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Driving sleepiness detection using electrooculogram analysis and grey wolf optimizer

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ABSTRACT

In modern society, providing safe and collision-free travel is essential. Therefore, detecting the drowsiness state of the driver before its ability to drive is compromised. For this purpose, an automated hybrid sleepiness classification system that combines the artificial neural network and gray wolf optimizer is proposed to distinguish human Sleepiness and fatigue. The proposed system is tested on data collected from 15 drivers (male and female) in alert and sleep-deprived conditions where physiological signals are used as sleep markers. To evaluate the performance of the proposed algorithm, k-nearest neighbors (k-NN), support vector machines (SVM), and artificial neural networks (ANN) classifiers have been used. The results show that the proposed hybrid method provides 99.6% accuracy, while the SVM classifier provides 93.0% accuracy when the kernel is (RBF) and outlier (0.1). Furthermore, the k-NN classifier provides 96.7% accuracy, whereas the standalone ANN algorithm provides 97.7% accuracy.

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1. INTRODUCTION

Safe and collision-free travel is essential in modern society [1]. The driver's Sleepiness is a condition varying between rapid eye movement sleep; this is the equivalent of an executive function debilitation required to carry out a driving task. An optimal framework for furthering driver sleep research includes identifying the physiological drivers, devising methods to classify sleep-deprived drivers reliably, and working with sleep-deprived individuals to define and calibrate and monitor physiological outcomes [2].

Sleepy driving is much more difficult to describe than drunk driving. If someone has consumed too much alcohol, a quick breath test will reveal it. There's also no technology on the market that can sense whether anyone has a solid sign of Sleepiness in the future. It is thus critical to tell the difference between Sleepiness and dangerous driving because Sleepiness progresses over time and can turn into a real danger at any moment. The rapid recognition of sleep-deficient driver status would probably reduce the total number of accidents in traffic [3]. The current driver drowsiness evaluation approaches were primarily divided into three groups. More explicitly, driver behaviors and driving efficiency can be lumped together into the same category. Another metric indicates it is image-based. Another form of adaptation is a test that focuses on biomedical observations. To find out specific information while asleep, signals such as electroencephalogram (EEG), Electrooculogram (EOG), and electromyogram (EMG) must be used. EEG is the most widely used methodology and most helpful in biomedical assessments to track brain electrical activity. In addition, EEG measurements represent driving requires both physical and mental tasks, and EEG signals may therefore lead to the identification of driving status. In this work, EOG analysis examined whether the brain network configuration is related to the driver. This research aims to offer a systemic approach using EOG signals. This system can examined changes from alarm to sleep and identify ideal neurophysiology indicators to detect drivers of drowsiness [2].

EOG is a physiological measurement used in our proposed system to access driver conditions. If a slower eye movement is detected, compared to the regular eye movement of a subject in the awake stage, the conclusion is that the subject is becoming drowsy. Though this type of measurement is very precise and leads to very small detection errors, it is not the most practical for real-world, real-time implementation due to its invasiveness and the complexity of the apparatus needed for the measurement [4], [5]. Figure 1 shows the general structure of driver drowsiness detection.

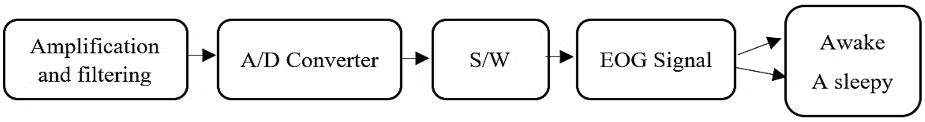

Figure 1. The general architecture of driver drowsiness detection

2. RELATED WORK

Machine learning (DL), a fast-developing branch of artificial intelligent (AI), has shown great power over the classification and detection of images and signal [6]. In fact, in recent years, much research indicated that brain networks were regarded as complex network structures for most studying driver drowsiness based on EEG and EOG signals. In addition, complex interactions of neuronal elements through the electrical activity will impact functional ties between neuronal networks, enabling us to understand neurons [2] better. In study [7], by using a wavelet packet transformation (WPT) to collect the time domain attributes of the EEG channel in question, proposed a new single channel EEG-based somnolence detection model. The resulting planned EEG and simulated virtual driving driver (SVdD) EEG sleep study, which is publicly available, achieves 94.45% and 85.3%, respectively. Murugan *et al.* [8] applied filters to the electrocardiogram (ECG) data from the state of the driver study for monitoring their physiological conditions ECG details and extracted 13 statistically significant features. Three classifiers were used to train the selected characteristics: vector machine support (SVM), k-nearest neighbor (k-NN), and ensemble support. The overall accuracy is 100%, 93.1%, 96.6%, and 96.6% in two groups: ordinary-drowsy, ordinary inattention and usual exhaustion, and normal-cognitive inattention. This research study demonstrates that two-class classification does work. Classification accuracy, however, for five-class detection, was lower to 58.3% using the ensemble classifier. Two techniques were used to diagnose a person's drowsiness [9] effectively. Firstly, eye monitoring, and extract features, and blink and threshold values are used to measure. Secondly, real-time Arduino sensors were used to determine the driver's and passenger's eyes blink to determine the threshold, the final option, and the driver's warning. The ULg multimodality somnolence database was used by the investigator [9] (called DROZY), the EEG database. Signals from the electrocardiogram and ECG have been extracted to Sleepiness is calculated. The k-NN algorithm has better accuracy on both datasets than the SVM. Using the EEG wearable one-canal pre-frontal instrument to test the driving experimental setup, the 10 participants in a driver's mind were automatically executed and tested. The device is connected with a warning system which works if the Arduino module fluctuates in brain activity. The machine performance methods of measuring tags 1 and 0 to outputs the system. For the drowsy, a value of 1 is given and 0 for the non-drowsy. Generally, 93.33% of the precision was obtained [10]. Kastle *et al.* [11] proposed an empirical approach to classify EEG signatures in situational awareness (SA) in various brain regions. The new data collection of 32 participants who have completed the psychology experiment building language (PEBL) SA test is obtained with the 32-channel dry-EEG headset. The approach suggested is to measure the similarity of the frequency bands b (12 30 Hz) to c (30 45 Hz) and SA. The highest accuracy achieved on test data among the results presented is 67%. The remainder of the paper is organized as follows. An introduction to grey wolf optimization is presented in section 3. Experiment's setup is described and formally introduced in section 4 we explain the method of feature extraction in section 5. Algorithms for classification are given in section 6. Next, we give some experiments results issues are given in section 7 and an extensive experimental study of SVM classifier in section 7.1. We discuss in section 7.2 some issues related to experimenting with the presented in k-NN classifier presented artificial neural network (ANN) classifier and grey wolf optimizer ANN (GWO-ANN) summarize in section 7.3 and section 7.4 most essential aspects of this work. Final section 8 presented the essay conclusion and works for the future.

3. GREY WOLF OPTIMIZER METHOD

Mirjalili in [12] proposed a new metaheuristic algorithm known as GWO that focuses on how grey wolves act in the natural environment. The population used to be made up of two species: wolf males and wolf females to control the other pack members. A social hierarchy is often to be found in any herd can be structured in the following manner: i) the dominant wolves are the alphas (α) who decide. They are issued (α) by the wolves; ii) the betas wolves (β) represent a class of second-level wolves. Betas assist and back dominant decisions; iii) Wolves of the Deltas (δ) represent the wolves of the third level; those who obey the alphas and betas Deltas have five primary classes; and iv) the omegas wolves (ω) representing the smallest in the pack Alpha, beta, and delta wolves dictate their plans. Omegas can eat the last. The alpha wolves are graded as the best in the GWO algorithm, and beta and delta wolves are the second and third solutions. The population cluster here is made up of omegas (ω); algorithm 1 lists the pseudo-code of the grey wolf [13]–[15].

Algorithm 1: The pseudo-code of the GWO algorithm

Input: Start the Grey wolf population Xi, in which i= 1, 2, 3, 4....
Start a, A, and C
Number total of iteration for optimization.
The fitness of each candidate solution is computed via equations:
$X(t+1) = X(t) - A.D$
$D = |C.X_p(t) - X(t)|$
$A = 2a.r_1 - a$
$X\alpha$, *is the first finest search agent*
$X\beta$, *is the second finest search agent*
$X\delta$, *is the third finest search agent*
Output: Optimal grey wolf position ($X\alpha$); and the best fitness value f($X\alpha$).
Begin
Generate the Grey wolf population Xi randomly.
While (*iteration* < *Maximum iteration number*)
{
for *each search agent*
Modify the current search agent ' s position via equation
$$X(t+1) = \frac{(X1 + X2 + X3)}{3}$$
end for
Modify A, C, & a
The fitness for all search agents is computed
Modify $X\alpha$, $X\beta$, & $X\delta$
iteration = *iteration* + 1
return $X\alpha$}
End

4. EXPERIMENT'S SETUP

Participants are voluntarily involved. Their ages are between 26-45 years old. All the pictures and EOG signal procedures in the experiment are carried out in 15 healthy people (8 men and seven women) who agreed to participate in the study. According to their self-reports, all participants are consistently visible or correctly to normal, have ordinary sensing and dominate the right. They own driving licenses, and for the past two years, they have been driving every day of the week. The participants are expected to get enough sleep the night before the experiment, and not drinking coffee or tea was requested. Neither of these individuals has sleep problems. The objective of the research and experimental protocol are explained when the participants arrive for the experiment.

Participants are advised to drive a vehicle in the real world. They can drive for 20 minutes to compensate for individual variations in ability levels (such as rest approximately 10 minutes before driving). The participants are recommended to prevent unnecessary movement in the recording of physiological data during the entire experiment. Two driving tasks consist of each experiment, which is process one and process two, respectively. Process 1 is, more specifically, the first case in which each participant has to drive in a clustered manner and other automobiles in the congested roadways have to be kept on a watchful eye and always remain alert. Regarding phase 2, each participant is asked to drive while drowsy on a busy road and in town. Even the experiments are planned every day simultaneously. Process 1 for the rest of the participants is separated by half an hour from process 2.

Data pre-processing is a primary and essential stage for obtaining final datasets that can be considered correct and beneficial for different machine learning algorithms [16]. This stage involves picking up signals of eye movement based on the computer architecture for the EOG using the atmage256 Arduino board with the AD8232 biological signal sensor and Arduino system programming IDE. The software is computer access and could be used for data collection. The data from the analysis have been registered with 15 satisfactory healthy participants (eight males and seven a woman). Then, 7 minutes' maximum EOG signal was recorded for each subject in two situations (normal and abnormal).

5. FEATURE EXTRACTION

Feature extraction is the method of extracting the signal's specific characteristics for easy understanding. It is a crucial step in signal processing as the extracted features will be used to classify the signal in various applications. In addition, the physiological behavior in the brain is reflected in the extracted characteristics. Currently, there is no standardized feature extraction technique to extract features from EOG signals. However, the statistical features that are explained in Table 1 are used.

Table 1. Parameters used in the proposed method [3]

Name parameter	Equation		Clarified of the equation
Mean	$\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i$	(1)	It has a high standard deviation, while a dark picture has a low standard. It comes out average in the picture.
Standard deviation.	$\sigma_i = \sqrt{\frac{\sum_i^N (s_i - \bar{s})^2}{N-1}}$	(2)	It is called a "root mean square," It solves the negative numbers, the number square of small numbers is smaller, and the positive numbers (Expanding effect); therefore, it enhances random noise.
Skewness	$\sqrt[3]{\frac{\sum_i^N (s_i - \bar{s})^3}{N}}$	(3)	The distribution is skewed to the mean; it's more typically darker or lighter than normal.
Energy	$E = \sum_i^N s_i^2$	(4)	Tells us about the grayscale distribution; The histogram tests the uniformity of severity.
Entropy	$Ent = -\left(\sum_i^N s_i \log s_i\right)$	(5)	The entropy tests how many bits are needed to represent the image; content is information; the randomness of intensity distribution is assessed.
Variance	$var = E[(s - \bar{s})^2]$	(6)	It is a grayscale measurement of the texture in the neighborhood of a pixel.
Root mean square (RMS)	$RMS = \sqrt{\frac{\sum_i^N (s_i - \bar{s})^2}{N}}$	(7)	Is an alternating and direct current meter (or voltage).
Power	$p = \frac{\sum_i^N s_i^2}{N}$	(8)	To explain the grayscale distribution and using with energy.
Peak amplitude	$s_p = Max\lvert s_i \rvert$	(9)	The absolute maximum deviation is achieved.
Kurtosis	$kur(s) = \frac{\frac{1}{N}\sum_i^N \sum_i^N (s_i - \bar{s})^4}{RMS^4}$	(10)	Specifies the grey level uniformity.
K-factor	$Kf = s_p \,.RM\ Or = cf \,.RMS^2$	(11)	The value of deferrable costs divided by the actual gross profit.
Crest fraction	$cf = \frac{s_p}{RMS}$	(12)	Shows the ratios of the height to the wavelength of the curves. Theoretically, short-crested waves add more to the overall wavelength.

6. ALGORITHMS FOR CLASSIFICATION

In this research, three different classifiers are used. The first classifier is SVM, which is based on statistical learning theory. The second classifier is k-NN, which is based on distance. The third classifier is based on ANN. Moreover, we proposed a new hybrid classifier, called GWO-ANN, combining the GWO and ANN. The four classifiers are explained in the following subsections.

6.1. Support vector machine classifier

SVM is a very popular machine learning technique that was used successfully in many areas. An efficient classifier simply changes the "kernel" function used to carry out the classifications in a linear and nonlinear manner [17], [18]. The fundamental principle of SVM is to create separate hyperplanes for the classification in high-dimensional spaces. The hyperplane that is the most distant from each class with a kernel function to the closest training data point achieves optimal separation. SVM has, therefore, been widely used in the field of EOG in recent years [2]. In SVM, four common kernels are used, linear, polynomial, radial basis function (RBF), and sigmoid. The first three are used in the proposed method, and specific results are obtained after the classification is done. Recognition (drowsy or non-drowsy) is performed [19].

6.2. k-nearest neighbor (k-NN) classifier

The supervised basic and simple classification technique is one of the famous k-NN [20]. When the distribution of the k-NN process is little or no known before, information is one of the first classification choices. The key concept is to recognize a driver's condition, whether the driver is drowsy or non-drowsy. The mark is assigned most often to the nearest k samples (number of neighbors). The k-NN rule classifies x; This means that a decision is made by assessing k-nearest neighbors' tags, and the distance is computed using Euclidean distance, and then a vote is taken [21].

6.3. Artificial neural networks (ANN)

In the hope of achieving human-like results, a neural network consists of a group of processing units. In contrast, one subdivision makes its independents computations and transfers them to a second one [22], [23]. ANN models have been studied for many years. Neural networks can reveal patterns and trends even though humans or other computer techniques cannot be found based on complicated or ambiguous data; ANN has an excellent performance in classification and performance approximation [24]. Therefore, it is possible to think of a qualified neural network as an "Expert" in the knowledge category to which it has been granted only evaluation. Given new situations of concern and addressing "what if" questions, this expert can then be used to provide predictions [25], [26].

6.4. The proposed grey wolf optimizer with artificial neural network

In the beginning, ANN is trained with GWO algorithms to find the optimum weights and biases, as listed in algorithm 2. The neural network is then equipped employing an efficient back-propagation network. Evaluate if the network has reached the correct error rate or exceeded the number of generations to complete the algorithm. The main flowchart of the proposed method is illustrated in Figure 2.

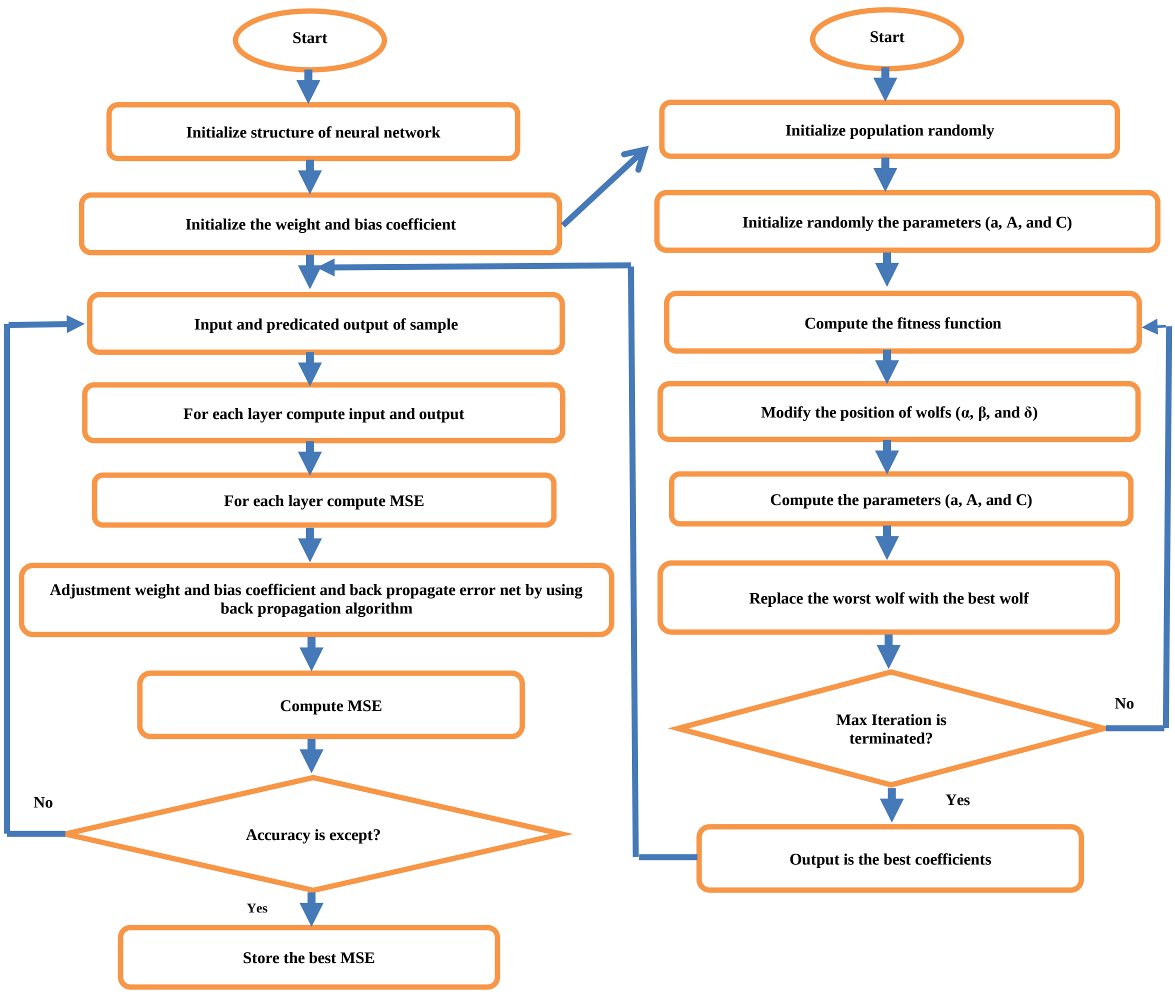

Figure 2. The flowchart of the proposed method

A two-layered network for the representation of the ANN can be considered:

$$\sum_{k=1}^{N} w_k f\left(\sum_{i=1}^{m} w_i x_i + b\right) \quad (1)$$

where (N) shows the number of neurons in the hidden layer, (w) is the weight of a net, b indicates the bias value, and in this case, (f) the activation function is the sigmoid function of each neuron. The mean squared error (MSE) is as (2):

$$MSE = {\sum_{t}^{z}(d^t - y^t)^2}/{z} \quad (2)$$

If the desired output is defined by (d) and the actual output is (y), z is the number of testing results, and by (3), T is the target value, and Y is the predicted output: It means a better model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - Y_i)^2} \quad (3)$$

Algorithm 2. The hybrid GWOANN method

```
Training ANN using GWO:
        Selection: number of population (Pack),
        Optimization: determine the Maximum of iteration,
        Creation: ANN form under back-propagation algorithm,
        Execution: GWO to find the better value of (weight and biases) under (3),
        Return: optimal of initial weight and biases,
Training ANN using optimize back-propagation algorithm by GWO:
        Selection: results of GWO as initial weight and biases,
              Return: optimal of ANN form as training,
```

7. EXPERIMENTS RESULTS

Several experiments have been carried out using the dataset obtained from 15 participants. Each experiment involves the following steps: i) EOG signal load (P1 and P2), ii) measurement of statistical characteristics listed in Table 1, iii) normalization step, iv) randomization step, v) classification by randomization step (SVM, k-NN, and ANN).

It is vital to discover which parameters are best for each classifier. a set of fixed values were used. Furthermore, for each classifier, three experiments were performed, each of which has a different training-testing percentage, namely we used (90%-10%), (80%-20%) and (70%-30%). Signals of eye movement are the critical base of data for testing the proposed method based on the computer architecture for the EOG. Two classification areas (as drowsy or non-drowsy) are considered in this paper. The technique proposed is focused on the classification of the signal. K-Fold cross-validation is carried out, as already stated, to guarantee the trained model for unseen subjects.

7.1. Results for SVM classifier

The SVM classifier score is expected to have higher when the following parameters are used, outlier=(0.1 and 0.2), K-Fold=(10 and 20), TrPer=(90%, 80% and 70%), counter=1000 and kernel=RBF. Table 2 shows the results of applying the SVM classifier using (90%-10%) training-testing percentages. It can be noticed that the SVM classifier achieved the best accuracy when outlier=0.1 and k-fold=10 in 8 out of 10 runs.

Table 3 shows the results of applying the SVM classifier using (80%-20%) training-testing percentages. It can be noticed that the SVM classifier achieved the best accuracy when outlier=0.1 and k-fold=10 in 7 out of 10 runs. Moreover, the results reported in Table 3 show that the accuracy percentages are decreased compared to results provided in Table 2 which means the (90%-10%) training-testing percentages provide better accuracy than (80%-20%).

Table 4 shows the results of applying the SVM classifier using (70%-30%) training-testing percentages. It can be noticed that the SVM classifier achieved the best accuracy when outlier=0.1 and k-fold=10 in 6 out of 10 runs. Moreover, the results reported in Table 4 show that the accuracy percentages are decreased compared to results provided in Tables 2 and 3, which means the (90%-10%) training-testing percentages provide better accuracy than (80%-20%) and (70%-30%).

7.2. Using k-NN classifier

It can be shown that the k-NN classifier score is taken by evaluating the labels on k-nearest neighbors. The distance is determined using the Euclidean distance, counter (1000), recording signal

(1:75-7:00) min, TrPer (90%, 80%, and 70%), and then a vote is taken. It is found that experimentally selecting a number K is done, and it was an odd number whatever was picked. A small number provides better precision, as illustrated in Tables 5 to 7.

Table 2. Accuracy of the SVM model when recording signal in (1:75 to 7:00) min and training data=90%

Run number	Training	Testing	Outlier=0.1 K-Fold=10 Acc.	Outlier=0.2 K-Fold=20 Acc.
1	90%	10%	91.0%	90.0%
2			89.0%	87.0%
3			92.0%	88.0%
4			92.0%	90.0%
5			91.0%	89.0%
6			90.0%	89.0%
7			89.0%	88.0%
8			89.0%	88.0%
9			87.0%	92.0%
10			88.0%	93.0%

Table 3. Accuracy of the SVM model when recording signal in (1:75-7:00) min and training data=80%

Run number	Training	Testing	Outlier=0.1 K-Fold=10 Acc.	Outlier=0.2 K-Fold=20 Acc.
1	80%	20%	88.0%	87.0%
2			87.0%	84.0%
3			89.0%	85.0%
4			85.5%	87.0%
5			86.5%	89.5%
6			85.5%	85.5%
7			88.5%	88.5%
8			88.0%	86.0%
9			86.5%	85.5%
10			86.0%	87.0%

Table 4. Accuracy of the SVM model when recording signal in (1:75-7:00) min and training data=70%

Run number	Training	Testing	Outlier=0.1 K-Fold=10 Acc.	Outlier=0.2 K-Fold=20 Acc.
1	70%	30%	85.3%	85.0%
2			85.7%	82.7%
3			86.7%	84.7%
4			85.7%	83.3%
5			83.0%	84.3%
6			84.0%	84.0%
7			84.0%	87.3%
8			83.3%	84.3%
9			83.7%	86.0%
10			86.0%	87.0%

Table 5. Accuracy of the KNN model when recording signal at (1:75-7:00) min and (90%-10%)

Run number	Training	Testing	K=3	K=5 K-Fold=10	K=7	K=3	K=5 K-Fold=20	K=7
			Acc.	Acc.	Acc.	Acc.	Acc.	Acc.
1	90%	10%	94.0%	91.0%	84.0%	95.0%	93.0%	87.0%
2			94.0%	87.0%	86.0%	96.0%	89.0%	87.0%
3			92.0%	91.0%	83.0%	96.0%	89.0%	86.0%
4			96.0%	87.0%	86.0%	96.7%	95.0%	84.0%
5			96.0%	92.0%	85.0%	96.0%	90.0%	87.0%
6			96.0%	89.0%	85.0%	96.0%	91.0%	87.0%
7			95.7%	89.0%	85.0%	96.0%	93.0%	86.0%
8			94.0%	90.0%	86.0%	94.0%	89.0%	88.0%
9			94.0%	89.0%	83.0%	96.0%	91.0%	85.0%
10			96.0%	87.0%	91.0%	95.0%	94.0%	86.0%

Table 6 shows the results of applying the k-NN classifier using (80%-20%) training-testing percentages. It can be noticed that the k-NN classifier achieved the best accuracy when k=3 and k-fold=20 in 7 out of 10 runs. Moreover, the results reported in Table 6 show that the accuracy percentages are decreased compared to results provided in Table 5 which means the (90%-10%) training-testing percentages provide better accuracy than (80%-20%).

Table 7 shows the results of applying the k-NN classifier using (70%-30%) training-testing percentages. It can be noticed that the k-NN classifier achieved the best accuracy when k=3 and k-fold=20 in 6 out of 10 runs. Moreover, the results reported in Table 7 show that the accuracy percentages are decreased compared to results provided in Tables 6 and 5, which means the (90%-10%) training-testing percentages provide better accuracy than (80%-20%) and (70%-30%).

Table 6. Accuracy of the k-NN model when recording signal at (1:75-7:00) min and (80%-20%)

Run number	Training	Testing	K=3	K=5 K-Fold=10	K=7	K=3	K=5 K-Fold=20	K=7
			Acc.	Acc.	Acc.	Acc.	Acc.	Acc.
1	80%	20%	93.0%	83.0%	81.5%	93.5%	87.5%	83.0%
2			93.0%	86.5%	82.0%	93.5%	90.0%	85.0%
3			93.0%	89.5%	86.0%	92.0%	86.5%	81.5%
4			93.5%	85.0%	80.5%	95.0%	88.5%	82.0%
5			92.5%	89.0%	83.0%	93.0%	87.0%	81.5%
6			92.0%	84.0%	82.0%	90.0%	87.0%	82.5%
7			91.0%	86.0%	79.5%	94.0%	86.5%	82.5%
8			92.0%	84.0%	85.0%	93.0%	88.5%	81.5%
9			90.5%	88.0%	83.5%	93.5%	84.0%	84.5%
10			92.5%	86.0%	81.0%	93.0%	88.0%	83.0%

Table 7. Accuracy of the k-NN model when recording signal at (1:75-7:00) min and (70%-30%)

Run number	Training	Testing	K=3	K=5 K-Fold=10	K=7	K=3	K=5 K-Fold=10	K=7
			Acc.	Acc.	Acc.	Acc.	Acc.	Acc.
1	70%	30%	90.0%	84.3%	80.3%	89.3%	84.7%	81.0%
2			92.7%	82.0%	83.7%	88.7%	84.0%	84.3%
3			90.0%	83.3%	80.7%	90.3%	86.0%	81.3%
4			90.7%	85.0%	80.0%	89.7%	85.3%	83.3%
5			92.7%	86.7%	83.0%	90.7%	87.3%	81.3%
6			89.7%	84.0%	83.0%	91.3%	84.7%	82.3%
7			88.0%	83.7%	81.0%	94.7%	83.7%	81.3%
8			88.3%	83.3%	82.3%	88.7%	84.3%	79.7%
9			89.3%	85.7%	79.3%	89.7%	85.0%	81.7%
10			93.0%	83.3%	81.7%	88.7%	84.7%	82.3%

7.3. Using ANN classifier

An MLP is used to design a network to classify the drowsiness of the driver. An ANN trained under a back-propagation algorithm will be constructed for performing classification for drowsiness of the driver. It can be shown that the standalone ANN classifier score is taken by the parameters used in Table 8. Table 9 shows the results of applying a standalone ANN classifier using (90%-10%), (80%-20%), and (70%-30%) training-testing percentages. It can be noticed that the ANN classifier achieved the best accuracy when (70%-30%) training-testing percentages. Moreover, the results reported in Table 9 show that the accuracy percentages are decreased in (90%-10%) and (80%-20%).

Table 8. Parameters used for a standalone ANN model

Parameters	Value
Max iteration	1000
Number of (neurons in I/P Layer)	12
Number of (Hidden Layer)	3
Number of (neurons in each Hidden Layer)	11, 9, 7
Number of (neurons in O/P Layer)	2

Table 9. The results provided by standalone ANN

Run number	Acc. (90%-10%)	Acc. (80%-20%)	Acc. (70%-30%)
1	81.4%	89.9%	97.7%
2	77.2%	85.4%	73.1%
3	77.4%	80.9%	80.6%
4	77.0%	90.0%	80.2%
5	79.8%	83.9%	87.1%
6	80.2%	82.8%	78.6%
7	89.0%	81.5%	85.6%
8	85.4%	85.9%	88.5%
9	75.6%	82.9%	65.5%
10	76.0%	78.8%	70.3%

7.4. Using GWO-ANN

Using GWO swarm to reduce the downsides of the back and find an accurate ANN the suggested approach consists of first training ANN with an initial weight and bias and subsequently training the network with the new results. Thus, the global optima back-prop is significantly speeded up. Weights and biases are treated as a part of the proposed process. It is calculated based on root mean square error (RMS error). In the ANN algorithm, GWO was used for this classification, which is more accurate than other classifications, as shown in Tables 10 and 11.

Table 11 shows the results of applying the proposed hybrid method (GWO-ANN) using (90%-10%), (80%-20%), and (70%-30%) training-testing percentages. Again, it can be noticed that the GWO-ANN method achieved balanced accuracy in all training-testing percentages. Table 12 shows the values of (best, worst, mean, and standard deviation) of applying four classifiers using (90%-10%), (80%-20%) and (70%-30%) training-testing percentages. It can be noticed that the value of STD in the proposed method achieved the lowest value compared to the classifiers (SVM, k-NN, and standalone ANN). It can be noticed that the value of (best, worst, and mean) achieved the highest value compared to the classifiers (SVM, k-NN, and standalone ANN). Thus, we conclude that the proposed method (GWO-ANN) is stable and gives specific results.

Table 10. Parameters based for GWO and ANN

Parameters based for GWO	
Parameters	Value
Iteration NO.	200
Population size	20
Parameters based for ANN	
Number of (neurons in I/P Layer)	12
Number of (Hidden Layer)	3
Number of (neurons in each Hidden Layer)	11, 9, 7
Number of (neurons in O/P Layer)	2
Max iteration	1000

Table 11. The results provided by GWO-ANN

Run number	Acc. (90%-10%)	Acc. (80%-20%)	Acc. (70%-30%)
1	99.6%	97.0%	97.2%
2	97.0%	98.5%	97.9%
3	96.2%	94.4%	97.5%
4	98.4%	96.3%	98.9%
5	97.4%	97.4%	97.4%
6	97.6%	97.6%	96.5%
7	99.0%	97.5%	96.9%
8	97.8%	98.1%	97.0%
9	98.0%	96.9%	98.5%
10	94.0%	96.9%	97.1%

Table 12. The results of classifiers models

Name classifier	(90% Training, 10% Testing)				(80% Training, 20% Testing)				(70% Training, 30% Testing)			
	Best Acc.	Worst Acc.	Mean	STD.	Best Acc.	Worst Acc.	Mean	STD.	Best Acc.	Worst Acc.	Mean	STD.
SVM	93.0%	87.0%	89.8%	0.0180	89.5%	84.0%	87.1%	0.0157	87.3%	82.7%	84.9%	0.0143
k-NN	96.7%	83.8%	95.7%	0.0215	95.0%	79.5%	93.1%	0.0208	94.7%	79.3%	90.4%	0.0173
ANN	89.0%	75.6%	79.9%	0.0413	90.0%	78.8%	84.2%	0.0348	97.7%	65.5%	80.7%	0.0905
GWO-ANN	99.6%	94.0%	97.5%	0.0148	98.5%	94.4%	96.7%	0.0107	98.9%	96.5%	97.5%	0.0070

In addition, all classifications taken into account in this work have reasonable precision, but the GWO-ANN classificatory reaches 99.6% in particular with the highest rating accuracy. The proposed solution may be an essential tool for understanding driver somnolence neurophysiology processes and future studies or future 'systems' vehicles as reference work. Table 13 shows the improvement rate of the proposed method in (90%-10%), (80%-20%) and (70%-30%) training-testing percentages and compare it with the three classifiers, where the (13) was used to compute the improvement rate:

$$Improvement\ rate = \frac{A1-A2}{A2} \tag{13}$$

where (A1) represents the accuracy of the proposed algorithm and (A2) represents the accuracy of another classifier.

Table 13. Improvement rate of GWOANN over SVM, KNN, and standalone ANN

	(90%-10%)			(80%-20%)			(70%-30%)		
Classifier	IR of best	IR of worst	IR of mean	IR of best	IR of worst	IR of mean	IR of best	IR of worst	IR of mean
SVM	7%	8%	9%	10%	8%	11%	13%	17%	15%
k-NN	3%	12%	2%	4%	14%	4%	4%	22%	8%
ANN	12%	24%	22%	9%	15%	15%	1%	47%	21%

8. CONCLUSION

In conclusion, a framework focused on EOG analysis was introduced in this paper. ANN and GWO have been combined to create an automated hybrid sleepiness classification system, where physiological signals monitor sleep. Three distinct classifier approaches are compared to the proposed system's performance, namely k-nearest neighbors, support vector machines, and artificial neural networks. The results show that the proposed hybrid method provides 99.6% accuracy, while the SVM classifier provides 93.0% accuracy when the kernel is (RBF) and outlier (0.1). Furthermore, the k-NN classifier provides 96.7% accuracy, whereas the standalone ANN algorithm provides 97.7% accuracy. Although the proposed method provided excellent results in accuracy, there is still room for improvement. In future work, behavioral approaches combine with physiological strategies can provide a very high distinction.

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