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Deep rhythm and long short term memory-based drowsiness detection

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ABSTRACT

In this paper, a deep-rhythm-based approach is proposed for the efficient detection of drowsiness based on EEG recordings. In the proposed approach, EEG images are used instead of signals where the time and frequency information of the EEG signals are incorporated. The EEG signals are converted to EEG images using the time-frequency transformation method. The Short-Time-Fourier-Transform (STFT) is used for this transformation due to its simplicity. The rhythm images are then extracted by dividing the EEG images based on frequency intervals. EEG signals contain five rhythms, namely Delta rhythm (0–4 Hz), Theta rhythm (4–8 Hz), Alpha rhythm (8–12 Hz), Beta rhythm (12–30 Hz), and Gamma rhythm (30–50 Hz). From each rhythm image, deep features are extracted based on a pre-trained convolutional neural network (CNN) model, with pre-trained residual network (ResNet) models such as ResNet18, ResNet50, and ResNet101. The obtained deep features from each rhythm image are fed into the Long-Short-Term-Memory (LSTM) layer, and the LSTM layers are then sequentially connected to each other. After the last LSTM layer, a fully-connected layer, a softmax layer, and a classification layer are employed in order to detect the class labels of the input EEG signals. Various experiments were conducted with the MIT/BIH Polysomnographic Dataset. The experiments showed that the concatenated ResNet features achieved an accuracy score of 97.92%. The obtained accuracy score was also compared with the state-of-the-art scores and, to the best of our knowledge, the proposed method achieved the best accuracy score among the methods compared.

1. Introduction

Drowsiness, which is indicated as low-level loss of consciousness, is one of the known causes of vehicular accidents worldwide [1]. The instantaneous reflex of the human mind, which is important in terms of its ability to make quick decisions, is weakened during the drowsiness state. Statistics have shown that most vehicular accidents occur due to driver drowsiness [2]. Thus, developing early warning systems against driver drowsiness are within the scope of car companies' development activities [1].

Driver drowsiness detection is generally accomplished through the use of cameras, wearable sensors, and with EEG signals. Wearable sensor-based methods use signal processing and learning approaches to recognize driver drowsiness. Camera-based approaches use numerous image processing techniques in order to recognize and analyze various driver behaviors. Recently, EEG-based methods have attracted considerable attention in the detection of driver drowsiness [3,4].

Budak et al. [1] proposed a hybrid approach for driver drowsiness detection using EEG signals. The authors used a series of feature extraction mechanisms based on zero-crossing rate distributions, energy, spectral entropy, and instantaneous-frequency. They also used mean values and standard deviation calculated from the instantaneous frequencies of Tunable Q-Factor Wavelet Transforms (TQWT). These deep features were also considered in their proposed method. The EEG signals were transformed into spectrogram images for deep feature extraction. Three different Long-Short-Term-Memory (LSTM) network classifiers were used. The outputs of the LSTM classifiers were then fused with a majority voting layer. The authors then tested their method using the MIT/BIH Polysomnographic Dataset (MIT/BIH-PD), and a 94.31% accuracy score was recorded.

Correa et al. [2] used Power Spectral Density (PSD) and Wavelet Transform (WT) in the detection of driver drowsiness. Frequency-based

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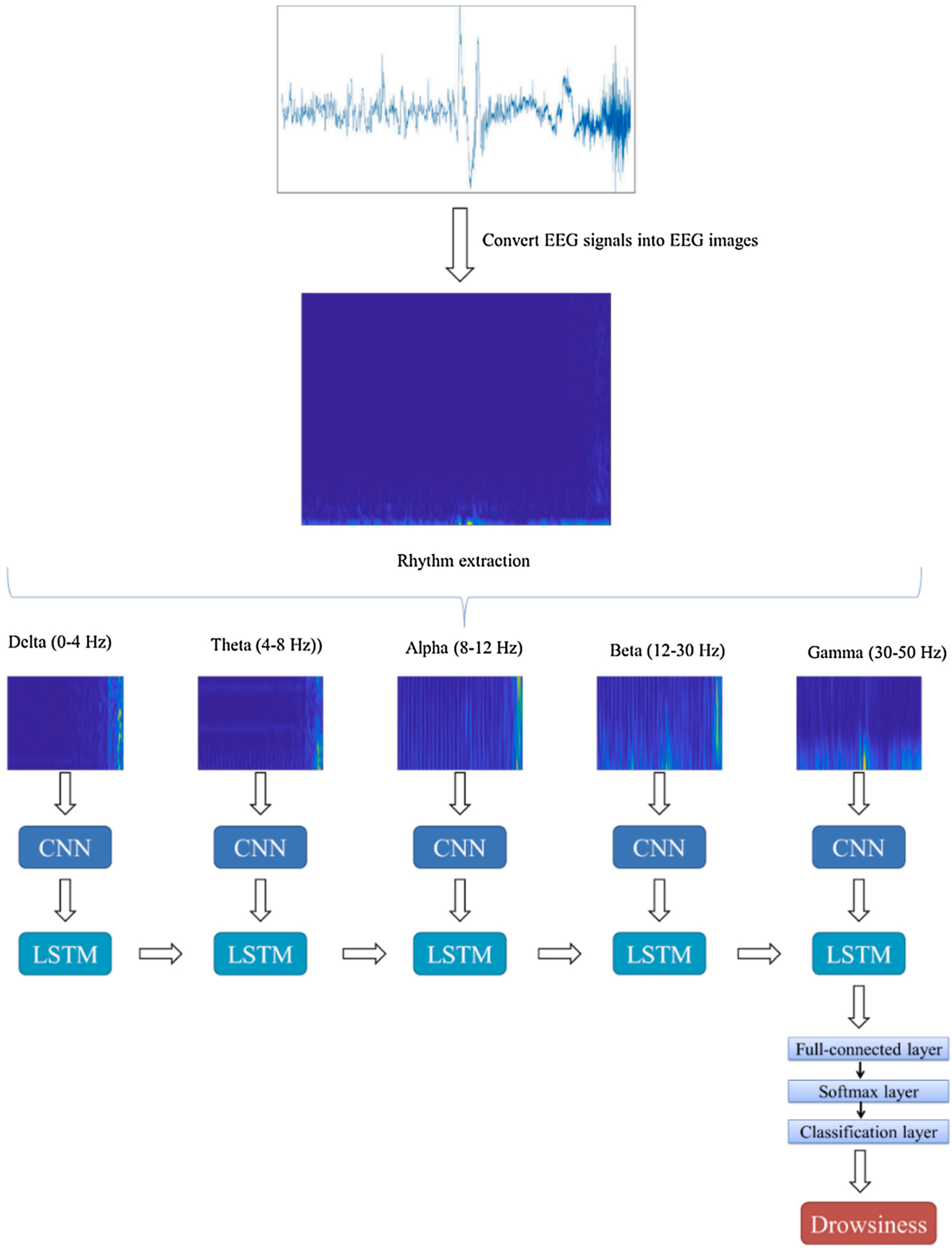

Fig. 1. Illustration of proposed method.

features were extracted from a total of 18 EEG signals. The authors opted to use Neural Networks (NN) classifier, recording an accuracy score of 84.1%. Later, Correa et al. [3] proposed another approach to driver drowsiness detection that employed spectral analysis and WT for feature extraction. In using the NN classifier, an 85.66% accuracy score was obtained in their study.

Belakhdar et al. [4] used windowed Fast Fourier Transform (FFT) for frequency-based feature extraction. The authors considered Support Vector Machines (SVM) and NN classifier methods for recognition purposes. The polysomnography database was used for performance evaluation of their proposed method, and an 84.75% accuracy score was obtained.

Silveira et al. [5] proposed an efficient WT-based approach for drowsiness detection. Specifically, the m-terms wavelet decomposition of EEG signals was used for feature extraction. The alpha and beta rhythms of the input EEG signals were used to discriminate between the subject's awake and drowsy states. The authors used the PhysioNet Sleep EEG dataset, and achieved a 98.7% accuracy score in their tests.

Chen et al. [6] used WT, FT and eyelid movements in their study on drowsiness detection. While the wavelet sub-bands were used for nonlinear feature extraction, FT was used for spectral feature extraction from the input EEG signals. For eyelid-movement-based feature extraction, Electrooculography (EOG) was used. The extracted features were concatenated and Extreme Learning Machine (ELM) classifier was then used for drowsiness detection. The authors used night-channel EEG recordings, and a 95.6% accuracy score was recorded.

Taran et al. [7] used the coefficients of the Adaptive Hermite Transform (AHT) as features and ELM classifier for drowsiness detection. The basis function of the HT was selected by using an optimization algorithm. The obtained features were then classified by k-Nearest Neighbor (k-NN), ELM, SVM, and Bayesian-based classifiers. MIT/BIH-PD was used in their experiments, and a 92.5% accuracy score was yielded.

Boonnak et al. [8] proposed an EEG-based drowsiness detection approach based on WT, and consisted of two stages. First, energy coefficients were calculated from WT coefficients, and then NN was applied. The authors used the MIT/BIH-PD and a 90.27% accuracy score was recorded. A drowsiness detection system, where the alpha relative power of EEG signals was used, was proposed by Picot et al. [9], and a dataset containing 40 EEG recordings was used in their experiments, achieving an accuracy score in testing of 84.2%.

Silveira et al. [10] developed a drowsiness detection system which was simple, portable and environment-free. Wavelet packet transform, spectral features and Wilcoxon signed rank measure were used in their developed detection system. The authors used a dataset with data collected from 20 subjects, and the experimental results evaluated according to their classification accuracy.

Anitha et al. [11] developed a multi-modal drowsiness detection system based on recorded videos and bio signals. Various image and signal processing routines were employed in the analysis of the video and bio-signal. A visually-stimulated-potential-based drowsiness detection system was proposed by Hashemi et al. [12], in which the steady-state visually stimulated potential was investigated in order to determine the eye state of the subject, i.e., closed or open. NN and frequency domain features were used for drowsiness detection, and a 97.0% accuracy score was obtained.

A perceptual function was designed by Chuang et al. [13] for drowsiness detection. Frequency domain features were extracted from the EEG recordings of 10 subjects. The experimental works showed that an 88.7% accuracy score was obtained. Rundo et al. [14] proposed a CNN-based drowsiness detection system. Their end-to-end CNN architecture consisted of seven layers, and was trained on EEG spectrogram images. In their proposed CNN architecture, there were three convolution layers, three max-pooling layers, and one fully-connected layer. Their experimental works reported an 86.0% accuracy score.

An EEG rhythms-based drowsiness detection approach was proposed by Taran et al. [15]. The Hilbert-Huang transform was initially applied to the input EEG signals, with an instantaneous frequency calculated. For rhythm extraction, empirical mode decomposition was applied. In their experiments, MIT/BIH-PD was considered and a 90.6% accuracy score was reported. Tripathy et al. [16] used a filtering-based approach to extract the sub-bands of EEG signals. Variance and entropy-based features were extracted from the sub-bands of the EEG signals, and deep NN classifier was used for the detection of drowsiness. MIT/BIH-PD was used in their experiments, and an 85.51% accuracy score was reported by the authors.

In the current study, a novel hybrid scheme is proposed for driver drowsiness detection by using EEG signals. The proposed method uses deep rhythm features and LSTM network for the efficient classification of drowsiness and awake states. Input EEG signals are initially converted into T-F EEG images by using the STFT method. Rhythm extraction is then carried out on the T-F image domain. Thus, five different rhythm images are produced from the input EEG T-F images. CNN-based deep feature extraction is applied on the rhythm images. To this end, a pre-trained CNN model was adopted. The ResNet architectures were considered due to their efficient structures, with ResNet18, ResNet50 and ResNet101 models used in the experiments. The obtained deep features from each rhythm image were then fed into different LSTM layers, and the LSTM layers were then sequentially connected to each other. Following the final LSTM layer, a fully-connected layer, a softmax layer, and a classification layer were employed in order to detect the class labels. MIT/BIH-PD was used in the experiments, and the performance of the proposed hybrid scheme evaluated with 10-fold cross-validation testing. The calculated average accuracy score was 97.92%, which is superior when compared to the results from other methods published in the literature.

The remainder of this paper is organized as follows. Section 2 introduces the proposed method and the related theories, whilst Section 3 details the experimental works and the results, and the paper concludes with Section 4.

2. Proposed method

An illustration of the proposed method is presented in Fig. 1. The input EEG signals are initially converted into time-frequency (T-F) images by using Short-Time-Fourier-Transform (STFT) [17]. The obtained T-F images are then divided into EEG rhythm images. As EEG signals contain five rhythms, Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz), and Gamma (30–50 Hz), five different EEG rhythm images are obtained. Then, deep features are extracted for each rhythm image using the fully-connected layers of pre-trained CNN models (ResNet18, ResNet50, and ResNet101). The obtained deep features from each rhythm image are then fed into the LSTM layer, and the LSTM layers sequentially connected to each other. Following the final LSTM layer, a fully-connected layer, a softmax layer, and a classification layer are employed in order to detect the class labels of the input EEG signals.

2.1. Convolutional neural networks

Traditionally, neural networks are suited to simple classification problems having a low dimensional input size. However, image recognition problems with a very large input size, such as image recognition, leads to an impractical number of parameters in the learning process [18]. Convolutional Neural Networks (CNNs) can decrease the number of these parameters compared to fully-connected neural networks. CNNs generally consist of a convolution layer, pooling layer, and a fully-connected layer [18,19]. The convolution layer performs feature mappings from the input images. The feature mappings process can be expressed using the parameters shown in Eq. (1),

$$X_j^l = f\left(\sum_{i\in M_j} X_j^{l-1} * k_{ij}^l + b_j^l\right) \tag{1}$$

where X_j^l and X_j^{l-1} represent the current and previous convolution layer, respectively, k_{ij}^l denotes the convolution learnable kernel filter, and b_j^l is the bias vector used to prevent over-fitting of networks. In addition, f() denotes the activation function, which generally uses rectified linear (ReLU) functions owing to their performance, and Mj is the map selection indices. Then, pool layers are used to downsize the feature mappings [19]. The pooling process can be expressed as shown in Eq. 2:

$$X_j^l = down\left(X_j^{l-1}\right) \tag{2}$$

where down(.) denotes the downsizing function. Average or maximum pooling techniques are generally used in the pool layer.

A fully-connected (FC) layer classifies the discriminative features obtained from the previous convolution and pooling layers. In the training phase, optimization algorithms [20,21] such as RMSprop, Adaptive Moment Estimation (ADAM), and Stochastic Gradient Descent with Momentum (SGDM) are used in order to achieve the best performance. The weights are then updated according to the SGDM optimizers with Eqs. (3,4) [19].

$$V_t = \beta V_{t-1} + a\nabla_w L(W, X, y) \tag{3}$$

$$W = W - aV_t \tag{4}$$

where L denotes the loss function, a represents the learning rate, and W denotes the weights to be updated.

2.2. LSTM

The LSTM invented by Hochreiter and Schmidhuberm et al. is an improved version of the Recurrent Neural Network (RNN) [22–25]. In terms of structural aspects, LSTM's are more complex than RNNs, with LSTMs containing a memory cell and gate mechanism to overcome gradient problems. The gate mechanism consists of a forget gate (f_t), an

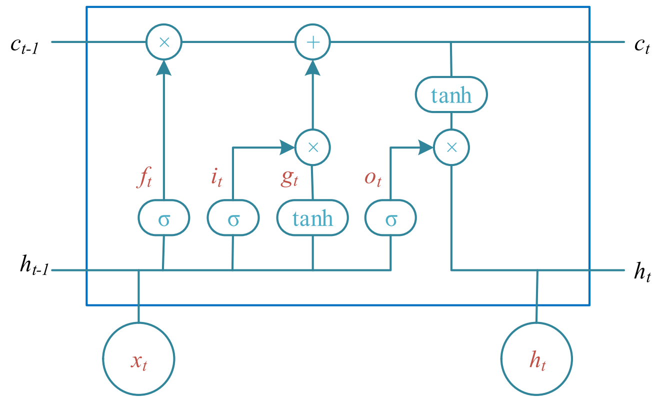

Fig. 2. Architecture of LSTM model.

input gate (i_t), an update gate (g_t), and an output gate (o_t). A typical LSTM structure is illustrated in Fig. 2 [23].

The memory cell state executes add or remove for any information in the chain with the help of others. The process can be defined mathematically by the following six equations [24,25].

$$f_t = \sigma\left(w_f x_t + w_f h_{t-1} + b_f\right) \quad (5)$$

$$i_t = \sigma(w_i x_t + w_i h_{t-1} + b_i) \quad (6)$$

$$g_t = tanh\left(w_g x_t + w_g h_{t-1} + b_g\right) \quad (7)$$

$$c_t = f_t * c_{t-1} + i_t * g_t \quad (8)$$

$$o_t = \sigma(w_o x_t + w_o h_{t-1} + b_o) \quad (9)$$

$$h_t = o_t * \tanh(c_t) \quad (10)$$

where f_t, i_t, g_t and o_t symbolize the outputs of the respected gate, c_t is the memory cell state, h_t refers to the output of the LSTM, w is the weights matrix, b refers to the bias vector, σ(·) is the sigmoid function given in Eq. (6) and tanh(·) refers to the hyperbolic tangent function given in Eq. (7).

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (11)$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (12)$$

Based on Eqs. (5) to (12), detailed adjustments can be made to the inputs and inner states, which affect the memory cell [25].

2.3. Transfer learning

Transfer Learning is an approach used to solve different problems using pre-trained weights of a model developed as a solution to a certain problem. This approach applies fine-tuning to pre-trained deep architectures. In the current study, fine-tuning was performed based on the transfer of new layers, instead of the last three layers, of pre-trained deep networks in order to adapt to the problem of driver drowsiness.

Deep feature extraction is an approach based on extracting features learnt from layers of pre-trained CNN architectures. This approach was used to solve the driver drowsiness problem in the current study, with effective deep features obtained from the fully-connected layer (fc1000) of the ResNet18, ResNet50, and ResNet101 models. The extracted deep properties were then classified and tested using the traditional machine learning method.

Table 1
Training parameters and values.

Parameter	Value
Initial learning rate	0.0001
Learn rate schedule	Piecewise
Learn drop period	100
Learn drop factor	0.001
Gradient threshold	1

Table 2
Performance of transfer learning methods (Deep features + SVM and Fine tuning of CNN) on whole EEG images.

Model	Accuracy (%)
ResNet18 + SVM	85.47
ResNet50 + SVM	84.08
ResNet101 + SVM	83.74
ResNet18 + CNN	84.78
ResNet50 + CNN	83.04
ResNet101 + CNN	82.01

3. Experimental works & results

MATLAB software was used in all experimental works in the current study. The computer used in the experiments has an Nvidia M4000 GPU with 8 GB of memory. Cross-validation and average accuracy score were considered as performance measures in evaluating the proposed method. During the EEG image construction, the parameters of the SFTF were set heuristically. The length and overlap parameters of the Hanning window were set to 32 ms and 16 ms, respectively. In addition, the number of the FFT points was set to 512 points. The obtained EEG images were represented by the dB power scale and were saved with jet color map. In the training phase of the proposed method, a LSTM model, which consisted of a bidirectional LSTM layer, softmax layer, a fully-connected layer, and a classification layer, was used. The number of hidden units in the bidirectional LSTM layer was set to 100. The output of the fully-connected layer was in two classes. The training parameters and values are presented in Table 1.

Considering the parameters given in Table 1, the epoch number and batch size were tuned in the range of [10 80] with a step size of 5. Prior to applying the data to the LSTM network, the data was normalized using zero-center normalization. The "adam" solver was used in the training of the LSTM network.

Various experiments were conducted using the drowsiness dataset. The initial experiment was conducted on whole EEG images. In other words, rhythm extraction was not conducted and whole EEG images were directly conveyed to the feature extraction phase. The results obtained from this initial experiment are shown in Table 2. The cubic kernel function and one-vs-all approach in these experiments for SVM classifier parameters. As can be seen in Table 2, deep features from the ResNet18, ResNet50, and ResNet101 models were classified using the SVM. Moreover, the fine-tuning results for the ResNet18, ResNet50, and ResNet101 models were also tabulated in Table 2. While the first three rows of Table 2 indicate the deep features results, the other three rows show the fine-tuning results. The classification accuracy results obtained with deep features and SVM classifier were 85.47%, 84.08%, and 83.74%, respectively. The ResNet18 model produced the highest accuracy score with an accuracy score of 85.47%, whereas the second highest accuracy score of 84.08% was produced by the ResNet50 model, and the lowest accuracy score of 83.74% was produced by the ResNet101 model. From these results, it can be seen that the shallow ResNet models (ResNet18 and ResNet 50) produced better results than the ResNet101 model using the drowsiness dataset.

From Table 2, it can also be seen that the fine tuning of the ResNet models did not produce better results than the deep features and SVM methods. Fine tuning of the ResNet18 model produced an 84.78%

Table 3
Performance of proposed deep rhythm-based approach.

Model	Accuracy (%)
Rhythm-based approach (ResNet18)	95.50
Rhythm-based approach (ResNet50)	96.54
Rhythm-based approach (ResNet101)	95.50
Rhythm-based approach (ResNet18 + ResNet50)	96.19
Rhythm-based approach (ResNet18 + ResNet101)	96.19
Rhythm-based approach (ResNet50 + ResNet101)	96.89
Rhythm-based approach (ResNet18 + ResNet50 + ResNet101)	97.92

accuracy score, whilst fine tuning of the ResNet50 and ResNet101 models produced 83.04% and 82.01% accuracy scores, respectively. From these scores, it can be seen that fine tuning of the ResNet18 model produced the highest accuracy score for the drowsiness detection dataset.

In our next experiment, we evaluated the proposed rhythm-based deep features and LSTM networks. To this end, various experiments were conducted with the ResNet18, ResNet50, and ResNet101 models. The results of these experiments are presented in Table 3.

The first three rows of Table 3 present the results for the ResNet18, ResNet50, and ResNet101 models, respectively. When the results from Tables 2 and 3 are compared, it can be seen that dividing the input EEG images into rhythm images improved the classification accuracy level.

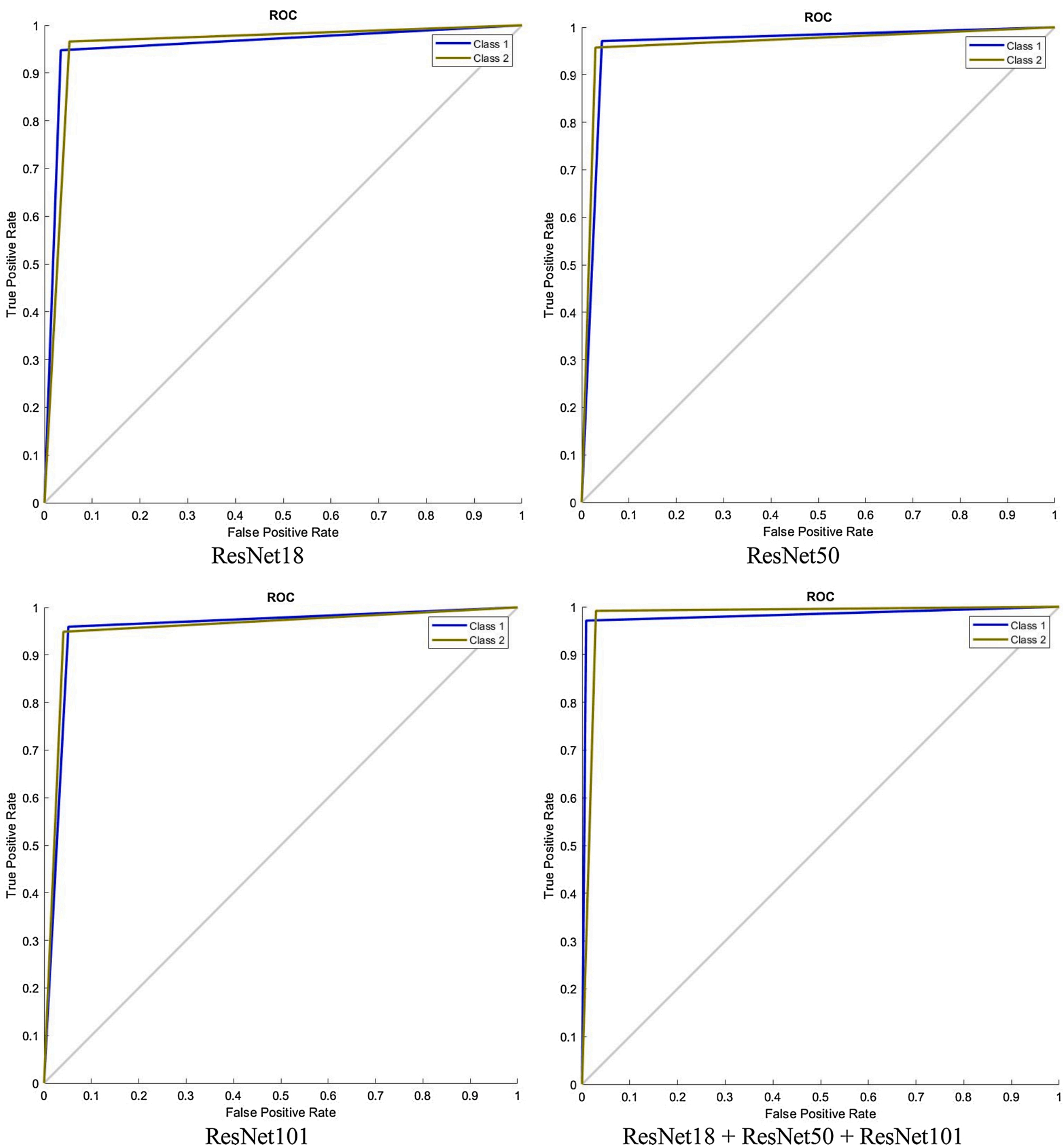

Fig. 3. ROC curves for single ResNet Models and concatenated ResNet models.

Table 4
Performance of each rhythm.

Rhythm	Accuracy (%)
Delta (0–4 Hz)	88.58
Theta (4–8 Hz)	91.35
Alpha (8–12 Hz)	85.47
Beta (12–30 Hz)	87.20
Gamma (30–50 Hz)	87.89

Table 5
Performance comparison of proposed method with other studies on MIT/BIH-PD.

Method	Accuracy (%)
Correa et al. [2]	84.10
Belakhdar et al. [4]	84.75
Tripathy et al. [16]	85.51
Correa et al. [3]	85.66
Anitha [11]	87.20
Boonnak et al. [8]	90.27
Taran et al. [7]	92.28
Budak et al. [1]	94.31
Proposed method	97.92

While the ResNet50 model produced a 96.54% accuracy score, the ResNet18 and ResNet101 models both produced accuracy scores of 95.50%. Concatenation of CNN models was also investigated, with two-way concatenation of the ResNet18 and ResNet50, ResNet18 and ResNet101, ResNet50 and ResNet101 models, plus a three-way concatenation of the ResNet18, ResNet50, and ResNet101 models. From these concatenation arrangements, the highest accuracy score was 97.92% from the three-way concatenation of the ResNet18, ResNet50, and ResNet101 models. The two-way concatenation of the ResNet50 and ResNet101 models produced the second best accuracy score of 96.89%, whilst concatenations of the ResNet18 and ResNet50 models, and also the ResNet18 and ResNet101 models each produced an identical 96.19% accuracy score.

Fig. 3 tabulates the ROC curves for the ResNet18, ResNet50, and ResNet101 models, as well as concatenations of these same models. From Fig. 3, it can be seen that the singular (nonconcatenated) ResNet models produced almost identical ROC curves, whilst the concatenated ResNet18/50/101 model produced the better ROC curve. In addition, Area Under Curve (AUC) values were calculated for the ResNet18, ResNet50, and ResNet101 models and the three-way concatenated ResNet18/50/101 model as 95.67, 96.41, 95.40, and 98.12, respectively. From these AUC scores, it can be seen that the highest result was for the three-way concatenated ResNet18/50/101 model.

We further investigated the effect of each rhythm image on the classification of drowsiness. Each rhythm image was independently used for deep feature extraction and for LSTM-based classification. The concatenation of the ResNet18, ResNet50, and ResNet101 models was used, and the calculated accuracy scores are as presented in Table 4.

From Table 4, it can be seen that a highest accuracy score of 91.35% was obtained for the Theta rhythm, whilst the second best accuracy score of 88.58% was produced by the Delta rhythm. The Beta and Gamma rhythms produced accuracy scores of 87.20% and 87.89%, respectively, with the lowest accuracy score produced by the Alpha rhythm at 85.47%.

A further comparison of the proposed method was conducted against some of the other methods published in the literature, the results of which are shown in Table 5.

As can be seen in Table 5, prior to the current study, the highest accuracy score achieved was 94.31%, produced by the method proposed by Budak et al. [1]. Taran et al. [7] also presented a notable accuracy score achievement for drowsiness detection, with an accuracy score of 92.28%, whilst Boonnak et al. [8] published an accuracy score of 90.27% for their proposed method. The other compared results were generally lower than the 90% accuracy score mark, with 87.20% presented by Anita et al. [11], and Correa et al.'s [2,3] two published methods achieving accuracy scores on drowsiness detection of 85.66% and 84.10%, respectively. Similarly, Tripathy et al. [16] and Belakhdar et al. [4] presented accuracy scores in their studies of 85.51% and 84.75%, respectively.

4. Conclusions

In this paper, a new approach was proposed for the detection of driver drowsiness. The proposed method was based on EEG recordings, with rhythms of the EEG recordings investigated in the detection of drowsiness. The most efficient ResNet models were used in deep rhythm-based feature extraction, and the following conclusions are drawn from these experimental works:

1) Without rhythm division, the combination of deep features and SVM classifier did not produce any notable accuracy results.
2) The deep rhythm-based features and LSTM layer method achieved impressive results on drowsiness detection, and especially with the concatenation of three ResNet models producing the highest accuracy score.
3) Investigations of each rhythm revealed that the Theta rhythm (4–8 Hz) produced the best accuracy score of the all rhythms.
4) Comparison with the state-of-the-art methods in the literature demonstrated that the proposed model produced a 3.61% accuracy score improvement over the best existing methods.
5) In future works, we plan to extract deeper features from the some of the convolutional layers of the ResNet models. In addition, feature selection mechanism will be investigated in order to obtain the most efficient of the deep features.

CRediT authorship contribution statement

Muammer Turkoglu: Methodology, Software, Writing - review & editing. **Omer F. Alcin:** Methodology, Writing - original draft. **Muzaffer Aslan:** Visualization, Writing - review & editing. **Adel Al-Zebari:** Validation, Investigation. **Abdulkadir Sengur:** Supervision, Software.

Declaration of Competing Interest

Not declared.

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.2020.102364.

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