https://doi.org/10.1051/bioconf/20249700007

Driver Drowsiness Detection using Evolutionary Machine Learning: A Survey

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Abstract. One of the factors that kills hundreds of people every year is driving accidents caused by drowsy drivers. There are different methods to prevent this type of accidents. Recently Machine Learning (ML) and Deep Learning (DL) have emerged as very effective and valuable approaches for detecting driver drowsiness. Moreover, the optimization of machine learning (ML) and deep learning (DL) models may be achieved through the utilization of evolutionary algorithms (EA). This survey aims to offer an overview of recent studies in driver drowsiness detection-based machine learning and deep learning models that have been improved by EA. This survey divides the approaches for detecting drowsiness into two groups: those that rely on ML, and DL, and those that rely on models-based deep learning and machine learning that are optimized by evolutionary algorithms.

1 Introduction

According to the World Health Organization (WHO), approximately 1.3 million people die each year as a result of road traffic crashes[1], meanwhile between 20 and 50 million individuals incur injuries that are not fatal. One of the causes of these accidents is the driver's drowsiness or fatigue in addition to other reasons. The researchers worked on studying and finding appropriate solutions and alerting the driver promptly. Various techniques have been used for detection vehicle driver drowsiness and exhaustion detection. It`s good and feasible to identify driving drowsiness in its early stages and alert the driver to prevent any potential accidents. Drowsy drivers display a variety of indicators, including frequent yawning, frequent eye closing, and frequent departure from their assigned lane on the roadway [2].

Therefore, various studies were presented to detect driver drowsiness based on indicators of driver's drowsiness or fatigue. That falls into four categories: firstly, using measurements that are located inside the vehicle. For instance, measurements based on the vehicle itself may be collected by the angle of the steering wheel, data from the accelerator pedal and information on lane departure from an external sensor [3]. Secondly, the technique of observing the driver's behavior may be determined by continuous recording with a camera that has been mounted in the vehicle. This recording can track the amount of time in which the driver's eyes are closed, how many times that the driver blinks their eyes, head movement and attitude, and yawing [4]. Thirdly, the biologically-based measurements that are related to bio-signals of the driver . They may be detected by the installation of specialized sensors on the driver's physique such as electrocardiogram (ECG) [5] and electroencephalogram (EEG) [6]. Finally, employing more than one metric referred to as measures based on hybrid approaches [7].

This survey is organized into the following sections : section II describes literature review on what the researchers had presented to detect drivers' drowsiness using machine learning and deep learning. Section III describes and includes literature reviews on drivers' drowsiness detection using deep learning and its improvement by evolutionary algorithms. Section IV discusses the related works that were reviewed in the two previous sections. Finally, the conclusions are presented in Section V.

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2. Driver drowsiness detection using Machine / Deep Learning

Driver fatigue detection continues to be a crucial subject of investigation in the realm of transportation safety. The increasing capabilities of machine learning (ML) and deep learning (DL), which are significant tools in the field of artificial intelligence (AI), have great potential for constructing advanced and precise detection systems. This study investigates the utilization of ML and DL techniques to address this significant problem. The objective is to make a valuable contribution to the advancement of dependable and resilient drowsiness detection systems, ultimately leading to safe roads. [11]. Table 1 presents a comprehensive compilation of systematic reviews that are relevant to the inquiry at hand.

Tona H et al. [12] have created a deep neural network model that first extracts facial representations from global faces using a convolutional neural networks (CNN) and feeds them to ConvCGRNN to learn temporal relationships to detect driver sleepiness in real time. The authors test the model using the available NTHU-DDD dataset. Their model achieves 84.81% accuracy and 100 fps inference speed without post-processing. The model exhibited good accuracy, however it was only evaluated on the NTHU-DDD dataset, which may have limited its applicability. The test set was tiny, therefore the suggested model may not detect tiredness induced by variables other than facial expressions.

Magán et al. In[13] have presented two distinct approaches to address the issue of fatigue detection. The first approach utilizes deep learning techniques, specifically a combination of recurrent neural networks (RNN) and CNN , to analyze a sequence of driver images. The second approach involves the integration of DL techniques and AI to extract significant features from the images. Subsequently, these data are fed into a fuzzy inference system that determines whether the driver is drowsy or not using the UTA-RLDD dataset.This had achieved up to 65% accuracy on training data and 60% accuracy on test data. Both systems are not yet ready to be installed in the Advanced Driver Assistance System (ADAS) of a real vehicle due to their low resolution.

RM Salman et al In [14] . have used different CNN algorithms : CNN1, CNN2, and CNN3 to identify and investigate the level of tiredness. That based on yawning frequency with particular position and occlusion change after applying the propose on the YawDD dataset. Achievement gets rates of up to 90.3%, precision rates of 97%, and F1 score rates of 93%. This outcome outperformed the conventional CNN-based technique. This work has several limitations, such as the authors' inability to evaluate the compatibility of the presented models with real-world occurrences. Instead of utilizing numerous datasets, the experiment used just one.

M. Dua et al. in [15] have created a model using the FlowImageNet, AlexNet, ResNet, and VGG-FaceNet deep learning models. These models are taken as input the RGB videos of drivers and aid in detecting drowsiness by analyzing features like behavioral features, hand gestures, head movements and facial expressions. The author has worked with the NTHU-DDD dataset to detect drowsy driving in videos. The study achieved model accuracy results: Ensemble 85% While FlowImageNet 83.11%,AlexNet76.48%, ResNet 81.34%. and VGG-FaceNet 87.09%,

In [16], Valeriano et al. have provided a comparison of DL-based algorithms for classifying driver's behavior based on data from 2D cameras, and they employ CNNs for the automated recognition of the driver distractions. The State Farm data set has been examined and analyzed. The method that based on deep learning to classify data with a success rate of 96.67%. Results from testing the suggested method on a single dataset may not be transferable to other datasets. The suggested method is tested using 2D cameras, and its efficacy might be influenced by factors such as camera quality and illumination.

Y Jeon et al. [17] have offered a new approach employing steering wheel and pedal pressure sensors. Using an ensemble of CNNs, the study authors identify long- and short-term tiredness in driving. They suggest an unbalanced data-handling strategy that partially removes normal driving data to balance the dataset's normal and sleepy driving data. Each subnetwork uses time series analysis to fuse features to detect long- or short-duration sleepy driving. In-vehicle sensors collected 198.3 hours of driving simulation data to validate the model. The recommended ensemble CNN achieved 94.20% accuracy and 94.18% F1-score. They showed that the ensemble CNN performs well using a comparative study, but additional research is needed before they can use these findings.

M Gjoreski et al. in [18] have proposed Driver Distractions -based machine ML approaches for identifying driver distraction utilizing multimodal data as follows. Firstly, the identication of the best features then use the classical ML (XGB) using the emotional and facial action untis(AUs) as an input with a window size of 60 seconds realized high performance and outperformed DL methods. Secondly, comparison of traditional ML with end-to-end deep learning (ResNet) models for driver distraction detection. The experimental data are collected from research by Pavlidis et al.[19].The greatest result attained in this research for identifying driver distractions was an F1-score of 94% when using extreme gradient boosting (XGB). The best-performing deep learning model was a spectro-temporal ResNet, which scored an F1-score of 87% when identifying entire driving sessions. The research employed a driving simulator, which may not perfectly match real-world driving circumstances and distractions. The research employed a very small dataset of 68 participants, which may not be typical of the overall population.

B Reddy et al.in [20] have developed an optimized deep neural network model for detecting driver drowsiness. This model involves two key steps: joint face detection and alignment, and drowsiness detection. To accomplish the alignment task and face detection, Multi-Task Cascaded Convolutional Networks (MTCNN) were utilized for real-time driver drowsiness detection. The authors collected datasets using a Logitech C920 HD Pro Webcam, which was then applied to the model. The results of the study demonstrated an accuracy of 89.5% on 3-class classification and a speed of 14.9 frames per second (FPS) on Jetson TK1. However, the research did not delve into the potential effects of external factors such as lighting conditions and camera angles.

For classification of drowsiness in drivers using head movement and eye blink, Mariella Dreißig et al. [21] have designed and assessed a feature selection technique by using the k-Nearest Neighbor algorithm. Blink-related characteristics are captured and extracted from eyelid movement signals using a camera-based method. The author collected data for this proposal from three driving simulator sessions totaling roughly 134 hours. The method used has shown success up to an 84.2% balanced validation accuracy in the binary classification and 70.0% in the multiclass classification. The study's authors acknowledged that further upgrades to the system are possible and may lead to even better outcomes.

In [22], multi-task ConNN models are utilized to identify driver weariness in real-time. Driver's eye and mouth data are reliably identified with the help of the Dlib algorithm. Then, Multi-task ConNN models are used to train the system to calculate fatigue parameters. The model may be used with both YawDD and Nthu-DDD datasets. The suggested model was 98.81% accurate across two separated datasets. The model's success hinges on its ability to correctly identify aspects of the eyes and mouth, which may be impacted by variables like lighting, camera quality, and individual variances in face features.

In [23], the authors have employed Tiny Machine Learning (TinyML) to a real-time driver drowsiness detection. The researchers have proposed five DL models. They andapplied three DL models: AlexNet, CNN and SqueezeNet and they depended on two pre-trained models (MobileNet-V3 and MobileNet-V2). Then they ware optimize DL by using Dynamic range quantization (DRQ) ,quantization-aware training (QAT) and full-integer quantization (FIQ). It applied the models on two datasets the Closed Eyes in the wild and YawDD. The models have achieved the following accuracy MobileNet-V3 98.32% ,MobileNet-V2 99.60% ,AlexNet 99.25%, CNN 96.67% and SqueezeNet 99.47%.

R Alharbey et al. In [24] have developed two models for driver fatigue detection.The first is an ML-based support vector machine model, while the second is a DL-based CNN model. The ML model using to process the EG signal and the DL model using to process the video stream. The study compares the performance of these approaches with other fatigue detection algorithms. Compared to others ,the proposed algorithms achieved the highest detection accuracy. The paper uses a well-tested dataset called the ULg Multimodality Drowsiness Database, which is divided into two parts.The CNN models provide up to 99% accuracy, while the SVM classifiers provide up to 98% of accuracy.

R Florez et al. in [25] have developed a proposal for identifying driver drowsiness by digital image processing using Mediapipe to extract the ocular area. Using transfer learning, three CNN architectures—InceptionV3, VGG16, and ResNet50V2—were trained. The NITYMED dataset was used in the research. The findings demonstrated that three networks have accuracy as shown InceptionV3 99.31%, VGG16 99.41%, and ResNet50V2 99.71% had good sleepiness detection accuracy in the eye area. However, the approach's performance may change when used with other datasets or in real-world situations.

A model based on CNN and LSTM was developed by MW Gomaa et al, in [26]. CNN can extract features, while LSTM can learn sequential relationships. To detect driver drowsiness, the novel model combines CNN with long short-term memory (LSTM . The NTHU video dataset is used by the authors. With the ultimately suggested model. The achieved accuracy was 98.3% for testing and 97.31% for training.

In [27] Belakhda et al, have proposed a model for ANN and SVM classifiers that have both been investigated and their performance in terms of drowsiness detection has been analyzed and assessed. The authors conducted the EEG analysis using the MIT-BIH database, and for feature vector calculation, they employed the fast Fourier transform. This vector has nine different characteristics. After that, these attributes were sent into an ANN and an SVM classifier so that they could determine which one was the most suited. According to the early findings, the ANN demonstrated a maximum accuracy of 86.5% for the identification of sleepiness and an accuracy of 83% for the detection of alertness

In [28], S Anber et al, have proposes and evaluated two trained CNN-based algorithms. That may be used to categorize photos taken from the NTHU driver sleepiness dataset to identify instances of driver weariness. The first techniqe makes use of AlexNet's transfer learning capabilities, while the second way makes advantage of AlexNet's capabilities as a feature extractor by using SVM. The accuracy of the feature extraction SVM-based model was 99.65%, which was much higher than the accuracy of the suggested transfer learning model, which was 95.7%.

Using visual features, the authors of [29] have offered a model that can identify drowsiness in real-time in a driver. key feature extraction such as the areas of interest where characteristics such as mouth aspect ratio, eye aspect ratio, and head position features are retrieved from the image. Sequential neural network, linear support vector machine and random forest have been used to categorize the features. NTHUDDD was the dataset that was utilized for this research, and the models (Sequential neural network, linear support vector machine and random forest) attained an accuracy of up to (96% ,80%, and 99%). Therefore, variables like lighting conditions, camera angle, and driver position have the potential to alter the accuracy of the system. In addition, the performance of the suggested system was assessed using a particular dataset; nevertheless, it is possible that its performance would change when applied to other datasets or real-world circumstances.

Table 1. An Overview of Existing Studies of driver drowsiness detection using machine / deep learning.

Ref. and Year	Dataset	Datasets type	ML / DL	Methods	Performance
Toan H et al. 2019 [12]	NTHU-DDD	video dataset	CNN, ConvCGRNN, voting layer	CNN learns global face representations and feeds them to ConvCGRNN to learn temporal dependencies. Voting layer subclassifies predict a drowsiness state.	accuracy 84.81%
Magán et al.2022[13]	UTA-RLDD	frontal videos	CNN,RNN	The model will recognize recurring elements in a photo set thanks to the combination of CNN and RNN architectures.	•65% over training data •60% on test data
RM Salman et al.2021[14]	YawDD	video dataset	CNN	It used four distinct CNN methods on the YawDD dataset to identify tiredness based on yawning frequency across a range of poses and occlusions.	accuracy is 90.3% Precision 97% F1 score 93%
M. Dua et al.2022[15]	NTHU-DDD	Video dataset	AlexNet FlowImageNet CNN ResNet VGG-FaceNet	VGG-FaceNet,ResNet, FlowImageNet and AlexNet are using RGB videos of drivers as input the input of ensemble algorithm (SoftMax classifier) provided of the output of four models	•Sensitivity 82% •Accuracy 85%. •Precision 86% •Specificity 87% •F1Score 84%
Valeriano et al.2018[16]	State Farm	Video dataset	CNN	A comparison of different deep learning-based methods using data from 2D cameras to classify driver's behavior	Accuracy 96.67%
Y Jeon et al. 2021[17]	It was collected through driving simulations	vehicle internal sensor information	CNN	By uses vehicle internal sensor information propose Ensemble CNN	• Accuracy 94.2%. • F1-score 94.18%. •Precision 93.90% •Recall 94.47%
M Gjoreski et al.2020[18]	The data was obtained from a prior driving simulation research.	Eye tracking, pupil size, nasal EDA (nEDA), and physiological sensors such as heart rate,	XGB, ResNet	For classifying distracted and not distracted driving sessions, It evaluated seven classical for both end-to-end DL methods and ML	•F1-score 94% •F1-score 87%

 https://doi.org/10.1051/bioconf/20249700007

		breathing rate, and palm electrodermal activity (pEDA)			
B Reddy et al.2017[20]	By using a Logitech C920 HD Pro Webcam was collected datasets	Video and image	MTCNN	MTCNN used For the alignment task and face detection	accuracy89.5%
M Dreißig et al.2020[21]	During three driving simulator studies recorded about 134 hours of material	head position, gaze direction, and eyelid closure	KNN	KNN is using for the driver's state classification through select feature	Accuracy •84.2% in the binary •70.0% in the multiclass classification
BK Savaş et al. 2019[22]	•YawdDD •NTHU_DDD	video dataset	CNN	In real-time Multi-task ConNN models are used to detect driver fatigue	Accuracy 98.81%
NN Alajlan et al.2023[23]	YawDD	video dataset	TinyML, AlexNet, CNN	to find the best model in terms of results. CNN ,AlexNet and SqueezeNet adopted two pretrained models (MobileNet-V3 and MobileNet-V2)	Accuracy of CNN: 96.67% AlexNet 99.25% SqueezeNet : 99.47% MobileNet-V3 : 98.32% MobileNet-V2 : 99.60%
R ALHARBEY et al.2022[24]	•DROZY EEG s •the DROZY video	EEG, Video stream	CNN SVM	The ML model that handled the EEG signal and the DL model that handled a video stream	Accuracy of 98% (SVM) Accuracy of 99% (CNN)
R Florez et al. 2023[25]	NITYMED	Video dataset	CNN	The fully connected network employed in the categorization process is recommended to have its architecture changed.InceptionV3, VGG16, and ResNet50V2 are used as a basis	InceptionV3 99.31% VGG16 99.41% ResNet50V2 99.71%,
MW Gomaa et al .2022[26]	NTHU	video dataset	CNN, LSTM	LSTM can learn sequential dependencies , whereas CNN has feature extraction ability	98.30% for training accuracy 97.31% for validation accuracy

I Belakhda et al.2016[27]	MIT-BIH	ECG	ANN, SVM	ANN and SVM classifiers to select the most appropriate from features	An accuracy for • ANN : drowsiness detection :86.5 % alertness detection: 83% •SVM: drowsiness detection 73% alertness detection 68%
S Anber et al .2022[28]	NTHU	video dataset	AlexNet	Feature extraction based on SVM and NMF using by AlexNet	accuracy of 99.65%
Y Albadawi et al.2023[29]	NTHU	video dataset	RF, SVM, and Sequential NN	The classification of labeled features is using sequential neural network, random forest, and linear support vector machine classifiers.	Accuracy Sequential NN: 96% SVM: 80% RF: 99%

3 Driver Drowsiness Detection using Evolutionary Deep Learning

To enhance driver sleepiness detection, researchers have employed evolutionary algorithms (EA) to develop ML and DL models. EA may identify essential characteristics in deep learning networks and optimize hyperparameters to enhance their design. EA also finds the optimal weight and bias values and has a faster convergence speed [30]. Evolutionary methods with deep neural networks aim to improve detection. In Table 2 you can see several examples of systematic reviews that address this issue.

In [31], EEG signals are broken down into Hermite basis functions using the Adaptive Hermite Decomposition (AHD). In AHD, various evolutionary optimization algorithms (GA, PSO, and ABC) are put to the test for adaptive parameter selection for decomposition. All EOAs in AHD are fairly compared by taking into account the following standard experimental conditions. The extreme learning machine (ELM), is used to identify drowsiness and test the retrieved features. The MIT/BIH Polysomnographic database has been used. Comparing to other current methods, the suggested method has the highest classification accuracy (92.28%) with the fewest features. This article did not account for the sensor's bounce rate of the body because it was primarily concerned with accuracy.

In [32], Ashlesha Kumar et al. have proposed a computer vision-based approach to recognizing driver distractions that uses a genetic algorithm-based ensemble of sets distinct deep neural architectures, including VGG-16, EcientNet B0,AlexNet,InceptionV3 + BiLSTM, Vanilla CNN and Modied DenseNet. The researchers tested on two datasets: the State Farm Driver Distraction Dataset and the Distracted Driver (V1) dataset from the American University of Cairo. On the first dataset, they have attained an accuracy of up to 96.37%, and on the second, 99.75%

In [33], Kwok Tai Chui et al. have offered a general model employing a deep multiple kernel learning support vector machine that is tuned for multiple-objective genetic algorithms to identify both driver tiredness and stress. Multiple kernel learning (MKL) is used to tailor the kernel function of each SVM,the weighting factors for these kernels are optimized using MOGA. The module applies to two datasets: the cyclic alternating pattern (CAP) Sleep Database and the Stress Recognition in Automobile Drivers Database. Driver stress recognition had an average an accuracy of 96.9% , specificity of 98.4% and sensitivity of 98.7%, whereas driver sleepiness recognition had an accuracy of 97.1% , specificity of 98.3%, and sensitivity of 99%. The suggested algorithm's performance on actual data has not been tested; it has only been examined on a simulated dataset.

Hui Wang et al. in [34] determined the most effective EEG rhythm for recognizing fatigue. The suggested modeling approach uses a support vector machine (GA-SVM) based on a genetic algorithm. The fitness function of GA uses the SVM. The original signals are divided into several epochs in the model, and the signals from each epoch are then decomposed using either the db10 wavelet packet transform or the haar wavelet packet transform. The GA-SVM was then used to determine which rhythm was the most accurate in detecting snoozes. the Sleep EDF database's raw EEG data, which is utilized for study and analysis. The proposed new beat is 89.52% accurate.

In [35], Sepehr Sarabi et al. have provided two neural network techniques for tiredness detection using EEG inputs. The genetic algorithm technique was used to optimize the fitting function to boost the execution speed and decrease the occupied space of the microcontroller, and the perceptron neural network and radial base function neural network (RBF) were implemented for clustering the data into open and closed groups. The information was measured for 117 seconds using an EEG neuroheadset from the Emotive device, with an accuracy of 98%. Since a particular EEG neuroheadset was used in the research, the findings may not be generalizable to other EEG devices.

Chen et al. (36) have proposed a model for detecting drivers' fatigue using a DE-ELM approach, which is based on the ELM-based FDD technique. The input weights and biases of the hidden layer in the Extreme Learning Machine (ELM) are first assigned random values. Subsequently, the weights are optimized using the Differential Evolution (DE) method. The model was utilized to analyze the respiratory and cardiac signals of the driver. The aforementioned data points were obtained through the utilization of Doppler radar technology and a sophisticated wearable device known as a smart bracelet. In comparison to conventional techniques such as ELM and SVM, DE-ELM exhibits superior performance in the evaluation of driver weariness. Nevertheless, it is imperative to acknowledge that the efficacy of the approach might be contingent upon the caliber and volume of the data amassed, alongside the particular circumstances in which the data is gathered.

In [37], S Turner et al. have tried to improve evaluation performance metrics for driver drowsiness detection by using the Grey Wolf Optimizer (GWO) algorithm to optimize the weights of the Artificial Neural Networks(ANNs) and using the Levy Flight-Chaotic algorithm to fix problems that face the GWO of poor local searching and slow coverage rate. The study was applied to a group of 15 healthy not on public datasets. The new algorithm has an accuracy of 99.3%. Despite the excellent result of the proposed study, its results were not compared with a previous study on the same data set because the study was conducted on a set of data built from scratch.

In [38], X Wang et al. have developed a model based on GRNN that is optimized by GA to identify driver fatigue in real-time. The model was designed according to the binary Karolinska Sleepiness Scale to determine driver fatigue by building a simulated experience of a real drive. To detect faces was using Multi-Task Cascaded Convolutional Networks (MTCNN). The utilization of GA was employed in order to determine the appropriate smooth factor for a Generalized Regression Neural Network (GRNN) and to develop a fatigue driving detection model known as GA-GRNN. The study used data from simulated and real driving experiments. the system results have a precision rate of 92.9%, an accuracy rate of 93.3%, F1 score of 92.1% and a recall rate of 91.4%. Although the results presented must be taken into account the proposed method which was tested on a relatively small sample size of 30 drivers, which may limit the generalizability of the results.

Y Ma et al. in [39] have evaluated an algorithm to enhance performance based on the particle swarm optimization and the H-ELM classifier. (PSO) algorithm is used to optimize the parameters of the H-ELM algorithm to improve its performance in detecting drivers' drowsiness. The PSO algorithm searches for the optimal values of the H-ELM algorithm's parameters by iteratively updating the position and velocity of a population of particles. They applied four machine learning techniques KNN, ELM, SVM, and H-ELM, and Compared the result with the proposed model PSO-H-ELM. The techniques applied to EEG data had collected from six healthy adults. The PSO-H-ELM algorithm was found to have superior performance in detecting drivers' drowsiness compared to the other machine-learning techniques used in the study. The result achieved was an accuracy of 83.12%. The limitation of the study was the small size of the datasets

Al-libawy et al. In [40] have proposed a method to detect fatigue in naturalistic driving environments system using PSO and a Bayesian combiner. PSO is used to improve the performance of the Bayesian combiner. The proposal was applied to the Naturalistic Driving Study carried out by the Second Strategic Highway Research Program. The results achieved from the study were as follows accuracy (90.4%), specificity (90.7%), and sensitivity (92.6%). Despite the small size of the data, it achieved good results.

In [41], SS. Jasim et al. have presented a model for driving drowsiness detection. The proposed method was used for training the speech signal features. They employed GWO with ANN to determine the best weights and biases for the ANN. GWO methods are used during training. The neural network then makes use of ANN which is advanced by one step. To measure success, they apply a fitness function to the data. As a measure of fitness, they use the Mean Squared Error (MSE). The study used a speech dataset recorded through human interaction. And when the results were compared between GWO-ANN and ANN, it showed the superiority of the proposed algorithm, as it achieved results of up to 90.05% When employing a neural network architecture consisting of four hidden layers, of (30,20,13,7) and 89.96% when used (13, 9, 7, 5) neurons .

An accurate driver drowsiness classifier (DDC) was created by the authors in[42] utilizing an electrocardiogram genetic algorithm-based support vector machine (ECG GA-SVM). The suggested technology utilizes ECG signals to detect tiredness in real time and deliver an immediate warning to the driver before they fall asleep while behind the wheel. The ECG signals that were acquired from 20 healthy volunteers while they were doing a driving simulation were included in the dataset that was utilized for the research. According to the findings, the newly created DDC achieves an accuracy rate of 97.01% overall, with a sensitivity rate of 97.16% and a specificity rate of 96.86%. According to the findings of the study, the accuracy of the proposed technique is superior to that of cross-correlation and convolution kernels by a margin of more than 11%.

Additionally, the accuracy of the suggested method is superior to that of typical kernels such as linear, quadratic, and third-order polynomials.

in [43] V Vijaypriya et al. have apropose a model for sleepiness detection based on face features. Pre-processing is done in conjunction with the filtering process so that the accuracy of the processing may be improved. The flamingo search algorithm (FSA) has been used to improve the features extracted by (DTCWT) model, while the MCNN is used to do classification. The model was applied to two different data sets: NTHU-DDD andYAWDD and. The results reveal that the suggested MCNN with FSA model obtains a better accuracy value than the previous model: 98.26% for the NTHU-DDD and 98.38% for the YAWDD .

The researchers in [44] have proposed a novel feature selection method for drowsiness detection systems. This approach was founded on the concept of merging filter and wrapper feature selection methods to increase performance in contrast to the results obtained by using each of the filter and wrapper methods alone. This combination was carried out inside the framework of the ANFIS that had been created. A total of four distinct filter indices were computed for each feature before being sent into ANFIS to be utilized in the production of a significance degree for that feature. PSO is an evolutionary optimization approach.It was used in this process so that ANFIS parameters could be trained. In the end, the most essential characteristics based on the output of the ANFIS were chosen to be fed into the binary SVM classifier. This allowed for the driving condition to be classified into two classes: alert and sleepy. The study applied steering wheel data collected from experiments performed using a bus driving simulator (BI301Semi) at the K. N. Toosi University of Technology. Good results were obtained with an accuracy of 98.12%.

Table 2. An Overview of Existing Studies of driver drowsiness detection using evolutionary machine / deep learning.

Ref. and Year	**Dataset**	**Dataset type**	**ML / DL**	**EA used to optimize the Deep Learning**	**Optimized Methods**	**Performance**
S Taran et al.2018 [31]	MIT/BIH	EEG	DT,KNN, LS-SVM	GA, PSO , ABC	Evolutionary optimization algorithms (EOAs) adaptively pick Hermite functions as basis functions for each EEG signal.	Accuracy 92.28%
A Kumar et al. 2021[32]	•AUC Distracted Driver Dataset •State Farm Driver Distraction Dataset	Image	VGG-16, AlexNet, EcientNet B0, Vanilla CNN Inception V3+BiLSTM Modied DenseNet .	GA	This approach leverages a genetically optimized ensemble of convolutional neural networks.	Accuracy 96.37% on the AUC Accuracy 99.75% on the SFD
KT Chui et al .2020[33]	•the cyclic alternating pattern (CAP) Sleep Database •the Stress Recognition in Automobile Drivers Database	ECG	MKLSVM	MOGA	MOGA optimized deep multiple kernel learning SVM, Multiple kernel learning (MKL) is used to tailor the kernel function of each SVM; in cases when there are Nk kernels, the weighting factors for these kernels are optimized using MOGA.	Driver drowsiness recognition •sensitivity of 99%, •specificity of 98.3% •(AUC) of 97.1% . Driver stress recognition, •Average sensitivity of 98.7%, •Specificity of 98.4% •AUC of 96.9%.
H Wang et al .2021 [34]	the Sleep EDF [Expanded] database	EEG	SVM	GA	The SVM is used as the fitness function of GA	Accuracy of 89.52%

S Sarabi et al.2020 [35]	•a continuous EEG meter by EEG neurohead set Emotive device for 117 seconds	EEG	PNN, RBF	GA	The GA technique was used to optimize the fitting function to boost the execution speed and decrease the occupied space of the microcontroller	Accuracy of 98%
Long Chen et al. 2020[36]	Smart bracelets and doppler radar collect the driver's heartbeat and respiration signals	Respiratory and heartbeat signals	ELM	DE	Initial weights and biases in ELM are optimized with the help of the DE method.	Accuracy of 93%
S Turner et al. 2022[37]	It was collocated	EOG	ANN	GWO	GWO algorithm is used to optimize the weights of the ANNs	Accuracy of 99.3%
X Wang et al .2022[38]	used data from simulated and real driving experiments	Image	GRNN	GA	GA was used to find the optimal smooth factor of the GRNN and construct the GA-GRNN fatigue driving identification model	• Accuracy of 93.3% •A recall of 91.4%, •A precision of 92.9% •F1 score of 92.1%
Y Ma et al.2020 [39]	EEG data had collected from six healthy adults	EEG	ELM	PSO	Optimization the parameters of the H-ELM kernel function by PSO	accuracy of 83.12%
Hilal Al-libawy et al .2018[40]	Transportation Research Board of the national Academics of Science (2017)	accelerometers; vehicle network information; GPS	Bayesian algorithm	PSO	PSO is used to improve the performance of the Bayesian combiner	Accuracy (90.4%) Sensitivity (92.6%) Specificity (90.7%)
SS. Jasim et al.2022 [41]	a speech dataset recorded through human interaction	EEG	ANN	GWO	GWO is used to find the best ANN weight	Accuracy •90.05% (30,20,13,7) neurons •86.96% (13, 9, 7, 5) neurons
KT Chui et al.2016 [42]	The ECG signals were acquired from 20 healthy volunteers while they were doing a driving simulation	ECG	SVM	GA	GA is employed for finding the solution to the multi-objective optimization problem. This algorithm provides a good tradeoff between the required computational power and the accuracy of the solution	Accuracy of 97.01% Sensitivity of 97.16% Specificity of 96.86%

V Vijaypriya et al 2023[43]	YAWDD NTHU-DDD	video dataset	MCNN	FAS	The feature points are optimized with FSA integrated with the DL model MCNN.	Accuracy of 98.38% for YAWDD Accuracy of 98.26% for NTHU
S Arefnezhad et al.2022 [44]	The data used in this paper is steering wheel data collected from experiments performed using a bus driving simulator (BI301Semi) at the K. N. Toosi University of Technology.	voiced and silent clips	SVM	PSO	PSO is used to adjust the parameters of an adaptive fuzzy system	Accuracy 98.12%

4 Discussion

In this paper, we surveyed previous studies in driver drowsiness detection using DL and ML, as well as models enhance using EA. Researchers are classifying data across four dimensions: video/image, vehicle, biological, and hybrid. While systems based on vehicles are accurate, complicated, and costly, driver detection based on physiological characteristics is difficult but very accurate. Despite being impacted by lighting, sitting position, glasses, etc., driver identification based on behavioral characteristics is straightforward and inexpensive. Based on the results of the comparison, it is clear that no one method can provide reliable results by itself. Researchers must consider the pros and cons of each technique, including its precision, dependability, speed, and user-friendliness. It was also found via this in-depth research that although DL methods like CNN produced a high-resolution result, they took much too long to train the data. It was mentioned that sleepiness detection methods might benefit from a combination of existing methods.As ML or DL , CNN is a popular DL approach was used to identify drowsiness detection. GA and PSO algorithms, two of the most widely used meta-heuristic and EV, are applied to the problem of making CNNs and other DL models more effective. The architectures and hyperparameters of DL models are optimized with the help of EV. Additionally, researchers are classifying data across four dimensions: video/image, vehicle, biological, and hybrid.

5 Conclusion

This paper reviewed recent works in drowsiness detection based ML and DL models optimized by EV. One of the most popular deep learning methods for detecting sleepiness is CNN. GA and PSO algorithms two of the most widely used meta-heuristic and evolutionary algorithms, are employed in the process of enhancing CNN and other deep learning models for the purpose of drowsiness detection. In addition to other optimization algorithms The evolutionary algorithms are used to optimize the architectures and hyperparameter in machine and deep learning models. The most popular datasets for training deep learning models to detect drowsiness are YAWDD , NTHU-DDD and UTA-RLDD datasets. As a result, detecting driver drowsiness using ML/DL optimized by EA is a viable strategy for improving road safety.

Table 3: Of Abbreviations.

AI	Deep Learning
ML	Machine Learning
DL	Deep Learning
CV	Computer Vision
ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
MCNN	Multiscale convolutional neural network
RNN	Recurrent neural networks
GRNN	Generalized Regression Neural Network
SVM	Support Vector Machines
ReLU	Rectified Linear Unit
ECG	Electrocardiography
EEG	Electroencephalogram
EV	Evolutionary Algorithms
GA	Genetic Algorithm
MOGA	Multiple-objective genetic algorithm
PSO	particle swarm optimization
FSA	Flamingo search algorithm
GWO	Gray Wolf Optimizer

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