Received: July 15, 2023. Revised: September 15, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

AMVAFEx: Design of a Multispectral Data Representation Engine for Classification of EEG Signals via Ensemble Models

Komal R. Hole[1]* **Divya Anand[1]**

[1]*School of Computer Science and Engineering Lovely Professional University Phagwara, Punjab, India*
* Corresponding author's Email: komal9112@gmail.com

Abstract: The classification of EEG (Electroencephalogram) signals requires design of multidomain modules, including signal pre-processing, filtering, segmentation, extraction of features from segmented signals, reduction of features via statistical modelling, categorization of the signal into 1-of-N brain disease classes, and performing post processing operations. Researchers have proposed deep learning models with single domain features for representing EEG signals which limits performance capabilities, when used for multiple disease types. In deep learning models feature extraction & selection are wrapped in black-box containers, which is uncontrollable without compromising classification performance. To overcome this, design of multispectral data representation engine for classification via ensemble models used. The proposed engine represents input EEG signals into Mel frequency cepstral coefficient (MFCC), and iVector components. The MFCC feature vector is built using cepstrum, spectrum, power density, and other frequency domain features, while iVector is built using statistical entropy features. This combination of feature sets can improve feature representation efficiency assists in optimizing classification performance. A novel ensemble classification model is designed using multiple neural networks (MNNs) varies layer size with observation that proposed model showcased over 98.5% accuracy for classification. Proposed AMVAFEx model has outperformed than existing models like online transfer TSK fuzzy classifier (TTFC),Neuroglial Network model (NNM) and Local Binary Pattern Transition Histogram (LBP TH) in terms of accuracy, precision, recall & delay performance under different input conditions. With this advantage, proposed model is useful for real-time clinical applications.

Keywords: EEG, iVector, MFCC, Multispectral, Variance.

1. Introduction

Efficient design of EEG classification models involves design of design of signal filtering, region of interest (RoI) extraction, feature representation, feature selection, stratification & post-processing operations [1]. A highly effective EEG classification model needs design of models which will have high efficiency of classification with low computational delay. EEG data can be captured from real-time headsets and pre-processed to reduce effect of noise & other external & internal disturbances. After filtering, various temporal features are extracted which includes angular, spatial, and frequency-based feature vectors. These features aid in the recognition of the current brain state in time-domain analysis and can be combined to form various classes of brain-related diseases or brain states.

In the model depicted in Fig. 1, support vector machine (SVM), random forest (RF), K-nearest neighbour (KNN), decision tree (DT) & multilayer perceptron (MLP) models can be used in classification of extracted features into different types of emotions. These emotions can be utilized by external systems for identification of user behaviour, and thereby assist in psychometric analysis. It is plain to see that the extraction of features, the selection of features, and the categorization blocks have a significant role in determining the correctness of these models. In the next part of this article, we will go through the design of these blocks, as well as the performance characteristics derived from a wide variety of cutting-edge classification models. As a result of this conversation, it has come to our attention that these methods either employ a black-box model

Received: July 15, 2023. Revised: September 15, 2023.

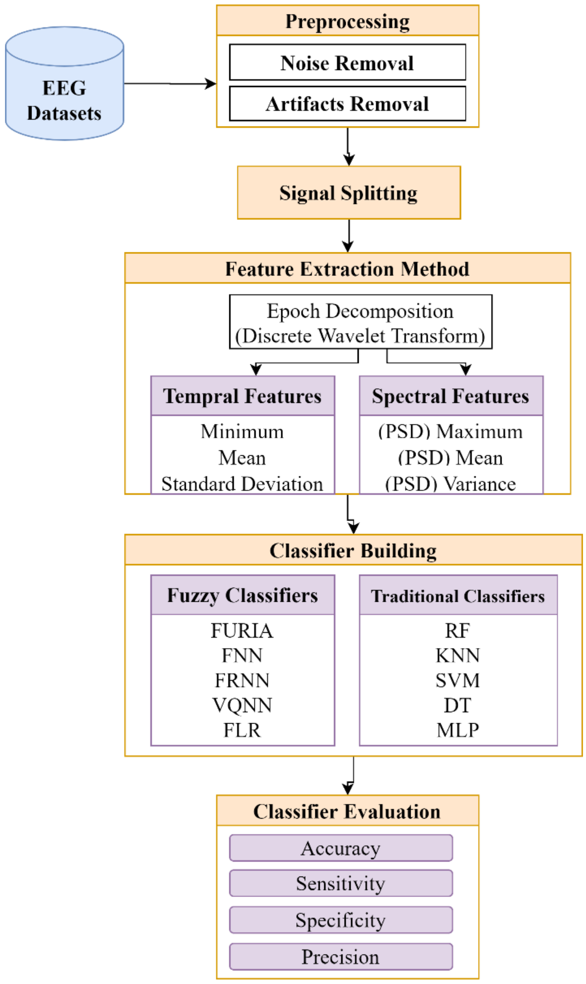


Figure. 1 A general approach for EEG classification model

or are overly general, which restricts the scale at which they can be used in terms of latency and accuracy performance.

Existing models also showcase some issues for real-time EEG datasets like accuracy of classification highly depends upon data density, which limits applicability & scalability of the model. Feature representation capabilities of these models are limited because they utilize uni-domain or bi-domain features reduces their real-time classification performance. Deep learning models utilize black-box methods; thus, their performance cannot be controlled & reconfigured via linear optimization techniques. Multidomain feature extraction & selection models have higher redundancies, which reduces their classification speed, and accuracy under real-time datasets.

The performance of the work includes following contribution:

1. This study's goal is to provide and examine the architecture of the suggested enhanced feature selection engine for multivariate analysis-based EEG categorization.

2. This will allow us to circumvent the problems associated with feature representation, slow speed, and restricted accuracy performance.

3. The MFCC and iVector approaches aid in assessing highly relevant features, while the variance-based model aids in choosing most variant features, hence minimising redundancy during the classification phases.

The article is organized in following manner: Section 2 gives a thorough analysis of the work on EEG signals using machine learning models. The proposed improved feature extraction engine for multivariate EEG classification is examined in section 3. Section 4 presents the effectiveness of the proposed model, and it is assessed by contrasting with other methods that are considered to be state-of-the-art. Lastly, this article draws to a close with some thought-provoking remarks on the suggested model and makes some suggestions for how to further enhance the model's performance in section 5.

2. Literature review

There is a diverse selection of models for characterizing EEGs that have been presented by scientists over the course of a lengthy period. These models differ from one another in terms of their applicability, precision, review, and delay in execution. For instance, the research presented in [2] RISC-V CNN coprocessors may complicate wearable devices and need more power and memory, reducing their ability to detect epilepsy in real time [3]. The Common Spatial Pattern (CSP) EEG signal diagnosis method for autism and epilepsy has limitations. CSP uses specified frequency ranges, which cannot capture patient-specific spectral patterns. CSP can also struggle with noisy EEG data and needs a professional application, limiting its clinical use.[4] investigates the use of a mix of LDA, KNN, SVM, and ANN [5]. Due to the wide range of epileptic symptoms, machine learning models for epilepsy detection can generate false positives or negatives in varied patient populations in [6] with CSP, and TTFC for the purpose of achieving improved characterization results. These models have a high level of precision, but their implementation must adhere to standards of accuracy due of the application-explicit characterisation attributes they possess. Modelling glial modulation of electrical rhythms in epilepsy involves intricate neuroglial interactions and parameters, making it challenging to accurately represent the system's complexityin [7], The unique pentylenetetrazol-induced epilepsy model used can restrict the application of low-intensity focused ultrasound stimulation to other epilepsy types or conditions in[8], there is discussion of expansions to this model, for multidomain EEG groups, NNM and LIFUS are utilised. In these models, a high level of accuracy is observed; yet, due to the high level of computational complexity, they cannot be scaled for quite some time. Multiple Recurrent MNN is a strategy that was provided in study [9], which assists with achieving greater accuracy and preferable flexibility compared to previously published models. The goal of this work is to further enhance versatility. Scientists have presented comparable models that make use of CNN with XWT [10], LBP TH [11], and MSMM [12]. Drawback of these single models may be sensitive to noise and artifacts in EEG data, leading to reduced classification performance in practical applications. These models make advantage of expanded element extraction methodologies to better refine and broadly characterize execution when epilepsy is being discovered.

Since these element extraction models have been worked on, the combination of a HC DL, a quadratic classifier with wavelet highlights, and MSNN DC is being discussed. [13-15] These existing models are computationally intensive, which can limit their utility in low-resource settings or real-time applications. Also these models make extensive use of inclusion extractions to handle EEG waveforms over a variety of ranges to achieve more effective grouping. Limitation of [16]Paediatric seizure prediction in scalp EEG utilising a multi-scale neural network with dilated convolutions may be computationally and resource-intensive. Dilated convolutions raise model computational needs, making real-time prediction and deployment on resource-constrained devices difficult. Temporal-spatial and multi-scale CNN with dilated convolutions provides promising output. However, these models only have a performance in moderately accurate way that is improvised in the work of [17, 18]. In these works, a progressive discriminative scanty portrayal classifier, a time area successive elements order utilizing a LSTM neural organization, and a DCNN neural organization are investigated [19]the quality of EEG data can vary significantly, and existing models may not always handle data of varying quality effectively. This work can help improve the accuracy of these models. These models contribute to the enhancement of EEG highlights, hence facilitating the development of order exactness for a variety of therapeutic applications. Comparable models are discussed in [20, 21], in which scientists suggest Extended K Nearest Neighbours and Joint visually impaired source division techniques for improved flexible implementation. These strategies are intended to help visually impaired individuals. Although these models use very simple highlight extraction algorithms, it is not possible to apply them to EEG datasets with a very broad scope [22, 23] EEG-based workers' stress recognition at construction sites is limited by cumbersome EEG equipment, worker discomfort, and difficulty distinguishing stress from other factors in a dynamic construction environment, reducing its practicality and accuracy. In this way, it is possible to show that the importance of very accurate models for large-scale arrangements is negligible, while applications requiring a high level of thoroughly accurate description cannot be employed with models with a high degree of adaptability [24, 25].To resolve these problems, the following section will provide a strategy a multivariate research-based wavelet pressure-based quadratic model for EEG order. The performance can be verified via various measures like Accuracy, Precision, Recall, and Specificity for all the classification algorithms [26]. For a number of clinical circumstances, this model will aid in the high-efficiency and high-adaptability EEG characterization [27, 28]. It presents innovative strategy integrating down sampling local binary patterns with LSTM for congestive heart failure and arrhythmia classification may require a lot of labelled data for training, which can be difficult to get in medicine. The model has struggled to generalise with limited data. limitations of [29] Deep learning techniques for EEG motor imagery signal classification have high computational resource requirements, which can limit their practicality, especially for real-time applications or resource-constrained devices, and may require specialised hardware for efficient implementation [30]. EEG's poor spatial resolution makes classification approaches for semantic relatedness and prediction difficult. EEG collects scalp-level brain activity, making it difficult to localise semantic processing brain areas, which can impair relatedness and prediction tasks. Key findings from the application of various approaches on diverse datasets are displayed in the table 1 below.

3. Proposed methodology

The literature research reveals that several machine learning algorithms for EEG categorization have been presented; each of these models is used to diagnose a certain kind of brain disorder. The performance for general purpose classification is restricted, while models whose scalability performance is better have worse precision, recall, and accuracy performance. An expanded feature extraction engine with quadratic classifier is presented

Table.1 The principal findings from utilising different approaches on various EEG datasets

Article	Datasets used	Techniques applied	Findings
[2]	National Cheng Kung University dataset	FE: CNN Classification: CNN	With the inclusion of the hardware coprocessor, AI techniques can be applied.
[3]	King Abdulaziz University dataset and MIT dataset	FE: CSP-LBP Classification: KNN	Diagnosis time is accumulated and neurological brain problems are diagnosed with greater precision.
[6]	Physio-net database	Classification: ANN	Can be distinguished between epileptic and non-epileptic people in real time.
[9]	Real data from CHB-MIT dataset	FE: MDCNN Classification: Brain Network + DL	Achieved improved characterization results.
[10]	Bern-Barcelona dataset	FE: XWT Classification: CNN	Delta rhythm found to be effective in real time signal analysis.
[11]	University of Bonn Epilepsy EEG Dataset	FE: DWT Classification: SVM	Small feature size and short input signals provides low computing requirements.
[13]	CHB-MIT database	FE: TL using a single DNN Classification: HNN	The Frequency and Time domain features are combined together for feature learning and epileptic state classification.
[15]	Bonn University experimental dataset	FE: - Classification: HD-SRC	The quantity of training samples has an impact on HD-SRC data.
[16]	CHB-MIT database	FE: CNN Classification: CNN	Temporal-spatial and multi-scale CNN with dilated convolutions provides promising output.
[17]	CHZU School of Medicine dataset	FE: spectral power feature method Classification: CNN	NN with LSTM architecture endow with promising result for BECT epileptic syndrome.
[18]	Bonn University dataset	FE: CNN Classification: FT-VGG16 with CWT	DCNN is persuasive in way of detecting seizures.
[20]	Bonn university public database	FE: DFT Classification: CRMKNN	Linear representation of the NN provides flexibility so to improve performance.
[22]	Experimental data	FE: PCA Classification: SVM	Fixed windowing approach with time and frequency domain features plots more accuracy.
[25]	SEED, DEAP and IDEA database	FE: MD-DE Classification: BiLSTM	In order to recognise emotions, the gamma band is a key band.
Proposed work	The Neuromed Epilepsy EEG Database	FE: iVector, MFCC Classification: ANN	Evaluation of highly significant features that contribute to excellent performance is made easier with the help of the MFCC and iVector approaches.

in this part as a means of overcoming the limitations brought about by the aforementioned shortcoming. This engine may be used for a broad range of classification tasks. Fig. 2 illustrates the suggested model's overall flow, which can also be seen as a visual representation of the model's inner workings. It can be seen that the incoming EEG signals are first compressed using wavelet compression, and then they are processed using MFCC and iVector based blocks. This sequence can be viewed from Fig. 3 and implementation flow from Fig. 2. These blocks contribute to the process of extracting multispectral features, which in turn contributes to a more accurate representation of the input signals. In order to achieve intelligent class-based feature choices, these features are processed using a variance maximization layer. This layer contributes to the overall process. In order to achieve final EEG stratification into various illness categories, the chosen characteristics are identified using a quadratic classifier. This classifier is constructed out of Multiple Neural Networks and helps in the achievement of final EEG stratification. The predicted result was used to identify the individual comes under which category of stress level from Algorithm 1.

It is possible to deduce from the model that the input EEG waves are first subjected to processing by

Received: July 15, 2023. Revised: September 15, 2023.

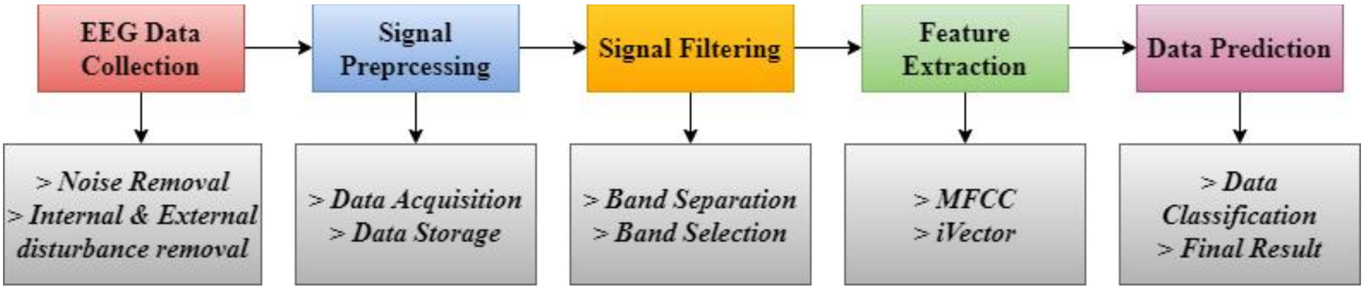


Figure. 2 Implementation flow of proposed work

Algorithm 1: Proposed algorithm

INPUT: EEG data	
OUTPUT	
Step 1	Assemble input EEG data.
Step 2	Preprocess and reconstruct the EEG signal.
Step 3	Filter out the signals bands with threshold lower and higher frequency.
Step 4	Minimize the EEG signal dimensions.
Step 5	Extracting approximate EEG & detail EEG components.
Step 6	Represent input EEG signals into MFCC components and iVector components.
Step 7	Construct MFCC feature vector using cepstrum, spectrum, power density and other frequency domain features.
Step 8	Construct iVector using statistical entropy features.
Step 9	Unite these MFCC and iVector features for wavelet compression.
Step 10	Extract N number of features in the form of feature vector.
Step 11	Discard Features that have variance lower than threshold value.
Step 12	Train the model for corresponding Deep Learning algorithm.
Step 13	Apply the K-fold cross validation technique to validate the model.
Step 14	Predict the result by using MNN.
Step 15	Utilize a confusion matrix to assess system performance.

a wavelet compression block, which plays a part in the process of feature reduction. The evaluation of the extraction of wavelet components is done using Eqs. (1) and (2) as follows,

$$EEG_{a_i} = \frac{x_i + x_{i+1}}{2} \tag{1}$$

$$EEG_{d_i} = \frac{x_i - x_{i+1}}{2} \tag{2}$$

Where, $EEG_a, and EEG_d$ represents approximate EEG & detail EEG components extracted by the Haar wavelet transform, while $x_i \& x_{i+1}$ represents current EEG signal & its next EEG sample values which are retrieved from the input EEG signals. These signals are also processed via Hilbert transform, which can be observed via Eq. (3),

$$\mathrm{H_{out}(x)} = 2^{\frac{j}{2}} \mathrm{H_{out}}(2^j \mathrm{x} - \mathrm{k}) \tag{3}$$

Where, k represents a wavelet constant. The output of this model is further augmented via Eq. (4) to obtain final Hilbert features,

$$\mathrm{f(x)} = \sum_{\mathrm{j,k=0}}^{\mathrm{N}} \mathrm{EEG_a} \times \mathrm{H_{out}(EEG_a)} \tag{4}$$

Where, N represents number of features extracted via the Haar wavelet transform's approximate components.

Due to Hilbert transform, the detail component is discarded, while approximate component is used for feature extraction. With this method, EEG signal dimensions are minimised while entropy is kept constant for a range of signal intensities. These approximate components reduce dimensions of input EEG signal by half, which assists in faster classification and better feature representations. To represent these components into features, MFCCs are extracted, which assists in frequency domain representation of input signals. To perform this task, initially Fourier transform of approximate components is extracted via Eq. (5),

$$F_{approx_i} = \sum_{j=0}^{N-1} EEG_{a_j} \times \left[cos\left(\frac{2 \times pi \times i \times j}{N}\right) - \sqrt{-1} \times sin\left(\frac{2 \times pi \times i \times j}{N}\right) \right] \tag{5}$$

The Where, N represents total number of extracted

Received: July 15, 2023. Revised: September 15, 2023.

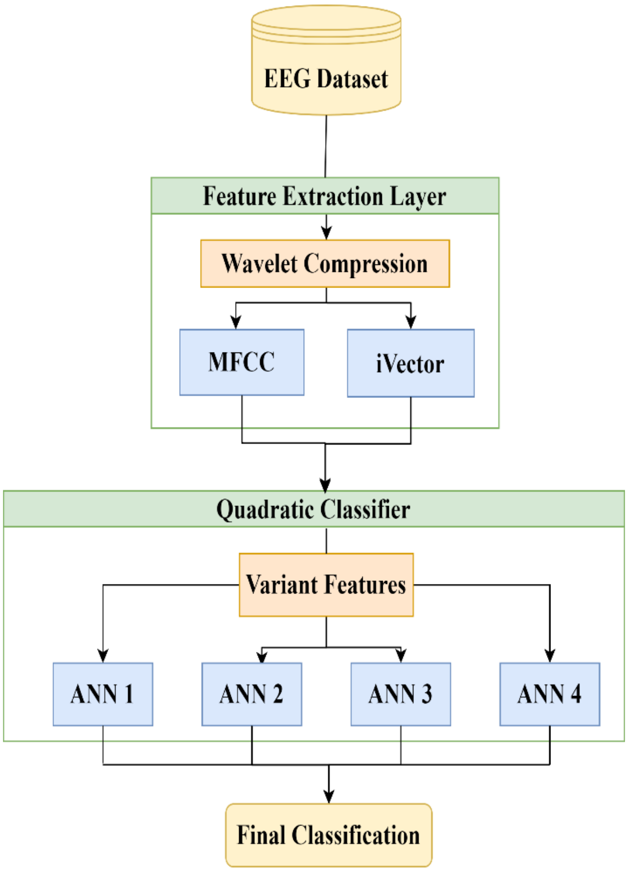


Figure. 3 The proposed AMVAFEx model

samples, and $i \in (0, N-1)$. Like Fourier, the discrete cosine components are evaluated via Eq. (6) as follows,

$$\mathrm{DCT_{out}} = \frac{1}{\sqrt{2N}} \times \mathrm{C_{DCT}} \times \sum_{x=0}^{N-1} \mathrm{EEG}(x) \times cos\left[(2 \times x + 1) \times i \times \frac{pi}{2 \times N}\right] \quad (6)$$

Where, N represents number of EEG components, while C_{DCT} is evaluated via Eq. (7) as follows

$$\mathrm{C_{DCT}} = \frac{1}{\sqrt{2}}, \text{ when} \mathrm{EEG} > 0, \text{ else, } \mathrm{C_{DCT}} = 1 \quad (7)$$

Fourier, Wavelet and DCT components are combined to form the final feature vector, which is used for classification purposes. These coefficients are processed further to evaluate MFCC for spectral analysis via Eq. (8),

$$\mathrm{MFCC_l} = \sum_{i=1}^{n} log(\mathrm{S_i}) \times \cos(\frac{pi}{n} \times l \times (i - 0.5)) \quad (8)$$

Where, $l \in (1, n)$, n represents number of MFCC components to be retrieved in its entirety, S represents Mel power spectrum coefficients, and are estimated via Eq. (9),

$$S_i = \frac{\sum_{j=1}^{N} F_{approx\,j} \times w_i}{N} \quad (9)$$

Here, i stands for the MFCC component number, and w_i for weight of MFCC component. It is this weight which is decided based on frequency & scale value of each input signal & can be modified as per model requirements. A total of 20 different MFCC components were extracted, and combined linearly to form a MFCC feature vector. High-performance iVector features were incorporated with this vector. The estimation of iVectors can be performed using Eq. (10) as follows,

$$\mathrm{iVector_i} = \begin{bmatrix} (1,1)_{var} & \cdots & (1,n)_{var} \\ \vdots & \ddots & \vdots \\ (n,1)_{var} & \cdots & (n,n)_{var} \end{bmatrix} \times \mathrm{F_{approx_i}} + \mathrm{MAX}\left(\cup_{j=1}^{N} \mathrm{F_{approx_j}}\right) \quad (10)$$

Where, $N stands for$ number of inputs, F_{approx} for Fourier transform of that input, and $(x, y)_{var}$ represents variance among Fourier components$x$&y, which was evaluated via Eq. (11) as follows,

$$(x, y)_{var} = exp\left(\frac{x^2}{2}\right) \times [2 \times pi \times var(y) \times var(x)]^{-1} \quad (11)$$

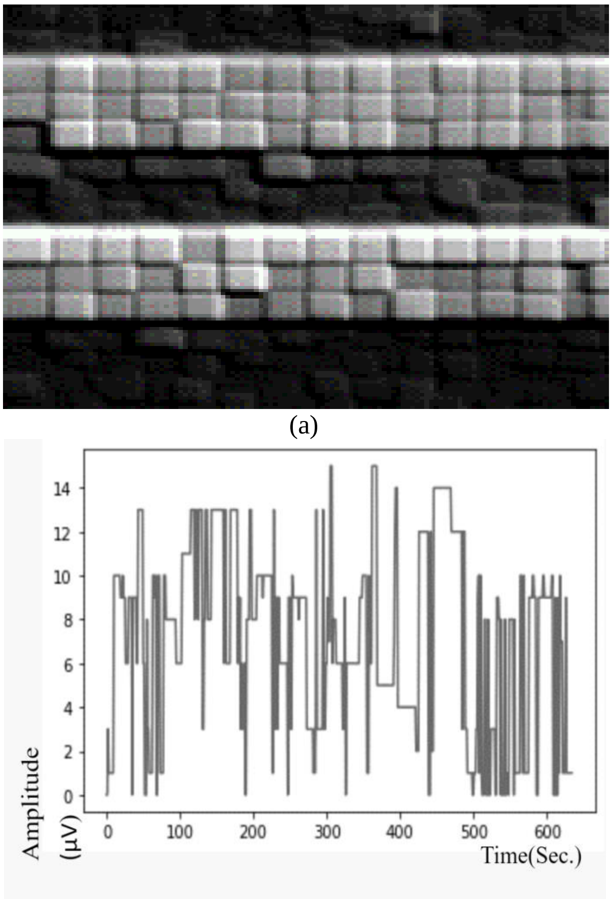
Where,x is the input and $var(x)$ is the variance of x and is used to check for consistency across inputs. This variance is evaluated via Eq. (12),

$$var(x) = \sum_{i=1}^{N} \frac{\left(x_i - \sum_{j=1}^{N} \frac{x_j}{N}\right)^2}{N-1} \quad (12)$$

Based on these identities, input Feature vectors are created from the EEG signal and can be utilised for classification and analysis at the end. Figs. 4 (a) and 4 (b) show the visualisation of the MFCC and iVector components respectively, where the evaluation of feature vectors was done using the same EEG input. The X-axis of an EEG signal with an iVector represents time in seconds, while the Y-axis represents amplitude in microvolts (µV).

They are merged to create a consolidated feature vector, which has a number of redundant features. A fresh inter-class variance threshold is assessed between these features to remove these redundancies. This variance is evaluated via Eq. (13), wherein inter-class information is utilized for estimation of final variance.

Received: July 15, 2023. Revised: September 15, 2023.



(a)

(b)

Figure. 4: (a) EEG signal with MFCC and (b) the same EEG signal with iVector

$$V_{th} = \sqrt{\frac{\sum_{a=1}^{m}\left(FV_a - \frac{\sum_{i=1}^{m}\sqrt{\frac{\sum_{j=1}^{n}\left(FV_j - \frac{\sum_{k=1}^{n} FV_k}{n}\right)^2}{n-1}}}{m}\right)^2}{m-1}} \quad (13)$$

Where, the value m indicates how many features there are in the current class, n represents total number of features in other classes, $FV$and represents feature vector value for the given set of features. Features that have variance lower than V_{th} are discarded, whereas others are utilized in the building of a classifier using MNN. Variance of features is evaluated via Eq. (14) as follows,

$$var(F) = \sum_{i=1}^{N} \frac{\left(F_i - \sum_{j=1}^{N} \frac{F_j}{N}\right)^2}{N-1} \quad (14)$$

Where, $F\&N$ represents feature vector value, and total number of features present in the feature vector respectively. The suggested classifier, which employs a quadratic neural network with growing neurons in order to perform effective EEG classification, is provided with the characteristics. For the neural network, various layers are coupled through neuron connections in order to provide a variety of output classes. Each NN model uses highly variant features for final classification. The combined QNN model uses $n, 2*n, 3*n, \& 4*n$ number of neural units in the final classification design. Here, n represents total number of features extracted via variance-based selection. Eq. (15) is used to control each NN's output, wherein the output class is created using feature vectors and the logarithmic ranges of those vectors.

$$C_{out} = -\frac{1}{2} \times \sum_{j=1}^{N}\left(VBF_j - \sum_{l=1}^{N} VBF_l\right) \times \left(VBF - \sum_{i=1}^{N} VBF_i\right)^T + \log\left(\sum_{i=1}^{N} VBF_i\right) \quad (15)$$

Where, $VBF, \&N$ represents extracted variance-based features, and the total number of different neural network topologies that were used in order to arrive at the final outcome of the classification. This classification is carried out for each classifier, and the final class is derived by the application of Eq. (16), which makes use of a mode operation for the aggregate of the several classes.

$$C_{out}^{final} = \bigcup_{i=1}^{N} C_{out_i} \quad (16)$$

To arrive at the final classification outcome, the mode operation chooses the most commonly occurring class from a group of output classes. The next portion of this article discusses how well the classification procedure performed in terms of recall, accuracy, and delay.

4. Notation

EEG_a	approximate EEG
EEG_d	detail EEG components extracted
x_i	current EEG signal
x_{i+1}	Next, the EEG sample value
H	Hilbert Transform
F	Fourier Transform
C_{DCT}	Discrete Cosine Transform
MFCC	Mel Frequency Cepstral Coefficient
VBF	extracted variance-based features

Received: July 15, 2023. Revised: September 15, 2023.

w_i	weight of MFCC component
$var(x)x$	variance of x
S	Mel power spectrum coefficients
i	MFCC component number

5. Performance evaluation

The AMVAFEx model employs many neural networks in order to arrive at a conclusive categorization of the EEG data. This performance was analysed by making use of a vast collection of EEG datasets with the purpose of classifying input waveforms into several distinct epileptic categories. It is possible to access the Neuromed Epilepsy EEG Database by going to https://clinicaltrials.gov/ct2/show/NCT04647825. The dataset involves 15 distinct leads for the EEG, all of which were used throughout the procedure for gathering data from a total of 500 individual patients. In light of the review's findings, a total of 5000 exceptional items had to be removed from the dataset. After that, for training and assessment, these items were divided into two groups, with the ratio of 60:40 being maintained between the two.

Based on this evaluation and Fig. 5, the proposed model consists of 5.2% more accuracy compared to TTFC [4], 4.3% compared to NNM [7], and 6.75% compared to LBP TH [11] for varied EEG signal types. The main reason for this accuracy improvement is due to combination of Wavelet, Hilbert, Fourier and Cosine transforms, along with feature selection & classification enhancements.

The accuracy, latency, precision and recall of the data were examined, and when contrasted with the results that were obtained from TTFC [4], NNM [7], and LBP TH [11]. This was carried out in order to provide evidence that the technique could be relied upon. Fig. 5 illustrates the observations that were made with regard to the accuracy, and they are as follows: It was discovered that the recommended model had a degree of accuracy that is 5.2 percent greater compared to TTFC [4], 4.3 percent higher compared to NNM [7], and 6.75 percent higher compared to LBP TH [11] for the several kinds of EEG data. [4, 7, 11]

The combination of Wavelet, Hilbert, Fourier, and Cosine transforms, combined with advancements to feature selection and classification, is the primary cause for this boost in accuracy. When paired with the MFCC and iVector features, this bolsters the feature representation capabilities of the model, which ultimately results in improved accuracy performance. Because of its capacity to represent features in high

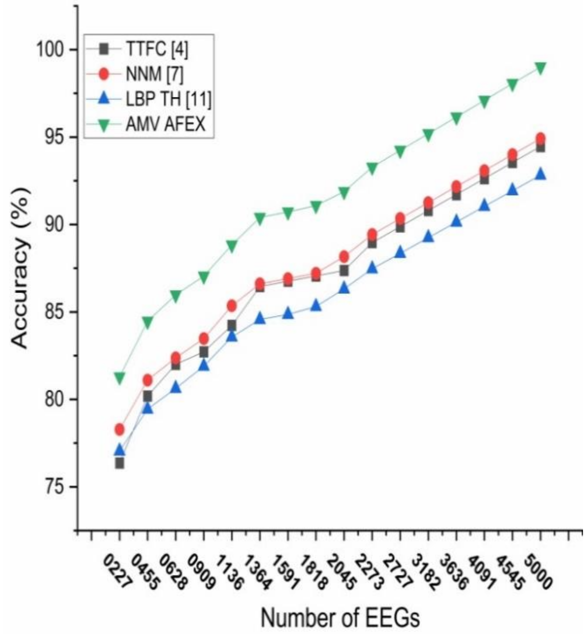


Figure. 5 Accuracy of a variety of EEG classification models

density, the CNN that was used in this scenario was able to contribute to the improvement of classification performance. This performance was accomplished by the use of Multiple NN in addition to the coupling of MFCC and iVector features. In a similar vein, one may evaluate the accuracy performance of these models from Fig. 5.

This performance was achieved when MFCC features & iVector features are used in combination, and use of multiple neural networks for highly efficient classification method.

On the basis of this examination and Fig. 6, it is possible to see that the proposed model is 3.8 percent more precise compared to TTFC [4], 4.95 percent precise compared to NNM [7], and 2.9 percent precise compared to LBP TH [11] for a variety of EEG signals. The combination of a number of various feature extraction techniques, in addition to advancements in selection and classification, is the primary factor responsible for this boost in accuracy.

When this is paired with the MFCC and iVector characteristics, the model's capability of feature representation is enhanced, which in turn leads to improved precision performance. Because of its capacity to represent features in high density, the CNN that was used in this scenario contributed to an improvement in the overall classification performance. This performance was accomplished by the use of MNN in addition to the coupling of MFCC and iVector features. This allowed for an extremely efficient classification procedure. Fig. 7 is representation of the performance of different models for recall.

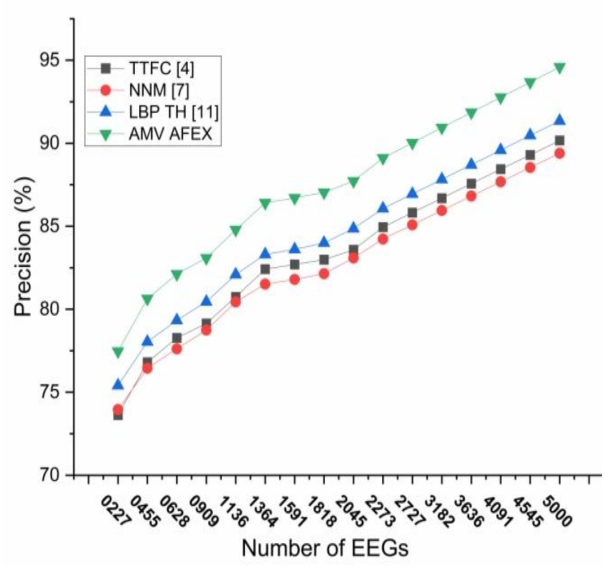


Figure. 6 Precision of different EEG classification models

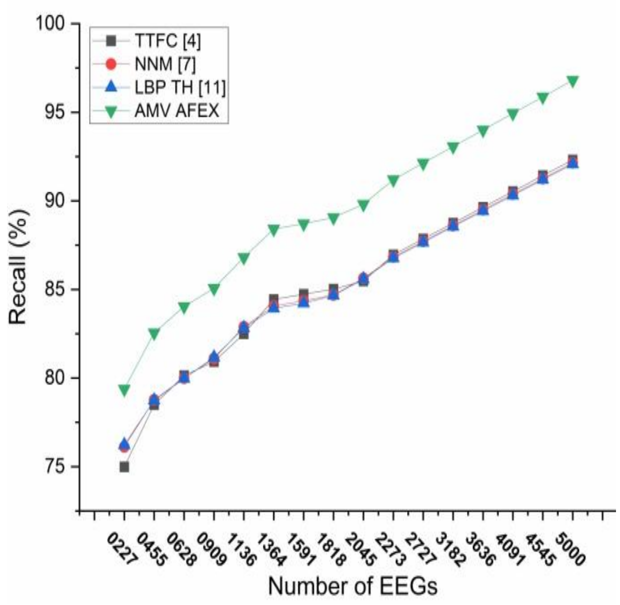


Figure.7 Recall of different EEG classification model

This performance was achieved when MFCC features are combined with iVector features, and MNN are used for highly efficient classification procedure.

On the basis of this assessment, it can be shown that the suggested model has a recall that is 5.3 percent high compared to TTFC [4], 3.9 percent high compared to NNM [7], and 4.5 percent high compared LBP TH [11] for several types of EEG data. The primary reason for this recall increase is the mixing of several feature extraction transforms, such as Wavelet, Fourier, Hilbert, and Cosine, together with advancements to selection and classification. When this is paired with the MFCC and iVector features, the

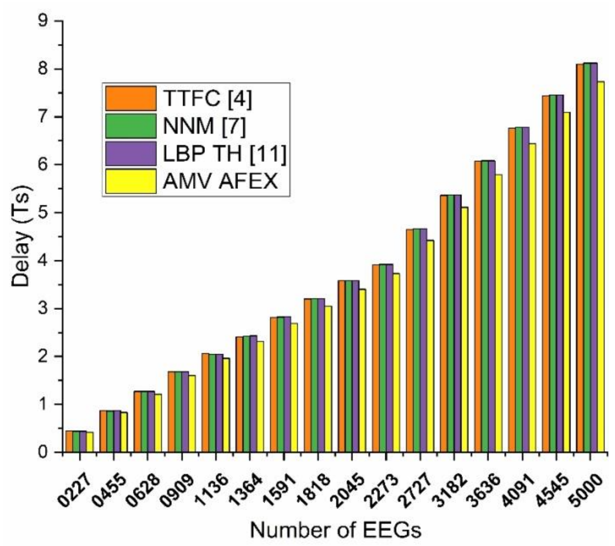


Figure. 8 Delay performance of several EEG classification methods

model's capability of feature representation is enhanced, which in turn leads to improved recall performance. Because of its capacity to represent features in high density, the CNN that was used in this scenario contributed to an improvement in the overall classification performance. This performance was accomplished by the use of MNN in addition to the coupling of MFCC and iVector features. This allowed for an extremely efficient classification procedure.

Fig. 8 provides a visual representation of the average delay required for the classification of a single EEG signal waveform. From this figure, it is possible to see that the proposed model has a delay that is 6.1 percent lower than that of TTFC [4], 4.9 percent less than that of NNM [7], and 5.5 percent lower than that of LBP TH [11] for different types of EEG signals.

The use of variance-based feature selection and low-complexity classifier operations is the primary factor that contributed to the shortening of this delay. When paired with the MFCC and iVector features, these advancements improve the model's capability of representing features, which results in a reduction in the amount of time needed for calculation. Because of its capability to represent high-density features and remove redundant information, the CNN that was used in this scenario was able to contribute to an improvement in classification performance. The use of the wavelet transforms in conjunction with a variance-based feature selection approach made it feasible for this to occur. The feature vector's size could be scaled back by the wavelet transform by up to fifty percent, and a variance-based feature selection model can aid in the identification of most variant features, which can then minimize duplication in output feature sets. As a result of this boost in performance, the model that has been suggested is now able to be utilised for numerous clinical applications in real-time.

6. Conclusion and future scope

In comparison to current models, the suggested AMVAFEx model performs way better as it combines feature extraction, feature selection & classification methods. The MFCC &iVector methods assist in evaluation of highly relevant features, while variance-based model assists in selecting most variant features, thereby reducing redundancy during the classification phases. The chosen features are classified by a multiple neural network classifier that runs in quadratic mode, and assists in top precision, top recall & highly accurate classification.

Comparing the proposed model to various state-of-the-art models revealed some interesting findings, it may increase classification accuracy. Because of this, the proposed model can be used in high-accuracy clinical settings. The proposed model was observed to have over 5% more accuracy than TTFC [4], over 4% more accuracy than NNM [7], and over 6% more accuracy than LBP TH [11] for different types of EEG signals. Similar performance was seen for recall and precision, which greatly increases the model's applicability to a variety of EEG categorization settings. Along with this enhancement in performance, the proposed model also showcases reduced delay, which largely results from utilization of feature reduction via variance-based optimizations. As a result, the proposed model has a 6.1% reduction in delay over TTFC [4], 4.9% less delay compared to NNM [7], and 5.5% less delay compared to LBP TH [11] for different EEG signal types. The scalability of the suggested model will eventually be determined by researchers by validating its performance on various EEG datasets. Moreover, researchers can also identify the merger of deep learning models, such as recurrent neural networks with long-short-term memory (LSTM) and gated recurrent units (GRUs) for superior survivability with several forms of brain diseases.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology KRH and DA; software, KRH; validation, KRH and DA; formal analysis, KRH; investigation, DA; resources, KRH; data curation, KRH; writing—original draft preparation, KRH; writing—review and editing, KRH and DA; visualization, KRH; supervision, KRH and DA; project administration, KRH and DA.

References

[1] Y. Lin, P. Du, H. Sun, Y. Liang, Z. Wang, Y. Cui, K. Chen, Y. Xia, D. Yao, L. Yu and D. Guo, "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*, Vol. 29, pp. 708-717, 2021.

[2] S. Lee, Y. Hung, Y. Chang, C. Lin and G. Shieh, "RISC-V CNN coprocessor for real-time epilepsy detection in wearable application", *IEEE Transactions on Biomedical Circuits and Systems*, Vol. 15, Issue 4, pp. 679-691, 2021.

[3] F. A. Alturki, M. Aljalal, A. M. Abdurraqeeb, K. Alsharabi, and A. A. A. Shamma'a, "Common spatial pattern technique with EEG signals for diagnosis of autism and epilepsy disorders", *IEEE Access: Practical Innovations, Open Solutions*, Vol. 9, pp. 24334-24349, 2021.

[4] Y. Zhang, Z. Zhou, W. Pan, H. Bai, W. Liu, L. Wang, and C. Lin, "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*, Vol. 18, pp. 1667-1678, 2021.

[5] L. I. Kesum, Ermatita and Erwin, "ELREI: Ensemble Learning of ResNet, EfficientNet, and Inception-v3 for Lung Disease Classification based on Chest X-Ray Image", *International Journal of Intelligent Engineering and System*, Vol. 16, Issue. 5, pp. 149-161, 2023, doi: 10.22266/ijies2023.1031.14.

[6] S. Chakraborti, A. Choudhary, A. Singh, R. Kumar and A. Swetapadma, "A machine learning based method to detect epilepsy. International Journal of Information Technology", *International Journal of Information Technology Springer*, 2018.

[7] V. Grigorovsky, V. L. Breton and B. L. Bardakjian, "Glial modulation of electrical rhythms in a neuroglial network model of epilepsy", *Ieee Transactions on Bio-Medical Engineering*, Vol. 68, Issue 7, pp. 2076-2087, 2021.

[8] T. Kim, J. Joo, R. Ryu, S. Lee, E. Park and Y.

Shon, “Modulation of EEG frequency characteristics by low-intensity focused ultrasound stimulation in a pentylenetetrazol-induced epilepsy model”, *IEEE Access: IEEE Engineering in Medicine and Biology Society Section*, Vol. 9, pp. 59900-59909, 2021.

[9] W. Dang, D. Lv, L. Rui, Z. Liu, G. Chen and Z. Gao, “Studying multi-frequency multilayer brain network via deep learning for EEG-based epilepsy detection”, *IEEE Sensors Journal*, Vol. 21, pp. 27651-27658, 2021.

[10] S. Modak, S. Roy, R. Bose and S. Chatterjee, “Focal epileptic area recognition employing cross EEG rhythm spectrum images and convolutional neural network”, *EEE Sensors Journal*, Vol. 21, pp. 23335-23343, 2021.

[11] M. Yazid, F. Fahmi, E. Sutanto, W. Shalannanda, R. Shoalihin, W. Horng, and Ariprihartha, “Simple detection of epilepsy from EEG signal using local binary pattern transition histogram”, *IEEE Access: Practical Innovations, Open Solutions*,Vol. 9, pp. 150252-150267, 2021.

[12] A. Furui, R. Onishi, A. Takeuchi, T. Akiyama and T. Tsuji “Non-gaussianity detection of EEG signals based on a multivariate scale mixture model for diagnosis of epileptic seizures”, *IEEE Transactions on Bio-Medical Engineering*, Vol. 68, pp. 515-525, 2021.

[13] D. Hu, J. Caoy, X. Lai, Y. Wang, S. Wang, and Y. Ding “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*, Vol. 68, pp. 1542-1546, 2021.

[14] P. Mishra, S. Agrawal, R. Panda, “Epileptic EEG signal classification using exponential energy and SVM”, *International Conference on Electrical and Electronics Engineering (ICE3). IEEE*, pp. 231-235, 2020.

[15] X. Gu, C. Zhang, and T. Ni, “A hierarchical discriminative sparse representation classifier for EEG signal detection”, *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, Vol.18, pp. 1679-1687, 2021.

[16] Y. Gao, X. Chen, A. Liu, D. Liang, L. Wu, R. Qian, H. Xie, and Y. Zhang, “Pediatric seizure prediction in scalp EEG using a multi-scale neural network with dilated convolutions”, *IEEE Journal of Translational Engineering in Health and Medicine*, Vol. 10, pp. 1-9, 2022.

[17] Z. Xu, T. Wang, J. Cao, Z. Bao, T. Jiang, and F. Gao,“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*, Vol. 29, pp. 1734-1743, 2021.

[18] R. A. Mahfuz, M. A. Moni, S. Uddin, S. Alyami, M. Summers, and V. Eapen, “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*, Vol. 9, pp. 1-12, 2021.

[19] N. M. Yawale, N. Sahu, and N. N. Khalsa, “Design of a Hybrid GWO CNN Model for Identification of Synthetic Images via Transfer Learning Process”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 3, 2023, doi: 10.22266/ijies2023.0630.23.

[20] J. Na, Z. Wang, S. Lv, and Z. Xu,“An extended K nearest neighbors-based classifier for epilepsy diagnosis”, *IEEE Access: Practical Innovations, Open Solutions*, Vol. 9, pp. 73910-73923, 2021.

[21] A. Liu, G. Song, S. Lee, X. Fu, and X. Chen, “A state-dependent IVA model for muscle artifacts removal from EEG recordings”, *IEEE Transactions on Instrumentation and Measurement*, Vol. 70, pp. 1-13, 2021.

[22] H. Jebelli, S. Hwang, and S. Lee, “EEG-based workers’ stress recognition at construction sites, Automation in Construction”, *Automation in Construction*, Vol. 93, pp. 315-324, January 2018.

[23] M. Nanjappan, P. Krishnadoss, J. Ali, G. Natesan, and B. Ananthakrishnan, “Task Scheduling Based on Cost and Execution Time Using Ameliorate Grey Wolf Optimizer Algorithm in Cloud Computing.”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, Issue 3, 2023, doi: 10.22266/ijies2023.0630.33.

[24] Y. S. Can, B. Arnrich, and C. Ersoy, “Stress detection in daily life scenarios using smart phones and wearable sensors: A survey”, *Journal of Biomedical Informatics*, Vol. 92, p. 103139, August 2018.

[25] V. M. Joshi and R. B. Ghongade, “IDEA: Intellect database for emotion analysis using EEG signal”, *Journal of King Saud University – Computer and Information Sciences. Elsevier*, pp. 1-15, 2020.

[26] F. Itoo, Meenakshi, and S. Singh, “Comparison and analysis of logistic regression, Naıve Bayes and KNN machine learning algorithms for credit card fraud detection”, *International Journal of Information Technology*, 2020.

[27] O. Amanuel and Y. Alazzawi, “Design and Implementation of EEG-Based Smart Structure”,

Received: July 15, 2023. Revised: September 15, 2023.

International Journal of Intelligent Engineering and Systems, Vol. 16, Issue 1, 2023, doi: 10.22266/ijies2023.0228.28.

[28] S. Akdag, F. Kuncan, and Y. Kaya, "A new approach for congestive heart failure and arrhythmia classification using downsampling local binary patterns with LSTM", *Turkish Journal of Electrical Engineering and Computer Sciences*, Vol. 30, Issue 6, pp. 2145-2164, 2022.

[29] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. Altuwaijri, W. Abdul, M. A. Bencherif and M. Faisal, "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review.", *Neural Computing and Applications*, Vol. 35, Issue 20, pp. 14681-14722, 2023.

[30] T. Trammel, N. Khodayari, S. J. Luck, M. J. Traxler, and T. Y. Swaab, "Decoding semantic relatedness and prediction from EEG: A classification method comparison", *NeuroImage*, Vol. 277, No. 120268, pp. 1-9, 2023.