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EEG Based Driver Fatigue Detection Using FAWT and Multiboosting approaches

***Abstract*—Globally, 14-20% of road accidents are mainly due to driver fatigue caused of which are instance sickness, travelling for long distance, boredom as a resistance of driving along the same route consistently and lack of enough sleep etc. This paper presents a flexible analytic wavelet transform (FAWT) based advanced machine learning method using single modality neurophysiological brain electroencephalogram (EEG) signals to detect the driver fatigues (i.e., FATIGUE and REST) and to alarm the driver at earliest for preventing the risks during driving. First signals of undertaking study groups are subjected to the FAWT that separates the signals into low and high pass channels. Subsequently relevant sub-band frequency components with proper setting of tuning parameters are extracted. Then, comprehensive low order features which are statistically significant for $p < 0.05$, are evaluated from the input subband searched space and embedded them to various ensemble methods under multiboost strategy. Results are evaluated in terms of various parameters including accuracy, F-score, AUC and kappa. Results show that the proposed approach is promising in classification and it achieves optimum individual accuracies of 97.10% and 97.90% in categorizing FATIGUE and REST states with F-score of 97.50%, AUC of 0.975 and κ of 0.950. Comparison of the proposed method with the prior methods in the context of feature, accuracy, modality profiles undertaken, indicates the effectiveness and reliability of the proposed method for real-world applications.**

***Index Terms*—Electroencephalograph (EEG), driver fatigue, FAWT and multiboosting**

I. Abbreviation

The abbreviations used herein are as follows. EEG: electroencephalogram; EMG: electromyography; EOG: electrooculography; ECG: electrocardiogram; BVP: blood volume pulse; LBP: local binary pattern; ANN: artificial neural network; SVM: support vector machine; PSD: power spectrum density; ICA: independent components analysis; DWT: discrete wavelet; RoF: rotation forest; k-NN: k-nearest neighbor; EMD: empirical mode decomposition; DBN: deep belief networks; fNIRS: functional near-infra-red spectroscopy; RF: random forest, DT: decision tree; CART: classification and regression tree; FAWT: Flexible Analytic Wavelet Transform; LP: low pass; HP: high pass; LDA: linear discriminant analysis; ME: misclassification error; Ac: accuracy; TRP: true positive rate, FPR: false positive rate; PRe: precision; F-Sc: F-score; FP: false positive; FN: negative; TN: true negative; TP: positive; BNN: Bayesian neural network; AUC: area under curve; CNN: convolutional neural network; DCBP: dynamic centre based binary pattern; FFT: fast Fourier transformation and MTTP: multi threshold based ternary pattern.

II. Introduction

FATIGUE detection and alarming the driver using advanced machine learning approach become essential to avoid unwanted road accidents [1], [2]. Fatigue indicates extreme tiredness, weariness, or exhaustion as a result of mental or physical exertion or illness. It reduces the attention, focus and concentration of driver and it accounts 14-20% of total road accidents globally [3]. It poses risk to the driver as well as other passengers, vehicles drivers, cyclists and pedestrians in the context injuries and fatalities. So, an automatic fatigue detection and monitoring system for alarming the driver just before feeling of fatigue is required. Such learning algorithm would have wide applications in Internet of things (IoT) based platform, smart phone, in-built car detection systems.

Earlier methods employed various physiological features [4] of electroencephalogram (EEG) [2], electromyography (EMG), electrooculography (EOG) [5], electrocardiogram (ECG) [6], and facial expression features during driver's yawning and blinking state [1]. Some approaches employed individual's self-reported fatigue [7] and video measurement of facial expression, reaction time, steering errors and lane deviation [2]. However, self-report based approach requires time to validate the the symptoms [2]. Also, they are potentially unreliable due to biased subjective feedback. Non-direct video based approach requires recording of driver face during on road condition that may violate the driver privacy issue. Also driver is aware of such recording setup for which finding of actual condition of driver becomes difficult. Recent real-time methods include embedded yawning state detection [8], drowsiness detection using independent multi-modalities blood volume pulse (BVP) and eye blink and yawn signals [9], combination of local binary pattern (LBP) and facial expression [10], eye-state detection [11] and deep-learning based methods [12], [13]. Wide spread use of various aforesaid signals through different methods and subsequent conclusions indicate reliability and effectiveness of signals and methods. Among them, EEG-based methods are considered to be more effective. It is due to fact that EEG carries inherent information contents of neurophysiological brain activities and considered as a good indicator of fatigue [40]. EEG signal can be recorded from the scalp attaching flat electrode and it can be divided into various frequency bands such as gamma (30-42 Hz), Beta (13-30 Hz), Alpha (8-13 Hz), Theta (4-8 Hz) and Delta (0.5-4 Hz) waves. Presence of beta wave indicates alertness of the person or may also be present early stage of sleep. Theta and delta associated with early stage of sleep and deep sleep, whereas alpha indicates relaxed condition and exhibits first sign of fatigue. Thus, it is comprehensive in nature for detecting the driver fatigues [1], [2], [14], [15]. It is worth mentioning that changes in heart rate variability [18] and in brain activities [19] are related to fatigue. Therefore, researchers focus on developing more realistic model by fully exploring EEG signals in all formats.

Previous methods employed various time, time-frequency, wavelet and statistical features, and learning strategies [20]. For instance, Vuckovic *et al.* [38] evaluated EEG signal time series of inter and intra-hemispheric cross spectral density and employed to artificial neural network (ANN) for classification of driver fatigue or alert. Method [21] converted time domain EEG signal to alpha, theta, beta and delta bands and evaluated frequency domain features for classification task. Hu *et al.* [21] evaluated functional spectrum based frequency domain features which were embedded into support vector machine (SVM). Method [22] adopted power spectrum density (PSD) and sparse representation classification combined with singular value decomposition in PSD to estimate driver vigilance level. Wang *et al.* [23] employed wavelet entropy and spectral entropy features for fatigue classification task. Many prior methods employed various forms of entropy features such as sample entropy [24], permutation entropy [25], and fuzzy entropy [26]. Various methods combined different statistical model with typical feature extraction methods for improving classification performance. Luo *et al.* [1] adopted an adaptive multiscaling factor algorithm and evaluated multi-scale entropy features which were embedded to the SVM. Chai *et al.* [2] combined blind source separation technique using independent components analysis (ICA) with autoregressive model. Then, extracted multivariate features were employed to the bayesian network for classification. Method [14] employed linear distributed current dipole over EEG wavelet search space and evaluated chaotic entropy for fatigue classification. Tuncer *et al.* [15] employed dynamic binary and ternary patterns based discrete wavelet (DWT) searched space and extracted low order measures were applied to various shallow classifiers including ANN, rotation forest (RoF), SVM and k-nearest neighbor (k-NN). Mu *et al.* [16] adopted fuzzy entropy based SVM tool for classification of normal and fatigue states. Also, Yin *et al.* [17] adopted fuzzy entropy based support system for mobile application. Method [18] employed spectrum entropy, approximate entropy, sample entropy and fuzzy entropy features from EEG signal. Method [19] employed empirical mode decomposition (EMD) features for fatigue detection. Method [41] and [42] employed sparse-deep belief networks (DBN) that combined both supervised and unsupervised learning and Hidden Markov Model (HMM) for EEG based fatigue detection. Despite significant achievements, many aforesaid methods have cons including theoretical bottleneck and multiple constraints associated with various traditional algorithm that limits the implementation in real-world problems. For instance EMD based method often suffers mode mixing problem [27]. Many prior methods employed various feature extraction techniques in single or multimodality format in order to detect fatigues.Multiple modalities based methods employed EEG and EOG [37], EEG, EOG and EMG [9], EEG, ECG, EOG and functional near-infra-red spectroscopy (fNIRS) [6], and EEG, EMG and respiration [36] and extracted features through different models which were then combined for final consequences. Although they focused to improve the performance, use of multiple process models for handling various modalities data increases the size as well as complexity of decision module which in fact obscure its real-time implementation. Additionally, as mentioned earlier, methods that based on EEG profile are more comprehensive in nature. Another important issue is that model performance depends on two aspects, one initial learning framework and proper choice of classification model. However, the most cited methods employed typical shallow classification models such as SVM [1], ANN, RF, k-NN [15], RoF, random forest (RF), decision tree (DT), classification and regression tree (CART) [28], deep learning, C4.5, LAD-tree etc.. Besides theoretical bottlenecks, they often pose curse of dimensionality, overfitting, instability issues during handing of large or small volume data. For instance deep learning often provides good learning ability but it introduces high degree of freedom due to multiple layer structures [27]. It work as black box that does not enable complete understanding of reason of higher classification performance. ANN requires trail and error strategy in learning stages for proper setting of optimal parameters and may suffer computational complexity issue in case of high order training space. SVM requires kernel parameter setting for good learning ability which needs multiple processing steps. Therefore, it is essential to develop more realistic technique either by introducing new input feature search space or using generalized version of performance boosting models or both for better way of fatigue detection and to promote human-machine interaction. In this context, typical learning models with embedded performance boosting strategies like boosting, multiboost [29] could eliminate the theoretical bottlenecks or others issues for smooth implementation in decision making platform for real-world applications. It could also ensure high and reliable performance over wide varieties of database or online data.

This paper addresses advanced ensemble learning method using flexible analytic wavelet transform (FAWT) [30] for fatigue detection in order to alert, focus and elicit the concentration of diver during on-road journey. The main contributions of the presented work are as follow:

1) It addresses the FAWT based feature extraction framework that allow to decompose signals into low and high pass channels with proper choice of inherent model parameters setting. FAWT is more robust signal processing method that extracts inherent information contents from signal for which it is widely popular in non-stationary signal analysis [31]. Processing of such input feature searched space through a given technique could lead to more relevant and discriminant features that could comprehensively represent the physiological process.
2) It employed publically available tested EEG data and subsequently various FAWT components are evaluated. Then, a set of low order statistical features is evaluated, followed by statistical significant test to extract comprehensive measures that could replicate the physiological information of signals.
3) It finally proposed a FAWT-based Adaboost learning algorithm for detection and alarming of driver fatigue. The algorithm is then validated with multiple partitioned

data sets which were collected from various male and female participants using standard EEG acquisition protocol. The performances of algorithm in classifying the FATIGUE and REST states are measured in terms of various markers. The improved performance markers ensure the robustness and reliability of FAWT based discriminant features as well as the proposed boosting based learning.

4) The performances of proposed algorithm are compared with various similar prior methods in the context of modalities profiles, type of features, complexity, limitations and performances. Results and subsequent comparative analysis reveal that the proposed FAWT-based multiboost learning is promising and thus, it ensures the real-time implementation in hardware setup for driver fatigue detection.

The article is organized as follows: Section III describes EEG database and theoretical basis of the proposed method, FAWT, feature extraction and reduction, and classification through multiboosting approaches. Section IV explains the results and discussion. Section V provides comparative study, and finally concludes with section VI.

III. Method

A. EEG dataset

This study employs open source EEG dataset [1] obtained using platform environment that includes a static ZY-31D vehicle driving simulator (Beijing-China Joint Teaching Equipment Co. Ltd.). The platform includes three 24-inch monitor and software teaching system ZM-601 V9.2 for driving simulations. The system includes 32 electrodes EEG collecting cap, computer system with window size of 7×64, EEG recording and processing software Neuroscan 3.2 and MATLAB-based signal analysis platform. The experiment included signals from sixteen valid candidates of age range 17-25 years. Before experiment, it was ensured that no individual get sick in week. In order to get valid outcomes, the individual took adequate sleep without consuming energy drink, alcohol, tea etc., in the night before the experiment. Furthermore, prior to experiment, individuals were informed about the experimental procedure, setup and electrode setting for smooth cooperation during experiment. After calm down to normal state, the laboratory assistant started acquiring EEG data of five minutes duration using software. These signals were assigned as normal EEG data. Then subjects are moved into the simulated driving state and asked for keep driving for a while. Different individual came into the state of fatigue at different times refer to Li's subjective fatigue scale and Borg's CR-10 scale. The experiment was considered as effective while result showed the candidate was in fatigue and EEG of same duration was recorded which were referred to as fatigue state and then data acquisition was completed. Details of recording procedure is mentioned in [1].

Signals were preprocessed by platform Neuroscan 3.2 software with proper setting of signal parameters, viz, sampling frequency of 1 kHz, bandwidth of 0.15-45 Hz and notch frequency of 50 Hz. Main preprocessing steps included removal of drift, noise, electrooculogram and epoch, baseline correction, artifact removal. Afterwards, each candidate results were separated into two normal and fatigue groups. Fig. 1 shows EEG signal of fatigue and rest.

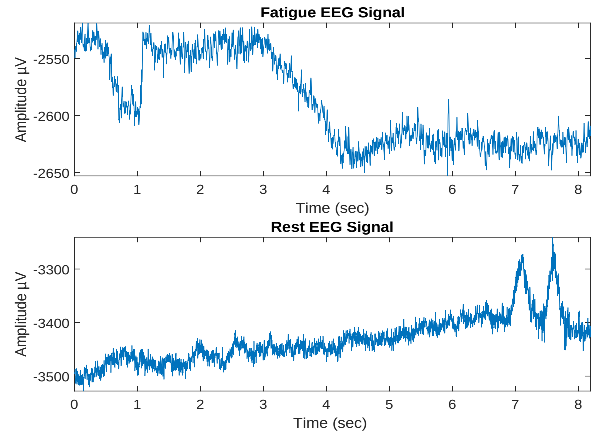

Fig. 1: EEG signals of fatigue and rest state of driver.

B. Flexible Analytic Wavelet Transform (FAWT)

FAWT [30], [31] is an advanced version of DWT that offers wide coverage of time-frequency scale of signal. It contains Hilbert transform pair of atoms which make it suitable for signal analysis that contains oscillation. The input controlling parameters of FAWT include quality factor (Q), number of decomposition (J) and redundancy (r), where Q limits the number of oscillations in mother wavelet which is defined in terms of frequency ratio and constant parameter β as [31],

$$Q = \frac{\omega_0}{\Delta\omega}, \beta = \frac{2}{Q+1} \tag{1}$$

ω_0 and $\Delta\omega$ are being central frequency and bandwidth of signal, and r controls the localization of wavelet time. The redundancy parameter r controls the time localization of the wavelet. FAWT decomposes the signal using iterative filter bank that contains high pass and low pass channels. In doing so, FAWT enables the specifying the proper choice of the dilation factor, Q and r through versatile adjustment of parameters namely, positive constant β and e, f, g, h. The parameter e and f are adjusted for up and down sampling of high pass filter, and g and h are adjusted for up and down sampling of low pass channel. It provides J decomposition levels in iterative way and each level comprises of low pass (LP) and high pass (HP) channels that separates the negative and positive frequencies respectively. The frequency responses $H(\omega)$ and $G(\omega)$ of HP and LP are as follows:

$$H(\omega) = \begin{cases} (ef)^{1/2} & |\omega| < \omega_p \\ (ef)^{1/2}\theta(\frac{\omega-\omega_p}{\omega_s-\omega_p}), & \omega_p \le \omega \le \omega_s \\ (ef)^{1/2}\theta(\frac{\pi-(\omega-\omega_p)}{\omega_s-\omega_p}), & -\omega_s \le \omega \le -\omega_p \\ 0 & |\omega| \ge \omega_s \end{cases} \tag{2}$$

$$G(\omega) = \begin{cases} (gh)^{1/2}\theta(\frac{\pi-\omega-\omega_0}{\omega_1-\omega_0}), & \omega_0 \le \omega < \omega_1 \\ (gh)^{1/2}, & \omega_1 < \omega < \omega_2 \\ (gh)^{1/2}\theta(\frac{\omega-\omega_2)}{\omega_3-\omega_2}), & \omega_2 \le \omega \le \omega_3 \\ 0, & \omega\epsilon[(0,\omega_0)\cap(\omega_3, 2\pi)] \end{cases} \quad (3)$$

Various parameters associated with above filter banks are $\omega_p = \frac{(1-\beta)\pi+e}{e}$, $\omega_s = \frac{\pi}{f}$, $\omega_0 = \frac{(1-\beta)\pi+e}{g}$, $\omega_1 = \frac{e\pi}{fg}$, $\omega_2 = \frac{\pi-e}{g}$, $\omega_3 = \frac{\pi+e}{g}$, $\epsilon \le \frac{e-f+\beta f}{e+f}\pi$. It is worth mentioning that the value of r that indicates the ration of input and output samples, needs to be greater than one in order to avoid information loss. It is defined as

$$r = (\frac{g}{h})\frac{1}{1-e/f} \quad (4)$$

For perfect reconstruction the value of β needs to be less than one and its limiting range is as follows, from where the Q is calculated.

$$1-\frac{e}{f} \le \beta \le \frac{g}{h} \quad (5)$$

Wide success of the FAWT in real-world applications such as myocardial infarction, focal EEG [32] is mainly due to its promising inherent characteristics of shift invariant, tunable oscillatory criteria and flexible time-frequency coverage.

C. Feature extraction and reduction

The implementation of FAWT is accomplished with chosen parameter with seven level of decomposition. Then sub-band signals are reconstructed in decreasing order of frequency for two state EEG signals. In evaluating the sub-bands of FAWT, the value of e/f is set at 3/4 (dilation factor) as suggested by [32] with fixed value of r and Q as mentioned. Furthermore, the value of g/h is set at 1/2 so as to get proper limiting value of r in order to avoid information loss. The value of r is chosen as per constraints expressed in (4). Then, analysis is carried out to extract suitable feature searched space of sub-band components. From the sub-bands of each signals, compact statistical measures such as mean, standard deviation, skewness and kurtosis are evaluated since FAWT provides high dimensional feature search space. Such statistical measures are shown to be promising in carrying inherent signal information [33]. Six such features include i) mean absolute values of coefficients in each sub-band, ii) average power of the coefficients in each sub-band, iii) standard deviation of the coefficients in each sub-band, iv) ratio of the absolute mean values of coefficients of adjacent sub-bands, v) skewness of the coefficients in each sub-band, and vi) Kurtosis of the coefficients in each sub-band. Thus, total ninety five statistical features are extracted and features are subjected to the linear discriminant analysis (LDA) to get optimum decision surface for better classification accuracy. LDA minimizes within-class variance and maximizes between-class variance to attain optimal discriminant features. Features are processed through typical significant test. The features that have $p < 0.05$ aRE considered statistically significant with 95 confidence level. Finally the best combination of significant feature matrix is evaluated by assessing the classification performance over training dataset.

D. Classification through multiboosting approaches

Typical machine learning models that work as weak learner suffer various difficulties as mentioned in the section II. They often fail in providing stable and reasonable performances despite of good feature extraction framework to the available feature search space. In that case, ensemble meta algorithms play crucial role in enhancing the performance by adopting various boosting strategies such as Adaptive boosting (AdaBoost) and multiboosting (multiBoost). They create and combine weak learner to build better classifier and better inferences reducing the variance and over fitting of the weak learners [34], e.g., CART. Thereby, it improves the performance of weak classifier and enhance the learning ability, performance and stability of weak learners [34]. It averages the outputs of all weak classifiers for final conclusion. It also employs voting (for classification) or averaging (for numeric prediction) to syndicate the output of individual model. It combines models of the same type, e.g., DTs. The boosting strategy emphases weight assignment to the models based on its confidence rather than giving equal weight to all models. Most popular boosting algorithm in classification and regression (e.g., C4.5 tree) is AdaBoost [29]. It is simple even far simpler than SVM and easy to implement, tremendous flexibility in choosing weak classifiers and provides effective results.

For a given training data $\{(x_i, y_i)\}_{i=1}^{N}$, where, N is the number of iterations, $x_i \in \mathbb{R}^K$ and $y_i \in \{1, 1\}$, there are large number of weak classifiers, denoted $f_m(x) \in \{1, 1\}$, and a 0-1 loss function I, defined as

$$I(f_m(x), y) = \begin{cases} 0, & \text{if} f_m(x_i) = y_i \\ 1, & \text{if} f_m(x_i) \ne y_i \end{cases}$$

Algorithm 1: Adaboost algorithm

for $i = 1$ to N, $w_i^{(1)}$
for $m = 1$ to M, **do**
Fit weak classifier m to minimize the objective function:
$\epsilon_m = \frac{\sum_i = 1^N w_i^{(m)} I(f_m(x_i) \ne y_i)}{\sum_i w_i^{(m)}}$
where $I(f_m(x_i) \ne y_i) = 1$ if $f_m(x_i) \ne y_i$ and 0 otherwise
$\alpha_m = ln\frac{1-\epsilon_m}{\epsilon_m}$
for all i **do**
$w_i^{m+1} = w_i^{(m)} e^{\alpha_m I(f_m(x_i) \ne y_i)}$
end for
end for

The final classifier after training is based on a linear combination of the weak classifiers

$$g(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_m f_m(x)\right) \quad (7)$$

It is a greedy algorithm that builds up incrementally a strong classifier $g(x)$ by optimizing the weights for, and adding, one weak classifier at a time. Its generalized version is M-array classifiers, i.e., multiBoost that has parallel model learning ability and high potential to eliminate the over fitting. They have high learning ability of non-linear dynamic and could provide better understanding of the source thereof. This study focuses on use of multiBoost based meta algorithm with various typical learning models for classification of fatigue and rest. It also aims to explore the proper feature extraction framework using FAWT and learning models

IV. Results and discussion

A. Performance markers

The performances of meta multiBoost algorithm are investigated in terms of various typical bio as well as statistical markers to ensure the integrity of the proposed FAWT-based feature extraction framework and learning strategy using EEG signal for fatigue detection. This study employs several weak learners with multiBoost with same sets of features to ensure quality of FAWT-based statistical features. K-fold cross-validation is employed to partition the dataset into 10 subsets. Then, one set is used training as well as for feature extraction and remaining sets are used for testing the models. Various parameters evaluated in this study including misclassification error (ME), accuracy (Ac), true positive rate (TPR), false positive rate (FPR), precision (PRe), and statistical parameters-F-score (Fsc) and kappa (κ) which are as follows:

$$ME = \frac{FP+FN}{TP+TN+FP+FN} \tag{8}$$

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$TPR = \frac{TP}{TP+FN}; FPR = \frac{FP}{TN+FP} \tag{10}$$

$$PRe = \frac{TP}{TP+FP}; FSc = \frac{(\beta^2-1).PRe.Re}{\beta^2.PRe+Re} \tag{11}$$

$$\kappa = \frac{P_0-P_e}{1-P_e} \tag{12}$$

Here ME indicates the fraction of incorrectly classified instances to all instances; Ac indicates total correct cases (fatigue and rest) classified by the model to the available cases in the datasets; TPR indicates positive cases (i.e., fatigue) correctly identified to the total cases, and whereas FPR indicates correct negative cases (i.e., rest) classified to all negative instances; PRe defines the ratio of instances correctly classified as positive to all instances classified as positive, and F-score (FSc) measures the balance while $\beta=1$ and favours PRe if $\beta>1$ and recall (Re) otherwise. Also P_0 and P_e indicate observed agreement and agreement expected by chance. The remaining terms associated the cited measures are false positive (FP) and negative (FN), and true negative (TN) and positive (TP). Two additional parameters are sensitivity and specificity $(1-FPR)$ that measure the correct rate of positive cases similar to TPR and negative cases. These parameters are estimated from the formulated confusion matrix. Additional parameters which are also estimated are area under curve (AUC) and Kappa coefficient (κ). The AUC indicates the degree or measure of separability and the kappa κ measures the agreement or disagreement of measurements ($\kappa=1$ or 0).

B. Classification performances

The EEG dataset is divided into multiple sets through cross-validation technique for training and performance measures. Each folded dataset contains same proportion of two states-FATIGUE and REST of driver, namely, FAT and REST. The estimated features evaluated through well-defined framework are subjected to the ensemble models in multiBoost mode to classify FAT and REST states through and repeated measures over folded datasets are reported in terms of mean values. Table I outlines the performances of the classifiers in terms of Ac, FSc, AUC, and κ. It is seen that the boosting inspired models specifically listed in the bottom of Table I show the most prominent as well as balanced parameter values. In addition to the accuracies, higher values of FSc, AUC and κ, indicate the efficacy of these inspired models as compared to the other models and their corresponding typical model. As is evident, multiBoost-SVM, multiBoost-ANN and multiBoost-rotation forest provide higher average recognition rates of 97.20%, 96.90% and 96.70%, and 97.90%, 96.50% and 96.30% in categorizing the FAT and REST respectively, whereas lowest recognition rate are 80.60% and 86.30% in case of Extra Tree. Furthermore, all models provide higher as well as uniform accuracies in classifying the REST which is presumably due to higher discriminant feature set of the REST groups as compared to the feature sets belonging to FAT groups. However, optimum level of Ac is obtained in case of inspired SVM with promising value of FSc of 97.5%, error of 2.50%, AUC of 0.975 and κ of 0.950. It is pertinent to be mentioned that the performances of learning models depend on two important aspects, one is how preciously the proposed feature search space framework extracts the relevant features that comprehensively indicate the inherent characteristics of signals associated with specific behaviours of drivers, and other one is configuration of the learning models. Another factor that influences the performance is the dimensionality of feature space, which are taken into consideration through the proper feature extraction strategy such as FAWT and subsequent processing stages. In the context of good performance, many deep learning such as DBN, recurrent neural network, convolutional neural network (CNN), deep neural network and deep Boltzmann machine show promising results in biomedical applications. However, major difficulties of such methods as mentioned earlier are dimensionality and lack of understanding of causes of good performance and they act as black box that limit their utilities in real-world setup [27]. The algorithm is implemented in MATLAB [Intel Core i5—, RAM, Processor, XXXXXXX] and the computation time falls in the range of xx–xx s including feature extraction and classification. Significant results over wide varieties datasets indicate robustness as well as stability of the proposed method. Many factors such as complexity, cost burden and ease of implementation promote to employ simple performance boosting models with efficient feature extraction and processing pipeline. As is evident, the proposed method is effective in

TABLE I: Classification performance of the models under multiboosting strategy in terms of various markers.

# Multiboost-model	Accuracy (Ac) [%] FATIGUE	Accuracy (Ac) [%] REST	Mean Ac [%]	Error [%]	F-Score [%]	AUC	Kappa (κ)
Extra Tree	86.30	87.30	86.80	13.20	86.80	0.868	0.735
Random tree	86.50	89.60	88.00	12.00	88.00	0.880	0.760
K-NN	90.40	94.40	92.40	7.60	92.40	0.955	0.848
REP tree	92.10	94.20	93.10	6.90	93.10	0.985	0.863
CART	92.50	94.80	93.60	6.40	93.60	0.984	0.873
C4.5	93.30	94.60	94.00	6.00	94.00	0.988	0.879
Random Forest	94.80	94.00	94.40	7.60	94.40	0.989	0.888
Rotation Forest	96.70	96.30	96.50	3.50	96.50	0.981	0.929
ANN	96.90	96.00	96.50	3.50	96.50	0.978	0.929
SVM	97.10	97.90	97.50	2.50	97.50	0.975	0.950

reducing various cited issues and outweighs the challenges of many typical classifiers. Thus, it also ensures the possibility of getting good results over wide range of database. The efficacy of the proposed method is also explored in comprehensive comparison study in following section.

V. Comparative study

In order to explore the efficacy of the advocated method in the context of modality profile, type of feature, model and its learning ability, this study focuses on many prior two-and three-class classification methods. Table II includes two-class methods that employed single modality profile EEG [1], [2], [15], [17]–[19], eye vision [12] and video [10] and multiple modalities profiles [6], [37], and three-class methods that employed multiple modalities [9], [14], [36]. It provides a quick lookout on recent progress of learning methodologies and performances with use of single or multiple modalities and typical models. Although our study focuses on single modality profile, however its comparison with various aforesaid methodologies in respect to their various attributes helps understanding the performance dependency profile, simplicity of feature extraction framework as well as the performances. Many methods employed multi-scale entropy [1], autoregressive coefficient for Bayesian neural network (BNN) [2], DWT-based dynamic centre based binary pattern (DCBP) and multi threshold based ternary pattern (MTTP) features [15], entropies, i.e., spectrum, approximate, sample and fuzzy entropy (SpEn, ApEn, SamEn, FuzEn) [18], EMD based intrinsic mode function features (EMD-EMF) [27], fast Fourier transformation (FFT) using EEG signals for detection of FAT, REST, normal (NOR), mild fatigue (M-FAT), excessive fatigue (EX-FAT), sleep-deprive (SLEEP-DEP) etc., and reported mean accuracies. However, use of DWT in feature extraction framework creates high dimensional feature space in terms of approximate and details coefficients (i.e., low and high frequency components). It also requires to choose the proper mother wavelet that often tricky. Proper choice of wavelet also depends on ground subjective knowledge and morphology of signal. In such circumstances, choice of specific components for feature extraction may fails in carrying inherent signal information. EMD based approaches often suffer mode mixing problem [27]. In such context, FAWT is more suitable for nonlinear problems as it offer more tuning parameters for proper processing and extraction of low frequency components for analysis. Some methods employed multiple modalities data such as driver facial expression [1] and video recording of facial expression along with reaction time and steering error [7] which are unreliable due to biased information. Some prior methods used various statistical forms of entropies [18], band power, and fractal density for fatigue detection and reported the inferences. However, random combinations of features may provide good performance over a limited dataset, but it may not ensure good performance over varieties of datasets. Their major limitations are involvement of multiple independent theoretical frameworks for parameter selection, and complexity at each stage which makes them unsuitable in real-world environment. On the other hand, many methods employed various combination of multiple modalities profiles such as EEG+EOG [37], EEG+EOG+EMG [9], EEG+ECG+EOG+fNIRS [6], and EEG+EMG+respiration [36] that embedded to the HMM, for feature extraction as shown in the Table II intending to enhance classification results. These methods require multiple processing frameworks for handling multiple modalities profiles. The processing steps associated with same or different types of mathematical frameworks significantly increase theoretical bottleneck as well as computational cost. Some methods employing eyes' closure duration or percentage and yawning frequency of mouth features and eye vision with multiple poses [12]. However, EEG comprehensively reflects brain activities that directly related to fatigue [15], [19]. In that case, choice of single profile based proper feature searched space framework is more suitable rather than considering multiple profiles based searched framework for consistent and reliable performances. Thus, EEG based fatigue detection with FAWT based feature extraction framework and advanced learning models that outweighs the challenges of various typical models.

It is seen that aforesaid approaches employed typical shallow models like SVM, SVM-RBF, ANN, k-NN, EMD, ICA-autoregressive, kernel SVM (k-SVM), LBP-SVM, principal component analysis-SVM (PCA-SVM), and RF models which are often considered as weak learners due to their inherent theoretical bottlenecks and requirements of various parameters tuning. For example, SVM-RBF requires proper setting of kernel parameter (γ) during training stages before final task, whereas shallow SVM suffers instability and over-fitting issues. Deep learning models such as DBN [35], CNN, BNN often provides good learning ability due to their multiple layer structures and nodes. However, they introduce high degree of freedom and computational cost, lack of model interpretations

TABLE II: Comparison of advocated method with the state-of-the-art methods in the context of feature, classifier, driver states and performance markers.

Method	Signal	Type of feature	Classifier	Subject	State	Ac [%]	AUC
Chai et al. [2]	EEG	ICA-AR	BNN	43	FAT,ALERT	88.20	0.930
Mu et al. [18]	EEG	(Sp, Ap,Sam, fuz)En.	SVM	12	FAT,REST	87.69	–
Yin *et al.* [17]	EEG	Fuzzy-entropy	SVM	12	FAT,NOR	95.00	–
Khushaba [37]	EEG,EOG	Fuzzy mutual-DWT	LDA,LSVM, KNN, k-SVM	31	DROWSINESS, FAT	95-97	–
Zhang et al. [9]	EEG,EOG,EMG	Approx. entropy	ANN	20	NOR, MILD,EX-FAT MOOD SWING,	~96.50	0.990
Aritra et al. [14]	EEG	ApEn, SamEn,	PCA-SVM	11	11 FAT STATES	86.00	–
Ahn et al. [6]	EEG,ECG,EOG, fNIRS	PSD-RPL	LDA	11	REST, SLEEP-DEP	84.50	–
Luo et al. [1]	EEG	multi-scale En	SVM	16	FAT, NOR	95.37	–
Zhang et al. [10]	Video	LBP	SVM, LBP-SVM Boost-LBP-SVM	1	FAT, NOR	85.85	–
Mandal et al. [12]	Eye Vison	Fused-feature	PCA-SVM	4	2 EYE STATES	~ 95.18	–
Zhao et al. [13]	Video (eye, mouth)	texture	DBN	30	DROWSINESS	96.70	–
Tuncer et al. [15]	EEG	DWT-(DCBP,MTTP)	KNN,RF,ANN,SVM	16	FAT,REST	97.29	–
Kaur et al. [19]	EEG	EMD-IMF	ANN	8	DROWSY,AWAKE	88.22	–
Fu et al. [36]	EEG,EMG, Respiration	Contextual	HMM	12	ALERT, M-FAT,FAT	–	0892
The Proposed	EEG	**FAWT-Features**	**Multiboost-SVM**	16	FAT,REST	**97.90,97.10**	**0.975**

and reason of higher performances. In contrast to them, the proposed FAWT-multiBoost ensemble method is simple, well-defined and it is single modality based approach. It adopts an advanced learning under unique multiBoost criteria and provides significant performances which are superior to the prior methods. In comparison to the various methods, the proposed method not only provides higher performance than single modality based methods [1], [2], [12], [14], [15], [17]–[19], but also even higher than multiple modalities based methods [6], [9], [10], [13], [36], [37]. It is to be mentioned that the proposed method shows very close performance with that of the method [15], however, unlike that our method employed well-defined FAWT based feature extraction framework and strong learning model. In context to feature, the proposed method enables an easy feature extraction pipeline as compared to other methods, specifically, multiple modalities based methods. In order to ensure effectiveness of the proposed feature extraction strategy and the estimated features are embedded to many ensemble models and performances are investigated over multiple partitioned datasets. Promising results outlined in Table I and subsequent comparison in II conclude many important aspects. First, EEG based methods are effective and the proposed feature extraction framework effectively extracts compact information contents that reflects brain physiological activities. Second, low order FAWT based features are comprehensive in nature for which multiple ensemble methods quickly learn due to their multifarious advantages and provide higher outcomes with minimum diversity on the outcomes. Importantly, the performance of classifiers even of the best classifier depends on the quality of features extracted by a given frame. Thus, it ensures high possibility of getting good performance over wide databases of same or different modality, although it is not undertaken in this study. Therefore, limitation of this study is that the performances are assessed over single dataset that was partitioned. Dataset was collected from few participants, future study will aim to include large dataset of more participants. It is also required to adopt the proposed scheme for classification of others fatigue related studies using diverse datasets. This issue is justified using multiple partitioned datasets and subsequently good inferences are obtained through cross-validation technique. Since all subsets are associated with same study groups, thereby, it is required to employ diverse dataset as per requirement of machine learning protocol, which will be studied as future work.

VI. Conclusion

This paper presents a flexible analytic wavelet transform based advanced learning model with unique performance boosting strategy for detection of driver fatigue states using EEG signals. In developing the proposed model, FAWT based feature extraction strategy was developed based on filtered EEG signals and subsequently significant statistical measures with $p < 0.05$ were evaluated. Then, features were embedded to ensemble learning models-SVM, CART, k-NN, ANN, RF, RoF, REP-tree, LAD-tree, C4.5 and classification performances were investigated in terms of accuracy and statistical parameters through the cross-validation technique. Promising performances of various learning models are compared with many state-of-the-art methods. The method achieves an optimum accuracy in case of multiBoost-SVM which is 97.90% in categorizing REST with an average accuracy of 97.50% over both states. Also reasonably higher values of F-score, AUC and κ also indicate the effectiveness of the advocated method. Thus, significant performances as well as comparison analysis with the prior methods evince the integrity and reliability of proposed method which utilized single modality data profile, for real-time implementation. The future work will be carried out over wide varieties of dataset and then on implementing wearable prototype device for real-world application.

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