JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1829 - 1835
https://publishoa.com
ISSN: 1309-3452

Exploring the use of electroencephalogram signals for medical diagnosis

Ms. Pranjali Deepak Nikam[1], Dr. Prashantha G. R.[2], Ms. Sonali Mahendra Sonavane[3]
[1]Assistant Professor,
Anantrao Pawar College of Engineering & Research, Parvati, Pune,
pranjali.amore@gmail.com
[2] Associate Professor,
Visvesvaraya Technological University, Karnataka,
prashanthagr.sjce@gmail.com
[3] Assistant Professor,
G. H. Raisoni College of Engineering and Management, Pune,
sonali.sonavane@gmail.com

ABSTRACT
A vast grouping of EEG portrayal models is put forth by research scholars all through the long haul, and everyone vary identical to congruity, exactness, survey, accuracy and concede execution. For instance, work in [2, 3, 4] looks at plan of lessened direction set (RISC)- V convolutional Neural Network (CNN) Coprocessor, KNN (k Nearest Neighbor), blend of direct discriminant examination (LDA), ANN (counterfeit brain organization) and support vector machine (SVM) with ordinary spatial model (CSP), and Transfer TSK Fuzzy Classifier (TTFC) for achieving better portrayal results. These models have extraordinary precision, yet need terms of exactness execution in light of their application-unequivocal portrayal characteristics. Developments to this model are discussed in [5, 6], wherein LIFUS (low-force trotted ultrasound energy) and NNM (Neuroglial Network Model) are used for multidomain EEG groupings. They have extraordinary exactness, yet can't be scaled for a long while in light of high computational unpredictability. To vanquish the above issues, next region proposes wavelet pressure based quadratic model for EEG request utilizing multivariate examination that helps high-capability and high flexibility EEG portrayal for various clinical circumstances.
Keywords: Electroencephalogram (EEG), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Neuroglial Network Model (NNM).

I. INTRODUCTION

Effective plan of EEG grouping models includes plan of plan of sign sifting, locale of interest (RoI) extraction, highlight portrayal, highlight determination, definition and post-handling activities. A profoundly powerful EEG arrangement model requires plan of these models with low computational deferral, and high effectiveness of characterization. A common EEG grouping model is imagined in Fig. 1, wherein change of EEG information into various feelings is portrayed. In this model, EEG information is caught from constant headsets, and pre-handled to diminish impact of commotion and other outer and inside unsettling influences. Subsequent to separating, different worldly highlights are extricated from it, which incorporates rakish, spatial, and recurrence based include vectors. These highlights address time-area translations of flow cerebrum state, and can be utilized for separation into various mind illness or cerebrum state classes.

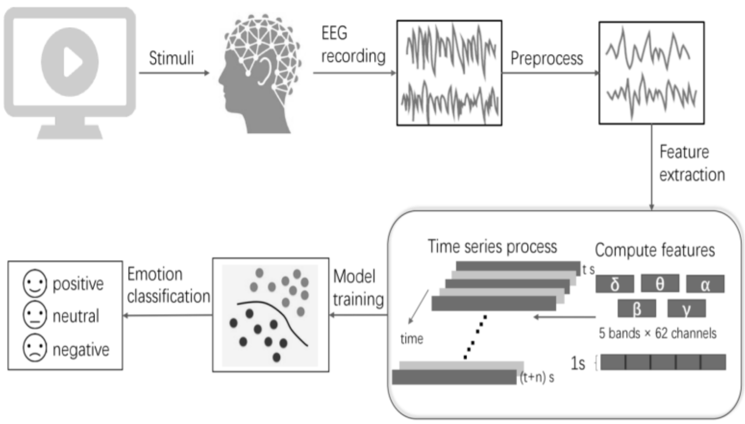

Fig. 1. A general-purpose EEG classification model

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1829 - 1835
https://publishoa.com
ISSN: 1309-3452

II. LITERATURE SURVEY

Work in [7] put forth plan of Multiple repeat Multilayer Neural Network (MFMBN) that helps with gaining higher accuracy and favoured versatility over as of late proposed models. Alike models that utilize CNN with cross wavelet change (XWT) [8], Local Binary Pattern Transition Histogram (LBP TH) [9], and Multivariate Scale Mixture Model (MSMM) [10] are presented by researchers. These models apply expanded component extraction procedures for additional growing for the most part portrayal execution during epilepsy disclosure.

Considering these component extraction models work in [11, 12, 13] propose mix of quadratic classifier with wavelet features, HC DL (Hand-Crafted Deep Learning EEG model) and MSNN DC (Multiple scaled NN with Dilated Convolutions) is discussed. These models carry out enormous degree incorporate extractions to address input EEG waveforms through various reaches for better gathering execution. However, they show moderate precision execution, which can be enhanced through the work in [14, 15, 16], wherein moderate discriminative meager depiction classifier, time region progressive components request using long transient memory (LSTM) brain association, and DCNN (Deep Convolutional Neural Network) are inspected. These models help increment of EEG features to additionally foster request precision for various clinical utilization. Tantamount models are talked about in [17, 18], wherein Joint outwardly hindered source division systems and Extended K Nearest Neighbors are proposed by researchers for good adaptability execution. These models utilize low multifaceted nature feature extraction systems, yet can't be applied to gigantic extension EEG datasets. As such, it might be seen that models with high precision are not important for gigantic degree courses of action, while models that have high versatility can't be used for significantly exact portrayal applications.

III. OBJECTIVES OF THE WORK

The main intention of the suggested proposal is to develop a system that can differentiate two classes of EEG signals and to find out different methods are suitable for the feature extraction from EEG data.

The most important two conditions of selecting a best approach, which are computational efficiency and accuracy are used in this research for evaluation. This work introduces a technique for two-class EEG signal classification that enhances the accuracy of classification and minimizes the computational time during program running. Evaluate the performance of the proposed method in two ways; (i) dividing feature set into two groups as training and testing set and (ii) using the validation method.

IV. WORK CARRIED OUT

From the writing survey it very well may be seen that a wide assortment of AI models were proposed for EEG order, and every one of these models are sent for a specific kind of cerebrum infection. Because of which their presentation for universally useful grouping is restricted, while models with higher adaptability execution have mediocre accuracy, review, and precision execution. To beat this disadvantage, an increased element extraction motor with quadratic classifier is proposed in this segment, which can be applied for a wide assortment of order applications. In general progression of the proposed model is portrayed in Fig. 2, wherein its inside working can be pictured.

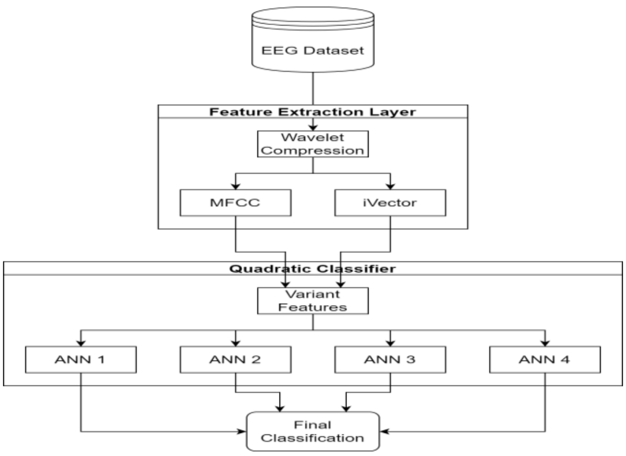

Fig. 2. Overall flow of the proposed model

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1829 - 1835
https://publishoa.com
ISSN: 1309-3452

Because of Hilbert change, the detail part is disposed of, while estimated part is utilized for include extraction. The reason for this interaction is to diminish aspects of EEG signals, while holding its entropy state for various sign levels. These estimated parts decrease aspects of information EEG signal considerably, which aids quicker characterization, and better component portrayals. To address these parts into highlights, Mel Frequency Cepstral Coefficients (MFCCs) are separated, which aids recurrence space portrayal of information signals. Fourier, Wavelet and DCT parts are consolidated to frame the last element vector, which is utilized for arrangement purposes. This weight is chosen in light of recurrence and scale worth of each info signal and can be changed according to show necessities. A sum of 20 unique MFCC parts were separated, and consolidated directly to shape a MFCC include vector. This vector was joined with exceptionally proficient iVector highlights. In light of these characters, input EEG signal is addressed into highlight vectors, which can be utilized for conclusive arrangement and investigation. These elements are joined to shape a combined component vector, which contains various component redundancies. To diminish these redundancies, a novel between class difference edge is assessed between these elements. The highlights are given to the proposed classifier that involves a Quadratic Neural Network with expanding Neurons for effective EEG arrangement. Each NN model purposes profoundly variation highlights for definite order. The consolidated QNN model purposes n, 2 * n, 3 * n, & 4 * n Neurons in the last classifier plan. Here, n addresses complete number of highlights separated by means of difference-based choice. The mode activity chooses most often happening class from given set of result classes to get the last grouping result. Execution of this characterization cycle concerning accuracy, review, exactness, and postponement is examined in the following part of this text.

V. RESULTS AND DISCUSSIONS

It tends to be seen that the proposed AMVAFEx model uses Multiple Neural Networks for conclusive EEG arrangement. Because of which, the model is fit for accomplishing better exactness, higher accuracy, preferable review over different methodologies. This presentation was tried on various EEG datasets for arrangement of info waveforms into Multiple epileptic kinds. These waveforms were extricated 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 advancements 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 passages were separated from this dataset, and were isolated into 60:40 proportion for preparing and testing individually. Results were assessed regarding exactness, accuracy, review and postponement, and were contrasted and TTFC [4], NNM [5], and LBP TH [9] for approval purposes. The outcomes for exactness can be seen in Table 1 as following:

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	78.28	79.69	78.25	82.88
455	81.10	81.74	80.04	85.22
682	82.37	82.93	81.27	86.51
909	83.48	84.42	82.74	87.94
1136	85.35	85.98	84.07	89.62
1364	86.61	86.76	84.72	90.56
1591	86.91	87.06	85.09	90.90
1818	87.22	87.69	85.82	91.48
2045	88.17	88.80	86.90	92.58
2273	89.43	89.89	87.91	93.76

2727	90.34	90.80	88.80	94.72
3182	91.26	91.71	89.70	95.67
3636	92.17	92.63	90.59	96.63
4091	93.09	93.54	91.49	97.58
4545	94.01	94.46	92.38	98.54
5000	94.92	95.37	93.27	99.49

In light of this assessment and figure 5, it was seen that the proposed model has 5.2% more precise than TTFC [4], 4.3% more exactness than NNM [5], and 6.75% more precision than LBP TH [9] for various sorts of EEG signals. The principle justification behind this exactness improvement is because of mix of Wavelet, Hilbert, Fourier and Cosine changes, alongside include choice and arrangement upgrades.

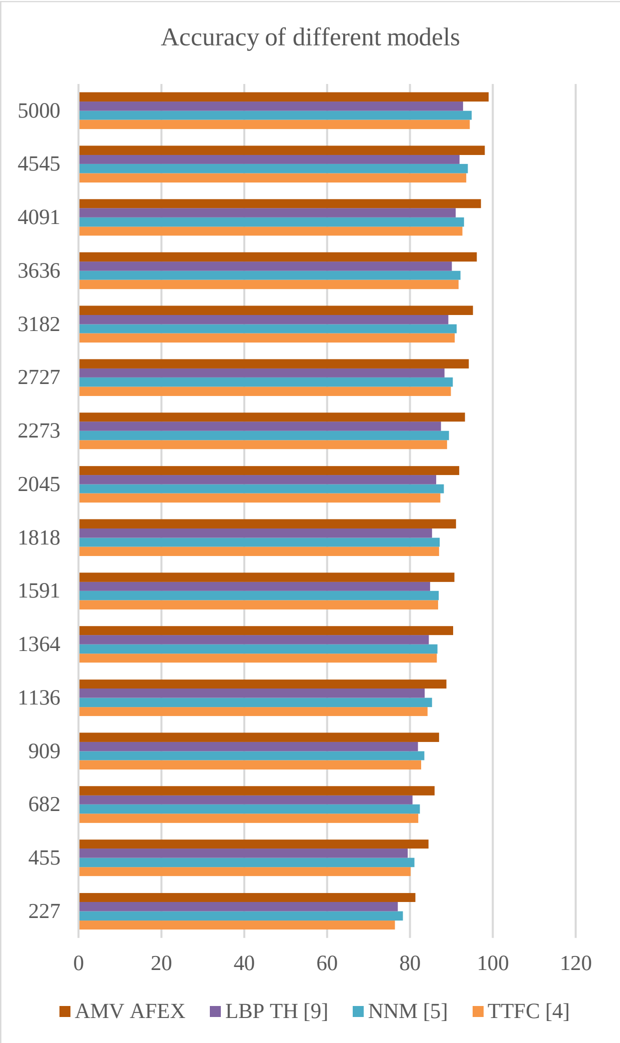

Fig. 2. Accuracy of different models

This when joined with MFCC and iVector highlights, increases include portrayal capacities of the model, along these lines upgrading exactness execution. The convolutional Neural Network utilized for this situation, likewise helps with further developing arrangement execution, because of its high-thickness include portrayal abilities. This exhibition was accomplished because of mix of MFCC and iVector elements, and utilization of Multiple Neural Networks for exceptionally productive arrangement process. Essentially, accuracy execution of these models is organized in Table 2 as following:

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	75.22	75.21	76.73	79.06
455	77.55	77.04	78.69	81.38
682	78.71	78.19	79.90	82.61
909	79.95	79.60	81.27	83.94
1136	81.59	80.98	82.70	85.60
1364	82.56	81.66	83.46	86.56
1591	82.85	81.98	83.81	86.88
1818	83.29	82.62	84.43	87.39
2045	84.27	83.66	85.47	88.42
2273	85.39	84.66	86.51	89.57
2727	86.26	85.52	87.39	90.49
3182	87.13	86.39	88.27	91.40
3636	88.01	87.25	89.15	92.32
4091	88.87	88.11	90.04	93.23
4545	89.74	88.97	90.92	94.14
5000	90.90	90.04	92.02	95.34

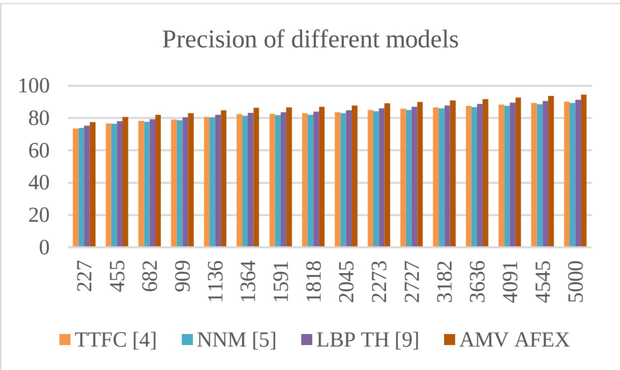

Fig. 3. Precision of different models

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1829 - 1835
https://publishoa.com
ISSN: 1309-3452

Conclusion and Future Work

The proposed model is fit for being sent for an enormous number of ongoing clinical applications. In future, specialists can approve execution of the proposed model on various EEG datasets, which will help with distinguishing its versatility. Additionally, analysts can likewise recognize combination of profound learning models incorporating intermittent Neural Networks with long-momentary memory (LSTM) and Gated Recurrent units (GRUs) for better practicality under various cerebrum illness types.

References

[1] 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.

[2] 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.

[3] 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.

[4] Zhang, Yuanpeng et al. “Epilepsy signal recognition using online transfer TSK fuzzy classifier underlying classification error and joint distribution consensus regularization”. *IEEE/ACM transactions on computational biology and bioinformatics* 18.5 (2021): 1667–1678. 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] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[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] 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.

[14] 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.

[15] 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.

[16] 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.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 1829 - 1835
https://publishoa.com
ISSN: 1309-3452

[17] 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.

[18] 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