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Modern drowsiness detection techniques: a review

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ABSTRACT

According to recent statistics, drowsiness, rather than alcohol, is now responsible for one-quarter of all automobile accidents. As a result, many monitoring systems have been created to reduce and prevent such accidents. However, despite the huge amount of state-of-the-art drowsiness detection systems, it is not clear which one is the most appropriate. The following points will be discussed in this paper: Initial consideration should be given to the many sorts of existing supervised detecting techniques that are now in use and grouped into four types of categories (behavioral, physiological, automobile and hybrid), Second, the supervised machine learning classifiers that are used for drowsiness detection will be described, followed by a discussion of the advantages and disadvantages of each technique that has been evaluated, and lastly the recommendation of a new strategy for detecting drowsiness.

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1. INTRODUCTION

Drowsiness and fatigue are one of the significant factors that affect road safety and cause serious accidents, casualties, and economic losses [1]. According to national highway traffic safety administration (NHTSA) report in the United States, between 2011 and 2015 about 2.4% of 153,297 road accidents, more than 1.25 million deaths annually, and 20-50 million people injured or disabled are caused by drowsy driving; In addition to the high cost which can be reached to $518 billion. In India, according to Ministry of Road transport and highways transport research wing report, there were about 449,002 accidents out of this number of data 33.65% was the mortality rate in 2019. While in Europe, in 2019 the mortality rate was 19% due to road accident. Statistics predicts that annually about 76,000 injuries and 1,200 deaths can caused because of fatigue and drowsiness through driving. As a result, by 2030 road traffics will become the fifth cause of death. In air traffic, Drowsiness and fatigue become a serious issue. According to recent surveys, long flight and busy schedule of the pilots lead them to take a short snap or snooze through their flight. Therefore, airline industry must ensure that their crew is a wake periodically or it will be a major problem. There are numerous factors that contribute to driver's fatigue such as: lack of rest, a long ride, wakefulness, consumption of alcohol, and mental stress. Those factors may lead to serious disaster if action does not take on time. Moreover, previous transportation system was not provided with tools or techniques to control those factors on roads [2]–[4].

Due to the dangerous accidents that fatigue poses on the roads, researchers developed different types of methods to detect driver's drowsiness. Despite the large number of methods conducted in this field and the numerous technologies available for driver's drowsiness detection, it is still unclear which one is the most appropriate depending on cars and driver's conditions; In addition, what enhancement can be done in the future about this topic. To conduct the best results from this review paper, searching keywords to collect the relevant information have been proposed. They focus on their search on journals and conferences that have high reputations. In this review paper, i) we classify the drowsiness detection techniques into three main categories and discuss for each category its pros and cons in addition to its limitations, ii) we review the machine learning classification techniques that are used to detect drowsiness, and iii) we recommend combining audio as a new feature with the three extracted features-based techniques to enhance the detection of drivers' drowsiness.

This paper is divided into six main parts. The second part describes the way that existing studies have been collected. Next following drowsiness detection techniques are presented in detail. Then presents a comparative study of drowsiness detection techniques using machine learning classification techniques. While the last part discusses the comparative analysis of machine learning classification for drowsiness detection techniques. Finally, discussed the conclusion of this study.

2. RESEARCH METHOD

The goal of this systematic review is to illustrate the workflow of machine learning to detect drivers' drowsiness, highlights the supervised machine learning techniques that have been successfully employed in real-world to detect drivers' drowsiness. In addition to define the pros and cons of each technique and provide suggestions to enhance those detection techniques. Therefore, the existing research papers relevant to drowsiness detection techniques have been collected from high reputed journals' search engines: IEEE Explore, arrhythmogenic cardiomyopathy (ACM), and Google Scholar. Based on the keyword search, about 2,500 existing papers were retrieved in primary search, as illustrated in Table 1. To make the selection and retrieving method more accurate, commands that compose of logic expressions and search keywords have been applied on abstract and title as shown in Table 2. As a result, the number of collected papers has been reduced to 48. Finally, we divided the 48 papers into three main categories depending on the extracted features that play important role in supervised drivers' drowsiness machine learning detection techniques, those categories are:

a. Vehicle features-based techniques,
b. Behavioral features-based techniques, and physiological features-based techniques.

Table 1. Description of search words

Search of word	Set of keywords
Drow*	Drowsiness, Drowsiness detection, Drowsiness technique, drowsy driver
Fatigu*	Fatigues driver, Fatigue detection, Fatigue detection technique
Biological*	Biological parameters, Biological measures
Physiological*	Physiological parameters, Physiological measures
Car*	Car measures, car movements
Vehicle	Vehicle measures, Vehicle movements
Re Behavioral*	Behavioral parameters, Behavioral measures
Classif*	Classifier, Classification technique, Classification Methods

Table 2. Search keywords commands

Commands	Description
Command1	(Biological*OR physiological*) AND (Drows*) OR (Fatigu*)
Command2	(Vehicle*OR Car*) AND ((Drows*) OR (Fatigu*))
Command3	(Behavioral*) AND ((Drows*) OR (Fatigu*))
Command4	(Behavioral*) AND (EOG*) AND ((Drows*) OR (Fatigu*))
Command5	(Classif**) AND ((Drows*) OR (Fatigu*))
Command6	(Emotion*) AND ((Drows*) OR (Fatigu*))

3. GENERAL WORKFLOW FOR DETECTING DRIVER DROWSINESS USING SUPERVISED MACHINE LEARNING TECHNIQUES

Supervised machine learning techniques are a common type of machine learning that used for predicting, forecasting or classification tasks. They are named supervised learning because the learning algorithm is carried out using label data. Figure 1 demonstrates the general steps for driver drowsiness detection using supervised machine learning techniques.

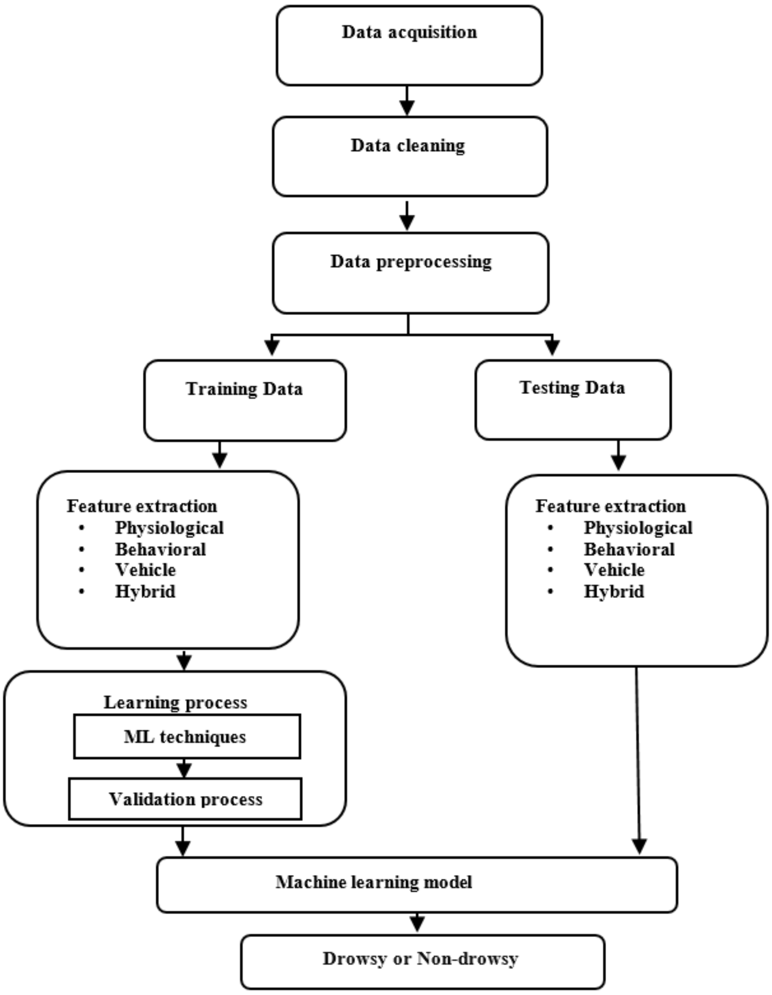

Figure 1. Supervised driver drowsiness detection techniques workflow

3.1. Data acquisition

The first step in any supervised machine learning technique is gathering or collecting data. The size of the data collecting, and the quality play a crucial role to build an accurate model. From the previous research papers, some authors use datasets that are published, validated, and accessed for free to detect drivers' drowsiness. For example, driver drowsiness detection (DDD) dataset [5], closed eyes in the wild (CEW) [6], National Tsing Hua University (NTHU) DDD dataset [7], [8], DROZY dataset [9], SleepEYE I project (SleepEYE) dataset [10], and yawning detection dataset (YawDD) [11], [12]. While others create their own dataset and validate it using different machine learning techniques as in [13]–[15]. Table 3 illustrates the types of datasets used in DDD.

Table 3. Types of datasets in DDD

Dataset Name	Vehicle Features	Behavioral Features	Physiological Features
DDD [5]		✓	
CEW [6]		✓	
YawDD [11], [12]		✓	
SleepEYE [10]	✓	✓	✓
NTHU-DDD [7], [8]		✓	
DROZY [9]		✓	

3.2. Data cleaning and preprocessing

Data that has been collected cannot be directly fed into machine learning workflow in its current format. Therefore, raw data must clean and transform to a format that can be understandable by the machine.

Data cleaning referred to the process of removing unnecessary or corrupted piece of data within dataset and fixing the errors that occurs in the data to assure reliable algorithms and outcomes. In DDD techniques, raw data can be in different formats. It can be gathered from sensors, images, and videos. For data that extracted from sensors, those data are in numeric format, to clean this type of data we must use the following steps: fill the missing values and remove noisy and null values. To clean image data, there are general steps that should be followed to clean data, those steps are cropping, filtering, rotating, or flipping images. For video preprocessing, video data should be split into frames, each frame treated as an image that follows the image preprocessing steps [16], [17].

3.3. Feature extraction

Feature is a fixed number of characteristics, which might be binary, categorical, or continuous that used to represent data. The terms "feature" represents input variable or attribute. Finding a good data representation is domain specific and dependent on the measurements that are available [17]. We classify supervised machine learning techniques depending on the extracted features into three main categories. Vehicular features-based techniques, behavioral features-based techniques, and physiological-based techniques. Figure 2 demonstrates the classification of drowsiness detection techniques.

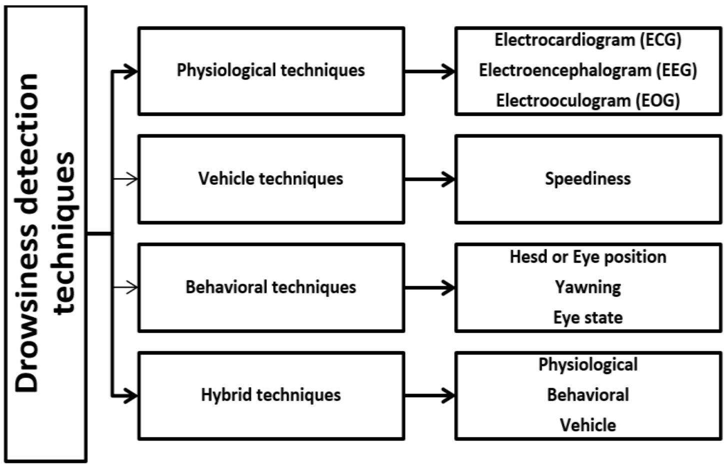

Figure 2. The basic structure of sleep detection techniques

3.3.1. Vehicular features-based technique

This type of features is extracted depending on the sensors that are installed in the steering wheel. Sensors are used to detect drivers steering behaviors by monitoring and measuring the steering movements. steering wheel angle (SWA), steering wheel velocity (SWV), and approximate entropy (AP) represent this type of features. McDonald *et al.* [18] apply the decision-tree (DT) after extracting the ApEn of SWA features to detect driver's drowsiness and gain an accuracy of 79%. On real time Li *et al.* [19] use the SWA features and AP features. They input the features into binary classifier. The results show that the proposed system has an accuracy of 78.01%. The work in [20] apply the random forest classifier (RFC) after extracting the SWA features to detect driver's drowsiness and gain an accuracy of 82%. For SWA Chai *et al.* [21] select four types of (SWA) features and fed them into three types of classifiers, the results show that using SWA features with multilevel ordered logit (MOL) classifier has better accuracy than the other two classifiers. Finally, Arefnezhad *et al.* [22] extracts vehicular features that is related to SWA and SWV; it uses the adaptive neuro-fuzzy feature selection to select the optimal features before inputting them to the support vector machine (SVM) classifier. The proposed model achieves 98.12 accuracy. Table 4 briefly summarized the vehicular feature-based technique. Techniques that use this type of features are more reliable. However, they face some limitations. As this technology has advantages is non-intrusive and disadvantage that effected by geometric characteristics of roads, unreliable [3], [4], [23]. Table 4 illustrates a brief utilization of vehicle techniques.

3.3.2. Physiological features-based techniques

Physiological techniques are based on features that extracted from driver's physical condition. Features such as: (heart, pulse, breath, and respiratory) rate; in addition to body temperature are represent this type of technique. Many previous studies use those features to detect drivers' drowsiness. While in [24], authors was developed a model that enhanced the electrocardiogram (ECG) and heart rate variability (HRV) feature and use the artificial neural network (ANN) to detect drivers' drowsiness. The accuracy rate for the technique in the detection of drowsiness was 90%. Li *et al*. [25] developed a model that enhanced the electroencephalogram (EEG) pulse and use the SVM based posterior probabilistic model (SVMPPM) to detect drivers' drowsiness. The accuracy rate for the technique in the detection of drowsiness was 91.25%. The research in [26] was used Bayesian-copula discriminant classifier (BCDC) based on the physiological features extracted from EEG signals. The accuracy rate for the proposed technique for the detection of drowsiness was 94.30%. The work in [27] proposed an algorithm to detect slow eye movement; It starts by extracting the EEG features from occipital O2 signal, then the extracted features are added to the horizontal electro-oculogram (HEOG) signal features set, after that maximum relevance and minimum redundancy (mRMR) feature selection method is applied to select the optimal feature which fed into the SVM learning. As a result, the accuracy has been increased by 1.4% when using the extracted EEG power features. Tabal and Dela Cruz [28] developed a model that enhanced the electrooculogram (EOG) blink pulse feature and use the nearest neighbor algorithm classifier to detect drivers' drowsiness. The accuracy rate for the technique in the detection of drowsiness was 87.14%. The work in [29] applied four types of classifiers (K-NN, SVM, CBR, and RF) to detect driver drowsiness after extracting the EEG, EOG features. Results showed that SVM achieved and accuracy of 93% for binary classification. While in [30] EEG signals have been extracted and divided into multiple frequency bands using wavelet packet transformation to determine if the functional brain network transitions from the warning state to the sleepy state. Two types of feature selection algorithms have been used synchronization likelihood (SL) and minimum spanning tree (MST). The selected features are input to four types of classifiers (SVM, K-NN, logistic regression (LR), and DT). The results show that K-nearest neighbors (K-NN) has accuracy of 98.6% when SL and MST are used together as a feature selection algorithm. The research in [13] applied a model that extracted the EOG signals features, they used a K-NN as a machine learning trainer and achieved and accuracy of 95.34%. Table 5 illustrates a brief utilization of physiological signs.

Table 4. Summary of artworks utilizing vehicle techniques

Ref	Year	Vehicle features	Supervised Machine Learning	Accuracy
[18]	2012	SWA	Random forest algorithm	79.00%
[19]	2017	SWA+AP	Binary classifier	78.01%
[31]	2017	ApEn of SWA	Decision-tree	82.00%
[21]	2018	SWA	MOL	72.92%
[22]	2019	SWA+SWV	Adaptive neuro-fuzzy feature selection with SVM classifier	98.12%

Table 5. Summary of artworks utilizing physiological signs

Ref	Year	Physiological Features	Supervised Machine Learning	Accuracy
[24]	2011	ECG, HRV	ANN	90%
[25]	2015	EEG	SVM based posterior probabilistic model (SVMPPM)	91.25%
[26]	2016	EEG signal	BCDC	94.30
[27]	2016	EEG signal	SVM	1.4%
[28]	2017	EOG signal	Nearest Neighbor	87.14%
[29]	2018	EEG+EOG	SVM	93%
[30]	2018	EEG signals	K-NN	98.6%
[13]	2019	EOG signals	K-NN	95.345%

3.3.3. Behavioral features-based technique

Behavioral techniques are non-invasive methods that depend on image processing to detect drivers' behavioral features captured from the camera installed in the vehicle to track the driver's actions and alert its. Features that are related to eyes, mouth, and head represent this type of technique. Saradadevi and Bajaj [31] suggested a methodology for detecting and alerting tiredness at an earlier stage and applied the SVM classifier on the extracted behavioral features that are associated with the mouth and yawing. Results show an improvement in accuracy of 83.3% on average. The work in [32] extracts eye index (EI), pupil activity (PA), and head poses (HP) to detect driver drowsiness, an SVM classifier has been used and record 94.84% accuracy. Head movement and eye closeness duration features have been extracted in [33] and fed into wavelet network classifier that based on neural network to detect drowsiness. The model achieved accuracy of 80%. Research [34] extracts mouth regions features based on circular Hough transforms and using a SVM as a classifier to detect drivers' drowsiness. It scores an accuracy of 98%. In [35] behavioral features that related to eyes, mouth and face are extracted using the Viola-jones algorithm and cascade classifier. Results show that the model has an accuracy of 90%. Pauly and Sankar [36] calculates the percentage of eye closures (PERCLOS) feature after detecting eye blinking, then the SVM are used, and the accuracy of the system was 91.6%. Kumar and Patra [37] presents a technique that based on facial landmarks (FL) to calculate the eye aspect ratio (EAR), mouth opening ratio (MOR), and nose length ratio (NLR) and uses the SVM to detect driver's drowsiness. The accuracy that the system achieved was 95.8%. Oliveira *et al.* [38] uses supervised machine learning classification (SVM, RF, ANN, gradient boosting tree (GBT), and KNN) 0n the features extracted from the video (head movement, eyelid opening, pupil diameter, and angle of the eye gaze). The results show that the classifiers record an accuracy of 89.15%.

While Mehta *et al.* [39] present a model that can detect FL, measure the EAR and the eye closure ratio (ECR) of the driver based on adaptive thresholds. Random forest (RF) classifier achieved an accuracy of 84% to detect drivers' drowsiness. Another work in [40] extracted the PERCLOS feature, eye blinking frequency (EBF), and maximum closure duration (MCD). All features are fed into different types of classifiers: (SVM, KNN, ANN, and LR). The results show that the KNN has an accuracy of 72.25% better than other classifiers. Costa *et al.* [41] presents a technique based on the eye and head tracker dataset (SEP), and uses the SVM and decision tree (DT) to detect driver's drowsiness. The results show that the DT has an accuracy of 93% better than SVM. The work in [42] extract 35 behavioral features that related to eye blinking (EB) and head movement, and then use a feature selection method to select the optimal feature set that input to K-NN classifier. The results show that the model record accuracy of 84.2%. Zhang *et al.* [43] extracts five types of features that categorized as behavioral features and use AdaBoost classifier. Features are PERCLOS, MCD, blink frequency (BF), average opening level (AOL), opening and closing velocity (OV) capacitance-voltage (CV). As this technology has advantages is non-intrusive easy to use, and its disadvantages are affected by illumination conditions [3], [4]. Table 6 illustrates a brief utilization of behavioral techniques.

Table 6. Summary of artworks utilizing behavioral techniques

Ref	Year	Behaviors features	Classification method	Accuracy
[31]	2008	Yawing	SVM	83.30%
[32]	2013	HP+PC+EI	SVM	94.84%
[33]	2014	Head Movement+Eye Closeness Duration	WN	80.00%
[34]	2014	Yawing	SVM	98.00%
[35]	2015	EBR+Yawing	Binary Cascade	90.00%
[36]	2015	PERCLOS	SVM	91.60%
[37]	2018	Eye Aspect Ratio+Mouth Opening Ratio+Nose Length Ratio	SVM	95.80%
[38]	2018	EOG signal+Head movement+Eyelid Opening+Pupil diameter+Eye gaze direction	SVM+RF+GBT	89.15%
[39]	2019	Facial Landmarks+eye aspect ratio (EAR)+eye closure ratio (ECR)	RF	84.00%
[40]	2019	PERCLOS+EBF+MCD	K-NN	72.25%
[41]	2019	Eye+Head	SVM	93.00%
[42]	2020	EB+Head Movement	K-NN	84.20%
[43]	2019	PERCLOS+BF+MCD+AOL+OV+CV	AdaBoost	86.00%

3.3.4. Hybrid featured-based technique

Some authors have merge two or more features from different types to diagnose driver drowsiness and improve the overall accuracy of the model in a way that reduces limitations of one technique by using the features of the others. Another work [44] combines physiological, behavioral, and vehicular features such as: blood pressure, heart rate, temperature, and PERCLOS. Fuzzy Bayesian has been employed to detect drivers' fatigue and record accuracy between 94% to 99%. Samiee *et al.* [45] extracts behavioral features and vehicular features for detecting drivers' drowsiness. By using neural network classifier, the model records an accuracy of 87.78% at worse case. Table 7 illustrates a brief utilization of hybrid techniques. The research [46] has implemented combined non-contact approaches based on the voice and vision of somnolence detection systems. By calculating PERCLOS and using voice as a feature, SVM classifier an accuracy of 98.6%. In Wang and Xu [47] extracts behavioral features and vehicular features and use MOL and ANN classifiers, results show that MOL has better accuracy than ANN classifier.

Emotional stimulus based on pressure was introduced by [48] as critical feelings in addition to electrodermal activity (EDA) features. SVM classifier has been applied to detect drivers' drowsiness and gain an accuracy of 85%. The study in [49] provided a novel technique for detecting drivers' drowsiness through emotion that uses EEG data to identify human emotions using a two-tier classifier that combines the KNN and NN classifiers. The results show that the emotion recognition is a better choice in the current trend. The combined KNN-NN classifiers produces maximum classification accuracy of 97.10%. To detect drivers' drowsiness, Li *et al.* [50] exploit the SWA features and the Yaw Angles feature. Both vehicular features and behavioral features are used as input to the multi-level back propagation neural network classifier. Experiment show that the proposed system has achieved an accuracy of 88.02%. An ANNs classifier was applied on a combinations of vehicular, behavioral, and physiological features in [51]. The results show that the following features eyelid closure, gaze, and head movements have better performance with accuracy between 87% to 98%. Zhang [52] introduced the five basic emotions (entertainment, frustration, indignation, fear, and disgust); three psychophysiological signals were recorded: tEMG, EDA, and ECG. SVM were used with an accuracy of about 97.98%. Fernandes [53] uses supervised machine learning classification (SVM, RF, KNN, and bagging classifier (BC)) on the SWA and ECG. The higher result shows that the SVM classifier record accuracy of 94%. For example [54] use EEG and ECG features with the behavioral features of a driver to recognize drivers' fatigue. The results show that the accuracy will be 78.7% when only the behavioral features are used while it increased to 89.8% when both physiological and behavioral features are used together in the RF classifier. Table 7 illustrates a brief utilization of hybrid methods.

Table 7. Summary of artworks utilizing hybrid methods

Ref	Year	Hybrid features	Classification method	Accuracy
[44]	2012	blood pressure+heart rate+temperature+PERCLOS	Fuzzy Bayesian	94% to 99%
[45]	2014	Eye status+lateral position+SWA	Weighted output of three trained neural networks	87.78%
[46]	2015	Voice+PERCLOS	SVM	98.60%
[47]	2015	PERCLOS, Pupil, BF, SWM Re, LP stdev	MOL	88.60%
[48]	2016	emotional stimulation, EDA signals	SVM	85.00%
[49]	2017	EEG signals for emotion recognition	K-NN+NN	97.10%
[50]	2017	SWA+YA	Neural Network	88.02%
[51]	2019	eyelid closure+gaze+head movement	ANN	87% to 98%
[52]	2019	essential feeling (entertainment, anger, outrage, dread, and disgust), (tEMG), (EDA), and (ECG)	SVM	97.98%
[53]	2019	SWA+ECG signals	SVM	94.00%
[54]	2020	(Electroencephalogram and electrocardiogram) signals and face	RF	78.70%

4. LEARNING PROCESS

In this step, extracted features must be input to the classifier, and then results are validated. Choosing the suitable classifier is a crucial step because it represents a key role in determining the accuracy of the prediction [55]. Therefore, knowing the pros and cons of each classifier can help in selecting the suitable classifier precisely. Machine learning classification approaches such as SVM, human visual system (HVS), Naïve Bayes (NB), and K-NN represent the most discriminatory and appropriate classifiers' techniques [56]–[58]. Table 8 illustrated the pros and cons of machine learning classifiers that help in detecting drivers' drowsiness.

Table 8. Machine learning classification approaches (pros and cons) [59]–[65]

Classifier Name	Pros	Cons
SVM	- Works well when the margin separator is clear, and the number of dimensions exceeds the number of samples. - Provide memory efficiency when works in high dimension spaces.	- It does not work well when the dataset is large because it consumes more time in training data. - Its performance will be less when the dataset has a lot of noise.
K-NN	- Easy to implement, especially for multi class classification. - Training step is not required. - Accuracy is not affected when new data is added.	- Performance less when dataset is large and has noise on it. - It required that input features must be homogeneous. -
Fuzzy Classifier	- Simple, justifiable, cost low, easy to implement, and has intuitive design.	- Stability is not assured, trial and error are used for optimization, and different tuning parameters are used.
RF	- It works well with nonlinear data. - Run efficiency when dataset is large. - It cannot affect by overfitting.	- Performance less when data is linear, and features are sparse. - It works slowly in training step.
ANN	- A great ability to predict. - Ideal for non-mathematical models. - The Capacity to extract meaning from complex or imprecise knowledge	- It takes unknown time to process. - It requires a large quantity of data for quality predictions

5. COMPARATIVE ANALYSIS OF DRIVER DETECTION TECHNIQUE AND DISCUSSION

From the reviewed research paper, we compare the techniques from two points of view: i) the featured based techniques and ii) the type of the classifier that has been used by the technique. For the featured based technique point, it was noticed that vehicular features can give good results if it is not affected by the road circumstances, while behavioral features-based technique are easy to use but their performance will be reduced in poor lightening. The physiological-based techniques are efficient and reliable, but their intrusive nature required to be resolved. Hybrid features based technique can help in reducing the limitations of one feature by using other features from different type to increase the accuracy of the technique. From the classifier point of view, the SVM classifier is the most used one that gives good results either by using each feature separately or by using hybrid features. While KNN gives better results with physiological features; Moreover, applying large dataset with a good feature selection method can improve the accuracy of the classifier.

6. CONCLUSION

This review paper aims to shed light on the existing studies of driver drowsiness techniques, especially those techniques that use supervised machine learning. In this paper we give a brief information about dataset, workflow of supervised machine learning, features, classification techniques that used for detecting driver drowsiness. Driver detection techniques have been classified into four categories (physiological, vehicle, behavioral and hybrid) depending on the type of features that have been extracted. Comparative analysis showed that no one of the techniques can give high accuracy if they work lonely. Physiological features-based techniques give accuracy better than other techniques, but they suffer from intrusive. Therefore, hybrid features based techniques represents better solution to reduce the limitation of one technique by using the other ones. Most popular supervised machine learning techniques have been presented with their pros and cons while a comparative study show different results of accuracy with different situations. However, results for SVM classifier give better results with different types of features. Finally, we recommend combining audio as a new feature with the three extracted features-based techniques to enhance the detection of drivers' drowsiness.

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