# Approach based on wavelet packet transform and 1D-RMLBP for drowsiness detection using EEG

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Early drowsiness detection may be crucial for the vehicle alertness system. Towards this, wearable technology, camera-based biophysical signals like electroencephalogram (EEG) approaches are utilised. In this Letter, the EEG-based approach is proposed to detect drowsiness. The proposed method consists of random sampling-based artificial signal augmentation, wavelet packet transform decomposition, logarithmic energy entropy, and one-dimensional region mean local binary pattern (1d-RMLBP) based feature extraction and classifier. k-Nearest neighbour and support vector machine classifiers are employed to detect the drowsiness. The MIT/BIH polysomnographic dataset has been used to test the proposed model. The proposed method has superior performance than the other methods using the same data set. The experimental results demonstrate that the proposed model could efficiently detect drowsiness from polysomnographic EEG signals.

*Introduction:* Drowsiness is defined as the intermediate state between awake and sleep [1, 2]. Drowsiness can cause an accident in traffic because of decreased alertness and decision-making ability. Driving in this situation can result in deaths, serious injuries, and economic losses. Drowsiness detection is vital to reduce this loss [1]. Drowsiness detection systems can be categorised as camera-based, wearable sensor-based, and biophysical signals-based approaches. The electrooculogram (EOG), the electroencephalogram (EEG), and electromyogram (EMG) are generally used in biophysical signals-based systems [2]. The researchers have proposed EEG signals-based methods for drowsiness detection methods to date. Budak *et al.* [2] composed the three stages for drowsiness detection from EEG signals. They used zero-cross rate, energy, spectral entropy, and instantaneous frequency (IF) as features in the first stage. In the second stage, the deep features extracted from spectrogram images of EEG signals. Tunable-Q wavelet transform (TQWT) is used to obtain mean values and standard deviation (SD) values of IF in the third stage. The authors employed long short-term memory classifier at all stages and in decision used majority voting. They classify drowsiness and awake with 94.31% accuracy. The fast Fourier transform-based nine features applied to inputs of artificial neural network (ANN) and support vector machine (SVM) classifiers in [3]. The authors achieved 84.75% accuracy. Correa *et al.* [4] used time, spectral and wavelet transform (WT) analysis to differentiate drowsiness to awake. In the work, seven selected parameters from 19 features were fed to the ANN classifier and 85.5% average accuracy was obtained. In [5], power spectral density and WT were combined to extract features such as central frequency, first quartile frequency, maximum frequency total spectrum energy, theta and alpha bands powers, and zero-crossing numbers. The authors report for drowsiness 86.5% accuracy and 81.7% accuracy for alertness states. Taran and Bajaj [6] exploit the Hermite transform (HT) and extreme learning machines (ELMs) to classify drowsiness and awake stages. They optimised the selection of Hermite basis functions by using the artificial bee colony method. Their method has 92.5% accuracy performance. Boonnak *et al.* [7] employed WT to calculate the energy of the coefficient. Then the authors revised the weight of the energy of the coefficient to simplify the classification. A 90.27% accuracy was obtained with the ANN classifier. In [8], the inter-beat (RR) time series and EEG signals were utilised to detect sleep stages. RR time series decomposed into intrinsic mode functions by using iterative filtering. EEG signals are separated into sub-bands by using band-pass filters. The dispersion entropy (DE) and recurrence quantification analysis features of RR time series and DE and variance features of EEG were combined to construct feature vector. The combined features were classified with deep neural network and 85.51% accuracy was obtained. Anitha [9] proposed a multimodal signal method. The multimodal approach consists of video and EEG signals. Bajaj *et al.* [10] used TQWT to decompose EEG signals to sub-bands. They calculate Hjorth mobility, minimum, maximum, mean, and SD parameters to form feature vectors. The features are classified by various methods and 91.84% accuracy was obtained. The works, as mentioned above, used MIT/BIH polysomnographic dataset [11, 12].

This Letter proposes an automatic drowsiness detection system by using MIT/BIH polysomnographic EEG dataset. The method exploits random-sampling-based artificial signal augmentation. The approach takes $1 \times 3000$ random sample from one raw EEG signal, and this process is repeated ten times. The wavelet packet transform (WPT) decomposes to time–frequency coefficients the augmented EEG signals. WPT decomposition reveals the concealed information in signal processing [13, 14]. The Shannon entropy and db3 wavelet family are selected heuristically in the WPT. Eight coefficients are obtained as WPT level choose equal three. Logarithmic energy entropy (LEE) and one-dimensional region mean local binary pattern (1d-RMLBP) of each the coefficients were calculated as a feature extractor. LBP is useful as a local descriptor in image processing [15, 16]. RMLBP has a better performance compared to the original LBP [15]. For the proposed method, 1d-RMLBP is improved its original RMLBP method. LEE is used for it is discriminative in biophysical signals [17]. The drowsiness is detected and is classified from the extracted features by using k-nearest neighbour (kNN) and SVM classifiers.

The main contributions of this work are listed as: (i) the random selection-based artificial data augmentation; and (ii) the 1d-RMLBP method developed to apply EEG for drowsiness detection.

*Data set:* The MIT/BIH polysomnographic EEG dataset was considered in the experiments. The data set was collected from 16 subjects [11]. Some of the channels of the EEG, namely C3-O1, C4-A1, and O2-A1, were used in the collection of the data set. The sampling rate and the length of the EEG signals are 250 Hz and 30 s. The labels, which included different sleep stages, were assigned by an expert [12]. In this Letter, the labels 'Awake stage' and 'Stage I' were considered as awake and drowsiness classes, respectively.

*Wavelet packet transform:* WPT is the extended version of the discrete wavelet transform (DWT) decomposition used to compensate for the DWT's lack of constant time–frequency decomposition [13]. WPT differs from DWT in terms of detail coefficients. WPT produces $2^k$ different sets of wavelet coefficients for $K$-level wavelet decomposition as each level's approximation and detail record. At the same time, DWT calculates the detailed coefficient of each level as $k+1$ by adding the final approximation coefficient [14].

*One-dimensional region mean local binary pattern:* LBP is a commonly used technique for detecting local texture information in image processing. Briefly, LBP assigns a new value to centre pixel Pc according to the relation of eight neighbours pixel in a 3 × 3 sized pixel region. The relation can be described in (1):

$$f(x) = \begin{cases} 0, & P_i \geq P_c \\ 1, & P_i < P_c \end{cases} \tag{1}$$

where $P_i$ and $P_c$ define eight neighbour pixels and the centre pixel, respectively. The LBP code can be expressed mathematically as:

$$\mathrm{LBP} = \sum_{i=1}^{n} f(x) 2^{i-1} \tag{2}$$

where $n$ is the number of neighbours and equal to eight for 3 × 3 pixels.

The researchers have developed various versions of LBP. Region mean local binary pattern (RMLBP) was proposed by Turkoglu *et al.* [15] for plant classification. In RMLBP, the region mean (RM) is also taken into account when calculating the new value of the centre pixel $P_c$ compared to traditional LBP methods. The relation of RMLBP is given in (3)

$$g(x) = \begin{cases} 1, & (\mathrm{RM} < P_c) \text{ and } (\mathrm{RM} < P_i) \\ 0, & (\mathrm{RM} < P_c) \text{ and } (\mathrm{RM} \geq P_i) \\ 1, & (\mathrm{RM} \geq P_c) \text{ and } (P_c < P_i) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where RM is the mean value of neighbour 3 × 3 pixels and calculated as following:

$$\mathrm{RM} = \frac{1}{n} \sum_{i=1}^{n} P_i \tag{4}$$

where $n$ represents the number of neighbours. The new value of $P_c$ is computed given (5):

$$\mathrm{RMLBP} = \sum_{i=1}^{n} g(x) 2^{i-1}. \tag{5}$$

In this Letter, the RMLBP method is adopted for signal processing by using a nine length window instead of a $3 \times 3$ pixel. A nine length sliding window is performed through the entire signal. 1d-RMLBP quantise the signal between 0 and 255 values [16]. The histogram of the quantised signal is used as drowsiness and alertness distinguishing features.

*Logarithmic energy entropy:* LEE is a measure of uncertainty and complexity of a signal. LEE of given a $x(t)$, $t = 1, 2, \ldots, N$, is defined in (6) [17]

$$\mathrm{LEE}(x) = -\sum_{i=1}^{N} (\log_2 (p_i(x)))^2 \qquad (6)$$

where $p(x)$ represents the probability density function of $x(t)$.

*k-nearest neighbour:* The kNN algorithm, which is a non-parametric learning algorithm, is one of the simplest and most widely used classification algorithms [18]. The classification task is performed by using a distance metric. Euclidean distance is generally used in the kNN algorithm. The kNN algorithm requires a training set to determine the distribution of the input samples. Then kNN in the training set is used for the classification of the test data [18].

*Proposed method:* The proposed approach is aimed to detect drowsiness and awake stages from polysomnographic EEG signals. In the proposed method, artificially, data augmentation is considered to improve performance. The approach takes a random $1 \times 3000$ sample in each raw signal. This random process is repeated ten times. So, the data set formed 6670 awake signal and 4880 drowsiness signal. The formed data set decomposes to three levels by using WPT. The WPT parameter Shannon entropy and db3 wavelet family were chosen heuristically in the experiments. 1d-RMLBP and LEE methods extract the distinctive feature from WPT coefficients of EEG signals. Optimal histogram bins number of 1d-RMLBP determined as 12 by Sturgess Rule [19]. From a WPT coefficient, a $1 \times 13$ feature vector is created with LEE. When all WPT coefficients are concatenated, $1 \times 104$ sized feature vector is obtained. All experiments are performed in MATLAB with 2.70 GHz CPU and 32 GB RAM. Five-fold cross-validation is employed to ensure the validation of the proposed method in experiments. The kNN classifier is used for the sake of performance. The parameters of the kNN chosen Euclidean distance metric and $k = 10$, consideration lowest error rate. The kernel function of SVM is selected as the linear kernel, which has better results compared to other kernels in testing. Performance and stability of the proposed approach were evaluated by using accuracy (Acc), sensitivity (Sens), specificity (Spec), precision (Prec), and $F1$ score ($F1$). These metrics were preferred because they are widely used in biomedical applications, as exemplified in [20].

*Results and discussion:* Table 1 shows the classification results. As seen in Table 1, the kNN has 96.93% accuracy, 96.54 sensitivity, 97.21% specificity, 96.20% precision, and 96.37% $F1$ score ($F1$). One can see that kNN has a better performance of about 3% than the SVM. Also, the SVM performed worse than kNN for all criteria.

**Table 1:** Performance results of the proposed methods

| Classifier | Acc (%) | Sens (%) | Spec (%) | Prec (%) | *F*1 (%) |
|---|---|---|---|---|---|
| SVM | 93.57 | 93.30 | 93.76 | 91.63 | 92.46 |
| kNN | 96.93 | 96.54 | 97.21 | 96.20 | 96.37 |

The receiver operating characteristic (ROC) curve helps to evaluate the overall classifier performance [20]. The value of area under the ROC curve is named area under the curve (AUC). The AUC has a value between 0 and 1. It can be said that the performance of the classifier is better when the AUC value is close to 1 and lower SD is lower [20]. The ROC curves are shown in Fig. 1 for both kNN and SVM classifiers, respectively. The AUC values are given Table 2.

Consideration of the ROC curve given in Fig. 1, the kNN has good and robustness performance than the SVM classifier. The AUC value of the kNN model is closer to 1 compared to the model with SVM. Also, the SD of kNN classifier (0.0019) is lower than SVM (0.0027). Fig. 1 and Table 2 show that kNN is a better classifier for drowsiness detection. The experiments are conducted to compare the proposed method with other state-of-the-art methods using the same data set in the literature. The comparative results are shown in Table 3.

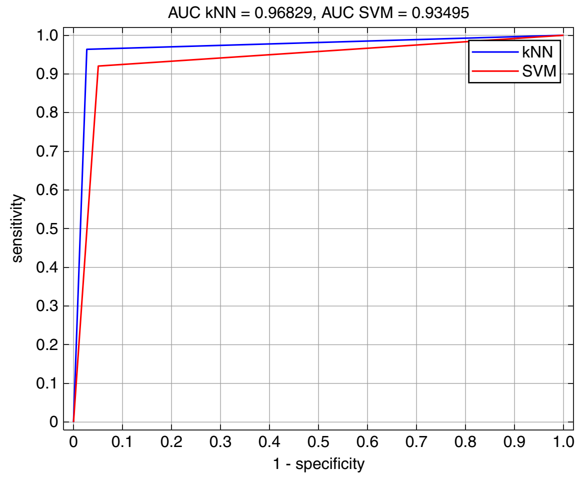


**Fig. 1** *ROC curves kNN and SVM classifiers*

**Table 2:** AUC and SD values of two classifiers

| Classifier | AUC value | Standard deviation |
|---|---|---|
| kNN | 0.9683 | 0.0019 |
| SVM | 0.9350 | 0.0027 |

**Table 3:** Comparison of the proposed method with other methods using same data set

| Methods | Acc (%) |
|---|---|
| Budak *et al.* [2] | 94.31 |
| Belakhdar *et al.* [3] | 84.75 |
| Correa *et al.* [4] | 85.66 |
| Correa and Leber [5] | 84.10 |
| Taran and Bajaj [6] | 92.28 |
| Boonnak *et al.* [7] | 90.27 |
| Tripathy and Acharya. [8] | 85.51 |
| Anitha [9] | 87.20 |
| Bajaj *et al.* [10] | 91.84 |
| proposed method | 96.93 |

As shown in Table 3, the state-of-the-art methods have an accuracy range of 84.10–94.31%. Accuracy of the proposed method is better than 2.62% Budak *et al.* [2], which shows higher accuracy among the methods given in Table 3. The results indicate that the proposed method is more accurate than the other methods using the same data set.

*Conclusions:* In this work, an efficient method is proposed for the early detection of drowsiness. The proposed method first applies artificial signal augmentation by using random-sampling. Then, the WPT is employed to obtain time–frequency coefficients of the augmented EEG signals. LEE, which has a proven performance in the EEG, the method is used for each WPT coefficients. At the same time, 1d-RMLBP was developed to conceal discriminative features from WPT coefficients. LEE and 1d-RMLBP features are concatenated to form the feature vector. SVM and kNN classifiers were used to detect drowsiness from the combined features. The kNN has 96.93% accuracy, whereas SVM performed 93.57% accuracy. The proposed method has been compared to other state-of-the-art methods using the same data set in the literature. The results indicate that the proposed model has superior performance compared to other methods in the literature.


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One or more of the Figures in this Letter are available in colour online.

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