

Driver Drowsiness Detection Using Gray Wolf Optimizer Based on Face and Eye Tracking

Sarah S. Jasim¹, Alia K. Abdul Hassan² and Scott Turner³

¹Department of IT, Technical College of Management-Baghdad, Middle Technical University, Baghdad, Iraq

²Department of Computer Science, University of Technology, Baghdad, Iraq

³Director of Computing, School of Engineering, Design, and Technology, Church Christ Church University, Kent, United Kingdom

Abstract—It is critical today to provide safe and collision-free transport. As a result, identifying the driver's drowsiness before their capacity to drive is jeopardized. An automated hybrid drowsiness classification method that incorporates the artificial neural network (ANN) and the gray wolf optimizer (GWO) is presented to discriminate human drowsiness and fatigue for this aim. The proposed method is evaluated in alert and sleep-deprived settings on the driver drowsiness detection of video dataset from the National Tsing Hua University Computer Vision Lab. The video was subjected to various video and image processing techniques to detect the drivers' eye condition. Four features of the eye were extracted to determine the condition of drowsiness, the percentage of eyelid closure (PERCLOS), blink frequency, maximum closure duration of the eyes, and eye aspect ratio (ARE). These parameters were then integrated into an ANN and combined with the proposed method (gray wolf optimizer with ANN [GWOANN]) for drowsiness classification. The accuracy of these models was calculated, and the results demonstrate that the proposed method is the best. An Adadelta optimizer with 3 and 4 hidden layer networks of (13, 9, 7, and 5) and (200, 150, 100, 50, and 25) neurons was utilized. The GWOANN technique had 91.18% and 97.06% accuracy, whereas the ANN model had 82.35% and 86.76%.

Index Terms—Artificial neural network, Drowsiness, Feature extraction, Gray wolf optimizer, Normalization, Segmentation.

I. INTRODUCTION

An essential in modern society is safe and collision-free travel. The rapid growth of traffic accidents impacts society and the individual level (Zhang, et al., 2017). Rapid eye movement is a signal for sleeping, one of the leading causes of traffic accidents. It is possible that using eye-tracking to alert drivers when their focus has strayed from the road could reduce the likelihood of collisions. Finding behavioral drivers and devising methods for classifying drivers that require an

artificial neural network (Priddy and Keller, 2005) requires flexibility, competence, the ability to simplify and overcome categorization challenges, as well as the ability to determine similarities in patterns. Several governments have already concentrated interest in driving safety in modern norms. For example, DAISY (Driver Assisting System), a monitoring and alert system for drivers on German highways, and the Robotics Institute at Carnegie Mellon University created Copilot (Wang, et al.). Therefore, drowsiness detection research for drivers has critical importance. Computer vision has the potential to be a non-intrusive means of detecting drowsiness. It can be used to determine the facial characteristics analyzed by changing face manifestations, such as blinking of an eye, eye closure, yawning, and tracking the head position is also crucial in this area (Zhang, et al., 2017).

Nevertheless, this strategy needs to be implemented at a minimal cost; the current methods tend to use only high-quality and costly cameras (Lawoyin, et al., 2014). Moreover, despite substantial research on driver drowsiness detection (DDD), the impact of these discoveries appears to be waning in the actual world because only a few concepts are applied in real life (Bamidele, et al., 2019).

Because of the diversity of faces, developing a reliable face detection method is complex (e.g., size, location, stance, orientation, and expression) and environmental changes (e.g., illumination, exposure, and occlusion). Several effective ways (e.g., Wang, et al., Lawoyin, et al., 2014) have been created to designate pixels as human skin, and color spaces such as RGB, HSV, and YCrCb have been used. To identify more difficult face features, you often need to use complicated tools, but balancing the behavior of complex ones can take too long. Many powerful algorithms, including neural networks (Rowley, et al., 1998), support vector machines (SVMs) (Kadhm and Hassan, 2015), hidden Markov model (Hong, et al., 2005), and active shape model, can detect faces in complex backdrops. However, these procedures are difficult and costly in terms of time. Viola and Jones created an Adaboost face detection system that uses rectangular features, integral pictures, and cascade classifier architectures to detect faces in photos quickly. Moreover, this method's false detection rate is still high in drowsiness detection systems (Liu, et al., 2012).

ARO-The Scientific Journal of Koya University
Vol. X, No.1 (2022), Article ID: ARO.10928, 8 pages
DOI: 10.14500/aro.10928

Received: 14 January 2022; Accepted: 18 April 2022
Regular research paper: 05 May 2022

Corresponding author's email: sara-sm@mtu.edu.iq

Copyright © 2022 Jasim, et al. This is an open access article distributed under the Creative Commons Attribution License.





Fig. 1. Image data samples for normal and abnormal cases.

This study developed a technique for acquiring images of a driver's face, including a recognition process on the driver's eye state, utilizing videos. The approach is divided into three phases, as illustrated in Fig. 1: extracting the eye's region, determining the state of eye recognition, and detecting sleepiness.

The remainder of the paper is organized as follows: First, the proposed system is presented in Section 3. Then, Section 4 shows the experiment's Results and Discussion. Final Section 5 presented the essay conclusion and works for the future.

II. RELATED WORK

Recent developments in artificial intelligence, or machine learning, have made enormous strides in image and signal recognition (Yu, et al., 2021). In recent years, a lot of research has shown that behavioral approaches are non-intrusive, such that they can capture the driver's alertness without any physical interaction with the driver. One of the first behavioral methods used in DDD was Percentage of Eyelid Closure (PERCLOS), which describes a threshold for the validation of subsequent systems (Alshaqqi, et al., 2013). Furthermore, intricate interconnections of neuronal elements through electrical activity will influence functional linkages between biological neural networks, potentially allowing us to comprehend neurons better (Chen, et al., 2018).

Kumar and Patra, 2018, computed the eye aspect ratio (EAR) and mouth opening ratio (MOR) to detect driver's drowsiness. Logistic regression (LR) and Haar cascade classifier were investigated to detect drowsiness and achieved 92% and 86% accuracy, respectively.

Mehta, et al., 2019b, extracted the EAR, nose length ratio (NLR), and MOR. All features were fed into their advanced DDD system (AD3S) and applied to different types of classifiers (boosting technique [BT], Naïve Bayes, SVM, random forest [RF], Bagging, and Voting). The results show that the BT had the best accuracy (89.5%) compared to the other classifiers tested.

The work by Costa, 2019, describes an approach based on combining eye and head trackers, smart eye pro technique. SVM and decision tree (DT) were used to detect driver sleepiness. The study demonstrates that DT has 93% accuracy score compared to SVM has 91%.

Another work in de Naurois, et al., 2019, eyelid closure (EC), gaze (G), head movements (HM), and driving time

was measured. Artificial neural networks (ANNs) were investigated to detect drowsiness and achieved an accuracy of 95% to detect drivers' drowsiness.

Combining EAR and eye closure ratio (ECR) to detect driver's drowsiness based on a RF classifier has been investigated (Mehta, et al., 2019a), with an overall accuracy was 84%.

Whereas authors in Gwak, et al., 2020, calculated the number of eye blinks (EB) and the percentage closure of eyes (PERCLOS), the features were fed into two classifiers a majority voting classifier and RF. In general, the best accuracy (89.8%) was obtained using RF.

The work in Dreißig, et al., 2020, extracted multiple behavioral features. In addition, some features related to HM and blinking (BM) evaluated the K-NN classifier's classification. The results show that the model achieves 84.2% and 70.0% in the binary and multiclass classification, respectively. Table I illustrates a brief utilization of behavioral techniques.

It is necessary to detect drowsiness in drivers before their driving ability is threatened. The problem of providing safe and collision-free transportation is crucial. For this purpose, an automated hybrid drowsiness classification technique includes the ANN and the GWO to distinguish human drowsiness and weariness.

III. THE PROPOSED SYSTEM

At present, researchers in pattern recognition and machine learning are increasingly recognizing the importance of swarm optimization for reducing data dimensionality and improving classification accuracy. Features can be selected using various swarm optimization techniques, such as Particle Swarm Optimization or Ant Colony Optimization. New swarm-inspired algorithms, such as GWO, have recently appeared (Hassan and Mohammed, 2020). Gray wolf optimization (GWO) is a new metaheuristic algorithm based on how gray wolves behave in the wild. To keep order, the group used to have two species: Wolf males and wolf females (Xu, et al., 2019). Any herd has a social hierarchy that looks like this:

1. The leaders, known as alphas (decide (α)), are male, and a female dominates wolves. The wolves problem them
2. Beta wolves (β) are second-level wolves. Beta's support dominant decisions
3. Delta's wolves (δ) are the third-level wolves who obey the alphas and betas

TABLE I
SUMMARY OF ARTWORKS UTILIZING BEHAVIORAL TECHNIQUES

References	Year	Behavioral features	Datasets	Machine learning methods	Accuracy (%)
Ghourabi, et al.	2018	EAR + MOR	Images of the driver's face in real time	LR	92.0
Gwak, et al.	2019	EAR + MOR + NLR	1200 images in real time of application users	BT	89.5
Hassan and Mohammed	2019	Eye, Head	The real-time images of 20 volunteers	DT	93.0
Hassan and Jasim	2019	EC + G + HM	The real-time image of 21 participants (11 men and 10 women)	ANN	95.0
Heidari, et al.	2019	EAR + ECR	The real-time images of 50 volunteers	RF	84.0
Hong, et al.	2020	EB + PERCLOS	The real dataset of 16 males	RF	89.8
Huang, et al.	2020	HM + BM	A large real-time dataset	K-NN	84.2

4. The omegas wolves (ω) signify the pack's most minor alpha, beta, and delta wolves' scheme. The GWO algorithm ranks alpha wolves best first, followed by beta and delta wolves. Omegas (ω) make up this population cluster (Heidari and Pahlavani, 2017). Algorithm I lists the pseudo-code of the gray wolf.

Algorithm I

THE PSEUDO-CODE OF THE GWO ALGORITHM

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

A. Proposed Drowsiness Detection System Based on the Optimized ANN using Gray Wolf Optimizer (GWO)

First stage: Using GWO for ANN training:
 Selection: Size of individuals (Packs),
 Improvement: Largest iterations are identified,
 Formation: Using the backpropagation algorithm in NN,
 implementation: GWO in as (5) used to get the better value of weights and bias,

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (T_i - Y_i)^2} \tag{5}$$

Restoring: Optimum of weights and bias,
 Second stage: GWO used to optimize backpropagation algorithms for training ANN:
 Selection: GWO outputs as the beginning of weights and bias,
 Restoring: Optimum training of ANN model.

B. Dataset

The dataset was a DDD video for this experiment provided by the National Tsing Hua University (NTHU) Computer Vision Lab and the link of download is available at Computer Vision Lab, November 2016. The total dataset (training, evaluation, and testing) includes 36 individuals of various nationalities. Table II explains the dataset. Using infrared lighting (IR) has been captured in videos. The resolution of the movie is AVI 640 × 480.

The total number of persons in the proposal is 17 of the international dataset (NTHU-DDD Dataset). The collection states normal and abnormal cases, as explained in Fig. 1.

C. Initial Pre-processing of Data

A data processing diagram is shown in Fig. 2. Pre-processing seeks to filter raw data and remove noise. Each frame tracks the driver's face before tracking his eyes to reduce the input dimension. One value represents each of the 307,200 inputs because the raw data currently at hand are a 640x480 pixel 15/30 fps video collection and each frame's respective drowsiness annotation. If this data were to be used, proposed machine learning classifiers would have 307,200 inputs/dimension values for each sample, which is very expensive. Then, each video's eye states that data were divided into 4 s segments. If 30 fps is employed, a 3 min video (180 s) would include 45 segments, each with 120 values. The 4-s duration was chosen since it is expected to elicit significant responses indicative of changes in alertness (Weng, et al., 2016). Finally, pupil eye detection is used to detect an open or closed eye to standardize the data. The following sections briefly describe these steps.

Face and eye detection

To assist the detection of a pupil of the eye from a dataset containing video frames; it is appropriate to convert into the grayscale image, after that an Adaptive Histogram

Equalization (AHE) is used, Viola-Johns applied to detect the face and eyes (this algorithm has high accuracy for object detection); alongside using contours and morphological operations (erosion and dilation). Erosion removes the image's white region while dilatation adds it. This model's binarized eye performs closing (dilation followed by erosion), erosion, and ultimately opening (erosion followed by dilation). The opening function removed noise (scanty white pixels) from the visual image, whereas the closing function closed small black dots in the image. The output will be confined to four values:

- A value of (0) indicates face detection
- A value of (0.50) indicates no face detection
- A value of (0.75) indicates one eye detection
- A value of (1) indicates (left and right) eye detection.

Segmentation and label of a video frame

The eye data are divided into 4 s segments in 3 min, and this means that each segment is treated as 120 values. Each eye contains 480 labels (3 min multiplied by 120 values). Therefore, each video will have four labels. Drowsiness, eye, head, and mouth are the four labels for each eye state, and each of these labels could have a distinct value. Like sleepiness and eyes labels, head and mouth labels have a value of 2 and are changed to 0.1. It eliminated the scenario of looking away while chatting or laughing because it does not represent sleep. As a result, if a threshold is the biggest from value (0.25), it is changed to 1, whereas if it is the smallest, it is turned to 0.

D. Extraction and Normalization of Features

Four features were derived from the eye state data. The features were calculated every 4 s within the video frame. The percentages of eyelid closure (PERCLOS), blink frequency (BF), maximum closure duration (MCD), and aspect ratio eye are the features calculated (ARE) using the following as 6, 7, 8, 9, and 10.

$$PERCLOS = \left(t_1 + t_2 + \dots + t_n / T \right) * 100 \quad (6)$$

$$BF = n / T \quad (7)$$

$$MCD = MAX(t_1, t_2, \dots, t_n) \quad (8)$$

$$ARE \text{ in Left Eye} = \frac{(p_2 - p_6) + (p_3 - p_5)}{2 * (p_4 - p_1)} \quad (9)$$

$$ARE \text{ in Right Eye} = \frac{(p_8 - p_{12}) + (p_9 - p_{11})}{2 * (p_{10} - p_7)} \quad (10)$$

Where, $(t_1 + t_2 + \dots + t_n) / T$ is a percentage of eyelid closure, $T=120$; n/T is the number of blinks per minute, and $Max(t_1, t_2, \dots, t_n)$ is the longest allowed of eye closure, as explained in Figs. 3 and 4.

After extracting the characteristics, the next and last step was to scale the data to normalize its range. This procedure is essential because machine learning models employ the Euclidean distance to calculate the distance between two values during the learning process. Moreover, the characteristics for this data were as follows: MCD is 0–120 because the length of each segment is 120, which

TABLE II
DESCRIPTION OF NTHU DATASET (BAMIDELE, ET AL., 2019)

Dataset category	Training group and evaluation group
Gender of driver	Female and male
Type of scenario	No glasses, glasses, sunglasses, night-no glasses, and night-glasses
Driver's behaviors	Yawning, nodding, looking aside, talking and laughing, sleepy eyes, drowsy, and stillness
Videos	Yawning.avi, slowBlinkWithNodding.avi, sleepyCombination.avi, and nonsleepyCombination.avi
Labels	Drowsiness.txt, head.txt, mouth.txt, and eye.txt
Labels No.	0, 1, and 2

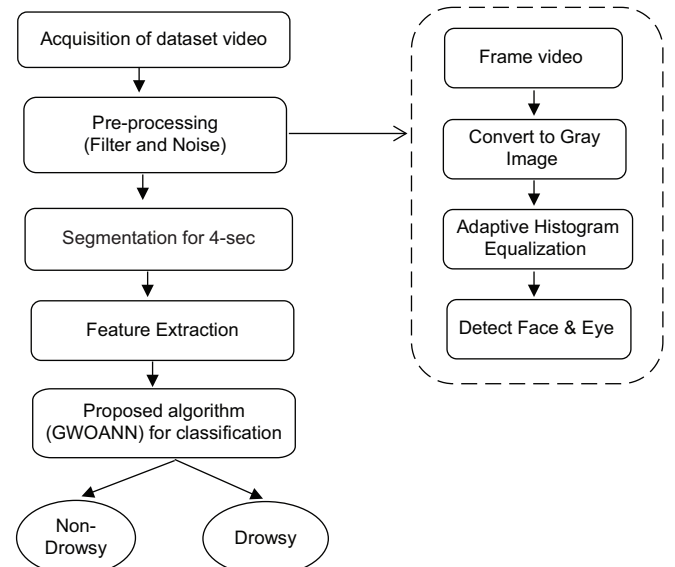


Fig. 2. Data processing protocol and classification model.

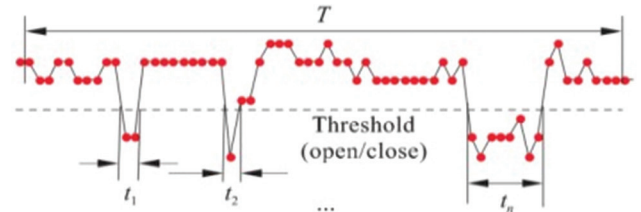


Fig. 3. PERCLOS, BF, and MCD Features (Zhang, et al., 2012).

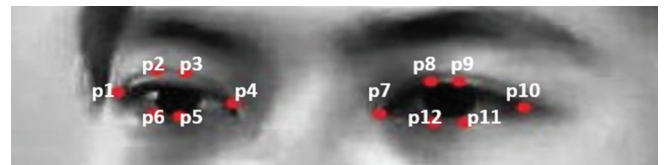


Fig. 4. Points in AER features.

is also the maximum time a person could have their eyes closed in a segment. PERCLOS is 0 to 100 since it is a percentage, and BF is 0–40. In machine learning, there are numerous techniques to normalize features. For example, standardization, as in Equation (11), rescales features to have a zero mean and unit variance. Because it is the most extensively used normalization technique for collecting machine learning algorithms employed, it was chosen.

$$\text{Standardization} = \frac{x - \mu}{\sigma} \quad (11)$$

Where, (x) is the data point, (μ) is the mean, and (σ) is the standard deviation.

E. Classification of Drowsiness

Only two states, namely, the state of sleepiness (1) and the state of alertness (0), are used to classify binary drowsiness. They employ machine learning technologies, for example, to identify DDD using machine learning methods, for example, SVM, KNN, ANN, DT, etc. The proposed approach (GWOANN) and the (ANN) were depended on in this study because they successfully solved problems of non-linearity, high-dimensional classifications, and even classification in EOG signals.

ANN

A neural network is a collection of processing units designed to produce human-like outcomes. On the other hand, one subdivision performs its computations and sends them to a second (Yusiong, 2012; Abdulwahed, 2018; Rashid and Abdullah, 2018). The network has three layers: Input, hidden, and output (Huang, et al., 2021; Nwobi-Okoye and Ochieze, 2018). ANN models have been developed for a long time. Even when people or other computer algorithms cannot find patterns and trends in complex or confusing data, neural networks can disclose them; ANN has good classification and performance approximation performance (Abed, 2019). As a result, a qualified neural network can be seen as an “Expert” in the knowledge category for which it has received only an assessment. This expert can then be utilized to make forecasts in new situations of concern and respond to “what if” queries (Bati and Adam, 2006, Hassan and Jasim, 2010).

The proposed GWOANN

In the starting, GWO algorithms are used to train ANN to identify the best weights and biases, as shown in Algorithm II. An effective backpropagation network is then used to equip the neural network. Finally, check to see if the network has reached the correct error rate or if the number of generations required to finish the algorithm has been surpassed, as shown in Algorithm III. Fig. 2 depicts the method’s main flowchart. For the depiction of the ANN, consider using a two-layered network, as follows in Equation (12).

$$\sum_{k=1}^N w_k f\left(\sum_{i=1}^m w_i x_i + b\right) \quad (12)$$

Where, (N) represents the number of neurons in the hidden layer, (w) represents the weight of a net, b represents the bias value, and (f) represents the activation function of each neuron in this example. As in Equation (13) is the mean squared error (MSE):

$$\text{MSE} = \frac{\sum_i^z (d^t - y^t)^2}{z} \quad (13)$$

If (d) is the desired output and (y) is the actual output, z is the number of testing outcomes, T is the goal value, and Y is the projected output, then as in Equation (14) indicates a superior model.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (T_i - Y_i)^2} \quad (14)$$

Algorithm II

THE HYBRID GWOANN METHOD

Using GWO to train ANN:

Input	Selection of number of people in the population (Pack), Optimization by defining the maximum number of iterations, Creation of the ANN shape by backpropagation technique Execution GWO to discover the best value for weight and biases in Equation (9),
Output	Return the optimum weight and biases at the outset,

Algorithm III

GWO’S OPTIMAL BACKPROPAGATION TECHNIQUE WAS USED TO TRAIN AN ANN

Input	GWO’s initial weight and biases are used in the selection process.
Output	Return the best ANN shape for training,

IV. EXPERIMENTS RESULTS AND DISCUSSION

The dataset has been used in several experiments, one of which used a video from the Computer Vision Lab at National Tsing Hua University (NTHU) to detect driver drowsiness. The following stages are included in each experiment:

- Pre-processing
- Features extraction
- Classification by ANN and GWOANN.

Discovering the parameters that work well for each classifier is critical. There were a set of predetermined values used. Three trials were run for each classifier, with a different training-testing proportion. These were 90–10%; 80–20%; and 70–30%. The suggested approach requires data on PERCLOS, BF, MCD, and ARE of eye movement. This research tested two classification categories (drowsy or not).

TABLE III
PARAMETERS USED FOR A STANDALONE ANN MODEL

Parameters	Value
Max iteration	1000
Number of (neurons in the I/P layer)	4
Number of (hidden layer)	4 and 5
Number of (neurons in each hidden layer)	(13, 9, 7, and 5) and (200, 150, 100, 50, and 25)
Number of (neurons in O/P layer)	2

TABLE IV
THE RESULTS PROVIDED BY STANDALONE ANN

Run number	13, 9, 7, and 5			200, 150, 100, 50, and 25		
	Acc. (90–10%)	Acc. (80–20%)	Acc. (70–30%)	Acc. (90–10%)	Acc. (80–20%)	Acc. (70–30%)
1	76.47	66.91	74.02	83.82	84.56	82.35
2	63.24	70.59	74.02	82.35	80.15	86.76
3	72.06	75.74	74.51	86.76	91.91	88.71
4	67.65	64.71	72.06	82.35	86.76	86.24
5	64.71	80.88	76.96	85.29	83.09	80.24
6	67.65	75	73.53	82.35	85.29	84.80
7	79.41	67.65	70.59	85.29	84.56	86.76
8	82.35	76.47	73.04	85.29	86.03	83.25
9	63.24	79.41	79.41	80.88	84.56	85.78
10	75	70.59	73.04	80.88	86.03	80.88

TABLE V
PARAMETERS BASED ON GWO AND ANN

Parameters	Value
Parameters based on GWO	
Iteration no.	100
Population size	100
Parameters based on ANN	
Number of (neurons in the I/P Layer)	4
Number of (hidden layer)	4 and 5
Number of (neurons in each hidden layer)	(13, 9, 7, and 5) and (200, 150, 100, 50, and 25)
Number of (neurons in O/P layer)	2
Max iteration	10,000 and 12,000

A. Using ANN Classifier

It is used to classify the driver’s sleepiness using MLP. Unsupervised learning is used to build an ANN that can classify driver drowsiness. The parameters used in Table III determine the standalone ANN classifier.

Table IV illustrates the results of utilizing a standalone ANN classifier with 90–10%, 80–20%, and 70–30% training-testing percentages. The ANN classifier had the best accuracy when the training-testing percentages were 70–30%. Table III shows that the accuracy percentages have reduced by 90–10% and 80–20%.

B. Using GWOANN

GWO swarm is used to find the best weights and biases in the training phase of the ANN. The suggested method involves first training the network with starting weights and biases, then updating the findings. Hence, the global optima backpropagation is sped up. The suggested technique includes weights and biases.

TABLE VI
THE RESULTS PROVIDED BY GWOANN

Run number	13, 9, 7, and 5			200, 150, 100, 50, and 25		
	Acc. (90–10%)	Acc. (80–20%)	Acc. (70–30%)	Acc. (90–10%)	Acc. (80–20%)	Acc. (70–30%)
1	91.18	86.76	87.43	88.24	88.97	88.24
2	82.35	89.71	86.76	82.35	91.18	86.76
3	86.76	86.03	77.45	77.94	88.97	85.29
4	80.88	82.35	77.45	94.18	83.82	88.73
5	85.29	80.88	81.86	92.65	81.62	81.86
6	77.94	77.94	75.49	97.06	88.24	84.31
7	89.71	83.82	87.75	85.29	90.44	85.78
8	88.24	86.03	81.37	88.24	84.56	81.27
9	83.82	84.56	86.76	83.82	85.29	83.82
10	88.24	80.88	78.92	88.24	86.03	84.31

It is based on RMSE. This classification is more accurate than the ANN classifier, as shown in Tables V and VI.

Table VI demonstrates the outcomes of implementing the proposed hybrid approach (GWOANN) with 90–10%, 80–20%, and 70–30% training-testing percentages. The GWOANN approach, once again, achieved balanced accuracy in all percentages of training and testing. To avoid overfitting, the algorithm’s lower number of parameters was used. It achieved higher simplicity and, reasonably, the lower the risk of overfitting, where it’s trained with more data can help the algorithm detect the signal better or using early stopping.

Tables VII and VIII display the best, worst, mean, and standard deviation of two classifiers employing 90–10%, 80–20%, and 70–30% training-testing percentages with neurons in hidden layers (13, 9, 7, and 5) and (200, 150, 100, 50, and 25). The proposed method’s STD value was the lowest compared to the ANN classifier. Compared to the ANN classifier, the value of best, worst, and mean achieved the highest value. Thus, the proposed approach (GWOANN) is stable and specific.

In addition, all classifications considered in this work have reasonable precision, but the GWOANN classificatory reaches 99.6% with the highest rating accuracy. Therefore, the proposed solution may be essential for future studies or future “systems” vehicles as reference work. Table IX compares the proposed method’s improvement rate with the ANN classifier in 90-10%, 80-20%, and 70-30% training-testing percentages.

$$Improvement\ rate = \frac{A1 - A2}{A2} \tag{15}$$

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

C. COMPARATIVE ANALYSIS OF RESULTS

Comparisons are made between the outcomes of the ANN and GWOANN algorithms and the findings of prior works using the labeled NTHU-DDD dataset. Results of this comparison are provided in Table X. It was observed that the results of the proposed paper had obtained high accuracy compared to previous works.

TABLE VII
THE RESULTS OF CLASSIFIERS MODELS

Name classifier	No. hidden neurons 13, 9, 7, and 5											
	(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. (%)
ANN	82.35	63.24	71.18	0.065477	80.88	64.71	72.80	0.052188	79.41	70.59	74.12	0.023581
GWOANN	91.18	77.94	85.44	0.03973	89.71	77.94	83.90	0.03280	87.75	75.49	82.12	0.04488

TABLE VIII
THE RESULTS OF CLASSIFIERS MODELS

Name classifier	No. hidden neurons 200, 150, 100, 50, and 25											
	(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. (%)
ANN	86.76	80.88	83.53	0.019502	91.91	80.15	85.29	0.028273	88.71	80.24	84.58	0.02647
GWOANN	97.06	77.94	87.80	0.05474	91.18	81.62	86.91	0.02956	88.73	81.27	85.04	0.023303

TABLE IX
IMPROVEMENT RATE OF GWOANN OVER STANDALONE ANN

Classifier	90–10%			80–20%			70–30%		
	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 (%)
Hidden neurons in ANN (13, 9, 7, and 5)	11	23	15	13	20	13	15	10	11
Hidden neurons in ANN (200, 150, 100, 50, and 25)	12	1	2	6	2	0	9	2	1

TABLE X
COMPARATIVE ANALYSIS OF THE NTHU DATASET TO OTHER RECENT STATE-OF-THE-ARTS

Method	Accuracy %
Alex Net (Krizhevsky, et al., 2012)	70.4
VGC-Face Net (Parkhi, et al., 2015)	63.8
LRCN (Donahue, et al., 2015)	68.7
Flow ImageNet (Donahue, et al., 2015)	56.3
DDD-FFA (Park, et al., 2016)	78.2
DDD-IAA (Park, et al., 2016)	69.8
CARL 3D DCNN (Yu, et al., 2018)	79.6
3D DCNN (Yu, et al., 2016)	75.1
K-NN (Ghourabi, et al., 2020)	72.55
MLP (Ghourabi, et al., 2020)	72.47
DNN (Vu, et al., 2019)	84.81
LeNet-5 CNN (Islam, et al., 2020)	93.57
CNN (Ravi Teja, et al., 2021)	89.00
Proposed ANN	86.76
Proposed GWOANN	97.06

V. CONCLUSION

This paper sought a low-cost, non-intrusive method of detecting driver drowsiness using face and eye monitoring by placing a good and inexpensive camera that types (CAM 313). Such eye state recognition is a highly accurate technology. This study examines the results of the input parameters that can be detected driver drowsiness early by measuring the percentage of eyelid closure (PERCLOS), blink frequency

(BF), maximum closure duration (MCD), and aspect ratio eye (ARE) characteristics. To prevent accidents, they can detect driver drowsiness early on. To compare, we found that using a hybrid approach gives us 91.18% and 97.06% accuracy, whereas using only an ANN gives us an accuracy of 82.35% and 86.76%, making the hybrid approach superior to the ANN algorithm. Even though the proposed method produced great accuracy results, there is still scope for change. Behavioral approaches combined with physiological strategies can provide a significant advantage in the future.

REFERENCES

Abdulwahed, M.N., 2018. Analysis of image noise reduction using neural network. *Engineering and Technology Journal*, 36, pp.76-87.

Abed, I.S., 2019. Lung cancer detection from X-ray images by combined Backpropagation neural network and PCA. *Engineering and Technology Journal*, 37, pp.166-171.

Alshaqqaq, B., Baquhaizel, A.S., Ouis, M.E.A., Boumehed, M., Ouamri, A. and Keche, M., 2013. Driver drowsiness detection system. In: *8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA)*, pp.151-155.

Bagci, A.M., Ansari, R., Khokhar, A. and Cetin, E., 2004. Eye tracking using Markov models. In: *Proceedings of the 17th International Conference on Pattern Recognition*, IEEE, pp.818-821.

Bamidele, A., Kamardin, K., Syazarin, N., Mohd, S., Shafi, I., Azizan, A., Aini, N. and Mad, H., 2019. Non-intrusive driver drowsiness detection based

- on face and eye tracking. *International Journal of Advanced Computer Science and Applications*, 10, pp.549-569.
- Bati, A.F. and Adam, N.E., 2006. Hybrid neuro-genetic based controller of power system. *Iraqi Journal of Computers, Communication, Control and Systems Engineering*, 6, pp.112-125.
- Chen, J., Wang, H. and Hua, C. 2018. Assessment of driver drowsiness using electroencephalogram signals based on multiple functional brain networks. *International Journal of Psychophysiology*, 133, pp.120-130.
- Computer Vision Lab, 2016. *Driver Drowsiness Detection Dataset*. Available from: <http://cv.cs.nthu.edu.tw/php/callforpaper/datasets/DDD> [Last accessed on 2016 Nov 12].
- Costa, M., 2019. Detecting driver's fatigue, distraction and activity using a non-intrusive ai-based monitoring system. *Journal of Artificial Intelligence and Soft Computing Research*, 9, pp.247-266.
- De Naurois, C.J., Bourdin, C., Stratulat, A., Diaz, E. and Vercher, J.L., 2019. Detection and prediction of driver drowsiness using artificial neural network models. *Accident Analysis and Prevention*, 126, pp.95-104.
- Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K. and Darrell, T., 2015. Long-term recurrent convolutional networks for visual recognition and description. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp.2625-2634.
- Dreißig, M., Baccour, M.H., Schäck, T. and Kasneci, E., 2020. Driver Drowsiness Classification Based on Eye Blink and Head Movement Features Using the k-NN Algorithm. In: *IEEE Symposium Series on Computational Intelligence (SSCI)*. p889-896.
- Ghourabi, A., Ghazouani, H. and Barhoumi, W., 2020. Driver drowsiness detection based on joint monitoring of yawning, blinking and nodding. In: *IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP)*. p407-414.
- Gwak, J., Hirao, A. and Shino, M., 2020. An investigation of early detection of driver drowsiness using ensemble machine learning based on hybrid sensing. *Applied Sciences*, 10, p.2890.
- Hassan, A.K. and Mohammed, S.N., 2020. A novel facial emotion recognition scheme based on graph mining. *Defence Technology*, 16, pp.1062-1072.
- Hassan, A.K.A. and Jasim, S.S., 2010. Integrating neural network with genetic algorithms for the classification plant disease. *Engineering and Technology Journal*, 28, pp.686-702.
- Heidari, A.A. and Pahlavani, P., 2017. An efficient modified grey wolf optimizer with Lévy flight for optimization tasks. *Applied Soft Computing*, 60, pp.115-134.
- Hong, K., Min, J., Lee, W. and Kim, J., 2005. Real time face detection and recognition system using Haar-like feature/HMM in ubiquitous network environments. In: *International Conference on Computational Science and its Applications*, Springer, Berlin. p1154-1161.
- Huang, X., Cheng, C. and Zhang, X.B., 2021. Machine learning and numerical investigation on drag reduction of underwater serial multi-projectiles. *Defence Technology*, 18, pp.229-237.
- Islam, M.R., Matin, A. and Kamruzzaman, T., 2020. Automatic Identification of Driver Inattentiveness Using Convolutional Neural Networks. In: *IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*. pp.21-24.
- Kadhm, M.S. and Hassan, A.K.A., 2015. Handwriting word recognition based on SVM classifier. *International Journal of Advanced Computer Science and Applications*, 1, pp.64-68.
- Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, pp.1097-1105.
- Kumar, A. and Patra, R., 2018. Driver drowsiness monitoring system using visual behaviour and machine learning. In: *2018 IEEE Symposium on Computer Applications and Industrial Electronics (ISCAIE)*, IEEE. pp.339-344.
- Lawoyin, S., Liu, X., Fei, D.Y. and Bai, O., 2014. Detection methods for a low-cost accelerometer-based approach for driver drowsiness detection. In: *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, IEEE. pp. 1636-1641.
- Liu, T., Xie, J., Yan, W. and Li, P., 2012. Driver's face detection using space-time restrained adaboost method. *KSII Transactions on Internet and Information Systems (TIIS)*, 6, pp.2341-2350.
- Mehta, S., Dadhich, S., Gumber, S. and Jadhav Bhatt, A., 2019a. Real-time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio. In: *Proceedings of international conference on sustainable computing in science, technology and management (SUSCOM)*, Amity University Rajasthan, Jaipur, India.
- Mehta, S., Mishra, P., Bhatt, A.J. and Agarwal, P., 2019. AD3S: Advanced driver drowsiness detection system using machine learning. In: *5th International Conference on Image Information Processing (ICIIP)*, IEEE. pp. 108-113.
- Nwobi-Okoye, C.C. and Ochieze, B.Q., 2018. Age hardening process modeling and optimization of aluminum alloy A356/Cow horn particulate composite for brake drum application using RSM, ANN and simulated annealing. *Defence Technology*, 14, pp.336-345.
- Park, S., Pan, F., Kang, S. and Yoo, C.D., 2016. Driver Drowsiness Detection System Based on Feature Representation Learning Using Various Deep Networks. In: *Asian Conference on Computer Vision*. Springer, Berlin. pp. 154-164.
- Parkhi, O.M., Vedaldi, A. and Zisserman, A., 2015. *Deep Face Recognition*.
- Rashid, T.A. and Abdullah, S.M., 2018. A hybrid of artificial bee colony, genetic algorithm, and neural network for diabetic mellitus diagnosing. *ARO The Scientific Journal of Koya University*, 6, pp.55-64.
- Ravi Teja, P., Anjana Gowri, G., Preethi Lalithya, G., Ajay, R., Anuradha, T. and Kumar, P., 2021. Driver drowsiness detection using convolution neural networks. In: *Smart Computing Techniques and Applications*. Springer, Berlin.
- Rowley, H.A., Baluja, S. and Kanade, T., 1998. Neural network-based face detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20, pp.23-38.
- Vu, T.H., Dang, A. and Wang, J.C., 2019. A deep neural network for real-time driver drowsiness detection. *IEICE Transactions on Information and Systems*, 102, pp.2637-2641.
- Wang, Q., Yang, J., Ren, M. and Zheng, Y., 2006. Driver Fatigue Detection: A Survey. *6th World Congress on Intelligent Control and Automation*.
- Weng, C.H., Lai, Y.H. and Lai, S.H., 2016. Driver drowsiness detection via a hierarchical temporal deep belief network. In: *Asian Conference on Computer Vision*. Springer, Berlin. pp. 117-133.
- Xu, L., Wang, H., Lin, W., Gulliver, T.A. and Le, K.N., 2019. GWO-BP neural network based OP performance prediction for mobile multiuser communication networks. *IEEE Access*, 7, pp.152690-152700.
- Yu, J., Park, S., Lee, S. and Jeon, M., 2016. Representation learning, scene understanding, and feature fusion for drowsiness detection. In: *Asian Conference on Computer Vision*, Springer, Berlin. pp. 165-177.
- Yu, J., Park, S., Lee, S. and Jeon, M., 2018. Driver drowsiness detection using condition-adaptive representation learning framework. *IEEE Transactions on Intelligent Transportation Systems*, 20, pp.4206-4218.
- Yu, X., Wang, S.H. and Zhang, Y.D., 2021. CGNet: A graph-knowledge embedded convolutional neural network for detection of pneumonia. *Information Processing and Management*, 58, p.102411.
- Yusiong, J.P.T., 2012. Optimizing artificial neural networks using cat swarm optimization algorithm. *International Journal of Intelligent Systems and Applications*, 5, p.69.
- Zhang, F., Su, J., Geng, L. and Xiao, Z., 2017. Driver fatigue detection based on eye state recognition. In: *International Conference on Machine Vision and Information Technology (CMVIT)*, IEEE. pp. 105-110.
- Zhang, W., Cheng, B. and Lin, Y., 2012. Driver drowsiness recognition based on computer vision technology. *Tsinghua Science and Technology*, 17, pp.354-362.