_j - \sum_{l=1}^{N} VBF_l) * \left(VBF - \sum_{i=1}^{N} VBF_i\right)^T + \log\left(\sum_{i=1}^{N} VBF_i\right) \dots (11)$$

Where, $VBF, \& N$ addresses removed fluctuation-based elements, and number of Neural Network setups used to acquire the last order result. This order is finished every classifier, and the last class is assessed through condition 12, that involves a mode activity for collection of various classes.

$$C_{out}^{final} = \bigvee_{i=1}^{N} C_{out_i} \dots (12)$$

The mode activity chooses most often happening class from given set of result classes to acquire the last grouping result. Execution of this grouping system concerning accuracy, review, precision, and deferral is examined in the following part of this text.

Result Analysis and Comparison

It tends to be seen that the proposed AMVAFEx model uses Multiple Neural Networks for definite EEG grouping. Because of which, the model is fit for accomplishing better exactness, higher accuracy, preferable review over different methodologies. This exhibition was tried on various EEG datasets for order of info waveforms into Multiple epileptic kinds. These waveforms were separated from Neuromed Epilepsy EEG Database, which can be gotten to from https://clinicaltrials.gov/ct2/show/NCT04647825 by means of open-source authorizing for research and improvements purposes. The dataset comprises of 15 distinct EEG drives, which were utilized to gather information of 500 unique patients. For this assessment, all out 5000 unique sections were separated from this dataset, and were partitioned into 60:40 proportion for preparing and testing individually. Results were assessed regarding exactness, accuracy, review and deferral, and were contrasted and TTFC [4], NNM [5], and LBP TH [9] for approval purposes. The outcomes for exactness can be seen from table 1 as follows,

This presentation was accomplished because of mix of MFCC and iVector highlights, and utilization of Multiple Neural Networks for profoundly proficient characterization process. Also, accuracy execution of these models is classified in table2 as follows, In light of this assessment and figure 17, it was seen that the proposed model has 5.2% more exact than TTFC [4], 4.3% more precision than NNM [5], and 6.75% more exactness than LBP TH [9] for various kinds of EEG signals.

In light of this assessment and figure 18, it very well may be seen that the proposed model is 3.8% exact than TTFC [4], 4.95% exact than NNM [5], and 2.9% exact than LBP TH [9] for various EEG signal sorts.

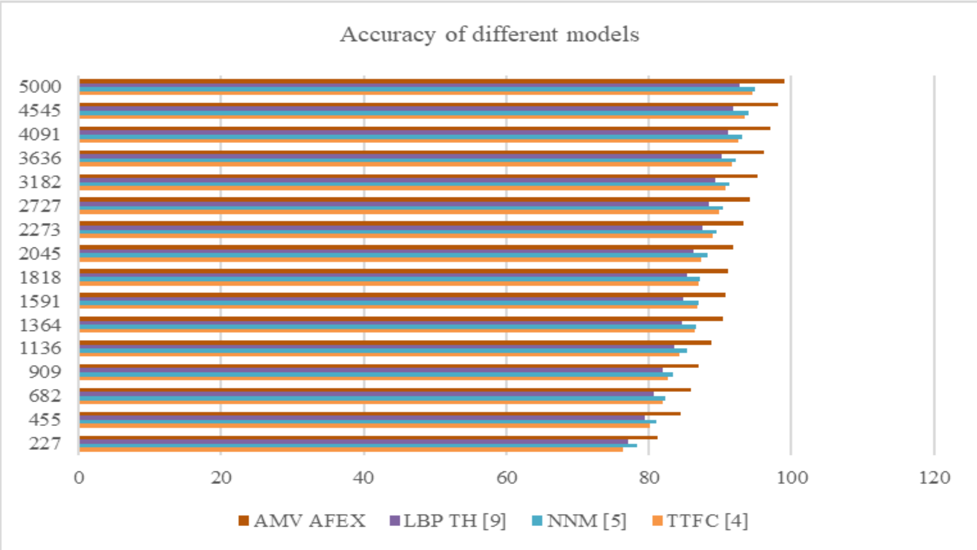

Figure 5. Accuracy of different models

Table 1. Accuracy of different EEG classification models

Number of EEGs	A (%) TTFC [4]	A (%) NNM [5]	A (%) LBP TH [9]	A (%) AMV AFEX
227	76.36	78.28	77.05	81.29
455	80.19	81.10	79.44	84.47
682	82.01	82.37	80.63	85.97
909	82.72	83.48	81.90	87.05
1136	84.23	85.35	83.57	88.83
1364	86.46	86.61	84.57	90.40
1591	86.76	86.91	84.86	90.72
1818	87.06	87.21	85.31	91.08
2045	87.37	88.16	86.32	91.88
2273	88.97	89.43	87.47	93.28
2727	89.88	90.34	88.35	94.24
3182	90.80	91.25	89.25	95.19
3636	91.71	92.17	90.14	96.15
4091	92.63	93.08	91.04	97.10
4545	93.55	94.00	91.93	98.06
5000	94.46	94.91	92.82	99.01

Table 2. Precision of different EEG classification models

Number of EEGs	P (%) TTFC [4]	P (%) NNM [5]	P (%) LBP TH [9]	P (%) AMV AFEX

227	73.63	73.96	75.41	77.47
455	76.81	76.45	78.04	80.64
682	78.28	77.62	79.34	82.12
909	79.14	78.75	80.45	83.09
1136	80.75	80.44	82.09	84.79
1364	82.42	81.52	83.31	86.41
1591	82.70	81.80	83.61	86.71
1818	82.99	82.15	84.00	87.04
2045	83.59	83.09	84.86	87.73
2273	84.95	84.23	86.07	89.11
2727	85.82	85.09	86.95	90.03
3182	86.69	85.95	87.83	90.94
3636	87.57	86.82	88.71	91.86
4091	88.44	87.68	89.59	92.77
4545	89.30	88.54	90.48	93.68
5000	90.17	89.40	91.35	94.60

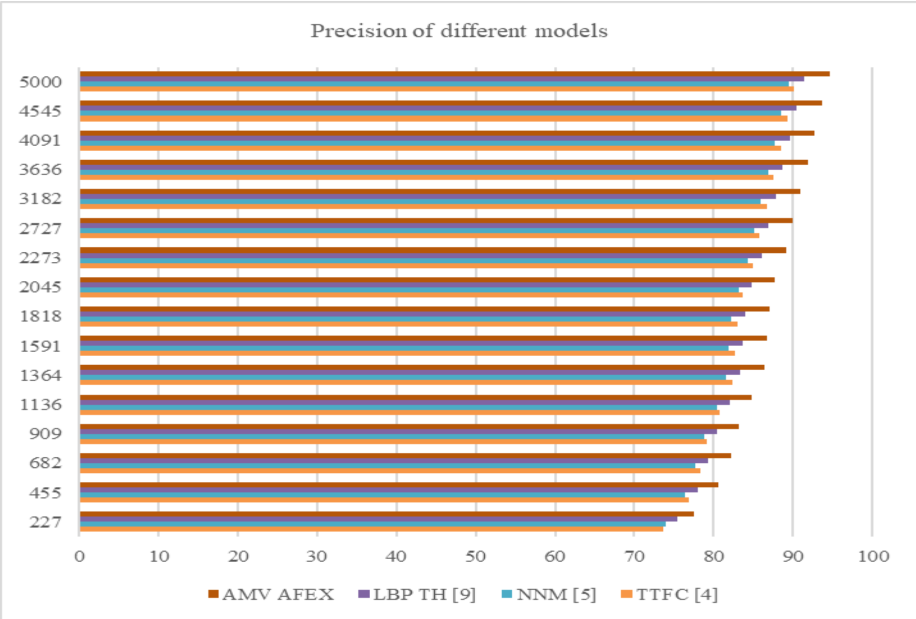

Figure 6. Precision of different models

This exhibition was accomplished because of mix of MFCC and iVector highlights, and utilization of Multiple Neural Networks for exceptionally productive characterization process. Likewise, review execution of these models is organized in table 3 as follows,

Table 3. Recall of different EEG classification models

Number of EEGs	R (%) TTFC [4]	R (%) NNM [5]	R (%) LBP TH [9]	R (%) AMV AFEX
227	74.99	76.12	76.23	79.38

455	78.50	78.77	78.74	82.55
682	80.14	79.99	79.98	84.04
909	80.93	81.11	81.17	85.07
1136	82.50	82.89	82.83	86.81
1364	84.44	84.06	83.94	88.41
1591	84.73	84.36	84.23	88.71
1818	85.02	84.69	84.66	89.06
2045	85.48	85.63	85.59	89.81
2273	86.96	86.83	86.77	91.20
2727	87.85	87.72	87.66	92.13
3182	88.75	88.61	88.55	93.07
3636	89.64	89.50	89.43	94.00
4091	90.53	90.38	90.31	94.94
4545	91.43	91.26	91.20	95.87
5000	92.31	92.15	92.08	96.81

In view of this assessment and figure 19, it tends to be seen that the proposed model has 5.3% more review than TTFC [4], 3.9% more review than NNM [5], and 4.5% more review than LBP TH [9] for various EEG signal sorts.

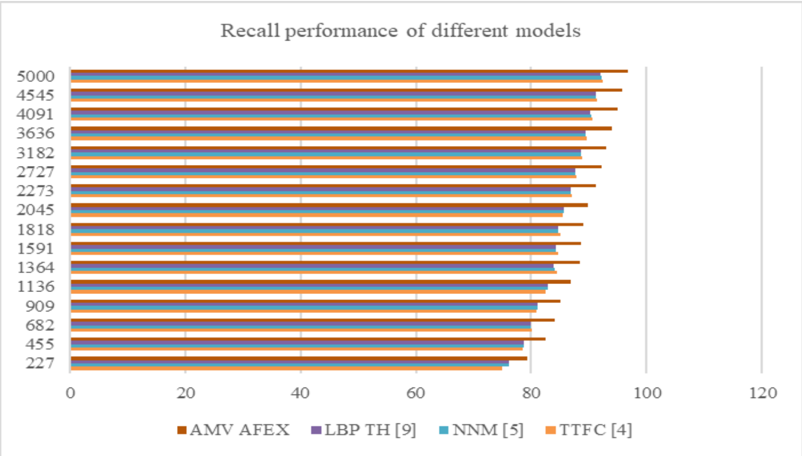

Figure 7. Recall of different models

This exhibition was accomplished because of blend of MFCC and iVector elements, and utilization of Multiple Neural Networks for profoundly proficient order process. Likewise, normal deferral for order of one EEG signal waveform is arranged in table 4 as follows,

Table 4. Delay of different EEG classification models

Number of EEGs	D (ms) TTFC [4]	D (ms) NNM [5]	D (ms) LBP TH [9]	D (ms) AMV AFEX
227	0.45	0.44	0.44	0.42
455	0.87	0.86	0.87	0.83
682	1.27	1.27	1.27	1.21

909	1.68	1.68	1.68	1.60
1136	2.06	2.05	2.05	1.96
1364	2.41	2.42	2.43	2.31
1591	2.81	2.82	2.83	2.69
1818	3.20	3.21	3.21	3.05
2045	3.58	3.58	3.58	3.40
2273	3.91	3.92	3.92	3.73
2727	4.65	4.66	4.66	4.42
3182	5.36	5.37	5.37	5.11
3636	6.07	6.08	6.08	5.79
4091	6.76	6.78	6.78	6.44
4545	7.44	7.45	7.45	7.09
5000	8.10	8.12	8.12	7.73

In light of this assessment and figure 20, it very well may be seen that the proposed model has 6.1% lower delay than TTFC [4], 4.9% lower delay than NNM [5], and 5.5% lower delay than LBP TH [9] for various EEG signal sorts.

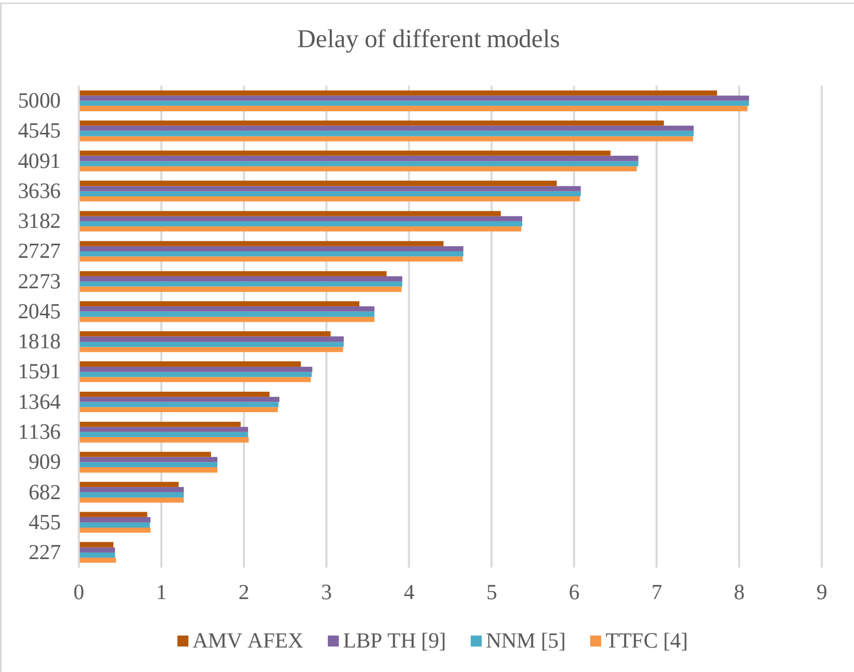

Figure 8. Delay performance of different models

This is conceivable because of blend of wavelet change with fluctuation-based highlight determination process. The wavelet changes decreases highlight vector size by half, while difference based include determination model aids recognizable proof of most variation highlights which lessens overt repetitiveness from yield highlight sets. Because of this exhibition improvement, the proposed model is fit for being conveyed for an enormous number of ongoing clinical applications.

Conclusion and Future Scope

The proposed AMVAFEx model purposes a blend of component extraction, include determination and characterization techniques to accomplish preferable execution over existing models. The MFCC and iVector strategies aid assessment of profoundly pertinent highlights, while changebased model helps with choosing most variation highlights, along these lines decreasing overt repetitiveness during the grouping stages. The chose highlights are characterized through a Multiple Neural Network classifier that works in quadratic mode, and aids high accuracy, high review and exceptionally exact arrangement. It was seen that the proposed model was equipped for further developing the order exactness when contrasted and different best in class models. Because of which the proposed model is fit for organization in high-exactness clinical conditions. It was seen that the proposed model had more than 5% more precision than TTFC [4], more than 4% more exactness than NNM [5], and more than 6% more precision than LBP TH [9] for various sorts of EEG signals. Comparable execution was noticed for accuracy and review, which makes themodel profoundly deployable for a wide assortment of EEG grouping situations. Notwithstanding this improvement in execution, the proposed model likewise grandstands decreased delay, which is principally because of use of component decrease through difference based enhancements. On account of which, the proposed model has 6.1% lower delay than TTFC [4], 4.9% lower delay than NNM [5], and 5.5% lower delay than LBP TH [9] for various EEG signal sorts. In future, specialists can approve execution of the proposed model on various EEG datasets, which will help with distinguishing its versatility. Additionally, scientists can likewise recognize combination of profound learning models incorporating intermittent Neural Networks with long-transient memory (LSTM) and Gated Recurrent units (GRUs) for better feasibility under various cerebrum sickness types.

References

1. Alturki, Fahd A. et al. “Common spatial pattern technique with EEG signals for diagnosis of autism and epilepsy disorders”. IEEE access: practical innovations, open solutions 9 (2021): 24334–24349. Web.
2. Dang, Weidong et al. “Studying multi-frequency multilayer brain network via deep learning for EEG-based epilepsy detection”. IEEE sensors journal 21.24 (2021): 27651–27658. Web.
3. Furui, Akira et al. “Non-gaussianity detection of EEG signals based on a multivariate scale mixture model for diagnosis of epileptic seizures”. IEEE transactions on bio-medical engineering 68.2 (2021): 515–525. Web.
4. Gao, Yikai et al. “Pediatric seizure prediction in scalp EEG using a multi-scale neural network with dilated convolutions”. IEEE journal of translational engineering in health and medicine 10 (2022): 1–9. Web.
5. Grigorovsky, Vasily, Vanessa L. Breton, en Berj L. Bardakjian. “Glial modulation of electrical rhythms in a neuroglial network model of epilepsy”. IEEE transactions on bio-medical engineering 68.7 (2021): 2076–2087. Web.
6. Gu, Xiaoqing, Cong Zhang, en Tongguang Ni. “A hierarchical discriminative sparse representation classifier for EEG signal detection”. IEEE/ACM transactions on computational biology and bioinformatics 18.5 (2021): 1679–

1687. Web.
7. Hu, Dinghan et al. “Epileptic state classification by fusing hand-crafted and deep learning EEG features”. IEEE transactions on circuits and systems. II, Express briefs: a publication of the IEEE Circuits and Systems Society 68.4 (2021): 1542–1546. Web.
8. Kim, Taekyung et al. “Modulation of EEG frequency characteristics by low-intensity focused ultrasound stimulation in a pentylenetetrazol-induced epilepsy model”. IEEE access: practical innovations, open solutions 9 (2021): 59900–59909. Web.
9. Lee, Shuenn-Yuh et al. “RISC-V CNN coprocessor for real-time epilepsy detection in wearable application”. IEEE transactions on biomedical circuits and systems 15.4 (2021): 679–691.Web.
10. Lin, Yuhang et al. “Identifying refractory epilepsy without structural abnormalities by fusing the common spatial patterns of functional and effective EEG networks”. IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society 29 (2021): 708–717. Web.
11. Liu, Aiping et al. “A state-dependent IVA model for muscle artifacts removal from EEG recordings”. IEEE transactions on instrumentation and measurement 70 (2021): 1–13. Web.
12. Mishra, Premananda, Sanjay Agrawal, en Rutuparna Panda. “Epileptic EEG signal classification using exponential energy and SVM”. 2020 International Conference on Electrical and Electronics Engineering (ICE3). IEEE, 2020. Web.
13. Modak, Sudip et al. “Focal epileptic area recognition employing cross EEG rhythm spectrum images and convolutional neural network”. IEEE sensors journal 21.20 (2021): 23335–23343. Web.
14. Na, Junying et al. “An extended K nearest neighbors-based classifier for epilepsy diagnosis”. IEEE access: practical innovations, open solutions 9 (2021): 73910–73923. Web.
15. Rashed-Al-Mahfuz, Md et al. “A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (EEG) data”. IEEE journal of translational engineering in health and medicine 9 (2021): 1–12. Web.
16. Susilo, C. B., Jayanto, I., & Kusumawaty, I. (2021). Understanding digital technology trends in healthcare and preventive strategy. *International Journal of Health & Medical Sciences*, *4*(3), 347-354. https://doi.org/10.31295/ijhms.v4n3.1769
17. Widana, I.K., Sumetri, N.W., Sutapa, I.K., Suryasa, W. (2021). Anthropometric measures for better cardiovascular and musculoskeletal health. *Computer Applications in Engineering Education*, *29*(3), 550–561. https://doi.org/10.1002/cae.22202
18. Xu, Zhendi et al. “BECT spike detection based on novel EEG sequence features and LSTM algorithms”. IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society 29 (2021): 1734–1743. Web.
19. Yazid, Muhammad et al. “Simple detection of epilepsy from EEG signal using local binary pattern transition histogram”. IEEE access: practical innovations, open solutions 9 (2021): 150252–150267. Web.
20. Zhang, Yuanpeng et al. “Epilepsy signal recognition using online transfer TSK

fuzzyclassifier underlying classification error and joint distribution consensus regularization". IEEE/ACM transactions on computational biology and bioinformatics 18.5 (2021): 1667–1678. Web.