IETE Journal of Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tijr20

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To cite this article: B. Venkata Phanikrishna, Allam Jaya Prakash & Chinara Suchismitha (2021): Deep Review of Machine Learning Techniques on Detection of Drowsiness Using EEG Signal, IETE Journal of Research, DOI: 10.1080/03772063.2021.1913070

To link to this article: https://doi.org/10.1080/03772063.2021.1913070

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Deep Review of Machine Learning Techniques on Detection of Drowsiness Using EEG Signal

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ABSTRACT
Electroencephalogram (EEG) is used to analyze the state of the brain. One of the critical states of the brain is drowsiness. Physical, mental tiredness, and unconsciousness are some of the reasons for drowsiness. Drowsiness state may lead to fatal crashes, severe injury, and property damage; sometimes, it can be analyzed and detected by using EEG. Analyzing EEG signals is complicated and tedious, so an automated diagnosis is required to interpret these signals effectively. In recent years, finding drowsy feeling while working has become an important research area. In this paper, the authors reviewed various drowsiness detection techniques in the literature and analyzed the performance of 15 different machine learning algorithms for the self-acquired feature set from the EEG.

KEYWORDS
Classification; Drowsiness; Drowsiness Detection; Electroencephalogram (EEG); Features; Scaling

1. INTRODUCTION

Drowsiness or fatigue is an unusual sleep during the day time. It is also defined as the state of transition from awake to sleepy that results from persistent mental and physical work, poor sleep habits, and unhealthy conditions [1]. A person's drowsiness affects his personal life by lowering his workability and energy level, making him irritable and making poor and undesirable judgments when needed [2]. Due to these reasons, sometimes a drowsy person is risking the lives of others while engaging in driving, crane operating, and mining blasting. Therefore, drowsiness detection (DD) is an important safeguard to prevent accidents.

1.1 Existing Methods for Drowsiness Detection

Four DD methods are becoming popular in recent days: (i) subjective-based, (ii) vehicle-based, (iii) behavioral-based, and (iv) physiological based. They are explained as follows:

- In **subjective-based DD method**, an instructor communicates with a person who has to find drowsiness with subjective scaling questions at different time intervals, according to their convenience. The main disadvantage of this method is frequent questioning, and the interaction always brings the drowsy person into normal awake state. This method is unrealistic in the real-time application perspective.
- In **vehicle-based DD method**, driver drowsiness is detected by observing vehicle and vehicle-steering movements. However, these techniques are highly dependent on the type of vehicle, and environment where the vehicle is used.
- In **behavioral-based DD method**, a person's drowsiness can be detected by analyzing drowsy behavioral patterns from images or videos captured using cameras. However, this abstraction may not be reliable in some cases, especially under dim lighting and foggy conditions.
- In **physiological-based DD method**, drowsiness is detected by analyzing the physiological (non-visual) signals obtained using biosensors from the person. However, during working hours like driving, operating crane, etc., the acquisition of physiological signals can cause discomfort to the individual.

Every DD method has individual advantages and disadvantages. Low processing time, accurate drowsiness detection techniques are helpful in real-time applications. Physiological-based methods have the high potential to achieve better accuracy by continuously monitoring and analyzing non-visual signals that correlate with physical signs like drowsiness and sleep. Biosensors are useful to obtain physical signals from the individual in any situation. These signals are very easy to processing time due to their single-dimensional shape. Physical signs used to detect drowsiness by monitoring wakefulness and drowsiness include electrooculogram (EOG)

[3], electrocardiogram (ECG) [4–6], electrodermal activity (EDA) [7], electromyogram (muscular) (EMG) [8], and other brain-related signals. The physiological signal activity produced by the brain is more reliable to determine drowsiness. The brain is always active whether the person is in sleep or alert or think or even dream state [9,10]. Among all cerebrum methods such as EEG (electroencephalogram), PET (positron emission tomography), MEG (magneto-encephalography), or fMRI (functional magnetic resonance imaging), EEG is the most adaptable and commonly used in sleep research [11–13]. It is convenient to gather information about brain activity by placing a few lightweight electrodes beneath the head. EEG discloses the changes in brain state according to different experimental conditions [14,15]. Drowsiness detection using the EEG signal is considered as a classification task. The features extracted from the EEG signals are classified as awake and drowsy using the Machine Learning (ML) classifier. Figure 1 explains this overall procedure.

1.2 Related Literature and Motivation

The acquisition of EEG data is done in a wired/wireless manner to the processor. Some researchers [16,17] simulation work is done on EEG data which were acquired by wired manner. However, the wired connection makes the person uncomfortable by restricting his movement

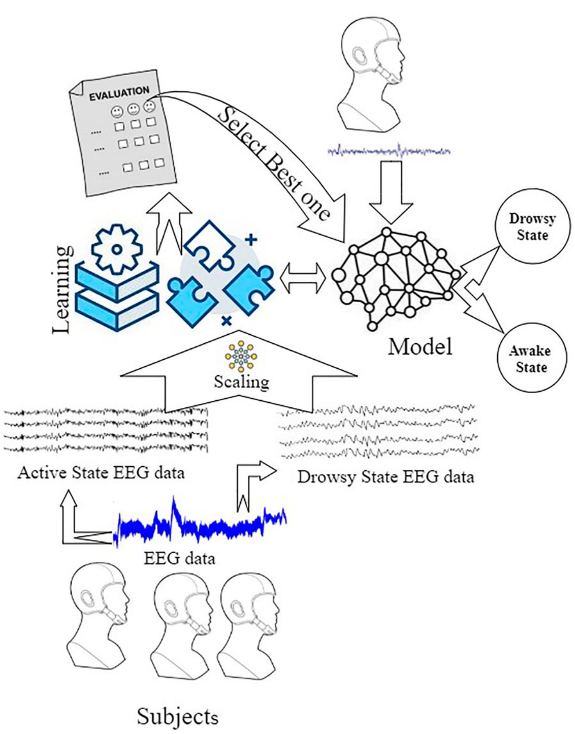

Figure 1: System model to detect the drowsiness using EEG signals

due to the wires attached. Lin *et al.* provide a solution by setting new remote sensors in a non-intrusive system [18]. The EEG signal acquisition can be through single-channel acquisition or multi-channel. Thus they are termed accordingly as multi-channel or single-channel EEG-based model.

1.2.1 Multi-Channel EEG-Based Model

A few other studies have explored the use of multi-channel EEG and blend of other physiological signal for detecting drowsiness. Li *et al.* [19] have used four-channel signals related to EEG and head movements to detect drowsiness and achieved 96% accuracy by Support Vector Machine Classification (SVM) classifier. In [20], detection is done with the help of multi-channel EEG in two ways such as spectral base features and nonlinear based features, and also by combining EEG nonlinear based and EOG features with accuracy of 91.6%. Similarly, Khushaba *et al.* [21] have found 91.2% accuracy using SVM classification with the help of three-channel EEG, ECG, and EOG. In [9], Yeo *et al.* uses 17 channel EEG data with SVM classifier that finds the drowsiness of person with 99.3% accuracy. The author of [22] uses the combination of EEG and MEG features and neural network classifier. His proposed techniques could differentiate alert, drowsy, and sleep states with 98% accuracy. With the help of three-channel EEG data and a combination of one EOG, and ECG signals drowsiness of a person identified in [23] with 99% accuracy. Several techniques are developed to detect pilot drowsiness using EEG sub-band and its combination-based features in [2,13,24,25]. In [2,13,24,25], 60 channels of EEG signal data are collected from 40 pilots used to prepare the model. The self-paced dynamic infinite mixture model (SDiMM) is proposed to label fatigue stages [2]. In [13], a deep belief network (DBN) was developed based on Poisson and gamma functions to detect fatigue and reported 93% accuracy using 5 EEG sub-band-based indices. The Gaussian mixture model (GMM) warped infinity model detected pilot fatigue behavior with a performance of 92.68% [24]. Hidden semi-Markov model (HSMM) with Hierarchical Dirichlet Process (HDP) and t distribution are combinedly used and selected the best features through the Treelet transform process to achieve a performance of 90.9% accuracy (average of seven dataset results) in [25]. The above-mentioned models provided better accuracy in drowsy recognition.

However, these devices typically have many sensors and a blend of multiple other physiological signals used in it. It is costly and not relevant for the real-time applications in working environments like mining areas and during vehicles driving, etc. Further, the information retrieval through multi-channel EEG sensors needs the person to wear a headband fitted with few electrodes onto it, making him very uneasy. In substance to this, a single-channel device can be only a little handle on the head with a potential loss of fidelity. In contrast, a method with single-channel EEG that balances both performance and convenience requirements is essential for real-time applications.

1.2.2 Single-Channel EEG-Based Model

Some researchers have explored and investigated the utilization of single-channel lightweight EEG system for DD. In [26], single-channel EEG data was gathered with the help of MUSE device and calculated the sub-band power spectrum density related features. With SVM supervised classifier system, they got 74% accuracy. The authors of [27] have used single-channel EEG sleep data and K-nearest neighbor (KNN) classifiers and have acquired 83% accuracy. Similarly, the authors in [17] have used 52 features and K-NN classifier with KD-tree search algorithm to prognosticate the drowsiness of a person with improved accuracy of 91%. In [16], 90% accuracy was acquired with 3 sets of 11 Recurrence Quantification Analysis (RQA) features gathered from single electrode EEG system. Also in [28] and [29], the authors have found the sleepiness using single-channel EEG data with some features and supervised ML algorithms. They have achieved 90% and 87.4% accuracy respectively. In [30,31], authors utilize hand-engineered features along with a deep learning classifier to detect drowsiness. Tripathi *et al.* [30] developed a deep neural network (DNN) classifier to classify drowsiness state and reached 86% accuracy. A combination of hand-crafted features along with Long short-term memory (LSTM) classifier is utilized to detect drowsiness state with an accuracy of 94% [31]. The authors of [18,32,33] detect the drowsiness with the help of single electrode EEG system using EEG sub-bands. Here the authors measure the drowsiness statistically with 82%, 90%, and 83% accuracy respectively, instead of using ML related algorithms. These records and procedures are promising from the perspective of using a single-channel EEG data for sleep or drowsy detection. However, these outcomes are orthogonal to the research carried out in this paper.

In this paper, a hypothesis has been considered that the single-channel EEG signal with multi-domain feature might provide better accuracy for detecting drowsiness of a person, which can be scaled by standard scaling technique. Several studies have utilized multi-domain features in EEG signal analysis. The authors of [34,35] have used multi-domain features for multi-channel EEG signals to classify the EEG signals for detecting epilepsy. This paper could be one of its types which assess the ability of multi-domain features with appropriate scaling to detect drowsiness. Following are the major contributions and highlights of the current work:

- A single-channel EEG-based automated system is designed instead of a multi-channel using multi-domain features related to time, frequency, and EEG sub-bands.
- The performance of multiple classifiers has been compared in detecting the onset of drowsiness and the result is validated with the combined-subjects wise and cross subject wise strategies.
- Additionally, clarify the job of scaling in ML in both linear and non-nonlinear strategies.
- A detailed qualitative and quantitative analysis for the performance of classifiers is carried out using standard EEG sleep dataset.

Furthermore, during this study, the performance of the classifiers is estimated using standard publicly available MIT-BIH Sleep EEG database which shows better results.

The remaining paper is organized as follows: the database description is presented in Section 2, the proposed methodology is explained in Section 3, Section 4 demonstrates the experimental results and the conclusion of this paper is discussed in Section 5.

2. DATABASE DESCRIPTION

The analysis of EEG signal requires real-time data recorded with a single-channel device. Most researchers obtain EEG data on specific tasks, such as driving with their own EEG device. This requires a virtual reality setup for recording of the data by allowing a subject to stay in a monotonous state for a longer period so that he may feel drowsy or go to the sleep state. Some researchers are using a standardized dataset, which is freely available online. Researchers who are interested in this topic, this free online dataset can be helpful to test, validate, and extend the existing work. Thus for the current work, we have used such freely available online dataset from physionet.org which is a standard organization of Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) depicted by researchers for the investigation and analysis of sleep stages [36]. The available data has been recorded for different durations for different subjects. Individual's EEG data is divided into five groups as wakefulness (W), non-rapid eye movement (NREM), rapid eye movement (REM), move state, and not scored state. The first category (W) is a state of conscious in

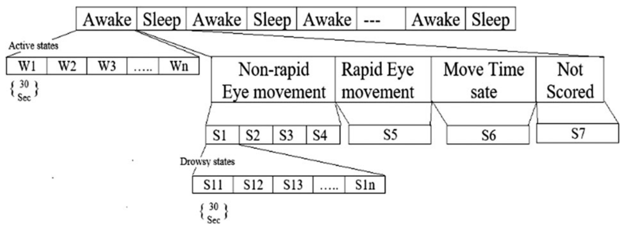

Figure 2: Modeling of recorded data

which a person is completely alert and can perform physical and mental tasks while maintaining complete attention. The second category, NREM, is divided into four stages: stage 1 (s1) is related to drowsiness and this stage is the step from attentiveness to rest, during which an individual can be woken quietly, and may not know that they were in a drowsy state. Here, EEG signals are low amplitude and low frequency, while other phases such as s2, s3, s4 are associated with some other states of sleeping [37].

During acquisition of EEG data from a brain, the subject can be considered as to be in either in the awake state or in any one of the sleeping states. However, we have considered the data as a series of alternate awake and S1 state of sleep states as shown in Figure 2.

The initial phase of the sleep state, *i.e.* the S1 stage is usually considered as the drowsy state as this state lies in between the awake and the deep sleep stage of a person. Thus the recorded data contains several epochs of 30 s duration each for the awake stage (W) and the $S1$ stage as indicated in Figure 2. The number of slots (or epochs) in the awake stages vary from person to person. The same is also true for the $S1$ stage.

Let A be all awake states W of a person.

$$A_i = \{w_i | w_i \in W\}$$

Let D be all sleep states $S1$ of a person

$$D_i = \{S1_i | S1_i \in S1\}$$

Thus for the present research, we considered all epochs in the S1 and W stages of each individual P. It is indicated as

$$P_i = A \cup D = \{X | X \in A \text{ } or \text{ } X \in D\}$$

where i is a person or subject, it is 1–39.

3. PROPOSED METHODOLOGY

The model used in the current research is proposed in Figure 3. The model consists of five steps such as data acquisition (as explained in Section 2), Artifacts removing, features calculation, Scaling and Classification. The details of the steps are as follows.

3.1 Artifacts Removing

Artifacts reduce the actual information in the EEG. Therefore, after obtaining the EEG data, it is necessary to find and remove the artifacts. The artifacts in the EEG are due to two factors. One is due to the hardwares used during the reading of EEG signal, and the other one is physiological-related artifacts occur due to subject movements such as eye-related artifacts due to eye movement, eye blinking, and muscle-related artifacts especially forehead muscle movement [38,39]. Hardware artifacts can be caused by real-time problems in EEG devices, such as the lack of proper contact with the EEG sensor and scalp of the head, and power fluctuations in the EEG reading machine. These problems can be easily resolved in real time, using the latest hardware tools. In this experiment, hardware artifacts are avoided by manually validating each epoch (*i.e.* 30 s timestamp window) data. If all (3000) samples (sampling frequency 100 Hz) of any timestamp window produce a straight line or no variations between samples, then we treat them as hardware artifacts and remove those epochs from the dataset.

During the EEG acquisition, if the person is in an uncomfortable posture or stays in the same posture for a long time, the physiological-based artifact may occur as he

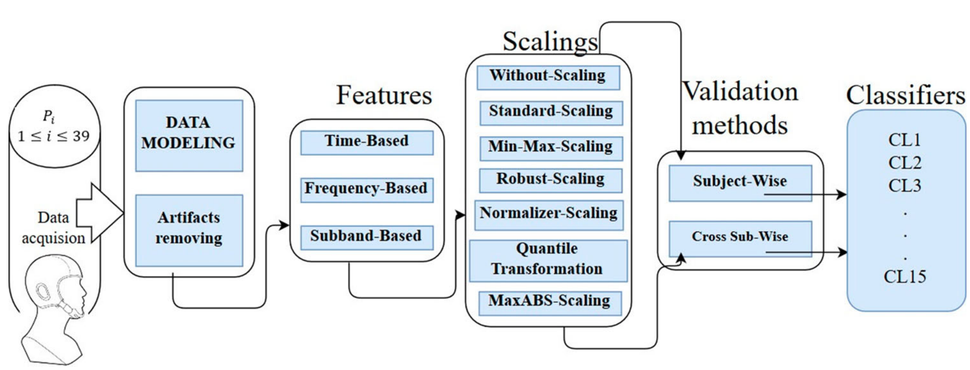

Figure 3: Stages of signal analysis for proposed drowsiness detection

might stretch his backbone, shoulder, and neck muscles. These body-based small movements interject EMG artifacts in EEG signal. Accumulating EEG at a high sampling rate is more likely to have unintended signals related to physiological artifacts such as noise spikes, EMG, eye movements, or other artifacts [40]. Moreover, this high sampling frequency EEG requires more space to store and time to analyze. The EEG signal used in this experiment was obtained in the laboratory under EEG-expert supervision at a sampling rate of 100 Hz [36]. Therefore, this signal has a maximum frequency of 50 Hz according to the Nyquist–Shannon model theory [41], without many physical artifacts. This type of EEG data recorded from 39 people was used for the proposed model.

3.2 Features Extraction

The raw EEG data does not provide any information about its state, such as being awake or drowsy. Feature extraction is the gathering of relevant information from raw EEG to describe its state after removing artifacts. However, not all features extracted from the EEG signal may have useful classification information, and so far, there is no standard feature extraction process available. Without compromising in classification performance, the extraction of easily calculable features by analyzing the EEG with simple signal processing techniques such as Fast Fourier transform (FFT) is more beneficial to the proposed model.

In this experiment, a total of 22 multi-domain features are identified from the time-domain signal, frequency-domain signal and its sub-bands (such as delta (0.5–4 Hz), theta (4–8 Hz), Alpha (8–12 Hz), Beta (8–12 Hz), and Gamma (12–30 Hz)) obtained using FFT. Based on observations in the literature, features that can be easily extracted from the EEG signal are used. They are described domain-wise in the following subsections.

3.2.1 Time-Domain Features

The time-domain signals of EEG awakening and drowsiness are shown in Figure 4. Time-Domain features are extracted from the direct EEG without transferring it to another domain and help to get signal morphological qualities. They have been identified to be appropriate in many real-time applications, such as diagnosing epilepsy problems.

In the current work, we have extracted total 10 features in time domain as listed in Table 1. A detailed description of these features and the computational procedure is described in Appendix.

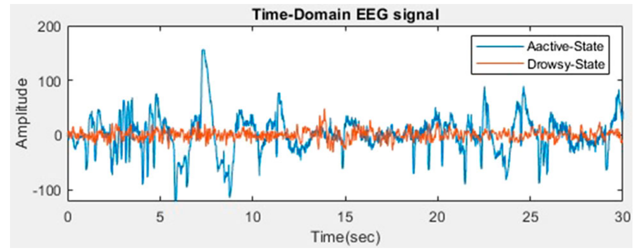

Figure 4: EEG time domain signal of awake and drowsy state

Table 1: List of time-domain features

S. no.	Feature name	
1	Power	
2	Entropy	
3	Skewness	
4	Kurtosis	
5	Hjorth parameters	Activity
6		Mobility
7		Complexity
8	Detrended fluctuation analysis	
9	Hurst exponent	
10	Zero-crossing rate	

3.2.2 Frequency-Domain Features

These are used to analyze the frequency-related information in EEG. Frequency-domain signal analysis helps to find the power of the signal in terms of the frequency and frequency of waves that cannot be detected in the time domain. Time-domain signals are converted into frequency domain with a mathematical operation called Transform. Signal transformation methods such as wavelet packet transform (WPT), Short-time Fourier transform (STFT), and FFT are mainly used to obtain frequency-related information from the EEG signal. Among them, FFT is easy to use and takes less time to obtain frequency-related information. Its mathematical operation is as follows:

$$X(f) = \sum_{t=1}^{N} x_t \times e^{\frac{-2\pi \times i \times t \times f}{N}} \tag{1}$$

where $x(t)$ is the EEG signal in time domain, $X(f)$ is the EEG signal in frequency domain, N is the size of the signal and $f = 1, 2, \ldots, N$. The frequency-domain signals of EEG awakening and drowsiness are shown in Figure 5.

A total of 12 features from the EEG frequency signal obtained by FFT were extracted for the present work. These are listed in Table 2 and their descriptions are given in Appendix.

3.2.3 Sub-bands Features

In this proposed work, EEG sub-bands such as such as delta (0.5–4 Hz), theta (4–8 Hz), Alpha (8–12 Hz), Beta

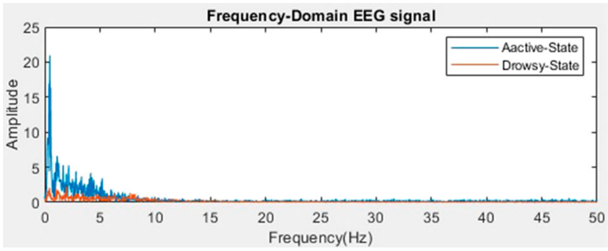

Figure 5: EEG frequency-domain signals of awake and drowsy state

(8–12 Hz), and Gamma (12–30 Hz) are extracted using FFT. Each sub-band of the EEG with respect to awakening and drowsiness is shown in Figure 6. As mentioned in Table 2, 12 frequency-related features are extracted from each sub-band.

Thus 10-features from the time domain, 12 features from frequency domain and from each sub-band (delta, theta, alpha, beta, and gamma) total 82 (*i.e.* $10+12+12*5$) features are measured.

3.3 Scaling

ML algorithms make guesses about provided information. The provided information such as feature vector has a different position, face values, and units; this inequality in computed features will decrease the performance

Table 2: List of frequency-domain features

S. No.	Feature name	
1	Spectral centroid	
2	Median frequency weight	
3	Dominant frequency	
4	Mahalanobis distance	
5	PSD parameters:	Min.
6		Max.
7		Mean
8		Median
9	Amplitude local maxima	Min. distance between peaks
10		Max. distance between peaks
11		Min. peak value
12		Sum of peak values

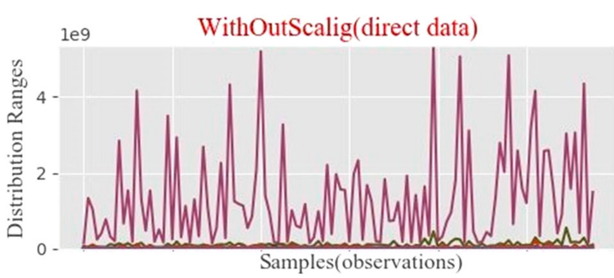

Figure 6: Distribution input data vectors before scaling

Table 3: List of scaling's with their minimum and maximum values

S. No.	Scaling	Min.	Max.
1	Without-Scaling	−0.7078	5350340893.26
2	Standard-Scaler	−2.7982	7.1684
3	Min-Max-Scaler	0.0	1.0000
4	Robust-Scaler	−2.0564	10.273
5	Normalizer	−1.39e-09	0.9994
6	Max-Abs-Scaler	−0.2700	1.0
7	Quantile-Transformer	9.9999e-08	0.999

of the ML algorithm in case of time and result. To conquer this, all individual features of the feature vector are sized at a similar level. Many feature transform methods are available for this task. However, there is no predefined strategy for finding the best scaling method for ML classifier algorithms. Which scaling is best for a particular ML algorithm is not addressed by contemporary researchers. That would make a very negative impact on the practicality of using state-of-the-art drowsiness detection techniques. So it is essential to compare some scaling methods for different ML algorithms and select the best scaling technique based on the performance of ML algorithms. Distribution of features vector without scaling is shown in Figure 7. In our proposed work, total 6-scalings such as Standard-Scaling, MinMax-scaling, Robust-scaling, Normalizer-scaling, MaxAbs-Scaling, and Quantile-Transformer methods are used to compare the performance of ML classifier algorithms. All these methods are collected from scikit-learn [42] and their descriptions are given in Appendix. Each scaling feature vector distribution is displayed in Figure 8 and the minimum and maximum values are shown in Table 3, with and without scaling.

3.4 Classifications

In ML, classification is the supervised process to perform a categorical prediction of newly available data based on old data. To perform this prediction, initially, the classifier must train with available information. During the training process, the ML classifier finds the relation between provided input data (let say X) and their corresponding type (let say Y). Here the input data is a feature vector contains m ($m = 82$ for this experiment) features (real) values, and the category type is either be drowsy state or awake state. This process is shown in the equation as follows:

$$X = \{x_1, x_2, x_3, \ldots, x_n\} \text{ where } x_i \in \mathcal{R}^m$$

$$Y = \{A, D\} \; where \begin{cases} A \in Awake\ State \\ D \in Drowsy\ State \end{cases}$$

The relation between X and Y is $Y = f(X)$.

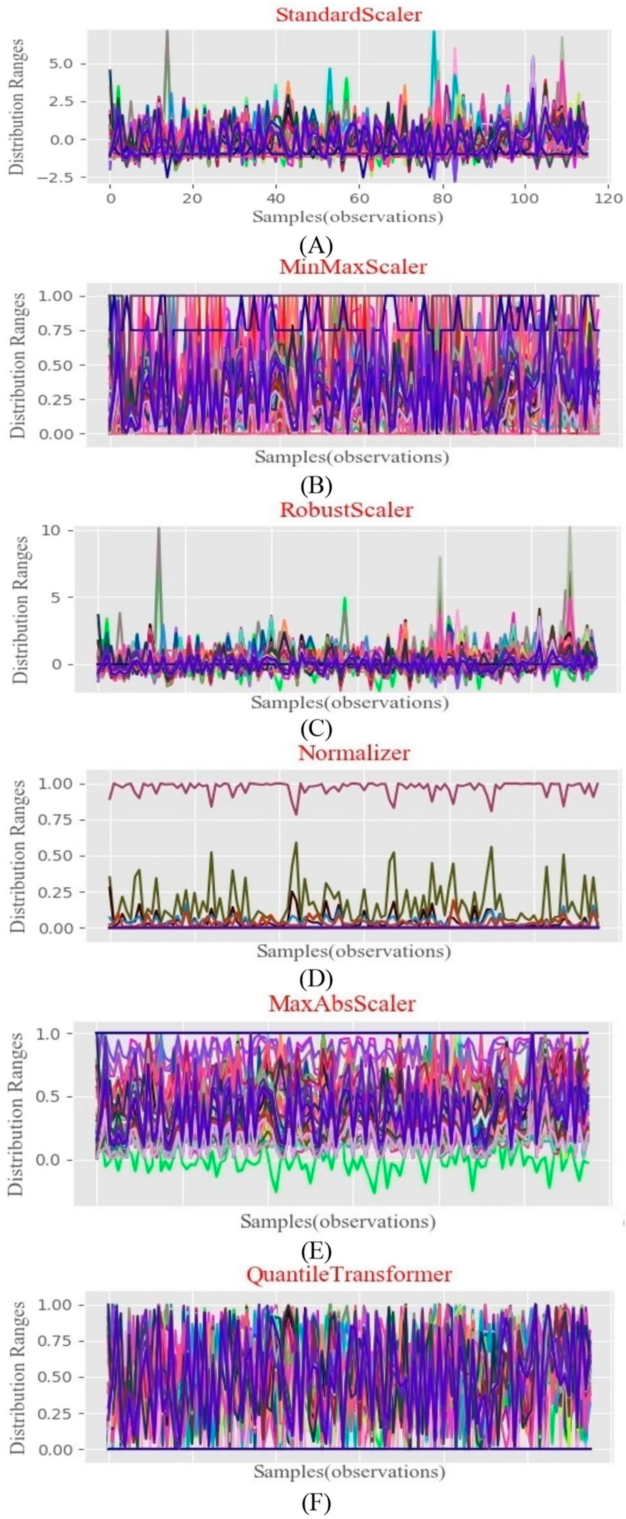

Figure 7: Distribution input data vectors after (A) standard scaling transformation, (B) MinMax scaling transformation, (C) robust scaling transformation, (D) normalizer scaling transformation, (E) MaxAbs scaling transformation, (F) quantile transformer

The obtained relation during training for X and Y is used to predict the future Y_{new} for new input variables X_{new}. There are too many ML classifiers to handle this process.

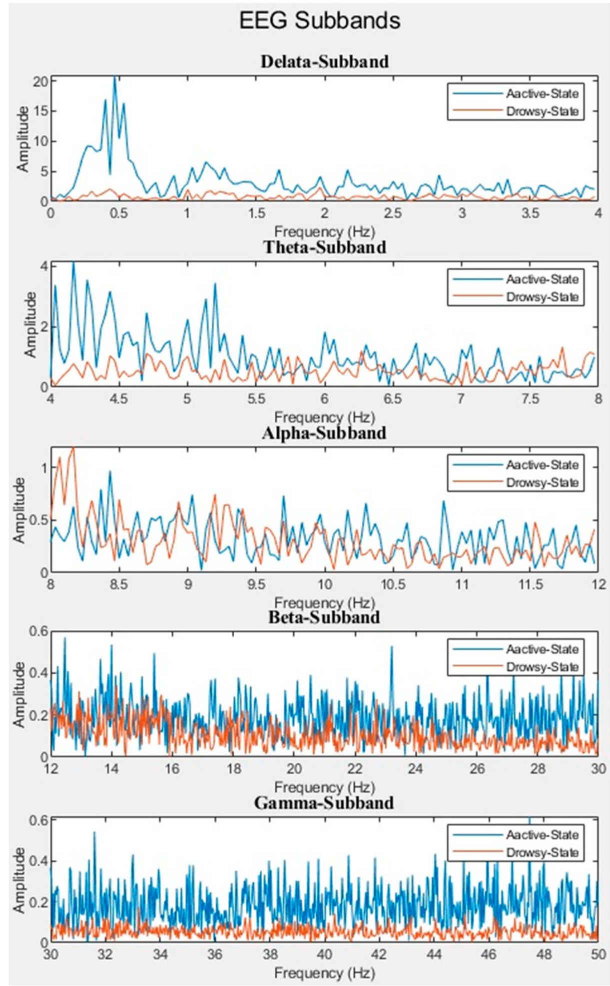

Figure 8: EEG five sub-bands of awake and drowsy state

However, as per [43] and [44], "no free lunch theorem," it is unwarranted to choose a classifier randomly. Because each classifier has its individual preferences, and no single classifier enjoys superiority for every classification task. In this experiment, using our features and appropriate scaling methods, a suitable classifier is selected that provides higher classification accuracy than the existing work. To achieve this, it is necessary to check and compare a handful of multiple classifiers. Classifiers that are used in these experiments are categorized into two groups: linear and nonlinear. These concepts are treated in different ways, but the goal is always the same.

Linear classifications: Here classifiers perform classification using a hyperplane made up of an $m+1$ randomly selected weight vector.

$W = \{w_0, w_1, , w_2, \ldots w_m\}$ where $w_i \in \mathcal{R}$

With the help of this weight vector (W) and feature vector (x), quantization (Z) is estimated for each sample by using the following formula:

$$Z = x \cdot \bar{w} = \sum x_i w_i$$

Therefore, if the set of coefficients w what has been determined is correct, then the classification done by the following way:

$$sign(Z) = \begin{cases} 0 \; when \; \in A \\ 1 \; when \; \in D \end{cases}$$

Some linear classifications that were used for this experiments are: Linear discriminant analysis (with hrinkage = “auto”) (LDA), Logistic Regression (LD), Quadratic Discriminant Analysis (QDA), Gaussian Naive Bayes (GNB) classifier, Stochastic Gradient Descent (SGD) Classifier, SVM-SVC (SVC), SVM-NuSVC (NuSVC) with kernel = “rbf”, and SVM-linearSVC (LSVC).

Nonlinear classifiers: In Linear-classification methodology, the output state is mapped with the linear combination of features. The classifications mentioned above are beneficial if the subjects are drowsy and awake stages are separable by a linear boundary. Linear-based methods give unsatisfactory results if features are not separable linearly. In such conditions, nonlinear separable classifications are best. For our analysis, some of the nonlinear classifiers used such as Decision Tree (DT) Classifier, Adaboost (AB) Classifier, Random Forest (RF) classifier, ExtraTrees (ET) Classifier, K-NN Classification (with k = 3), Nearest Centroid (NC) classifier, and artificial neural network (ANN) (with three hidden layers of 500, 250, and 40 neurons).

4. RESULTS AND DISCUSSION

To simulate our model, the Physionet EEG dataset collected from 39 people using the Fpz-Cz sensor, mentioned in Section 2, has been considered. The data has been recorded from 39 subjects (people) in different durations. The number of observations for each subject is not the same. After eliminating the artifacts from all subjects, each subject’s observations varies from 26 to 368. All experiments were conducted in a python 2.7 environment with a computer having an Intel Core i7-7700K@4.20 GHz CPU and 4-GB memory.

4.1 Evolution Standards

Performance evaluation depends on how the classifier is trained by the available input data (called in-sample) and how it forecast future data (called out-sample). In this paper, two different train-testing strategies have been adopted to check whether the proposed model works well.

- In the first strategy, we tested using the same procedure reported in [40], this involved combining all the individual data and subsequently using the 10-fold validation process. That is, all available features data was divided into 10 folds. Among that nine folds are considered as the training group and the remaining one fold as the testing group. Then the test accuracy is calculated. Repeat the same procedure by considering another fold for testing and union of remaining as the training set. This process is continued till all the 10 folds are considered once for testing. The final result of the ML classifier algorithm is the average of all these 10 possible test accuracies.
- In the second strategy, a cross-subject wise validation method is considered to test the generalizability of the proposed work. Here, 38 of the 39 people divide the data into a training group and the remaining one-person data into a test group, and then the test accuracy is calculated. The same process was repeated by making another person data as a test set and training set as the rest of the data. This process continues until each individual data is considered for one-time testing. Visual representation of cross-subject validation is shown in Figure 9.

The highlighted subject data for each round is test data, and the remaining data are train data. The average accuracy of these 39 rounds of test results is the final accuracy of the model. That is

$$Final\ Accuracy = \frac{1}{39} Accuracy(Round_i)$$

There are many metrics available for evaluating the performance of the classifier. For this experiment, confusion matrix matric is used. The confusion matrix parameters for this drowsy detection method are:

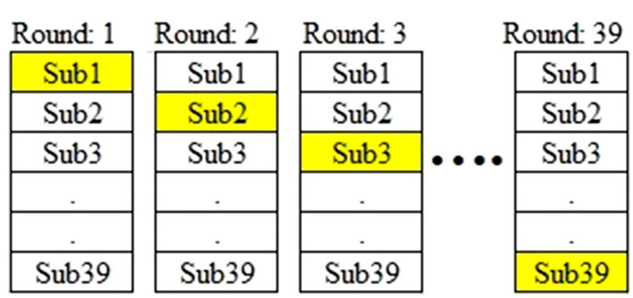

Figure 9: Cross-subject validation process

- True Positive (TP): The classifier correctly predicts the state of the person as drowsy when he is in drowsy.
- True Negative (TN): The classifier correctly predicts the state of the person as does not in drowsy when he is not in drowsy.
- False Positive (FP): The classifier incorrectly predicts the state of the person as drowsy when in fact they do not.
- False Negative (FN): The classifier incorrectly predicts the state of the person as not in drowsy when he is in drowsy.

Researchers used sensitivity (recall) and precision (positive predictive value (PPV)) metrics to assess their models. Those mathematical computations are:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

However, if all model predicts all observations as the drowsy state, then sensitivity goes to 100%. Furthermore, in the absence of TP (*i.e.* model didn't detect the drowsy states), the precision and recall are zero. In such cases, if the model is adjusted slightly to predict one drowsy instance correctly and remaining all drowsy instances incorrectly, then precision becomes 100% because there is no FP. Such models are not preferable in real time. Therefore, it is better to measure model performance using a combination of precision and recall, *i.e.* $F1_{score}$. Its calculation is as follows:

$$F1_{score} = 2 * \frac{precision * recall}{precision + recall}$$

In this experiment, totally 15 classifiers and 7 scaling techniques (including without scaling data) were employed and totally four (total accuracy, sensitivity, precision, and $F1_{score}$) metrics are used to evaluate the proposed model.

4.2 Experiment Results

As described in the previous section (*i.e.* Section 4.1), the proposed model evaluation was done in combination-subjects and cross-subject wise, and their results are shown in Figures 10–11. The LDA provides the best

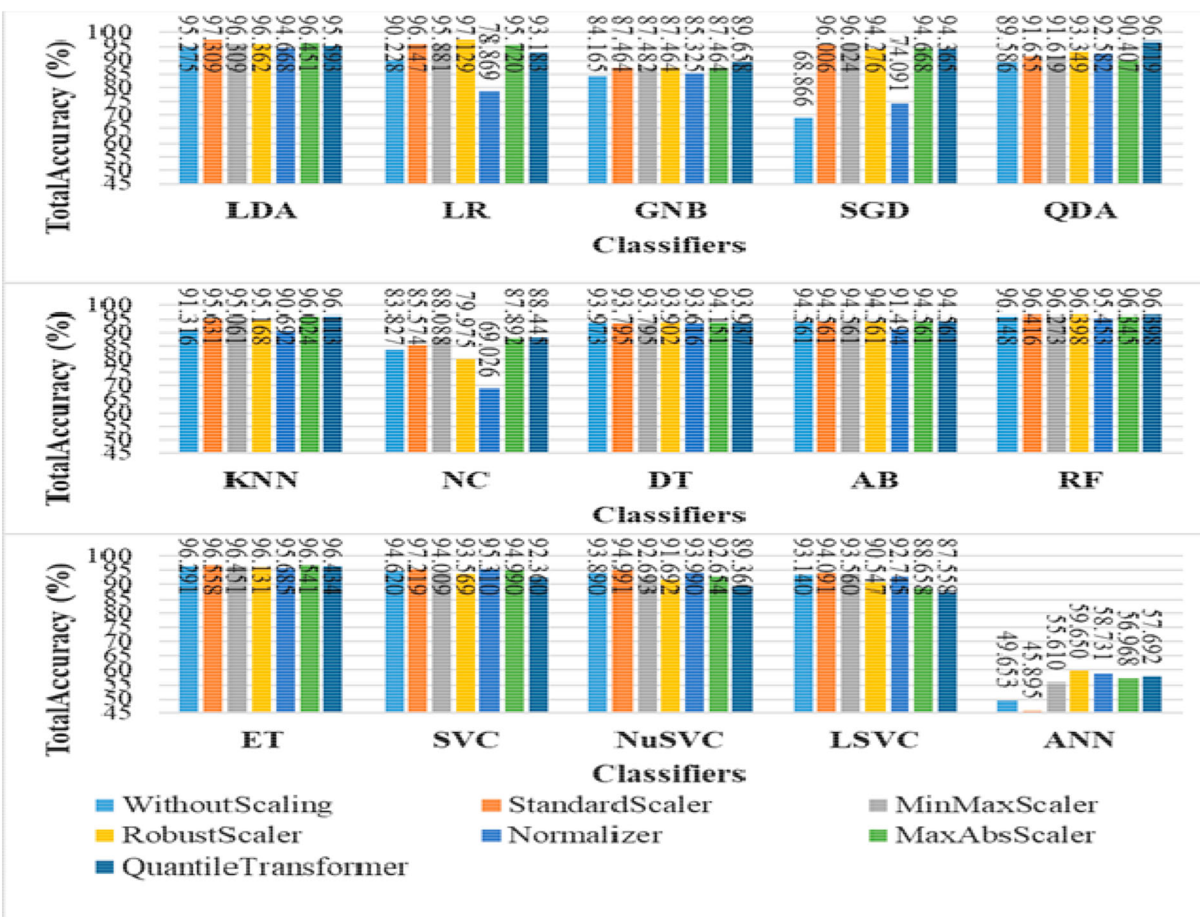

Figure 10: Classifier total accuracy results of a combined-subject validation procedure with respect to 7-scaling transformation methods

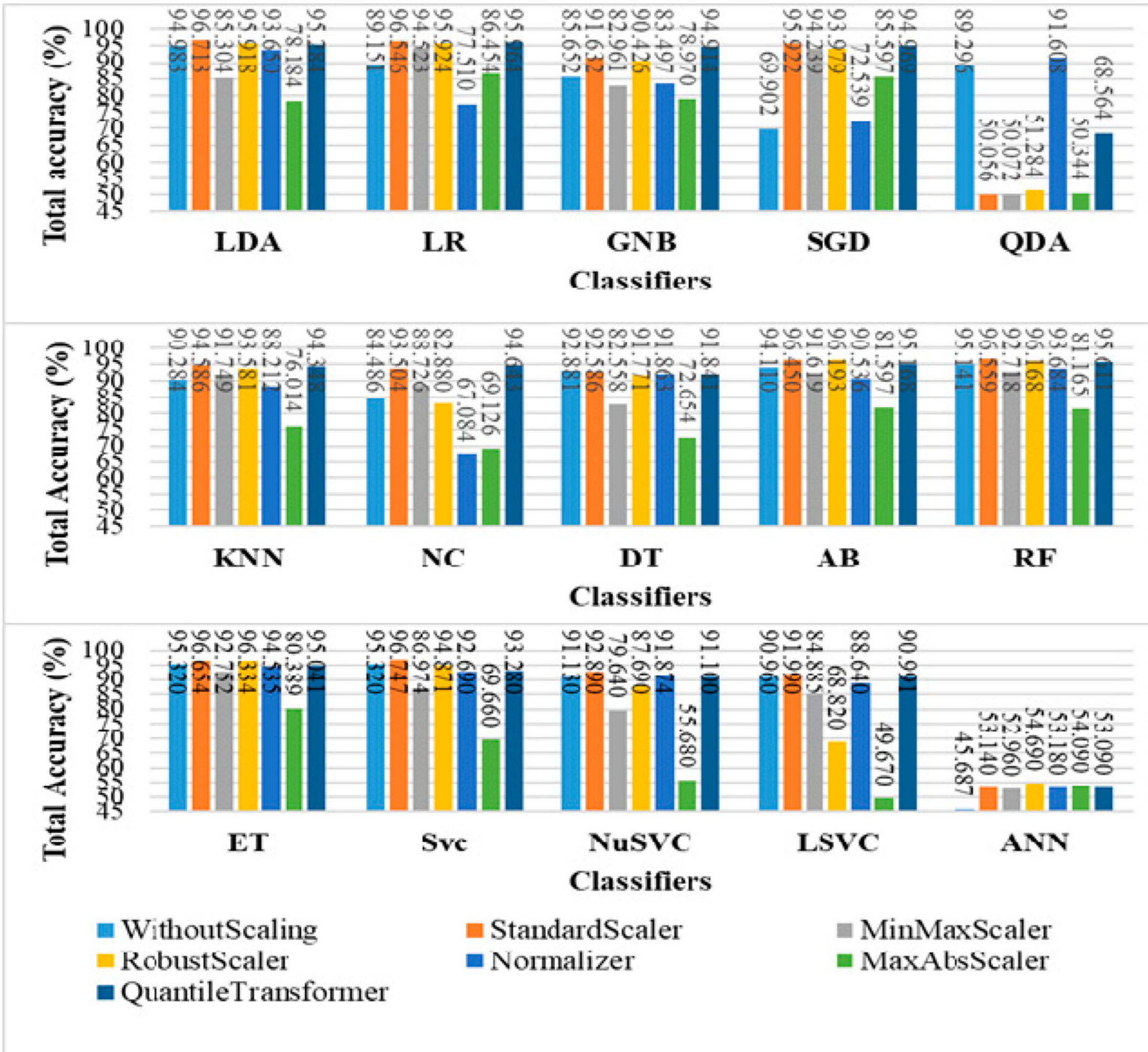

Figure 11: Classifier total-accuracy results of a cross-subject wise validation procedure with respect to 7-scaling transformation methods

results with the standard scaling transformation for the combined-subject validation process, and LDA and SVM-SVC both classifiers have been providing the best results with the standard scaling transformation for the cross-subject validation process. Classification metrics (Total-Accuracy (TOT), Sensitivity (SEN), Precision (Pre), and F1 score (F1S)) results of LDA and SVC for two validation processes are shown in Table 4. It is clear from Table 4 that the LDA and SVC classifiers with the standard scaling transformation offer almost the same total accuracy results. But LDA's F1S results are better than the SVC F1S results; therefore, it is finalized that LDA with the standard scaling transformation is best for our proposed model.

Table 4: **Classification metrics results of classifiers which gives high accuracy**

Validationmethods	Classifier	Tot	Sen	Pre	F1S
Combinedsubjects	LDA	97.309	95.36	94.96	95.16
	SVM	97.19	93.85	93.94	93.9
Cross subject	LDA	96.71	92.65	97.29	95.01
	SVM	96.747	91.87	95.51	93.7

4.3 Comparison with State-of-the Art Methods

Physionet dataset is an online free dataset, and many researchers have used it to detect drowsiness. We compared the proposed method with state-of-the-art using the same dataset, with the results of the commonly used combined-subjects process. Table 5 shows a detailed comparison of the metrics of our proposed model work with the work of [29–31,45–49].

4.4 Discussion

In this paper, a novel approach that has proven to be reliable and robust to detect drowsiness using EEG is

Table 5: Comparison of the classification accuracy results of the proposed method with state-of-the-art methods that used the same physionet EEG dataset.

Authors	Signal processing method	Classifier	Total accuracy
Proposed	FFT	LDA	97.3
[45]	TQWT	ELM	91.8
[46]	FFT	SVM	87.2
[31]	STFT, TQWT	LSTM	94.31
[47]	FFT	ANN	88.8
[30]	Band-pass filter	DNN	86
[48]	WPT	NA	NA
[29]	DWT, FFT	ANN	87.40
[49]	DWT, FFT	ANN	86.5

FFT, Fast Fourier transform; STFT, Short-time Fourier transform; TQWT, tunable Q-Factor wavelet transform; WPT, wavelet packet transform; LDA, linear discriminant analysis; ELM, extreme learning machine; SVM, support-vector machine; LSTM, long short-term memory; ANN, artificial neural networks; DNN, deep neural networks; NA, not available.

proposed by multi-domain features. The summary of the work is described below:

- Using deep learning (DL) algorithms [50,51], features can be extracted automatically. However, real-time applications, such as detecting drowsiness, are not sufficient to be implemented using DL in embedded systems. DL requires high-end hardware like graphics processing unit (GPU), a large data set for training, and high computational time. Furthermore, it has been demonstrated in [52] that EEG signal classification provides better accuracy with hand-generated features than with automatically acquired features. So, in our EEG classification model, to detect the drowsiness is developed on hand-engineered features. In [30,31], authors implemented deep learning algorithms with hand-engineered features for DD. However, the authors have used the band-pass filter, whose time complexity is O(NM), where N and M are the signal and filter sizes, respectively [30]. Moreover, this filtering process must be repeated for each subband. In [31], hand-crafted and automated features are utilized through STFT and TQWT signal processing methods for DD. STFT time complexity O (N.T.logN), where T is the length of the selected time window and TQWT requires O (N log N), whereas only one FFT with O (N log N) complexity was used in the proposed system.
- Each classifier performs differently for each scaling transformation. To find the optimal scaling transformation for an individual classifier, each classifier was checked with 7-scaling (including without scaling) transformed data. In this paper, four classifiers, such as Decision-Tree, AdaBoost, Random-Forest, and Extra-Tree in 15 classifiers, have been producing the best results with direct data, *i.e.* without scaling techniques. Quantile-Transform for Nearest-Centroid and SGD classifier, and Robust scalings for ANN have been affording good results. The other seven classifiers have yield good results with standard-scaling. Those results are shown in Figure 10 and Figure 11.
- EEG data used for this experiment is decidedly low sampling rate data and did not adopt any sampling-rate modification procedures like up-sampling. However, some of the high correlation features described in [29,48,53] cannot be calculable with these low sampling rate EEG data. Here, low sample rate EEG data has been analyzed using simple signal processing techniques such as FFT and easily measurable features. This makes to use of small disk space and low analysis time so that the model can be easily adaptable in low-cost embedded systems.
- The features used for our work were easily calculable with lighter computations from less number of samples data. These were identified, based on the observations of multiple researchers working in different applications. In some earlier research works, the feature selection process was used after the feature extraction process to reduce the size of the feature vector. However, EEG is a nonstationary signal, completely dynamic, and different from individual to individual. Therefore, the one feature may be good for one person's EEG and may not be for others. For this reason, all features are used directly without applying any feature selection/reduction methods.
- The proposed model accomplishes over 97.3% total accuracy, 95.36% sensitivity, 94.96% precision, and 95.16% F1 Score for combined subjects validation process with 10-fold cross-validation. We compared the performance of the proposed model with state-of-the-art DD methods that used same combined-subjects process and Physionet sleep-EEG dataset. This is shown in Table 5. It is clear from Table 5 that the proposed model is better than the existing models.
- In case of cross-subject validation, proposed model accomplishes over 96.71% total accuracy, 92.65% sensitivity, 97.29% precision, and 95.01% F1 Score. The proposed model works well with previously trained classifiers without any pre-existing samples of currently used person.

5. CONCLUSION

In this paper, a single-channel EEG-based drowsiness detection method is proposed along with a survey of the other techniques using a multi-domain feature set. The scaling problem in the ML approach is also solved in both linear and non-nonlinear strategies. The

Scaling transformation procedure impacts on the results of Linear ML-algorithms as compared with nonlinear algorithms. The proposed LDA classifier with the standard-scaling transformation produces 97.3% accuracy. In the case of the cross-subject validation process, the LDA and SVM classifiers gave almost the same efficiency (96%) results with standard-scaling. The proposed framework can be quickly adopted in an embedded system and has widespread use in the workplace.

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APPENDIX

In this section, we present 10 time-domain and 12 frequency-domain features computation process proposed in [29,54–57], which have been adopted in our work. If the EEG signal is represented as X of N $x_1, x_2, \ldots, x_N$ data points, then the computations of the considered features are:

Time-domain features:

- Power: $Power = \frac{1}{N}\sum_{i=1}^{N}(X_i^2)$
- Entropy: $Entropy = -\sum_{i=1}^{N} X_i \times log(X_i)$
- Skewness: $Skewness = \frac{\frac{\sum_{i=1}^{N}(X_i-\bar{X})^3}{N}}{S^3}$
- Kurtosis: $Kurtosis = \frac{\frac{\sum_{i=1}^{N}(X_i-\bar{X})^4}{N}}{S^4}$ where $S = \sqrt{\frac{\sum_{i=1}^{n}(X_i-\bar{X})^2}{N}}$ and $\bar{X} = \frac{\sum_{i=1}^{N} X_i}{N}$
- Activity: $Activity = \frac{\sum_{i=1}^{N}(X_i-\bar{X})^2}{N-1}$
- Mobility: $Mobility = \frac{rms\left(\frac{d(x)}{dt}\right)}{rms(X)}$
- Detrended fluctuation analysis (DFA): It is a method for determining the statistical self-correlation of a time-domain signal. Its computation process is as follows:

$$C(k) = \sum_{i=1}^{k}(x_i - mean(X))$$

where $k = 1, 2, \ldots, N$ 1-s signals C_t is divided into equal subparts with length of n (duration of each subpart is 0.25 s). It is represented as $y_n(k)$ for $n = 5$, then fluctuation is calculated as

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[C(k) - y_n(k)]}$$

Polynomial curve fit is computed on a logarithmic value of $\log(F(n))$ and n with a degree 1. $P(x) = p_1(x) + c$

DFA is the coefficient (p_1) of a polynomial curve $P(x)$.

- Hurst exponent (HE): $HE = E\left[\frac{R(N)}{S}\right]$

where S is the standard deviation, range R computation is $R(n) = \max(C_1, C_2, \ldots, C_n) - \min(C_1, C_2, \ldots, C_n)$

C is the cumulative sum of series of length n (in our work, we considered $n = 10$).

- Zero-crossing rate:

$$ZCR = \frac{1}{2N}\sum_{i=2}^{N}|sign(X_i) - sign(X_{i-1})|$$

Frequency-domain features:

Using FFT, as shown in Equation (1), time domain EEG signal X converted into frequency domain signal is represented as Y of $\frac{N}{2}$ $y_1, y_2, \ldots, y_{N/2}$ data points, and frequency vector f contains 0 to $\frac{F_S}{2}$ frequency values, where F_S is the sampling frequency, then the computations of the considered features are:

- Spectral Centroid (SE): $SE = \frac{\sum_{i=1}^{N/2} f(i)\times y(i)}{\sum_{i=1}^{N/2} y(i)}$
- Median frequency weight: $Median(Y) = y_{\frac{\frac{N}{2}+1}{2}}$
- Dominant Frequency (DF): The value of the ith index position of "F", and the same position is where the maximum value index position in "Y."
- Mahalanobis distance (MD)

$$MD(Y) = \sqrt{(Y - mean(Y))^T \times C^{-1} \times (Y - mean(Y))}$$

Power Spectrum Density (PSD) of a single using from FFT generated is calculated as follows:

$$PSD(f) = 2 \times \frac{1}{Fs \times N} \times abs(x(f)^2)$$

From*PSD*, four features such as min, max, mean and median are calculated. From *PSD* vs. *f* graph, Amplitude local maxima, *i.e.* peak powers in PSD are extracted and from these peaks, min and max distance between peaks, min peak value and sum of all peak values are calculated.

Scaling:

Here, we present six scaling process, which have been adopted in our work.

- Standard Scaler: Here features are regulated by removing the mean and scaling to unit variance. The outliers on each feature have different magnitudes, the spread of the transformed data on each feature is very different. But it is good only if data is normally distributed and no guarantee balanced feature scales in the presence of outliers.

$$x = \frac{x - \mu}{\sigma}$$

where $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ and $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$

- Min–Max Scaler: By using the following formula it rescales the features values in the range [0,1]. Unlike standard scaler, random distribution of features is not necessary. In case of minimal standard deviation, it is good. But it is sensitive to outliers, so if there are outliers in the data, it is not good.

$$x_i = \frac{x_i - min(x)}{max(x) - min(x)}$$

- Robust Scaler: It is similar to the Min–Max scaler, but instead of using min–max values it uses the interquartile ranges. So it uses less data for scaling. It is good when there are outliers in data. The ranges of the transformed features values are more than the remaining scaling methods.

$$x_i = \frac{x_i - Q_1(x)}{Q_3(x) - Q_1(x)}$$

Q_1 and Q_3 are the middle values of the first half and second half of the rank-ordered data respectively.

- Normalizer: It considered all the feature values of each Observation. Each feature value is divided by the sum of the other features of the same observation. This method is independent of the distribution of samples and after rescaling each sample has unit norms. But if the selected feature value has which sign (positive and negative) the transformed value lies in that sign only.

$$F_i = \frac{F_i}{F_1 + F_2 + F_3 + \ldots, + F_N}$$