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EEG-based driving fatigue detection using multilevel feature extraction and iterative hybrid feature selection

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ABSTRACT

Brain activities can be evaluated by using Electroencephalogram (EEG) signals. One of the primary reasons for traffic accidents is driver fatigue, which can be identified by using EEG signals. This work aims to achieve a highly accurate and straightforward process to detect driving fatigue by using EEG signals. Two main problems, which are feature generation and feature selection, are defined to achieve this aim. This work solves these problems by using two different approaches. Deep networks are efficient feature generators and extract features in low, medium, and high levels. These features can be generated by using multileveled or multilayered feature extraction. Therefore, we proposed a multileveled feature generator that uses a one-dimensional binary pattern (BP) and statistical features together, and levels are created using a one-dimensional discrete wavelet transform (1D-DWT). A five-level fused feature extractor is presented by using BP, statistical features of 1D-DWT together. Moreover, a 2-layered feature selection method is proposed using ReliefF and iterative neighborhood component analysis (RFINCA) to solve the feature selection problem. The goals of the RFINCA are to choose the optimal number of features automatically and use the effectiveness of ReliefF and neighborhood component analysis (NCA) together. A driving fatigue EEG dataset was used as a testbed to denote the effectiveness of eighteen conventional classifiers. According to the experimental results, a highly accurate EEG classification approach is presented. The proposed method also reached 100.0% classification accuracy by using a k-nearest neighborhood classifier.

1. Introduction

Driving fatigue is one of the essential factors for driving performance since it is a reason for a significant part of traffic accidents [1–3]. Driving fatigue is defined as the transition between sleepiness and wakefulness, and it reduces the desire to fulfill the driving task [4,5]. Driving is a combination of visual and engine coordination and requires constant attention [6]. Driving over a specific hour during a long road can cause fatigue [7,8]. Driver fatigue during driving can create several problems, including fatal accidents [9]. Usually, sleepiness is one of the most basic indicators of driving fatigue [10,11].

The driving fatigue situation can be defined in many ways such as deviation from the road lane without signaling and slow reaction time [12,13]. The driver's face identification achieves the closure of the driver's eyelids and the tendency of the face to sleep, and there are many studies based on this approach in the literature. Furthermore, Electroencephalogram (EEG) signals are used to detect depression, epilepsy, and fatigue as well. Together with EEG in fatigue detection, electrocardiogram (ECG) for heart rate and electrooculogram (EOG) for eye movements are used [13–16]. However, EEG is the most commonly used signal because it contains direct brain activity and has been used effectively in the sense of cognitive processes. The signals such as EOG, ECG, EEG utilized for accurate and robust detection of fatigue while driving can reach more stable results compared to the vision-based methods [17].

1.1. Motivation

Fatigue is the act of extreme sleepiness, exhaustion, or weariness resulting from physical or mental action or disease. Driving is one of the most critical applications and requires extreme attention and concentration. Fatigue is the driving effect felt by a driver. Fatigue occurs with

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factors such as driving for a long time without rest, illness, and stress. Driver fatigue can induce almost 75 percent of traffic accidents. Therefore, controlling driver fatigue is an important parameter to reduce accidents. Driver fatigue detection is the most popular research area for signal processing and machine learning since this technology can be adapted to smart vehicles. Therefore, we proposed a novel driver fatigue detection approach using hybrid feature extraction and an iterative hybrid feature selection. Our primary motivation is to achieve a perfect classification rate for driver fatigue detection by utilizing basic methods together. Injuries have induced so many deaths for the elder and the young, and it is time someone emerged and took the right steps to save deaths by reducing injuries. There are several types of research on the detection of driver fatigue. Some of the studies on driver fatigue detection in the literature are shown in Table 1.

As seen in Table 1, these methods used many EEG channels and did not achieve 100.0% classification accuracy for driver fatigue detection. Moreover single-channel EEG is used for driving fatigue detection [1], sleep staging [22,23] and epileptic seizure detection [24]. We aimed to improve the performance of fatigue detection by using single-channel EEG signals in this work.

Table 1
Previously presented works related to machine learning-based fatigue detection.

References	Year	Method	Evaluation Criteria	Channel	Accuracy results
Chen et al. method [2]	2019	Wavelet packet transform, Phase Lag Index	Accuracy, sensitivity, precision, false alarm rate	14 channels	94.4%
Wei et al. method [18]	2012	Grey Relational Analysis, Kernel Principle Component Analysis	Accuracy	16 channels	92.3%
Gao et al. method [5]	2019	Relative wavelet entropy complex network	Area under receiver operating characteristic curve	32 channels	over 95%
Chai et al. method [8]	2017	Bayesian neural network, independent-component analysis	Area under receiver operating characteristic curve, sensitivity, accuracy, specificity	32 channels	88.2%
Chaudhuri and Routray method [19]	2020	Chaotic entropy	Accuracy	19 channels	86.84% (10 fold cross validation)
Chai et al. method [20]	2017	Deep belief networks	Area under receiver operating characteristic curve, accuracy, specificity, sensitivity	32 channels	90.6%
Zhao et al. method [21]	2011	Kernel principal component analysis, wavelet packet energy, support vector machines	Accuracy, specificity, sensitivity	30 channels	98.8
Zheng et al. method [13]	2018	Residual learning	Accuracy	16 channels	98.62%

1.2. Proposed approach

Detection of driver fatigue can be achieved using EEG signals. Nevertheless, the use of EEG signals for robust driver fatigue detection creates numerous complications. An appropriate combination of the dimension reduction and feature extraction methods must be used to eliminate these complexities and improve the efficiency of classification. Besides, a suitable classifier should be employed to boost the performance of the classification. The brain signals are multi-dimensional, and machine learning methods for driver fatigue detection cannot be easily implemented. Hence, this study aims to develop a system with the right combination of feature extraction, feature selection, and machine learning methods to detect driver fatigue using single-channel EEG signals. EEG signals have been widely used to interpret brain activities, and one of these activities is driving fatigue detection. There are several research and studies for EEG-based driver fatigue detection in the literature. To accurately detect fatigue using EEG signals is one of the most critical problems of EEG signal processing. A novel EEG signal processing framework is presented to solve this problem. In this framework, multilevel feature extraction and a novel hybrid feature selection method (RFINCA) [25,26] are proposed to create EEG signal classification for fatigue detection. The main purpose of the presented multileveled feature extraction approach is to extract low, middle, and high-level features. For this purpose, we used textural and statistical features together. By using *four*-level 1D-DWT [27,28] with Symlets 4 filter, both feature extraction and multilevel pre-processing are employed because 1D-DWT is generally used for noise reduction and signal decomposition. To select meaningful features, RFINCA is utilized, and the selected features are classified using shallow classifiers.

1.3. Contributions

Main contributions of this work are given as follows:

- As it can be seen from Table 1, the state-of-the-art methods have utilized different feature generation, feature selection and classification methods to achieve high performance for the EEG-based driver fatigue detection. Binary pattern (BP) and statistical feature generation functions are utilized for feature extraction. Our main aim is to use the effectiveness of both textural and statistical features together. Discrete wavelet transform (DWT) is one of the useful signal decomposition methods for biomedical signals. The Symlet-4 is a mother wavelet filter and is mainly used for both noise reduction and decomposition. Therefore, DWT is utilized as a signal decomposition technique like convolution and pooling in the convolutional neural networks to generate levels. The presented multilevel feature generation framework can extract discriminative features in high, medium, and low levels with a low time complexity. Therefore, the proposed feature generation method is lightweight and improves the feature generation capability of the hand-crafted feature extraction functions.
- A hybrid iterative feature selection technique (RFINCA) is proposed to automatically select the optimum number of features. By using RFINCA, the most informative/meaningful features are selected automatically, and the effectiveness of the neighborhood component analysis (NCA) and ReliefF are used together.
- The proposed BP, statistical features, and RFINCA based EEG-based driver fatigue detection approach achieved 100% classification accuracy using a k-nearest neighbor (k-NN) classifier with a single-channel EEG. The presented multilevel fused feature generator and RFINCA feature selector-based approach have a general success since it achieved high classification performance with 18 classifiers.

2. The proposed driving fatigue detection approach

A multilevel learning framework is proposed for driver fatigue detection with a high accuracy rate using EEG signals in this work. The presented EEG signal processing framework has four main steps: signal decomposition, textural, and statistical feature extraction from each level of DWT decomposition, RFINCA based feature selection, and classification. The graphical representation of the presented framework is demonstrated in Fig. 1.

Fig. 1 shows that EEG signal decomposition levels are created using multilevel 1D-DWT (sym4 filter). In the signal decomposition phase, four low pass and four high pass filters are generated. Then, BP and statistical features are extracted from the raw EEG signals and four low pass filtered sub-bands of the original EEG signal. RFINCA selects the most meaningful features, and the selected features are employed as an input of the classifiers.

2.1. Signal decomposition using one-dimensional discrete wavelet transform

The first stage of the presented multilevel feature generation and RFINCA based driver fatigue detection framework is the signal decomposition. Mostly, deep learning methods employ multilayered architecture to generate low, medium, high-level features, and they have achieved high success rates for many problems. Our objective is to create a lightweight and highly accurate EEG signal classification framework. This model is inspired from deep learning methods, which have high computational costs. Multilevel 1D-DWT [29] is used as a pooling method to obtain a low-cost approach. Four level 1D-DWT has been widely used for noise reduction and decomposition of biomedical signals [22,30,31]. Therefore, we used 1D-DWT method for signal decomposition.

Step 0: Load the raw EEG signal.

Step 1: Apply *four* leveled 1D-DWT with sym4 filter to raw EEG signal.

$$[Low_1, High_1] = DWT(signal, sym4) \tag{1}$$

$$[Low_2, High_2] = DWT(Low_2, sym4) \tag{2}$$

$$[Low_3, High_3] = DWT(Low_3, sym4) \tag{3}$$

$$[Low_4, High_4] = DWT(Low_4, sym4) \tag{4}$$

where Low_i and $High_i$ are ith degree low and high pass filter coefficients of the 1D-DWT, $DWT(.)$ is a 1D-DWT function [32].

2.2. Feature extraction

In this step, textural and statistical features are extracted from the raw EEG signal and each level of the decomposed EEG signal sub-bands. BP is used to generate textural features, and seven statistical features are extracted by using the statistics of raw EEG and each sub-band. The used feature generation methods are explained below.

2.2.1. Binary pattern

BP is one of the most used textural feature extractors and is widely used for image and signal processing. It was first presented as an image feature extraction, and the main purpose of the local binary pattern (LBP) is to extract local features from neighborhood values (3 × 3 sized blocks). One dimensional version of the LBP (BP) uses nine-sized overlapping block and signum function together [33] to achieve a histogram-based feature extraction. The philosophy of BP is to generate meaningful global features by using local features. In this view, the philosophy of BP is similar to metaheuristic optimization methods. It has many advantages, which are given as follows [34,35].

- It extracts meaningful textural features.
- It is a lightweight feature extractor (computational cost is low).
- It has both image (LBP) and signal (BP) versions.
- Since the application of BP is easy, it is employed to solve many knowledge extraction problems as an image and signal processing technique.

Because of these superiorities, many LBP or BP-like feature extractor (microstructure) have been presented [36]. The procedure of BP is listed in Algorithm 1.

Algorithm 1. Pseudocode of the one-dimensional binary pattern.

Algorithm 1 clearly demonstrates that BP extracts 256 features, and the feature extraction process of the BP is independent of the length of the signal. Hence, it is one of the most useful feature extraction techniques.

2.2.2. Statistical feature extraction

The second feature generator uses seven statistical moments of the

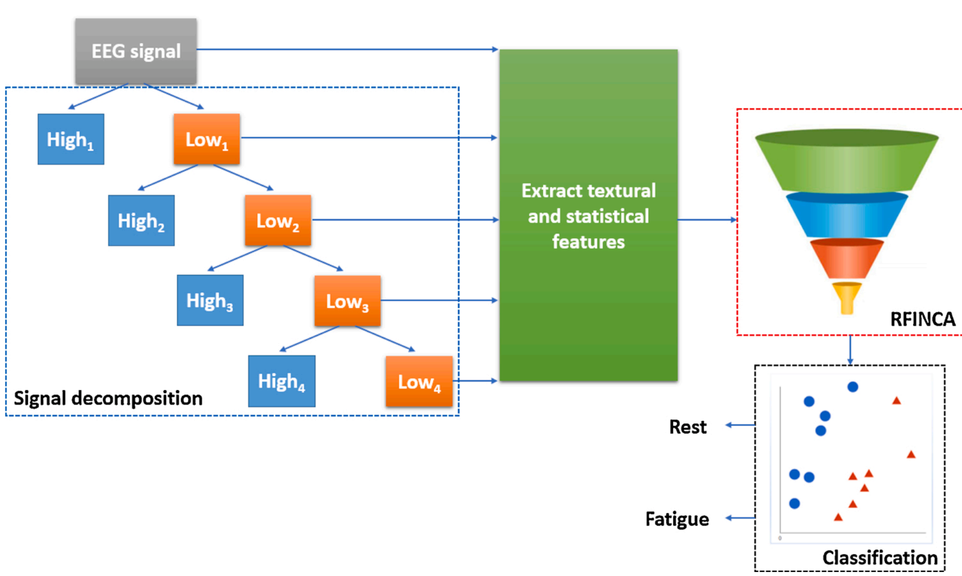


Fig. 1. Schematic demonstration of the developed multilevel hybrid feature extraction and RFINCA based driver fatigue detection framework.

Procedure: ***BP(data)***
Input: **One dimensional EEG signal or i^th^ degree low pass filter of the used EEG signal (*data*) with the length of *J***   Output: **BP feature ($bpfeat$) with a size of 256.**

$bpfeat = zeros(256)$; **// Define 256 sized histogram ($bpfeat$) and fill all values as 0.**
 for **i=1 to *J*-8** do
 $obl = data(i{:}\,i+8)$; **// Divide data into 9 sized overlapping block (obl).**
 $counter = 1$;
 $bpval(i) = 0$; **// Define BP value.**
 for **k=1 to 9** do
 if $k! = 5$ then // **All values of the block are compared to the center value (5^th^ value) to generate features.**
 $bpval(i) = bpval(i) + [obl(i) \geq obl(5)] \times 2^{8-counter}$; **// Binary feature extraction and decimal conversion. $[obl(i) \geq obl(5)]$ expresses signum function.**
 $counter = counter + 1$;
 end if
 end for k
 $bpfeat(bpval(i)+1) = bpfeat(bpval(i)+1) + 1$; // **Extract histogram and obtain BP features.**
 end for i

raw EEG and decomposed EEG signal sub-bands. The mathematical descriptions of these moments are given below [37].

$$f(1) = \frac{\sum_{i=1}^{J} data(i)}{J} \tag{5}$$

$$f(2) = \sqrt{\frac{\sum_{i=1}^{J} [data(i) - f(1)]^2}{J}} \tag{6}$$

$$f(3) = \sqrt{\frac{\sum_{i=1}^{J} data(i)^2}{J}} \tag{7}$$

$$f(4) = \frac{|data(i) - f(1)|}{J} \tag{8}$$

$$f(5) = \frac{J}{(J-1)(J-2)(J-3)} \sum_{i=1}^{J} \left(\frac{data(i) - f(1)}{f(2)}\right)^4 - \frac{3(J-1)^2}{(J-2)(J-3)} \tag{9}$$

$$f(6) = \frac{J}{(J-1)(J-2)} \sum_{i=1}^{J} \left(\frac{data(i) - f(1)}{f(2)}\right)^3 \tag{10}$$

$$f(7) = data^S\left(\left\lceil \frac{J}{2} \right\rceil\right) \tag{11}$$

In Eqs. (5)–(11), seven statistical moments for feature extraction are mathematically defined and $data^S$ is the sorted data. Eqs. (5)–(11) are applied to raw EEG signal and low pass filter coefficients of the decomposed EEG signal to extract statistical features. This process is called *SFE(.)*, and it extracts seven features from each EEG signal.

2.2.2.1. Feature extraction steps. In the proposed feature generation process, BP and the statistical feature extraction process are applied to the raw EEG signal and four low pass sub-bands of the decomposed EEG signal. The steps of this process are presented below.

Step 2: Extract features using BP and SFE functions.

$$feat^1 = conc(BP(signal),\ SFE(signal)) \tag{12}$$

$$feat^2 = conc(BP(Low_1),\ SFE(Low_1)) \tag{13}$$

$$feat^3 = conc(BP(Low_2),\ SFE(Low_2)) \tag{14}$$

$$feat^4 = conc(BP(Low_3),\ SFE(Low_3)) \tag{15}$$

$$feat^5 = conc(BP(Low_4),\ SFE(Low_4)) \tag{16}$$

As seen in Eqs. (12)–(16), five-level feature generation is processed in this phase. $feat^i$ defines i^th^ level features, and $conc()$ represents the concatenation function. 256 and seven features are extracted by using BP and SFE, respectively. Therefore, 263 features are totally extracted at each level.

Step 3: Concatenate features of each level and obtain the final feature vector (*feat*) with a size of 1315.

$$feat = conc(feat^1, feat^2, feat^3, feat^4, feat^5) \tag{17}$$

Step 4: Normalize *feat* using Eq. (18).

$$X = \frac{feat - min(feat)}{\max(feat) - min(feat)} \tag{18}$$

where X is normalized features in the range of [0,1], we used normalization to select the most discriminative features since RFINCA uses distance-based feature selectors.

2.3. Feature selection

One of the most critical problems of feature selection is to find the optimal number of features. Therefore, researchers have tried to find the optimal number of features using trial and error methods. We proposed RFINCA to solve this problem automatically. In the feature extraction phase, 1315 features are generated from an EEG signal. A novel iterative and hybrid feature selection technique is presented to choose significant k features from the extracted 1315 features. This feature selection uses ReliefF and NCA together [25,26]. ReliefF is a distance-based feature selection technique that calculates a weight for each feature using Manhattan distance and generates both negative and positive weights. NCA is one of the mostly used feature selection techniques and a weight-based feature selection algorithm to generate positive weights. Both ReliefF and NCA have bigger weights to define more distinctive features, smaller weights to represent less valuable features. Moreover, negative weighted features crated by ReliefF represent redundant features. Therefore, ReliefF is firstly applied to normalized features, and ReliefF weights are calculated to eliminate redundant (negative weighted) features. After eliminating the redundant features, NCA is applied to selected features by ReliefF to determine the range of the number of features. In this work, the initial and end values of the presented iterative feature selector are chosen as 40 and 1000 respectively. These features are utilized as an input to the k-NN classifier [38], which is an effective and fast classifier to calculate the error rates. Then, features with a minimum error are selected. Graphical demonstration of the RFINCA is given in Fig. 2.

Steps of the presented RFINCA are listed below.

Step 4: Apply ReliefF to normalized features (X) with a size of 1315 and calculate 1315 ReliefF features.

$$w^R = ReliefF(X, target) \tag{19}$$

Where w^R is weights of the ReliefF with a size of 1315.

Step 5: Select positive weighted features using w^R.

$$feat^R(k) = X(i),\ w^R(i) > 0\ k = k + 1 \tag{20}$$

where $feat^R$ is selected features by using ReliefF with the size of k.

Step 6: Calculate NCA weights using $feat^R$ and NCA function.

$$w^N = NCA(feat^R, target) \tag{21}$$

where w^N is NCA weights.

Step 7: Sort w^N by descending.

$$[w^N_{sorted}\ indice] = sort(w^N) \tag{22}$$

where w^N_{sorted} sorted weights, and *indice* is indices of these weights.

Step 8: Calculate errors by using a k-NN classifier with 10-fold cross-validation (CV). The procedure of the error calculation is given in Algorithm 2.

Algorithm 2. Error calculation for features.

Step 9: Find the minimum error.

$$[err_{sorted}\ ind] = min(err) \tag{23}$$

where *ind* is indices of the minimum error.

Step 10: Select final features ($feat^f$).

$$feat^f(i) = feat^R(indice(i)),\ i = \{1, 2, \ldots, 39 + ind\} \tag{24}$$

The proposed RFINCA selects 55 features from the extracted 1315 features. ReliefF selects 839 features, and 55 of them are the most effective.

2.4. Classification

The selected 55 features are utilized by different classifiers to show the success of the proposed framework. *Eighteen* classifiers are used to test the proposed BP, statistical features, and RFINCA feature selector-based driver fatigue detection approach with 10-fold cross-validation. The used classifiers are categorized into seven groups, and their parameter settings were given below.

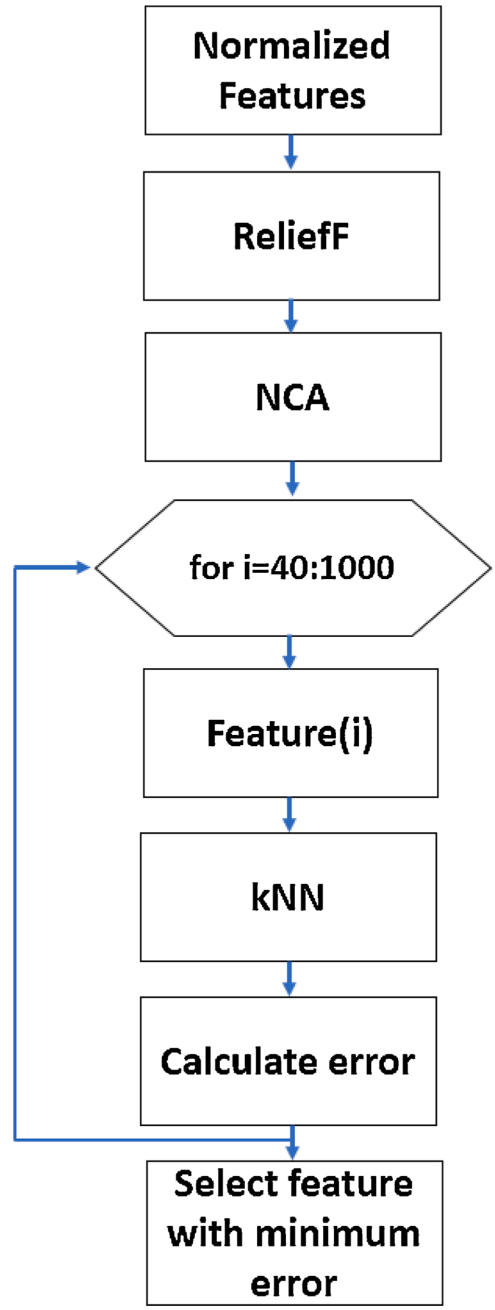


Fig. 2. Flow diagram of the proposed RFINCA.

2.4.1. Artificial neural networks

In this group, we used backpropagation ANN. It has been mostly used in classification tasks. Hyperparameters of the used ANN are given as follows. It has one hidden layer, with 130 neurons. It is a back-propagation network, and the scaled conjugate gradient training method is used to calculate optimal weights [39].

2.4.2. Logistic regression

Logistic regression is a binary classifier, and it is a nonparametric classifier [40].

2.4.3. Linear discriminant

LD is one of the most straightforward and linear classifiers in the literature, and it is a nonparametric classifier [41].

Procedure: Error Calculation: $ErrCalc(feat^R)$

Input: ReliefF features ($feat^R$) with size k.

Output: Errors (Err)

```
for m=0 to 960 do
    for n=1 to 40+m
        feat^N(:,n) = feat^R(:,inde(n)); // Feature selection by using NCA
    end for n
    err(m) = kNN(feat^N); // Calculate error for each selected feature.
end for m
```

2.4.4. Decision tree

In this category, two classifiers are used in MATLAB Classification Learner (CL). These are called Fine Tree and Medium Tree. Hyperparameters of these models are given as follows. Both Fine Tree and Medium Tree use Gini's diversity index. Maximum split numbers of Fine Tree and Medium Tree are selected as 100 and 20, respectively [42].

2.4.5. Support vector machine

SVM is one of the widely used conventional classifiers. It is an optimization-based classifier and uses numerous kernel functions. Therefore, it has several variations. In this work, we used linear, quadratic, cubic, and Gaussian kernels. These are called Fine Gaussian SVM, Quadratic SVM, Linear SVM, Cubic SVM in the MATLAB CL. Default settings of the models were used [43,44].

2.4.6. k-Nearest neighbor

k-NN is a distance-based classifier, where k represents a variable. Various k variables and distance metrics can be utilized in this category. We used five types of k-NN classifiers. These are called Cubic k-NN, Fine k-NN, Medium k-NN, Cosine K-NN, and Weighted k-NN. City block (Manhattan) distance metric was used in the Fine k-NN, Medium k-NN, and Weighted k-NN. Minkowski distance was used in Cubic K-NN, and Cosine distance was used in Cosine k-NN. k values were selected as 2, 10, 1, 1, and 2 for Weighted k-NN, Medium k-NN, Fine k-NN, Cubic k-NN, and Cosine K-NN, respectively. The squared inverse was chosen as distance weight for Weighted k-NN, and Equal was selected for others [38,45].

2.4.7. Ensemble

Four ensemble classifiers were used namely Bagged Tree, Boosted Tree, Subspace k-NN, and Subspace Discriminant in MATLAB CL. The number of learners and learning rates of all of them was set as 30 and 0.1 [46].

Step 11: Classify the selected features by using the chosen classifier with a 10-fold CV.

2.5. Overview of the proposed framework

Steps of the presented hybrid feature extraction and RFINCA feature selection-based driver fatigue detection approach was given in the previous sections. This method has a multilevel architecture, and transitions of the proposed multileveled fatigue driving detection approach are demonstrated in Table 2.

Table 2
Transitions of the presented perceptual hash.

Section	Process	Size	Objective
Level creation	Raw EEG signal	L	Load signal
	Apply 1D-DWT to raw EEG signal and obtain Low_1 sub-band.	$\frac{L}{2}$	Preprocessing and construction multileveled method.
	Apply 1D-DWT to raw Low_1 signal and obtain Low_2 sub-band.	$\frac{L}{4}$	
	Apply 1D-DWT to raw Low_2 signal and obtain Low_3 sub-band.	$\frac{L}{8}$	
	Apply 1D-DWT to raw Low_3 signal and obtain Low_4 sub-band.	$\frac{L}{16}$	
Feature extraction	Extract textural and statistical features from the Raw EEG signal.	263	Low, medium and high level feature extraction.
	Extract textural and statistical features from Low_1 signal.	263	
	Extract textural and statistical features from Low_2 signal.	263	
	Extract textural and statistical features from Low_3 signal.	263	
	Extract textural and statistical features from Low_4 signal.	263	
	Concatenate extracted features	1315	
	Normalize features	1315	
Feature selection with the proposed RFINCA	Generate weights of ReliefF	1315	Selection of most distinctive features.
	Eliminate redundant ones	839	
	Calculate weights of NCA	839	
	Select optimum features	55	
Classification	Classify selected 55 features	18 classifiers	Classification

Table 2 distinctly illustrates the transitions of the presented driver fatigue detection method. By using Table 2, the time complexity of the presented method can easily be calculated. The complexity of the presented multilevel feature generation method was found as $O(nlogn)$, and the time complexity of the other phases was calculated as $O(n)$. RFINCA feature selector has more complexity. It uses an iterative feature selection. A range was used to reduce the time complexity of the RFINCA. The optimal number of features is determined by using iterative feature selection. Shallow classifiers are utilized in the classification phase. Therefore, the time complexity of the classification phase is low. The time complexity of each phase is shown below to better express the presented model.

$$\text{Feature extraction}: \ O(nlogn)$$

$$\text{Feature selection}: O(n^2 + Rn^2) = \ O(Rn^2)$$

Classification : $O(kd)$

where R defines the range, k is the number of features, d represents the dimension of the used dataset. Both ReliefF and NCA use a nested loop to generate optimal weights of the features. Therefore, the time complexities of both feature selectors are the same, and they are calculated as $O(n^2)$. However, the feature selection process of the NCA is used iteratively. The time complexity of INCA is found as $O(Rn^2)$. Moreover, the pseudocode of the proposed approach is given in Algorithm 3 to summarize the presented model compactly.

Algorithm 3. The presented multilevel feature generation and hybrid feature selection-based EEG driver fatigue detection model.

3. Results and discussion

3.1. Dataset

A publicly available EEG dataset[1] is utilized in this study. A brain cap with 32-electrode was used to collect the EEG signals. Therefore, the used dataset contains EEG signals with 32-channels. The EEG signals were collected by using a driving simulator and a brain cap. Subjects did not use stimulants such as alcohol, tea, or energy drinks prior to the experiment. The experiment was carried out using a vehicle driving simulator. The age range of the subjects was determined as 17–25, and the EEG signal was collected from 16 healthy subjects. These are eight males and eight females. EEG signal collection took 5 min for each subject, and these signals were segmented. After the experiment, 480 fatigue and 480 rest EEG signals were collected [47].

3.2. Experimental setup

A publicly available driving fatigue EEG dataset was downloaded, which was explained in Section 3.1 for testing our proposed method. To realize the presented fused feature generator and RFINCA feature selector-based driving fatigue detection approach, MATLAB2018a was used on a laptop computer. This laptop computer has simple configurations, which are 8 GB RAM and i5 8th generation CPU (1.8 GHz). Any parallel programming and GPU core were not used to implement the experiments. In the classification phase, MATLAB classification learner and ANN toolboxes were used. There are 480 instances for fatigue and 480 instances for the rest. Since the number of instances are limited, 10-fold cross-validation is utilized in the classification phase.

3.3. Experimental results

In this section, the presented multilevel hybrid feature extraction and RFINCA feature selection-based driver fatigue detection approach are evaluated using the classifiers' performance metrics. These performance metrics are geometric mean (*gm*), sensitivity (*sen*), accuracy (*acc*), specificity (*spe*). These performance evaluation metrics have been widely used for classification methods, and mathematical equations of these performance metrics are given in Eqs. (25)–(28) [48–50].

$$Acc = \frac{ntp + ntn}{ntp + ntn + nfp + nfn} \tag{25}$$

$$Sen = \frac{ntp}{ntp + nfn} \tag{26}$$

$$Spe = \frac{ntn}{nfp + ntn} \tag{27}$$

$$Gm = \sqrt{Sen \text{ x } Spe} \tag{28}$$

where ntp, ntn, nfp, and nfn describe the number of true positives, true negatives, false positives, and false negatives, we used 18 classifiers in 7 categories. The obtained results are listed in Table 3.

As seen from Table 3, the Fine k-NN classifier reached 100.0% classification accuracy, and the most successful category is k-NN because all classifiers of k-NN achieved higher than 90% classification accuracy and geometric mean.

3.4. Discussions

In this study, a novel EEG signal classification framework for driver fatigue detection is presented. A multilevel feature extraction BP and statistical feature-based multilevel feature extraction process was used to generate low, middle, and high-level features. In order to automatically select meaningful features, the RFINCA method was presented. By using RFINCA, 55 features were selected. These features were utilized as the input of the 18 classifiers in 7 categories. The best classifier was found as a Fine k-NN classifier, and it reached 100.0% classification accuracy. The best category is the k-NN because all classifiers in this category achieved higher than 90.0% classification accuracy. ANN also achieved 98.85%, 98.96%, 98.75%, and 98.85% accuracy, sensitivity, specificity, and geometric mean, respectively. The worst classifier is LR, and the geometric mean of it 71.23%.

To demonstrate the success of the presented hybrid feature extraction and RFINCA feature selection-based driver fatigue detection framework, the success rates of state-of-the-art fatigue detection methods and proposed method are listed in Table 4. Table 4 clearly demonstrates that the presented method reaches higher classification rates by using eight classifiers than the best of other methods. By using the Fine k-NN classifier, we reached 4.69% higher classification accuracy than the best of other methods. The statistical attributes of the selected 55 features by RFINCA are shown in Fig. 3 by using boxplot analysis to prove this high classification success.

Fig. 3 shows the obtained high classification rates, and the selected 55 features by RFINCA are separable because they have distinctive statistical characteristics. Advantages of the proposed hybrid feature extraction and RFINCA feature selection-based driver fatigue detection framework are given as follows:

- Statistical and texture-based feature extraction methods are used together, and high classification accuracies were obtained by using these features and RFINCA feature selection approaches.
- By using the proposed hybrid feature extraction method, low level, middle level, and high-level features are extracted with low computational complexity ($O(nlogn)$).
- The number of features is parametrically selected by the feature selection methods (ReliefF and NCA-based feature selection). The proposed RFINCA based feature selection method uses the advantages of these two feature selection algorithms, and the number of most discriminative features are automatically selected.
- 18 classifiers in seven categories were used to test the performance of the proposed hybrid feature extraction and RFINCA feature selection-based fatigue detection framework. By using these classifiers, a comprehensive benchmark was obtained.
- The proposed hybrid feature extraction and RFINCA feature selection-based driver fatigue detection approach reached higher classification rates than other methods using eight classifiers (See Table 4). These results distinctly indicate that the performance of the proposed framework is very efficient.
- Excellent classification performance (100.0%) was achieved by using the proposed framework for driver fatigue detection (see Tables 3 and 4).

[1] https://data.mendeley.com/datasets/dpgvc22rth/1.

Procedure: The presented multilevel fused feature generation and iterative feature selection based driver fatigue detection model

Input: EEG dataset (D) with 960 observations

Output: Results

00: Load dataset
01: **for** h=1 to 960 **do**
02: Read each EEG signal from dataset
03: $X(h, 1{:}263) = conc(BP(signal), SFE(signal));$
// Extract textural features using binary pattern and generate statistical features using 7 statistical moments from EEG signal ($signal$). Herein $conc(.,.)$ is concatenation function.
04: **for** i=1 to 4 **do** // Generate multilevel features using DWT.
05: $[low, high] = DWT(signal);$
06: $X(h, i*263+1{:}(i+1)*263) = conc(BP(low), SFE(low));$
// Extract and merge features using the low-pass filter coefficients.
07: $signal = low$; // Update signal to implement multilevel decomposition
08: **end for i**
09: **end for h**
10: Apply ReliefF and eliminate redundant features.
11: Select the optimal number of feature deploying INCA.
12: Classify the selected features using a shallow classifier with 10-fold cross-validation
13: Calculate results

Table 3
Classification performances (%) of the proposed hybrid feature extraction and RFINCA feature selection-based fatigue detection method.

Category	Classifier	Acc	Sen	Spe	Gm
ANN	ANN	98.85	98.96	98.75	98.85
LR	LR	71.35	75.41	67.29	71.23
LD	LD	72.08	75.42	68.75	72.01
Tree	Fine Tree	90.42	90.63	90.21	90.42
	Medium Tree	84.17	81.25	87.08	84.11
SVM	Linear SVM	73.85	78.75	68.96	73.69
	Quadratic SVM	87.50	88.75	86.25	87.49
	Cubic SVM	90.10	90.42	89.79	90.10
	Fine Gaussian SVM	98.02	97.92	98.13	98.02
k-NN	Fine k-NN	100.0	100.0	100.0	100.0
	Medium k-NN	99.38	98.96	99.79	99.37
	Cubic k-NN	91.04	92.71	89.38	91.03
	Cosine k-NN	94.06	94.79	93.33	94.06
	Weighted k-NN	99.79	99.58	100.0	99.79
Ensemble	Boosted Tree	98.12	98.33	97.92	98.12
	Bagged Tree	98.33	98.54	98.13	98.33
	Subspace Discriminant	72.92	74.16	71.67	72.90
	Subspace k-NN	99.48	98.96	100.0	99.48

- This method is simple and can be easily implemented in smart vehicles.

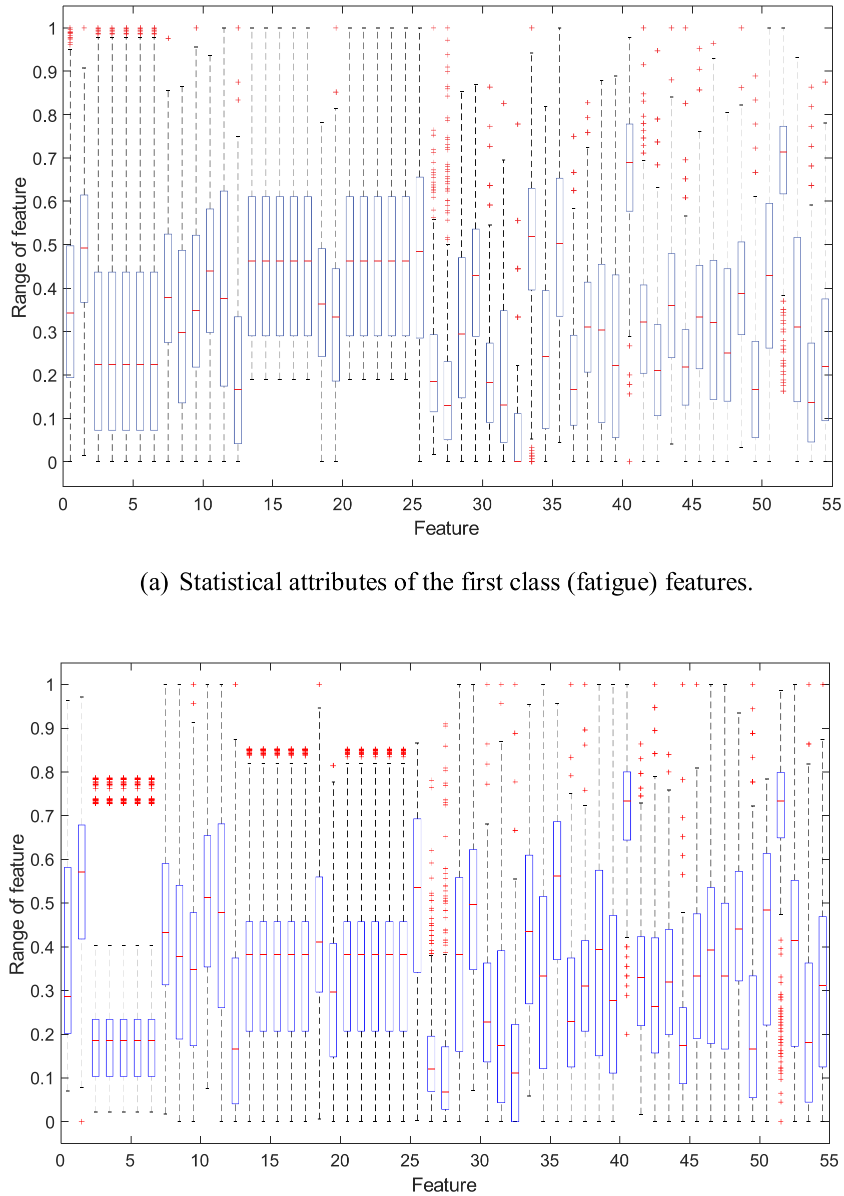
The disadvantage of the presented model is the high time complexity of the RFINCA feature selector. Although it is a very effective feature selector, it has a high execution time. In the near future, lightweight and effective feature selectors like RFINCA can be used.

Table 4
Classification accuracies (%) of the previously presented methods and the proposed hybrid feature extraction and RFINCA feature selection-based fatigue detection method.

Method	Dataset	Split ratio	Classification accuracy
Wang et al. method [51]	Collected data	30-fold cross validation	90.70%
Li et al. method [18]	Collected data [52]	Unspecified	91.50%
Luo et al. method [1] (Single-channel)	Collected data	80:20	95.37%
Hu method [53] (Single-channel)	Collected data	Leave-one-out cross-validation	96.60%
Li et al. method [54] (Single-channel)	Collected data	67 training 33 testing	98.86%
Our method + ANN (Single-channel)	Qiu dataset [47]	10-fold cross-validation	98.85%
Our method + Fine Gaussian SVM			98.02%
Our method + Fine k-NN			100.0%
Our method + medium k-NN			99.38%
Our method + Weighted k-NN			99.79%
Our method + Boosted Tree			98.12%
Our method + Bagged Tree			98.33%
Our method + Subspace k-NN			99.48%

4. Conclusion and future directions

This paper proposes two effective methods as a feature generator and a feature selector. In feature generation, two lightweight and straightforward feature generation functions are employed to use effectiveness of them. These functions are BP and statistical feature generation. As mentioned before, DWT is one of the significant transformations for signal decomposition. Thus, DWT is selected to create levels; BP and seven statistical moments are utilized for a fused and multilevel feature generation. The biggest problem for the feature selection is to select the



(a) Statistical attributes of the first class (fatigue) features.

(b) Statistical attributes of the second class (rest) features.

Fig. 3. Graphical demonstration of the selected 55 features statistical attributes according to class by using boxplot analysis.

most informative and discriminative features automatically. RFINCA is proposed to solve this problem and use the superiorities of both NCA and ReliefF together. The presented fused and multileveled feature generator and RFINCA feature selector were tested on a publicly available fatigue driving EEG dataset. Our feature generator extracts 1315 features, and RFINCA selects 55 most valuable of them. These features are utilized as the inputs of 18 shallow classifiers. 10-fold cross-validation was chosen as a validation and test strategy. 100.0% classification accuracy was obtained by using the Fine k-NN classifier, which is also utilized as an error calculator of RFINCA (See Table 3). Comparisons clearly showed that the proposed feature extraction and RFINCA feature selection method had achieved excellent performance since we reached higher success rates than the state-of-the-art methods using 8 classifiers (See Table 4). The effectiveness of the extracted and selected features was also presented (See Fig. 3). These results obviously demonstrated the success of our cognitive strategy for EEG based driver fatigue detection approach.

In future works, an automated and intelligent driver assistant system can be developed for driver fatigue detection by using the presented hybrid feature extraction and RFINCA feature selection framework. RFINCA is a significant feature selector, and it can be used in other fields as well. Our main intention is to propose a real-time driving fatigue detection model using EEG signals. Our intended real-time EEG-based driver fatigue detection strategy is summarized as follows. According to this work, the gathered EEG signals can be received every minute, and these EEG signals can be used as the input of the proposed framework. In the training phase, the best feature combination can easily be determined by using RFINCA. Therefore, RFINCA can only be used in the training phase. By using the proposed fused feature generator, features of the EEG signals can be extracted, and the best combination (the determined feature index by RFINCA) can be selected, and these features can be classified by using any shallow/conventional classifier to detect driver fatigue. Furthermore, we can use the matching method by using a trained dataset instead of a classification. Our future direction about the real-time application is shown in Fig. 4.

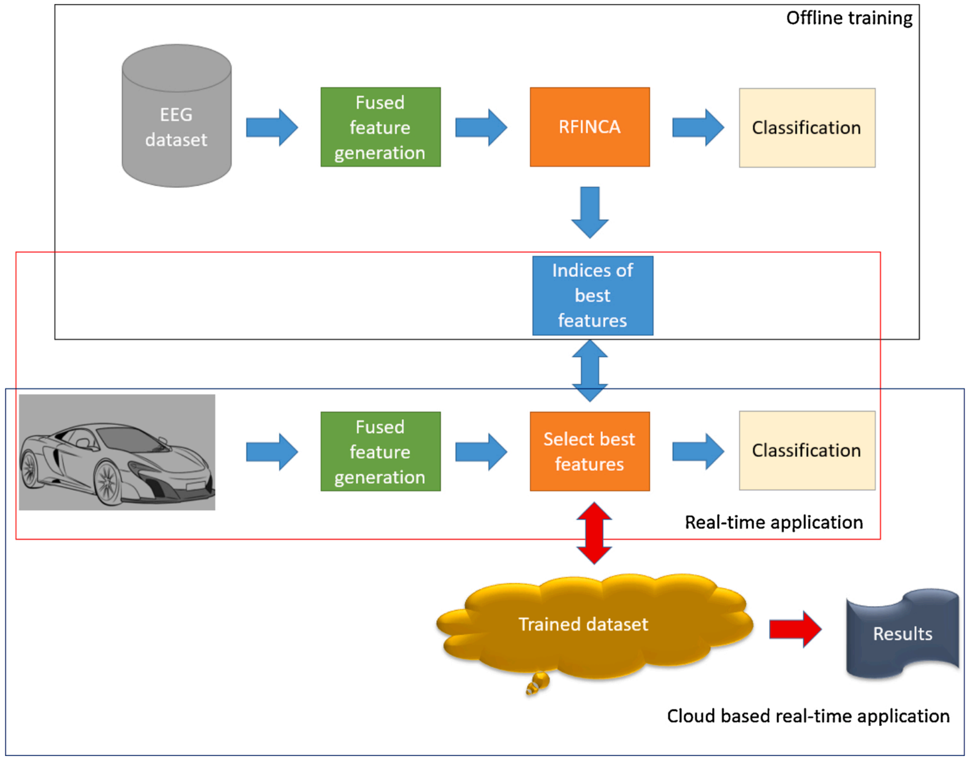


Fig. 4. Our presented scenarios about real-time EEG-based driving fatigue detection. Red arrows express cloud-based real-time applications.

CRediT authorship contribution statement

All algorithm codes are written and run by **Turker Tuncer**. Part of Methods and results are written by **Turker Tuncer**. Part of Introduction and Conclusion are written by **Sengul Dogan**. Part of Introduction, Methods, Results and Discussion are written by **Abdulhamit Subasi**. The whole manuscript revised by **Abdulhamit Subasi**.

Declaration of Competing Interest

The authors report no declarations of interest.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at https://doi.org/10.1016/j.bspc.2021.102591.

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