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Driver Drowsiness Detection using Evolutionary Deep learning

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Abstract: Driver drowsiness is among the main causes of fatal traffic accidents or injuries of varying severity around the world. Every year, numerous studies and research projects address this topic. Considering the enormous potential of artificial intelligence especially the deep learning technologies, the current focus is on developing deep convolutional neural networks (CNNs) specifically designed to detect driver fatigue. Designing these networks is difficult because most methods rely on experimentation and optimization to determine hyperparameter values. This article presents a method to enhance the hyperparameters of a convolutional neural network (CNN) by using a modified version of the Walrus Optimization Algorithm (WaOA). The algorithm (M-WaOA) incorporates a logistic map to prepare the primary generation and the Mantegna's algorithm accelerating access to the optimal solution .To enhance the accuracy and reliability of drowsiness detection. The YAWDD dataset is used to obtain driving-related videos to achieve this goal. The footage is converted into individual frames, and a facial recognition algorithm is used to recognize the driver's face. The algorithm also identifies the driver's eyes and mouth. Furthermore, employing CNN to classify individuals as alert, sleepy, or asleep. The proposed technique achieved an accuracy of up to 98%. The proposed approach achieved better results compared to previous models

Keywords: Driver drowsiness, Convolutional Neural Networks, Walrus Optimization Algorithm, Mantegna's algorithm, YAWDD dataset

1. Introduction

Road traffic accidents are the leading cause of death across all age groups and are in the top 10 causes of mortality. These occurrences greatly affect low- and middle-income countries, making for 93% of all traffic deaths[1]. Drowsiness is one of the main contributing factors to traffic accidents. Drowsiness is a complex phenomenon that affects various physiological activities. Sleepiness results in compromised cognitive function, leading to decreased reaction time and diminished decision-making capabilities[2].To mitigate and avert fatigue and drowsiness-induced traffic accidents, it is imperative to devise a highly efficient approach for predicting driver somnolence[3].One approach to accomplish this objective is to develop a system that actively monitors drivers during their journeys and detects signs of fatigue. Creating such a system is a difficult undertaking that requires intelligence [4]. Fortunately, it is now feasible to identify and notify drivers in the early phases of weariness and drowsiness,which could significantly decrease the occurrence of accidents. This is accomplished by recognizing various signs of fatigue, including frequent eye closures, noticeable yawning, and recurrent lane drifting[5].Scientists have employed many approaches from diverse disciplines to create driver drowsiness detection systems[6].Artificial intelligence, particularly machine learning (ML) and deep learning (DL) has been found to effectively address issues associated with conventional approaches and has significantly contributed to the development of extremely precise systems[7]. The indicators of drowsiness can be categorized into four main groups based on the approach used for identification[8]. They can be recognized in video or pictures sequences recorded by cameras that monitor the facial expressions of drivers[9]. Sensors can be installed on the drivers' bodies to detect biological

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signals. Moreover, it is feasible to see and track the motion and activities of automobiles. There are also hybrid ways that can be used to achieve the same objective[10].Researchers have also been working in recent times to take advantage of the features of metaheuristic algorithms to reach the most optimal solutions [11]. This feature has been used to improve systems for detecting driver drowsiness by combining them with the branches of artificial intelligence ML and DL. It has been proven that this process has high superiority in achieving high accuracy [12]. Due to the limited number of studies on driver drowsiness detection that use enhanced deep learning. This paper introduced a model based on CNN and the M-WaOA algorithm is composed of the Walrus Optimization Algorithm (WaOA) with Mantegna's algorithm. To determine the optimal hyperparameters for CNN. The model(M-WaOA-CNN) is trained using the yawdd dataset. The video frames are retrieved and the most noticeable features, such as the face, lips, and eyes, are identified. About the condition of being very tired or sleepy while operating a vehicle. The article is structured in the following manner: Section 2 discusses the relevant literature on the topic of detecting drowsiness during driving. Section 3 provides a comprehensive explanation of our suggested approach. It delves into the specifics of the different branches utilized to create the dataset, the WaOA algorithm, and the CNN model. Section 4 provides the assessment results acquired from our experiments and a comparison analysis of the previous studies completed on the dataset. Section 5 provides the conclusion and findings of our paper, as well as outlines the potential areas for further research.

2. RELATED WORKS

The recent advancements in ML and DL have expanded the possibilities across many sectors. Especially in the field of detecting driver drowsiness, therefore, in this part, we will present a group of previous literature that contributes to solving this problem, and we will focus on the literature that adopted ML, DL, or both, in addition to using optimization algorithms.

In[13] Xiaofeng Li et al. They have developed a driver tiredness detection system that utilizes a CNN and face alignment technique. The system utilizes a speed-optimized SDM algorithm to accurately classify faces into two states: "normal" and "distract", depending on the head yaw angle. The technology identifies driver fatigue by assessing the condition of the head position, lips and eyes in both regular and "distract" images. RM Salman et al [14] present a video-based driver drowsiness detection model using CNN on the YawDD dataset. Four CNN techniques were applied, with the Ensemble Convolutional Neural Network (ECNN) outperforming traditional approaches with an F1 score of 0.935. Jonathan Flores-Monroy et al[15]. developed a driver's fatigue and distraction detection system for mobile devices, using Media pipe Face and Viola-Jones algorithm, and CNN-based driver state categorization. The system achieves a maximum accuracy of 96.67% under normal illumination settings, while its lowest accuracy of 94.67% is observed when glasses are used.

In [16] Mohammed Imran et al.proposed a project to create a sophisticated method for identifying driver drowsiness by utilizing CNN and VGG16 models. The CNN model achieved an accuracy rate of 97%, recall and F-score values of 99%, and precision of 99%. The VGG16 model attained a precision level of 74%. The study utilized a dataset obtained from YAWDD. I-Hsi Kao et al [17] proposed apply of deep learning models to identify drowsiness by assessing human facial features and examining the attention of individual neurons. The study consists of three models, which are categorized into four phases: pre-processing, sleepiness recognition, Grad-CAM, and KNN-Sigma, and applied on the UTA-RLDD dataset. The Grad-CAM algorithm improves both accuracy and efficiency.

X Wang et al[18]. propose a method for identifying driver fatigue in real-time using GA-GRNN, a genetic algorithm (GA) optimized for generalized regression neural network(GRNN) models. Face detection is performed using the Enhanced MTCNN algorithm. Additionally, a fatigue identification model is created by utilizing several characteristic characteristics ,to construct the GA-GRNN model for fatigue-driving diagnostics GA is used to find the optimal GRNN smooth factor. Feng You et al[19]. developed an algorithm to identify sleepiness in real-time driving by analyzing facial motion information. The technique uses an enhanced YOLOv3-tiny convolutional neural network, a Face Feature Triangle, and a Face Feature Vector to detect fatigue at over 20 frames per second with an accuracy of 94.32%. Phan et al[20]. proposed a driver drowsiness detection model using four adaptive neural networks: InceptionV3, DenseNet, LSTM, and VGG16. They detected faces and head regions by SSD-ResNet-10 from surveillance video frames, achieving a high accuracy of up to 98%.

Ed-Doughmi et al. In[4] a method for fatigue prediction employed a multi-layer, model-based 3DCNN architecture, based on an RNN model, to identify fatigue. The researchers identified weariness by analyzing the drowsy behaviors, such as eye closing, head nodding and yawing, in the videos from the NTHUDDD collection. A precision of 97.3% was achieved. Maior C et al. In [21] have developed a low-cost model to instantly identify drowsiness in drivers using ML and computer vision by analyzing the eye aspect ratio (EAR). The model uses multilayer perceptron (MLP), support vector machines (SVM), and random forest (RF). The system was tested and confirmed to be accurate in the DROZY dataset.

In addition, there are several studies[22] that utilize more intricate metrics, such as EEG[23] or ECG[24]signals, as well as data derived directly from the vehicle [25]. SS. Jasim et al in [26]. have proposed a model to identify driving tiredness. The researchers utilized the Gray Wolf algorithm in conjunction with an ANN. GWO approaches are employed during training to ascertain the optimal weights and biases for the ANN. The research utilized a speech dataset that was obtained through direct human interaction. When utilizing a neural network structure with four hidden layers, specifically with neuron configurations of (30,20,13,7) and (13,9,7,5), the achieved results were 90.05% and 89.96% respectively. Kwok Tai Chui et al [24]. developed a model using a deep multiple kernel learning SVM and a multiple-objective GAl to detect driver fatigue and stress. The model achieved an average accuracy of 96.9% in stress detection and 97.1% in sleepiness recognition. . McDonald et al[27]. suggested examining lane departure by utilizing the RF algorithm and SWA data. The scientists conducted a comparison between their approach and another method for measuring tiredness based on images, which utilized PERCLOS. The comparison revealed that the SWA measure exhibited superior accuracy, achieving a rate of 79% and the ability to predict tiredness 6 seconds ahead of time

3. METHODOLOGY

The proposed approach and model architecture are detailed in this section. (Fig. 1 shows the complete method for detecting drowsiness in drivers). This work proposes an effective method to detect drowsiness in drivers. Extracting video frames is the first step in preparing a face detection dataset using the Dlib library. The next step is to extract features associated with drowsiness, such as the mouth and eyes. After that, the pre-generated frames are processed. The last step is to obtain the best hyperparameters for the CNN using (M-WaOA).

A. Dataset

A subset from the more recent iteration of the YawDD dataset [28] is selected, an openly available dataset that includes recordings of both female and male drivers of various ethnic backgrounds, some of whom are wearing sunglasses and others who are not wearing any glasses. The videos were recorded using an RGB camera at a frame rate of 30 frames per second with a resolution of 640 × 480 pixels. Are comprised of two distinct variations of the database. The first one, which was taken by a camera that was fixed on the side mirror of the vehicle, contains a total of 322 films, while the second one contains 29 videos that were captured by a camera that was shown on the dashboard of the vehicle[29].

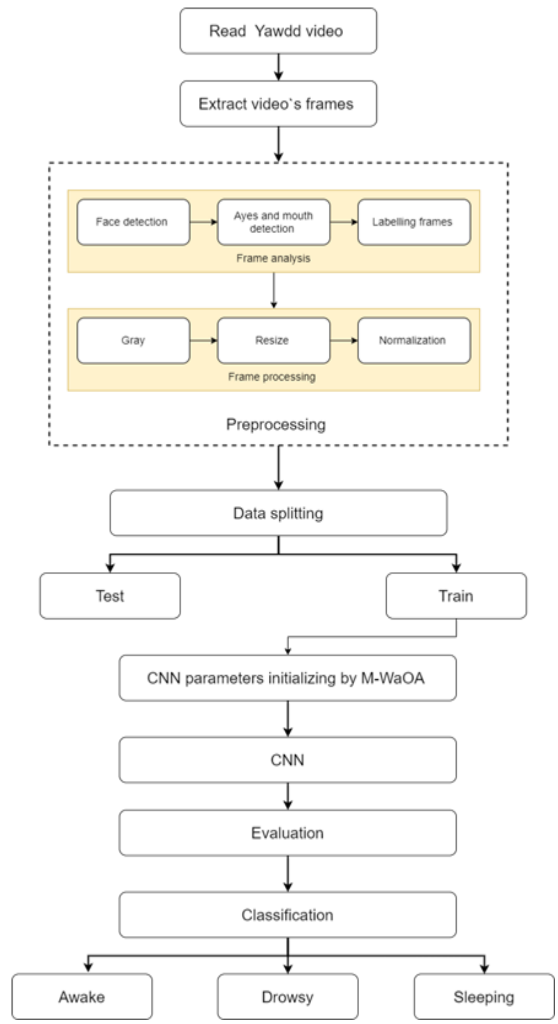

Figure1. Diagram of the proposed model

B. Preprocessing

This section will primarily address the procedure of data preparation for the training and testing phases, to achieve optimal outcomes. which goes through several phases.

1)Analyzing the frames: After reading the video, we extract its component frames. Fig.2 depicts a subset of the retrieved frames. Images from videos are extracted at a rate of 20 frames per second. Since this frame doesn't contain values as features, we need process frames with the Dlib library to predict 68 facial landmarks [30] to detect the face, eyes, and mouth in the frame Fig.3. which can then be analyzed to calculate measures like the Eye Aspect Ratio (EAR)(1) and Mouth Aspect Ratio (MAR)(2). Analyzing the eye and mouth aspect ratios (EAR and MAR) involves geometrically examining specific facial landmarks to infer the driver's state of alertness [31].

Figure 2. a subset of the retrieved frames

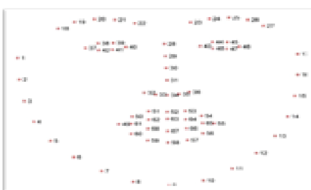

Figure 3. 68 facial landmark coordinates of Dlib's shape_predictor method

a) EAR: calculates a relative metric of eye openness by comparing the distances between horizontal and vertical points around the eye[29] as shown in Fig. 4.

$$EAR = \frac{(|p_2 - p_6| + |p_3 - p_5|)}{(2 \times |p_1 - p_4|)} \quad (1)$$

b) MAR: assesses the degree of mouth openness by measuring the distances between points around the lips. A high MAR often corresponds to a yawn, which can indicate drowsiness. These metrics are powerful because they turn subtle and subjective visual cues into quantifiable data[32] as shown in Fig. 5.

$$MAR = \frac{A}{C} \quad (2)$$

then based on the estimated EAR and MAR The categorizes the frame condition as sleeping, drowsy, or awake. Fig.6 shows the categorization of frames

2) *Processing the frames*: After analyzing the frames and extracting characteristics associated with drowsiness at this stage the dataset's frames are all processed through

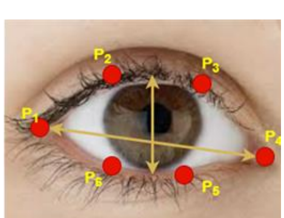

Figure 4 : Eye Aspect Ratio

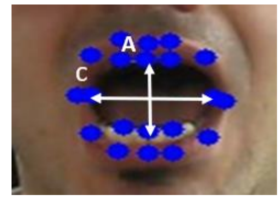

Figure 5:Mouth Aspect Ratio

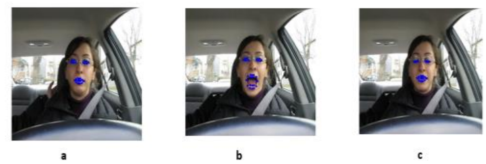

Figure 6: (a) awake, (b) drowsy, (c) sleeping.

several stages For usage in the suggested model and to eliminate extraneous information, initially, the converting it to grayscale. The images are then resized to 64 by 64 pixels and normalized by dividing each pixel by 255. In the last step split the dataset to train and test .

C. *Proposed Model*

The research study proposes a method for detecting driver drowsiness that primarily relies on the CNN model. The selection of hyperparameters for the convolutional network is based on a trial-and-error procedure, which demands significant effort and time. The metaheuristic approach was employed to select the optimal parameters that would enhance the accuracy of the model. The (M_WaOA) algorithm is utilized, which is an enhanced version of the (WaOA) algorithm. The following provides a comprehensive overview of the WaOA algorithm, the CNN model, and strategies for enhancing the WaOA algorithm.

1) *Walrus Optimization Algorithm (WaOA)*

Pavel Trojovský et al in 2023 proposed a novel metaheuristic algorithm named the Walrus Optimization Algorithm (WaOA), inspired by the behaviors of walruses in nature[33]. The algorithm is formulated into three phases: exploration, migration, and exploitation.

a) Algorithm initialization: The algorithm's initialization procedure randomly creates a population of walrus locations, which symbolizes the solutions to the optimization problem(3).

$$\mathcal{X} = \begin{bmatrix} \mathcal{X}_1 \\ \vdots \\ \mathcal{X}_i \\ \vdots \\ \mathcal{X}_N \end{bmatrix}_{NM} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{m} \end{bmatrix}_{NM} \quad (3)$$

X represents the population of walruses, x_i is the i-th potential solution, x_{ij} is the value of the j-choice variable that the i-th walrus suggested, N represents the overall quantity of walruses, while m is the total number of decision variables. Each walrus serves as a potential solution to the problem, and the objective function F(X) may be evaluated by considering the proposed values for the decision variables.

b) WaOA as a mathematical model: The movement of walruses within the WaOA is simulated in three phases according to their natural patterns.[33].

- Phase 1: feeding strategy (exploration). The walruses' position update process is mathematically represented according to the feeding mechanism, driven by the most crucial member of the group. A new position for the walrus is first created based on (4). If the new location enhances the goal function's value, it supersedes the prior position, (5).

$$x_{ij}^{p1} = x_{ij} + r_{ij}(SW_{ij} - I_{ij}x_{ij}) \quad (4)$$

$$X_i = \begin{cases} X_i^{P1}, \ F_i^{p1} < F_{i,} \\ X_i, \ else, \end{cases} \quad (5)$$

Where X_i^{p1} is the newly generated position for the i th walrus, r_{ij} are random numbers from the interval [0, 1], SW_{ij} is the best objective function, I_{ij} are integers selected randomly between 1 or 2

- Phase 2: Migration. The WaOA utilizes the migration process to identify appropriate locations within the search space. This model implies that each walrus moves to a randomly picked position of another walrus in a different part of the search space. Hence, the suggested new location is initially created according to (6). If the new location increases the goal function's value, it will replace the walrus's former position as per (7).

$$x_{ij}^{p2} = \begin{cases} x_{ij} + r_{ij}(-I_{ij}x_{ij}), \ F_k^{p2} < F_{i,} \\ x_{ij} + r_{ij}(x_{ij} - x_{kj}), \ else, \end{cases} \quad (6)$$

$$X_i = \begin{cases} X_i^{P2}, \ F_i^{p2} < F_{i,} \\ X_i, \ else, \end{cases} \quad (7)$$

X_i^{P2} represents the new position of the i-th walrus in the second phase. X_{ij}^{p2} is the j-th dimension of this position, and F_i^{p2} is its objective function value. x_k where k is in the range of {1, 2, ..., N} and k ≠ i, indicates the location of the selected walrus towards which the i-th walrus will migrate. x_{kj} represents the j-th dimension of this location, and F_k is its objective function value.

- Phase 3 the act of avoiding and confronting predators (exploitation).to simulate this this occurrence in WaOA, a locality is established surrounding each walrus. Subsequently, a new position is generated at random inside this region using (8) and (9). If there is an improvement in the value of the objective function, the new location will replace the previous position according to (10).

$$X_{ij}^{p3} = x_{ij} + lb_{local,j}^{t}(ub_{local,j}^{t} - r.lb_{local,j}^{t})) \quad (8)$$

$$local\ bounds = \begin{cases} lb_{local,j}^{t} = \frac{lb_j}{t} \\ ub_{local,j}^{t} = \frac{ub_j}{t} \end{cases} \quad (9)$$

$$X_i = \begin{cases} X_i^{P3}, \ F_i^{p3} < F_{i,} \\ X_i, \ else, \end{cases} \quad (10)$$

X_i^{P3} denotes the updated location of the i-th walrus during the third phase, X_{ij}^{p3} is its j-th dimension, F_i^{p3} represents the value of the objective function, whereas t refers to the iteration contour, ub_j and lb_j are upper and the lower bounds of the j-th variable, and $ub_{local,j}^{t}$ and $lb_{local,j}^{t}$ are local upper and lower bounds allowed for the j-th variable to facilitate local search near the candidate solutions .

2) CNN model :The CNN architecture was specifically developed to train the model in identifying the condition of a driver's eyes and lips in order to accurately assess the level of drowsiness. The design comprises a Conv2D layer with a "relu" activation function and kernel initializers, in addition to MaxPooling2D, Flatten, and Dropout layers. For the output of multilabel classification, a dense layer is employed with a "softmax" activation function. The "categorical_crossentropy" loss function was employed to address this multiclassification problem, allowing optimization methods such as Adam to modify the model parameters during training in order to reduce loss. A suitable learning rate was determined to assist the "Adam" algorithm in adapting the model's parameters.

3) Logistic Map : A basic one-dimensional map used extensively in complicated behavioral modeling, biology population dynamics, and cryptography[34].The subsequent text provides a mathematical depiction of the chaotic source map employed to produce the pseudorandom sequences, specifically the one-dimensional logistic map(11).

$$x_{n+1} = r x_n (1 - x_n) \tag{11}$$

Where n= 0, 1, 2,..., I is the number of iterations, r control parameter r ∈ (3.999, 4) to guarantee the chaotic sequences .

4) Mantegna's algorithm: Mantegna's approach generates random numbers that follow a symmetric Lévy stable distribution[35] The development of this was undertaken by R. Mantegna[36]. Random numbers are generated according to (12)

$$s = \frac{u}{|v|^{1/\beta}} \tag{12}$$

where u and v are normally distributed stochastic variables. That is

$$u \sim N(0, \sigma_u^2)\,,\ \ v \sim N(0, \sigma_v^2) \tag{13}$$

Where σ

$$\sigma_u = \left[\frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma\frac{(1+\beta)}{2}\beta 2^{\frac{1-\beta}{2}}}\right]^{\frac{1}{\beta}} \tag{14}$$

This distribution obeys the expected Lévy distribution.

5) Mantegna`s - Walrus Optimization Algorithm(M-WaOA): to enhance the speed and precision of the WaOA algorithm, a multistrategy approach is proposed. This approach involves incorporating the logistic map and Mantegna's algorithm into the WaOA algorithm.

- Firstly, the initial population is formed using (12) during the initialization stage. The initial population's distribution has a direct impact on the algorithm's optimization performance. As the population distribution increases in size, the convergence rate becomes more uniform.

- Secondly, the Levy Step is determined by using (13). Additionally, the parameter r in (5) and (7) is substituted with the Levy Step. This adjustment aids in expediting the convergence of the method and safeguarding against being trapped in local minima.

- Description of M-WaOA :The pseudocode of the M-WaOA algorithm is presented in Algorithm 1

Algorithm 1: pseudocode of M-WaOA

Start
1 Input all relevant details of the optimization problem.
2 N= walrus population, T= number of iteration
3 Initialize the initial population of walruses by utilizing (11).
4 For t=1;T
5 Based on an objective function determent the strongest walrus
6 For i=1;N
7 Calculate the levy step using (12)
8 r= levy step
9 Phase 1: exploration (feeding strategy).
10 Calculate the new location of the jth walrus using (4)
11 Update the ith walrus location using (5)
12 Phase 2: Migration
13 Select the ith walrus's immigration destination.
14 Using (6), determine the jth walrus's new location
15 Update the ith walrus location using (7)
16 Phase 3: Defending against predators and escaping (exploitation).
17 Determine the ith walrus's new location by applying (8) and (9).
18 Update the ith walrus location using (10)

end

Save the best candidate solution so far.

end

Output the best optimal solution

End

4. EXPERIMENTAL RESULTS

This section provides an analysis and explanation of the outcomes obtained from the trained models, utilizing the testing data retrieved from the Yawdd dataset. The optimum model for drowsiness detection was identified by analyzing the accuracy, precision, F1 score, recall, and test loss. This section additionally contrasts the outcomes of the suggested method with previous systems designed to detect driver tiredness. During the implementation of this system, we utilized a laptop that was equipped with an Intel Core i7 CPU and 32 gigabytes of random access memory (RAM). Regarding the development environment, we utilized Spyder within the Anaconda distribution and implemented the system using Python 3.9.

YAWDD Dataset was used. The datasets are presented in Table I. The YAWDD dataset training and testing are conducted based on three classes such as awake, drowsy, and sleepy The dataset distribution is in the ratio of 70% for the training,10 for validation, and 20% for the testing.

The outcomes of the trained models are presented in Table II and Fig. 7. The results indicate that the M-WaOA_ CNN model obtains the highest level of performance. The data analysis reveals that the M-WaOA_ CNN model exhibited exceptional performance, with an accuracy rate of 98.54%. while the WaOA-CNN model had a 98.06% accuracy rate. The CNN model achieved the lowest performance, with an accuracy rate of %.97.71

TABLE I. DESCRIBES THE DATA SET USED

No.video	Video `s distribution				
	Male	*Female*	*With classes*	*Without classes*	*Total frames*
11	5	6	4	7	10,100

TABLE II. RESULTS OF THE PROPOSED SYSTEM

Model	Performance				
	Accuracy	*Precision*	*Recall*	*F1-Score*	*Test loss*
CNN	97.74%	97.71%	81.88%	87%	0.0631
WaOA-CNN	98.06%	95.89%	84%	86.9%	0.0602
M-WaOA-CNN	98.54%	98.29%	88.29%	92.25	0.0558

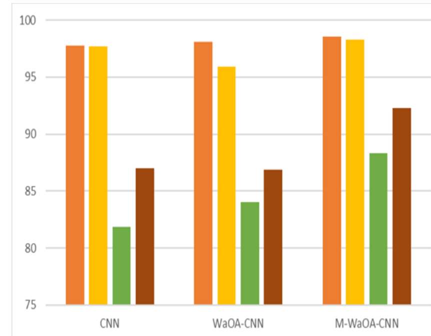

Figure 7: Result of the proposed model

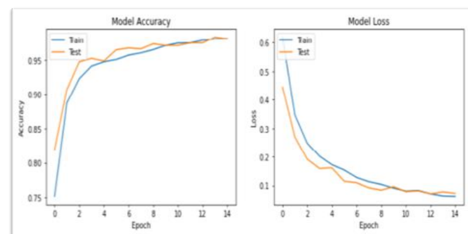

Figure 8: Loss and accuracy of the training and testing process for M-waOA-CNN.

The conclusive findings indicate that employing an algorithm WaOA for hyperparameter selection resulted in a modest enhancement in the model's accuracy. However, the use of the enhanced M-WaOA algorithm led to a substantial improvement in the model's performance efficiency. The utilization of the logistic map in generating the initial population facilitated the diversification of the proposed solutions. Additionally, the integration of Mantegna's algorithm with WaOA enabled the calculation of changes in solution locations, thereby accelerating the algorithm's convergence to the optimal solution with minimal iterations. Furthermore, this integration effectively eliminates the risk of getting stuck in local minimum values.

It appears that integrating optimization techniques with the convolutional network has significantly contributed to raising the model's accuracy, which is 98.54%. The model was trained for 15 epochs, under various driver visual conditions, including scenarios with and without glasses, as well as scenarios with sunglasses. Fig.8 presents The model's performance during the training and test epochs for the M-waOA-CNN model.

Table III and Fig.9 shows a comparison of the approaches' accuracy detecting drowsiness for driver. Most of the preceding methods focus on binary classification. While the studies demonstrated satisfactory accuracy, the binary classification method may not effectively detect and alert potential issues, particularly when the driver is in a sleeping position .

This is due to the significant variations in reactions towards a sleeping individual. To address this, the proposed system suggests three alternative classifications that could potentially enhance the alerting process. In the initial stages of the enhanced alert system for detecting tiredness.

TABLE III. EVALUATION OF THE SUGGESTED MODEL AGAINST PREVIOUS DROWSINESS DETECTION METHODS

Authors	*Year*	*Algorithm*	*Accuracy*
M Imran et al[16]	2023	CNN ,VGG16	CNN:97% VGG16: 74%
X Wang et al[18]	2022	GRNN, GA	93.3%
RM Salman et al.[14]	2021	CNN	90.3%
Xiaofeng Li et al [13]	2021	SDM	89.55%
Feng You et al.in [19]	2020	SVM	94.32%
Proposed model	2024	M-WaOA ,CNN	98.54%

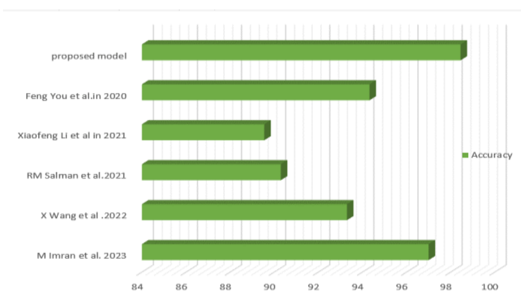

Figure 9 : Evaluation of the suggested model against previous drowsiness detection methods

Conclusion

This article presented a model capable of determining driver drowsiness by interpreting the driver's facial features. This study proposed the M-WaOA--CNN model, where the M-WaOA algorithm selects the best parameters for the CNN. This process contributed to increasing the efficiency of the model. The study uses the YAWDD data set to train and test the model. The results showed that the proposed model succeeded with an accuracy of up to 98.54%. Future research can use transfer learning models, and try to link the analysis of the driver’s facial features with his physiological indicators to increase the accuracy of the diagnosis and alert the driver on time. Which in turn contributes significantly to reducing accidents

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