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A Survey on State-of-the-Art Drowsiness Detection Techniques

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ABSTRACT Drowsiness or fatigue is a major cause of road accidents and has significant implications for road safety. Several deadly accidents can be prevented if the drowsy drivers are warned in time. A variety of drowsiness detection methods exist that monitor the drivers' drowsiness state while driving and alarm the drivers if they are not concentrating on driving. The relevant features can be extracted from facial expressions such as yawning, eye closure, and head movements for inferring the level of drowsiness. The biological condition of the drivers' body, as well as vehicle behavior, is analyzed for driver drowsiness detection. This paper presents a comprehensive analysis of the existing methods of driver drowsiness detection and presents a detailed analysis of widely used classification techniques in this regard. First, in this paper, we classify the existing techniques into three categories: behavioral, vehicular, and physiological parameters-based techniques. Second, top supervised learning techniques used for drowsiness detection are reviewed. Third, the pros and cons and comparative study of the diverse method are discussed. In addition, the research frameworks are elaborated in diagrams for better understanding. In the end, overall research findings based on the extensive survey are concluded which will help young researchers for finding potential future work in the relevant field.

INDEX TERMS Digital image processing, driver drowsiness, sensors, fatigue detection, supervised learning, classification, support vector machine (SVM).

I. INTRODUCTION

Drowsiness or fatigue is one of the main factors that threaten the road safety and causes the severe injuries, deaths and economical losses. The increased drowsiness deteriorates the driving performance. Lack of alertness, generated by the unconscious transition from wakefulness to sleep, leads to several serious road accidents. The U. S. National Highway Traffic Safety Administration (NHTSA)[1] reports that drowsy driving resulted in almost 100,000 road accidents and more than 1,500 deaths per year. A driver's fatigue can have multiple causes such as lack of sleep, long journey, restlessness, alcohol consumption and mental pressure. Each of which can lead to serious disaster. Nowadays, road rage is in the multiples of the past, which causes stress on drivers. Therefore, previous transportation system is not enough to handle these hazards on roads. Thus, by embedding the automatic fatigue detection systems into vehicles, several deadly accidents can be prevented. The drowsiness detection system continuously analyzes the drivers' attention level and alerts the driver before the arrival of any serious threat to road safety.

Due to the hazards that fatigue create on the roads, researchers have developed various methods to detect driver drowsiness and each technique has its own benefits and limitations. To conduct a valuable review of Drowsiness Detection Techniques (DDT) and appropriate classification methods, we build search strings to gather relevant information. We keep our search focused on publications of well reputed journals and conferences. We established a multi-stage selection criteria and assessment procedure.

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[1]https://crashstats.nhtsa.dot.gov/Api/Public/Publication/811754. Last Access:2018-11-14

Based on devising criteria, 41 research papers are filtered out from a detail search of 1020 research papers. We found a great rising in the trends of drowsiness detection systems, but still there is space for further improvement in present measures of drowsiness detection.

In this literature review, we (1) classify the existing models into three major categories and then review each model in chronological order sharing its novelty, main features and limitations (2) discuss Hybrid approaches (3) explore, top supervised learning techniques used for drowsiness detection have been explored (4) present the pros and cons and provide a comparative study of techniques are discussed (5) elaborate the research methods in the form of frameworks for better understanding.

This paper is subdivided into seven main sections. Section 2 describes the research methodology for performing effective analysis of drowsiness techniques, detailed analysis and evaluation of selected papers is discussed. In section 3, Detailed review of drowsiness detection techniques is presented in the form of tables. In section 4, the comparative study of DDT is presented. Section 5 illustrated the hybrid approaches of DDT. Classification methods used for drowsiness detection are listed in Section 6. A comparative study of classification is discussed in section 7 and the conclusion of this study are discussed in the end.

II. RESEARCH METHODOLOGY

The purpose of this systematic review paper is recognition and categorization of the best possible techniques, measures, tools and classification methods for drivers' drowsiness detection. The systematic reviews help to recognize what we know in the concerned domain. All the data gathered from primary studies is categorized. Once the systematic review of empirical studies is done, we gather relevant information and identify the research gaps in the existing research studies [1]. The population of systematic review consists of research papers relevant to drowsiness detection.

A. DATA ACQUISITION AND SELECTION

A systematic and well organized, search is conducted to extract meaningful and relevant information from the buckets of data. Research papers, case students, NHTSA on road accidents and reference lists of related publication were examined in detail. The websites containing information regarding to road safety, dangers of driver's fatigue, reasons of fatigue, and techniques of drowsiness detection are all searched. Keywords used to search information relevant to drowsiness are listed in TABLE 1. The search string is as follows

- (Drows* OR Fatigu*) AND (Biological* OR physiological*)
- (Drows* OR Fatigu*) AND (Vehicle * OR Automobile*)
- (Drows* OR Fatigu*) AND (Behavioral*)
- (Drows* OR Fatigu*) AND (Classif*∗)
- (Drows* OR Fatigu*) AND (SVM*)
- (Drows* OR Fatigu*) AND (CNN*)
- (Drows* OR Fatigu*) AND (HMM*)

TABLE 1. Description of search words.

Search Word	Set of keywords
Drows*	Drowsiness, Drowsiness detection, Drowsiness technique, drowsy driver
Fatigu*	Fatigues driver, Fatigue detection, Fatigue detection techniques
Biological*	Biological parameters, biological-measures, biological conditions
Physiological*	Physiological parameters, Physiological measures, Physiological conditions
Vehicle*	Vehicular measures, vehicular movements
Automobile *	Automobile measures, Automobile movements
Behavioral*	Behavioral parameters, behavioral measure
Classif*	Classifiers, Classification techniques, classification methods
SVM*	SVM classifier, support vector machine
CNN*	CNN classifier, Convolutional Neural Network
HMM*	HMM classifier, Hidden Markov model

We perform our initial study on search engines such IEEE explore, ACM, Springer, Google Scholar, IJCS and MDPI to extract information relevant to drowsiness detection. We found 1020 research papers in primary search.

The initial search procedure produces 1020 research papers; from those we have selected 105 papers based on title relevant to our study. Abstract of selected papers is examined which lead to extraction of further 74 research papers. Then these extracted papers are studied thoroughly, and 41 research papers are filtered out as our primary study. The complete selection process is illustrated in Figure 1.

Thorough study of full research papers seeks the answers of certain quality control questions. Current systematic research follows the quality assessment questions like a) Is the paper relevant to the research domain? and b) are the papers published in well reputed journal or conference? The detailed analysis of drowsiness detection systems is categorized based on drowsiness measures and classification methods. A complete details of existing drowsiness systems are summarized in tabular form. Answers of research questions are generated as well as pros and cons found in studies are evaluated, suggestions and conclusions are drawn.

III. DROWSINESS DETECTION TECHNIQUES

A detailed review of mentioned drowsiness detection techniques and their pros and cons are discussed in this section. Furthermore, the comparative analysis of such techniques is performed on different types of driving conditions The Driver Drowsiness detection system continuously monitors the drivers' physical behavior, vehicular movement pattern or environmental conditions based on the technique being used.

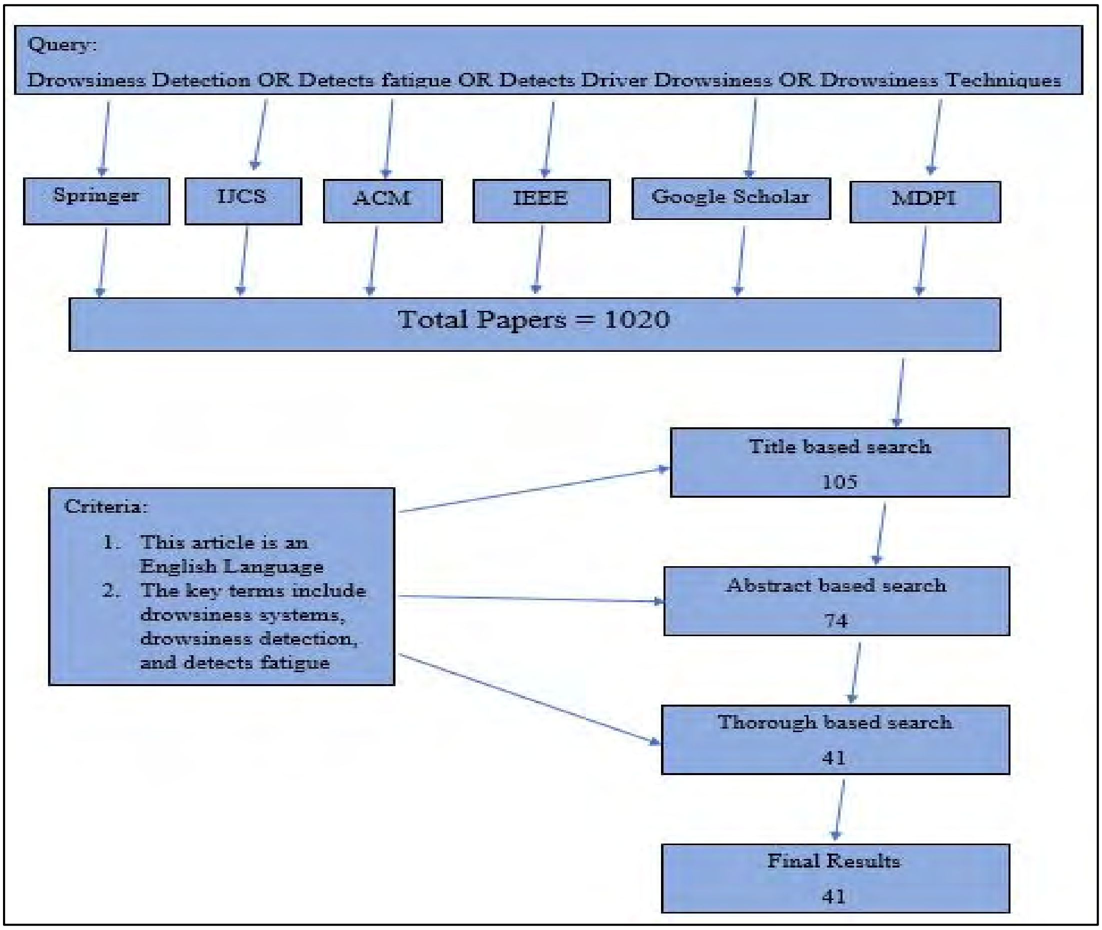

FIGURE 1. The research papers selection process.

Drowsiness detection methods are generally classified into three main categories:

1) Behavioral parameter-based techniques
2) Vehicular parameters-based techniques
3) Physiological parameters-based techniques

Figure 2 illustrates the basic architecture of Drowsiness Detection Techniques

A. BEHAVIORAL PARAMETER-BASED DDT

Behavioral parameters are non-invasive measures for drowsiness detection. These techniques measure drivers' fatigue through behavioral parameters of driver such as eye closure ratio, eye blinking, head position, facial expressions, and yawning. The Percentage of eye Closures (PERCLOS) is one of the most frequent used metrics in drowsiness detection based on eye state observation. PERCLOS is the ratio of eye closure over a period, and then on the result of PERCLOS, eyes are referred as open or closed. Yawning based detection systems analyze the variations in the geometric shape of the mouth of drowsy driver such as wider opening of mouth, lip position, etc. Behavioral based techniques used cameras and computer vision techniques to extract behavioral features. The general framework of process in behavioral pattern-based drowsiness detection techniques is presented in *Figure 3*.

A list of drowsiness detection system based on behavioral patterns is presented in Table 2.

The problems associated with behavioral measures are environmental factors, such as the illumination, brightness, and road conditions influence the credibility and accuracy of measurement [2].

1) EYE TRACKING AND DYNAMIC TEMPLATE MATCHING

To avoid road accidents, real time driver fatigue detection system based on vision [3] is proposed. Firstly, system detects the face of driver from the input images using HSI color model. Secondly, Sobel edge operator is used to locate the eyes positions and gets the images of eye as the dynamic template for the tracking of eye. Then the obtained images are converted to HSI color model to decide that whether the eyes are close or open to judge the drowsiness of driver. The experiments use four test videos for the tracking of eyes and face detection. The proposed system is compared with the labeled data which is annotated by the experts. The average

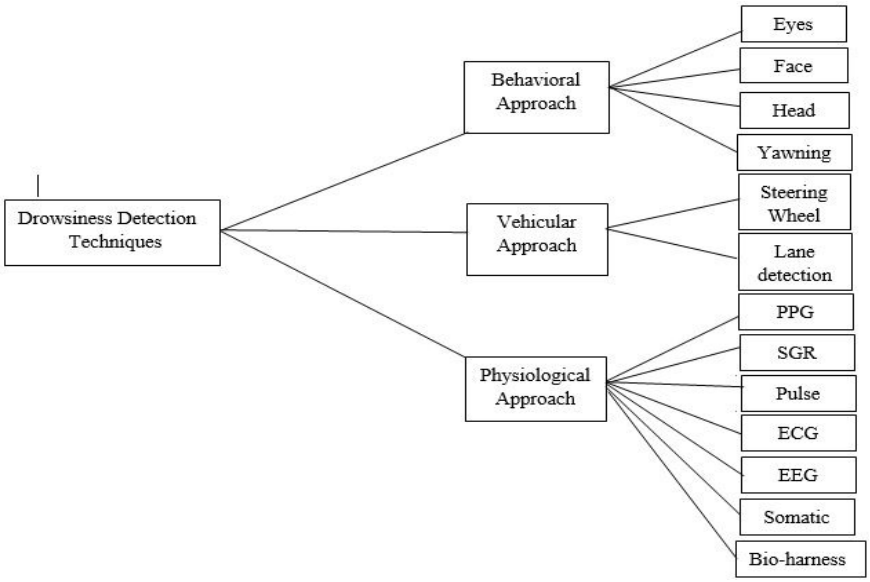

FIGURE 2. Architecture of drowsiness detection techniques.

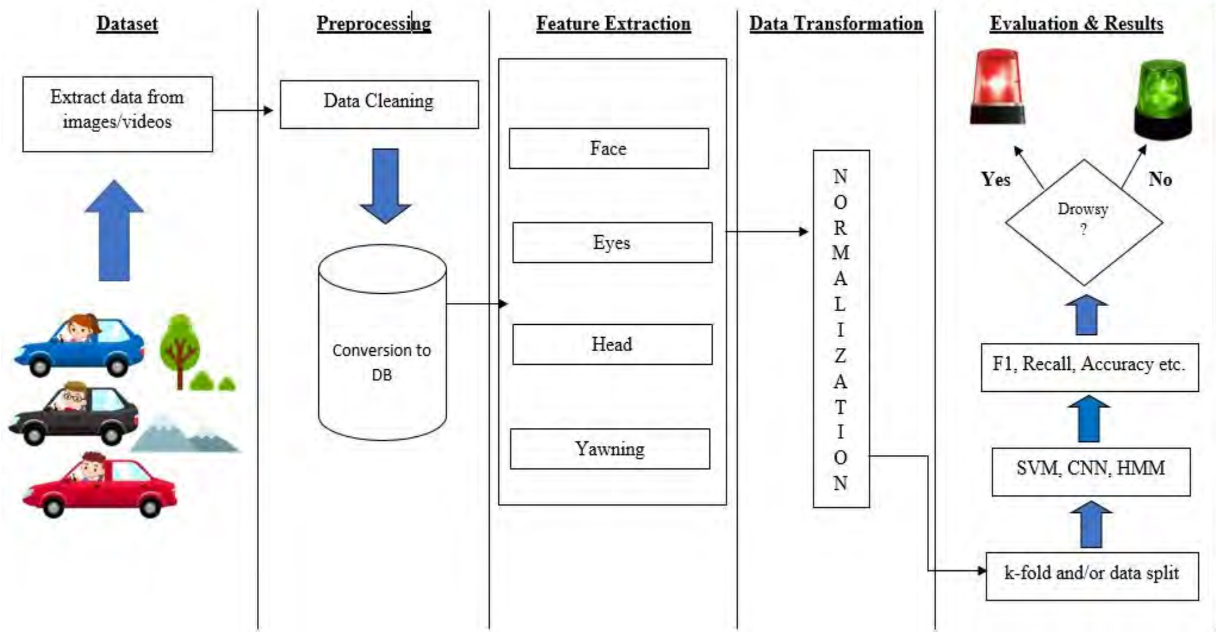

FIGURE 3. A general framework of Behavioral Pattern-based techniques.

correct rate of proposed system reaches up to 99.01 % and the precision to 88.9 %.

2) MOUTH AND YAWNING ANALYSIS

Fatigue is the major reason for road accidents. To avoid the issue, Saradadevi and Bajaj [4] proposed the driver fatigue detection system based on mouth and yawning analysis. Firstly, the system locates and tracks the mouth of a driver using cascade of classifier training and mouth detection from the input images. Then, the images of mouth and yawning are trained using SVM. In the end, SVM is used to classify the regions of mouth to detects the yawning and alerts the fatigue. For experiment, authors collect some videos and select 20 yawning images and more than 100 normal videos as dataset. The results show that the proposed system gives better results as compared to the system using geometric features. The proposed system detects yawning, alerts the fatigue earlier and facilitates to make the driver safe.

3) FACIAL EXPRESSIONS METHOD

Laboratory condition using Finite Element Analysis is used by the researchers which is a complex system that contains

TABLE 2. Behavioral-parameter based drowsiness detection systems.

Ref	Behavioral Features	Method & Classifier	Description	Efficiency
[3]	Eye tracking	HSI color model, Sobel edge detection method	HSI color model is independent of brightness. Sobel edge detection to locate eyes.	88.9
[4]	Yawning	Cascade classifier. SVM, Viola-Jones algorithm	applied SVM to train mouth and yawing images. Detects fatigue using cascade.	Nil
[5]	Face components (eyebrow raising, eye closing, yawning)	Background subtraction method, Horizontal projection technique	Used infrared light-based hardware to monitor the eye closing and eyebrows rising to detect drowsiness levels of driver.	Nil
[6]	Yawning	SVM, CHT	Used three steps face extraction, mouth region selection and wide, mouth open detection using SVM. CHT is applied to the results proposed wide, mouth open detector.	98%
[7]	Head movement, eye closeness duration	Viola Jones algorithm, WNC classification	Detects drowsiness based on eye blinking and head pose. A novel WNC based supervised method is proposed.	88.57%
[8]	Eye blinking and yawning	Haarcascade classifier, Active Contour Method, Viola Jones Algorithm	Used eye blinking duration and yawning to detect drowsiness. The System give better results if drivers are without glasses and moustache.	Nil
[9]	Eye state and blinking rate	Viola-Jones method & CART method, Binary cascade classifiers	Used cascade object identifier from vision tool box of mat- lab to eye region. Average drowsiness is calculated, and closed eye is regarded as zero.	90%
[10]	Eye state	Viola-Jones technique, Standard Ada-Boost (Adaptive Boosting) training method & PERCLOS method	Provides user friendly GUI. System requires compact hardware to execute on mid– range, microprocessor or it may be implemented on smart phone having hardware and software requirements.	95%
[12]	Eye blinking	Viola Jones algorithm, Adaboos computational approach, Haar cascade classifier, Luminosity Algorithm & Harris Corner Detector	Non-intrusive and work well in real time. Requires clear visibility of the eye. In poor lightening or sun glasses, system become unable to detect eye region and fails.	94% (in good lightening condition)
[13]	Head tilting and eye blinking frequency	Haar Cascade Classifier	Detection using eye blinking rate and head level, but efficiency declines in poor lightening and with sun glasses.	99.59

the database of facial expression as a template and detect the drowsiness on the basis of results from database. Similarly, Assari and Rahmati [5] present the hardware-based Driver Drowsiness Detection system based on facial expressions. The hardware system uses infrared light as it has giving many benefits like ease of use, independent of lightning conditions of environment. The system firstly uses the technique of background subtraction to determines the face region from the input images. Then using horizontal projection and template matching, facial expressions are obtained. After that in the tracking phase, elements found earlier are followed up using template matching and then investigates the incidence of sleepiness using the determination of facial states from the changes of the facial components. Changing in the three main elements such as eye brow rising, yawning and eye closure for the certain period are taken as the initial indications for drowsiness and the system generates the alert. The experiment is performed in the real driving scenario. For testing, images are acquired by the webcam under different conditions of lighting and from different people. The results investigate that the system produces appropriate response in the presence of beard or glasses and mustache on the face of driver.

4) YAWNING EXTRACTION METHOD

Fatigue or drowsiness is the major reason for road accidents. To prevent the issue, Alioua *et al.* [6] proposed the efficient system for monitoring the driver fatigue using Yawning extraction. Firstly, face region is obtained from the images using Support Vector Machine (SVM) technique to reduce the required cost. The proposed method is used to localize the mouth, edge detection technique is used to detects facial edges, then compute vertical projection on the lower half face to detect the right and left region boundaries and then compute the horizontal projection on the resulting region to detect the upper and lower limit of mouth and mouth localized region is obtained. Finally, to detect the yawning, Circular Hough Transform (CHT) is executed on the images of mouth region to identify the wide-open mouth. If the system finds notable number of continuous frames where the mouth is widely open, system generates the alert. The results are compared with the other edge detectors like Sobel, Prewitt, Roberts, Canny. The experiment uses 6 videos representing real driving conditions and results are presented in the form of confusion matrix. The proposed method achieves 98% accuracy and outperforms all other edge detection techniques.

5) EYE CLOSURE AND HEAD POSTURES METHOD

Teyeb *et al.* [7] proposed the Drowsy Driver Detection using Eye Closure and Head postures. Firstly, video is captured using webcam and for each frame of video, following operations are performed. To detect the ROI (face and eyes), viola-jones method is used. The face is partitioned in to three areas and the top one presenting the aye area is browsed by the Haar classifier. Then to detect the eye state, Wavelet Network based on neural network is used to train the images then the coefficients learning images is compared with the coefficients of the testing images and tells which class it belongs. When the closed eye is identified in the frames then the eye closure duration is calculated, if the value exceeds the pre-defined time then the drowsiness state is detected. Then the developed system estimates the head movements which are: left, right, forward, backward inclination and left or right rotation. The captured video is segmented into frames and extract the images of head and determines the coordinates of image. Then the images are compared to determine the inclined state of head and same case with other head postures. Finally, the system combines the eye closure duration and head posture estimation to measure the drowsiness. To evaluate the system, experiment is performed on 10 volunteers in various situations. And results show that the systems achieve the accuracy of 80%.

6) REAL TIME ANALYSIS USING EYE AND YAWNING

Kuamr *et al.* [8] proposed the real time analysis of Driver Fatigue Detection using behavioral measures and gestures like eye blink, head movement and yawning to identify the drivers' state. The basic purpose of the proposed method is to detect the close eye and open mouth simultaneously and generates an alarm on positive detection. The system firstly captures the real time video using the camera mounted in front of the driver. Then the frames of captured video are used to detect the face and eyes by applying the viola-jones method, with the training set of face and eyes provided in OpenCV. Small rectangle is drawn around the center of eye and matrix is created that shows that the Region of Interest (ROI) that is eyes used in the next step. Since the both eyes blink at the same time that's why only the right eye is examined to detect the close eye state. If the eye is closed for certain amount of time it will be considered as closed eye. To determine the eye state, firstly the eye ball color is acquired by sampling the RGB components on the center of eye pixel. Then the absolute thresholding is done on the eye ROI based on eye ball color and intensity map is obtained on Y-axis that show the distribution of pixels on y-axis. Which gives the height of eye ball and compared that value with threshold value which is 4 to distinguish the open and close eye. After that, if the eye blink is detected in each frame it will be considered as 1 and stored in the buffer and after the 100 frames, eye blinking rate is calculated. Then to detect the yawning motion of the mouth, contour finding algorithm is used to measure the size of mouth. If the height is greater than the certain threshold. It means person is taking yawning. To evaluate the performance of the proposed system, system has been measured under different conditions like persons with glasses, without glasses, with moustache and without moustache for 20 days in different timings. The performs best when the drivers are without glasses and moustache.

7) EYE BLINK DETECTION METHOD

Ahmad and Borolie [9] proposed the Driver Drowsiness System based on non-intrusive machine-based concepts. The system consists of a web camera which is placed in front of the driver. Online videos as well as saved videos for simulation purposed are considered. Firstly, camera records the facial expressions and head movements of the driver. Then the video is converted into frames and each frame is processed one by one. Face is detected from frames using Viola-jones algorithm. Then the required features like eyes, mouth and head from face are extracted using cascade classifier. Region of interest on face is indicated by rectangles. Here the main attribute of detecting drowsiness is eyes blinking, varies from 12 to19 per minute normally and indicates the drowsiness if the frequency is less than the normal range. Instead of calculating eye blinking, average drowsiness is calculated. The detected eye is equivalent to zero (closed eye) and non-zero values are indicated as partially or fully open eyes. The equation (1) is used to calculate the average.

$$\%d = \frac{No.\ of\ closed\ eyes\ found}{no.\ of\ frames} * 100 \tag{1}$$

If the value is more than the set threshold value, then system generates the alarm to alert the driver. Moreover, yawning is also considered to generate the alert. Online and offline are videos are used for experiment which are performed on two different systems. The results show that the system achieves the efficiency up to 90%.

8) EYE TRACKING SYSTEM

Nguyen *et al.* [10] proposed an eye tracking system to detect drowsiness. The system includes camera, simple alarm and the laptop having developed (proposed) software and provides user-friendly GUI. Web cam is connected to laptop through USB port. Firstly, the system receives images from the webcam, system adjust the brightness and contrast and converts them into frames. Secondly, to detect the face region to locates the eye region, top-down model approach is used. If the face is not found in the input images, the system continues to take the images from the webcam until the face is found. After face detection, eye region is extracted using viola-jones algorithm and Ada-Boost (Adaptive Boosting) [11]. Algorithm firstly extracts face features like eyes and nose when Haar-like features are applied on the sub-image and Ada-Boost classifier is used for training of features. The system uses the popular method of PERCLOS for drowsiness detection. The fatigue level of driver S is calculated as S=H/L, where H is the height and L is the length of drivers' eye. Each frame of input video is categorized using the measured value of S. PERCLOS is measured as given in Equation (2).

$$PERCLOS = \frac{No.\, frames\ of\ closed\ eyes}{3\,\mathrm{min}\ interval\ of\ all\ frame - blinking\ time} \tag{2}$$

0.15 is used as the highest drowsiness level for PERCLOS alarm. When the level of drowsiness reaches to severe, system activates the alarm to alert the driver. The experimental results show that it works in all lighting conditions.

TABLE 3. Vehicular parameter-based drowsiness detection systems.

Ref	Vehicular features	Method & Classifier	Description	Accuracy
[3]	Lane detection, eye blinking duration	Hough Transformation, Voila Jones method, Otsu thresholding, Canny edge detection, Circle detection Hough Transform	Detects lane changing pattern and eye closeness to detect drivers' drowsiness level. Works good in low lightening conditions as well.	Nil
[17]	Steering wheel behavior	Temporal detection window	Uses novel approach of time series analysis of steering wheel angular velocity to detect drowsiness.	Nil
[18]	Steering wheel angle	SWA-based fatigue detection method, binary classifier, DTW & ApEn based Adaptive Piecewise Linear Approximation	Detects driver drowsiness in real time using SWA data collected from sensors.	78.01%
[19]	Steering wheel angle, yaw angles	Approximate entropy (ApEn) features, Back propagation neural network classifier	Detects driver drowsiness using steering wheel and yaw angles in real time driving.	88.02%

9) EYE BLINK MONITORING METHOD

Drowsy or sleepy driver is the main reason for road accidents. To handle the problem, Rahman *et al.* [12] proposed an eye blinking based monitoring method to determine the drowsiness of driver. Firstly, receives the video from capturing device and converted into frames. Face region is detected from the frames using voila-jones technique. After the identification of face, ROI is set to face region, Viola-Jones cascade classifier technique is again applied to this region to eyes detection. Cascade classifier uses Haar-like features to detect eyes. Both eye regions are extracted for further processing. Then the proposed Eye-blink detection technique is applied. The method firstly converts the color eye image into grayscale using Luminosity algorithm. Then to detect the two-upper eye corner and one lower eye lid points, Harris corner detector is used. After the points identification, mid-point value between the upper two corner points is calculated. Let (x_1, y_1) be the coordinates of left upper corner and (x_2, y_2) be the right upper corner. The mid-point is calculated as follows:

$$\left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}\right) \tag{3}$$

Then using distance formulae, midpoint from lower eye lid is calculated given by Pythagoras theorem as given in Equation (4).

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 + y_1)^2} \tag{4}$$

finally, the decision is made for the state of eyes using the distance d value. if the value is zero or closed to zero the eye is considered as closed else open. The blink duration is ranges from 0.1-0.4 seconds for normal person so, if the driver is drowsy the blink rate is beyond this interval. 2 seconds is set as threshold value, if the eyes are closed for more than two seconds the system generates the alarm to alert the driver. The proposed algorithm is tested under different lighting conditions. Under normal or bright lighting, system achieves high accuracy but gives poor result in bad lights. The proposed method is compared with the previous methods like eye blink monitoring based on mean sift algorithm, face and eye monitoring based on neural networks & visual information, computer vision & machine learning algorithm, electrooculogram and vehicle-based measures. The proposed system achieves the accuracy of 94 % and less complex as compared to others.

10) EYE CLOSENESS DETECTION METHOD

Khunpisuth *et al.* [13] creates an experiment the calculates the drowsiness level of driver using Raspberry Pi camera and Raspberry Pi 3 model B. Firstly Pi camera captures video and to detect face regions in the images, Haar cascade classifier from Viola-Jones method is used. Several images are trained in different lights. The percentage of 83.09 % is achieved based on the case study with 10 volunteers. Blue rectangle shows the Region of Interest (ROI) that is face. Again, Haar cascade classifier is applied on the last obtained frame which reduces the size of ROI. After the face detection, drowsiness level is calculated using eye blink rate. Eye region is detected using template matching on the face and authors uses three templates to check the eye blink and aye area. CV_TM_CCOEFF_NORMED from OpenCV is considered as it gives improved results than other methods of template matching. The integration of eyes and face detection permits the checking of an eye blinking and closeness rate. If the eyes are closed, then the value of closed eye is higher than the open eyes and opposite case if eyes are open. Authors assumed that the Haar cascade classifier will work if the face is front facing position. That why authors proposed the method to rotate the tilted face back in to the front-facing position. Firstly, determines whether the head is tilt or not then calculates the degrees of rotation (angle). After the accurate detection of face and eyes, drowsiness level of driver is determined. If the drivers blink eyes too frequently, he system indicates he drowsiness. When the level reaches to one hundred, a loud sound will be generated to alert the driver. The proposed method is compared with Haar cascade and results shows that the proposed method achieves the accuracy of 99.59 %. It works in all lighting conditions and able to detect the face wearing glasses.

B. VEHICULAR PARAMETER-BASED TECHNIQUES

Vehicular parameter-based techniques try to detect driver fatigue based on vehicular features such as frequent lane

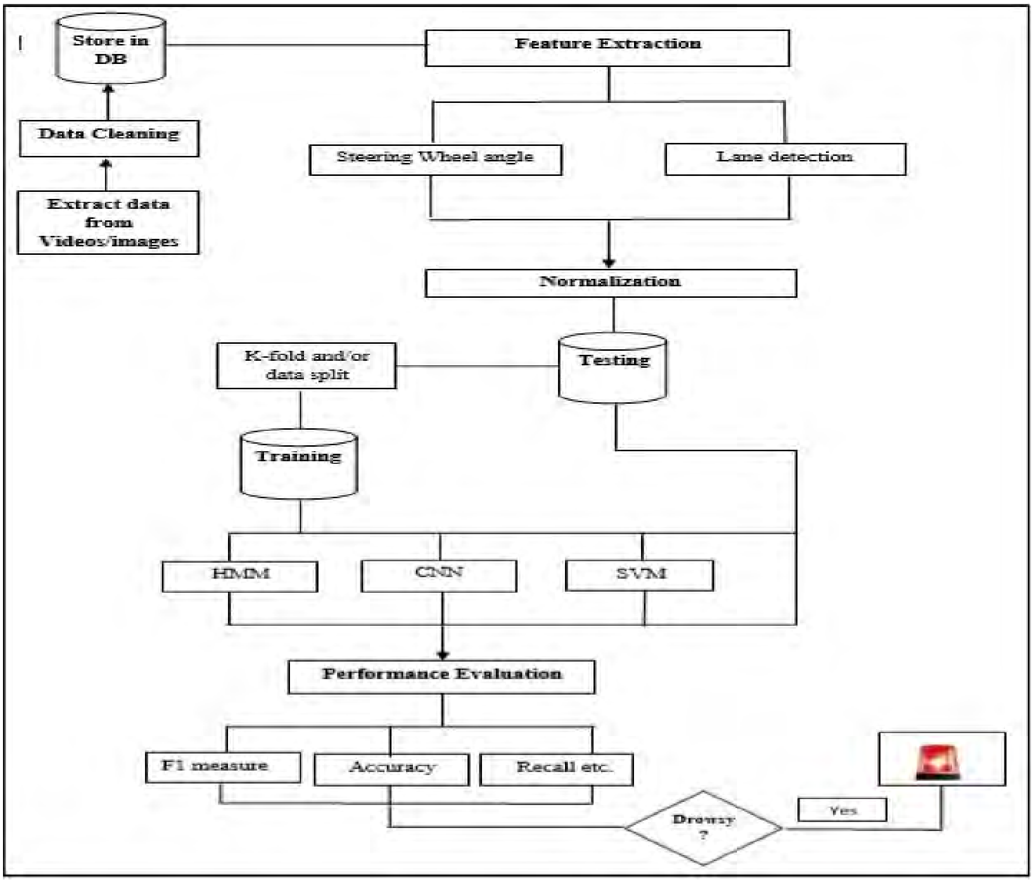

FIGURE 4. A general framework of vehicular pattern-based techniques.

changing patterns, vehicle speed variability, steering wheel angle, steering wheel grip force, etc. These measures require sensors on vehicle parts like steering wheel, accelerator or brake pedal etc. The signals generated by these sensors are used to analyze the drowsiness of drivers. The main goal of these techniques is to observe driving patterns and detect a decline in driving performance due to fatigue and tiredness. A general framework of a drowsiness detection system based on vehicular measures is represented in *Figure 4*.

A list of vehicular measures-based driver drowsiness detection systems is listed in Table 3. It is widely used in the vehicle-based measure by using the steering angle sensor for detecting the drowsiness of the driver. A single angle sensor is placed under the steering of the car used for detecting the drivers steering behaviors. During the drowsiness the driver made the steering wheel reversal, then the normal drivers. For reducing the effect of the lane change, the researcher considered only the change of little degree (0.5 to 5).

Figure 5 shows the SWM base detection technique. Normally, the behaviors of the drowsy driver also create an effect on the behavior of the driving tasks (like speed, acceleration, driver states, lane wide).

However, measuring driver fatigue, according to the vehicle movement is limited because the measurement values

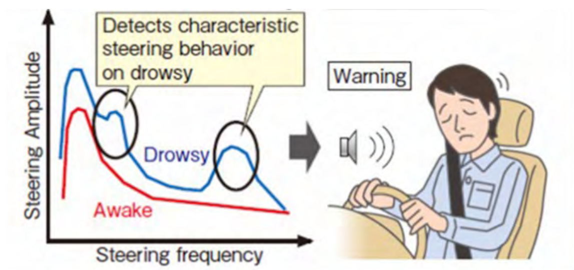

FIGURE 5. Steering movement-based detection.

can be easily affected by external factors such as the geometric characteristics of roads and weather conditions [14]. Steering wheel grip force measures seem fancy in drowsiness detection. But the problem with steering wheel grip force measures is that they are closely related with diver mood swings and road conditions as on an empty road driver may not grip the steering with that pressure with which he grips the steering on a busy road as well as grip force on a straight road is very much different with that on a dangerous mountain road. So the steering wheel grip force measures can be used for other category approaches such as eye movement for better results [15]. Sometimes drowsiness does not change the vehicular interaction, thus vehicular parameters-based techniques became unreliable in such cases.

1) REAL TIME LANE DETECTION SYSTEM

Road accidents have become common in the present era, causing the severe damage to the property and also to the lives of people travelling. There are many reasons of road accidents like: rash driving, inexperience, ignoring signboards, jumping signal etc. To address the issues, Katyal *et al.* [16] proposed the Drivers' Drowsiness Detection system. The system works in two phases: firstly, detects lane based on hough transform. Secondly, detects the drivers' eyes to detect the drowsiness. For eye detection, firstly use viola jones method to detect face, then do the image segmentation, after that otsu thresholding is done and canny edge detection is applied. The obtained results is integrated with the circle detection hough transform method to detect eyes to detect the fatigue level. It will also work in low lightning conditions. Result shows that the proposed system is useful for the drivers travelling on lengthy routes, driving late night, drivers who drink and drive.

2) TIME SERIES ANALYSIS OF STEERING WHEEL ANGULAR VELOCITY

To avoid the road accidents, Zhenhai *et al.* [17] proposed the Driver Drowsiness Detection method using time series analysis of steering wheel angular velocity. The method firstly analyzes the behavior of steering below the fatigue, then temporal detection window is used as the detection feature to determine the angular velocity of steering wheel during time-series. In the temporal window, if the detection feature satisfies the variability constraints and extent constraints, then the state of drowsiness is detected accordingly. The experiment based on real testers is performed, and results shows that the proposed method outperforms the previous methods and useful in the real world.

3) STEERING WHEEL ANGLE FOR REAL DRIVING CONDITIONS FOR DDT

To avoid road accidents, Li *et al.* [18] proposed the online detection of Drowsiness Detection System to monitor the fatigue level of drivers under real conditions using Steering Wheel Angles (SWA). The data of SWA is collected from the sensors attached on the steering lever. The system firstly extracts the features of Approximate Entropy (ApEn) from fixed sliding windows on time series of real time steering wheel angles, then the system linearizes the features of ApEn using the deviation of adaptive linear piecewise fitting method. After that the system calculates the warping distance between the series of linear features of sample data. Finally, system determine the drowsiness state of drivers using warping distance according to the designed decision classifier. The empirical analysis uses the data collected in 14.68 hrs. driving under real road conditions and evaluated on two fatigue levels: drowsy and awake. Results show that the proposed system is capable for working online with an accuracy of 78.01 % and useful for the prevention of road accidents caused by drivers' fatigue.

4) AUTOMATIC DETECTION OF DRIVER FATIGUE

To address the issue of drivers' fatigue, an online detection of drivers' fatigue using the Steering Wheel Angles (SWA) and Yaw Angles (YA) information in the real driving conditions [19] is proposed. The system firstly investigates the operation features of SWA and YA in the different states of fatigue, after that calculates the ApEn features on time series of shot sliding window, then using the dynamic time series of non-linear feature construction theory and taking features of fatigue as input, designs a 2-6-6-3 multi-level Back Propagation (BP) neural network classifier to determine the fatigue detection. For empirical analysis, 15 hours long experiment is performed in real road conditions. The experts evaluated the retrieved data and categorized in three levels of fatigue: drowsy, very drowsy, and awake. And the experiment achieves the average accuracy of 88.02 % in fatigue detection and valuable for the engineering applications.

C. PHYSIOLOGICAL PARAMETER-BASED TECHNIQUES

The Physiological parameters-based techniques detect drowsiness based on drivers' physical conditions such as heart rate, pulse rate, breathing rate, respiratory rate and body temperature, etc. These biological parameters are more reliable and accurate in drowsiness detection as they are concerned with what is happening with driver physically. Fatigue or drowsiness, change the physiological parameters such as a decrease in blood pressure, heart rate and body temperature, etc. Physiological parameters-based drowsiness detection systems detect these changes and alert the driver when he is in the state, near to sleep. The advantage of this approach is that it alerts the driver to take some rest, before the physical symptoms of drowsiness appear. A general framework of a drowsiness detection system based on physiological parameters is presented in *Figure 6*.

A list of physiological condition-based drowsiness detection system is listed in Table 4. These measures are invasive, so require electrodes to be directly placed on the drivers' body. This method sometimes gets irritating for a driver so becomes difficult to implement.

1) EEG-BASED DRIVER FATIGUE DETECTION

The drivers' fatigue detection system using Electroencephalogram (EEG) signals [20] is proposed to avoid the road accidents usually caused due to drivers' fatigue. The proposed method firstly finds the index related to different drowsiness levels. The system takes EEG signal as input which is calculated by a cheap single electrode neuro signal acquisition device. To evaluate the proposed method, data set for simulated car driver under the different levels of drowsiness is collected locally. And result shows that the proposed system can detect all subjects of tiredness.

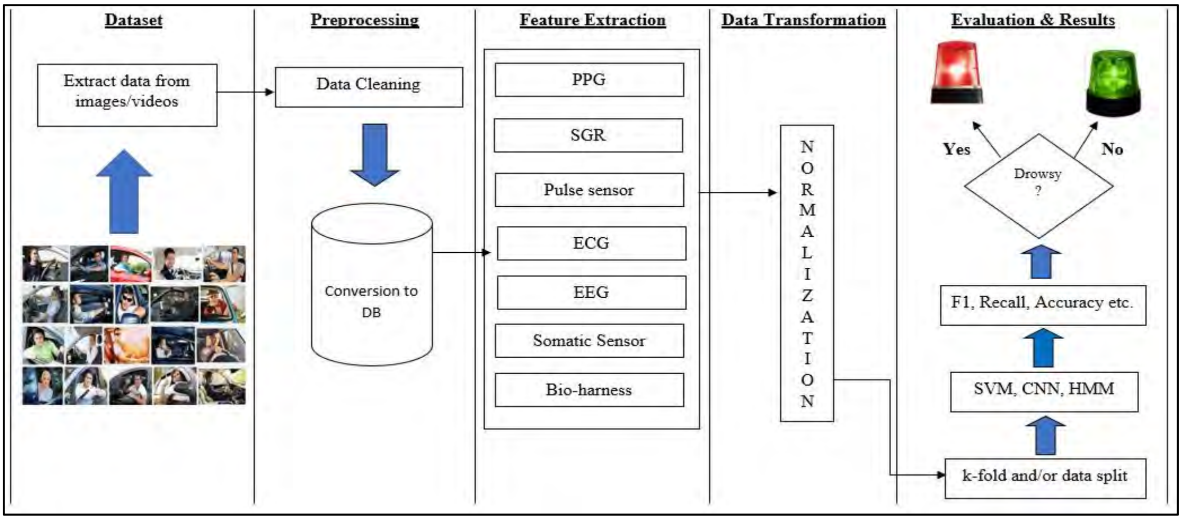

FIGURE 6. A general framework of Physiological parameters-based techniques.

TABLE 4. Physiological parameters-based drowsiness detection systems.

Ref	Biological Parameter	Sensor	Method & Classifier	Description	Efficiency
[20]	Brain physiological changes	EEG	IIR Band-pass Filter, PSD, Features Fusion	Based on low-cost Mind Wave Neuro-signal acquisition device to detect drowsiness using EEG signals.	Nil
[21]	Heart rate analysis	PPG	SVM classification, PERCLOS, Karolinska sleepiness scale (KSS), ROC analysis, wavelet transform method	Detects the driver drowsiness using heart rate analysis and wavelet method	95%
[22]	Heart pulse wave	Pulse sensor	HRV frequency domain, LF/HF ratio	Used non-intrusive sensor to sense heart pulse wave from driver finger or hand to calculate the drowsiness level.	Nil
[23]	Heart rate, respiratory rate, pulse rate, stress level	PPG, SGR	SVM, adaptive threshold method	Proposed wearable driver drowsiness detection mechanism in real driving conditions and does not require installation of components in the vehicle.	98.3%
[24]	Heart rate, breathing rate, RR interval	Bio Harness sensor	FFT, PSD, neural network classification	Works in two phases: design wearable Bio-harness sensor to detect biological parameters of driver and mobile based drowsiness detection system is designed.	Nil
[25]	Core body temperature, pulse rate	Somatic sensor, Temperature sensor LM-35, PPG	Viola- Jones algorithm, Haar Cascade classifier,	Used combination of behavioral and biological parameters to detect driver drowsiness.	80.55%
[26]	Heart rate, time domain measures, frequency domain measures	ECG, EEG	SVM, KSS	Used features extracted from EEG and ECG to detect drowsiness. Indicates that both physiological signals give better performance together.	80%

2) WAVELET ANALYSIS OF HEART RATE VARIABILITY & SVM CLASSIFIER

Li and Chung [21] proposed the driver drowsiness detection that uses wavelet analysis of Heart Rate Variability (HRV) and Support Vector Machine (SVM) classifier. The basic purpose is to categorize the alert and drowsy drivers using the wavelet transform of HRV signals over short durations. The system firstly takes Photo Plethysmo Graphy (PPG) signal as input and divide it into 1-minute intervals and then verify two driving events using average percentage of eyelid closure over pupil over time (PERCLOS) measurement over the interval. Secondly, the system performs the feature extraction of HRV time series based on Fast Fourier Transform (FFT) and wavelet. A Receiver Operation Curve (ROC) and SVM classifier is used for feature extraction and classification respectively. The analysis of ROC shows that the wavelet-based method gives improved results than the FFT-based method. Finally, the real time requirements for drowsiness detection, FFT and wavelet features are used to train the SVM classifier extracted from the HRV signals. The performance of classification using the wavelet-based features achieve the accuracy of 95%, sensitivity to 95% and specificity to 95%. The FFT-based results achieve the accuracy of 68.85. The results show that wavelet-based methods perform better than the FFT-based methods.

3) PULSE SENSOR METHOD

Mostly, previous studies focus on the physical conditions of drivers to detect drowsiness. That's why Rahim *et al.* [22] detects the drowsy drivers using infrared heart-rate sensors or pulse sensors. The pulse sensor measures the heart pulse rate from drivers' finger or hand. The sensor is attached with the finger or hand, detects the amount of blood flowing through the finger. Then amount of the blood's oxygen is shown in the finger, which causes the infrared light to reflect off and to the transmitter. The sensor picks up the fluctuation of oxygen that are connected to the Arduino as microcontroller. Then, the heart pulse rate is visualizing by the software processing of HRV frequency domain. Experimental results show that LF/HF (Low to high frequency) ratio decreases as drivers go from the state of being awake to the drowsy and many road accidents can be avoided if an alert is sent on time.

4) WEARABLE DRIVER DROWSINESS DETECTION SYSTEM

Mobile based applications have been developed to detect the drowsiness of drivers. But mobile phones distract the drivers' attention and may cause accident. To address the issue, Leng *et al.* [23] proposed the wearable-type drowsiness detection system. The system uses self-designed wrist band consists of PPG signal and galvanic skin response sensor. The data collected from the sensors are delivered to the mobile device which acts as the main evaluating unit. The collected data are examined with the motion sensors that are built-in in the mobiles. Then five features are extracted from the data: heart rate, respiratory rate, stress level, pulse rate variability, and adjustment counter. The features are moreover used as the computation parameters to the SVM classifier to determine the drowsiness state. The experimental results show that the accuracy of the proposed system reaches up to 98.02 %. Mobile phone generates graphical and vibrational alarm to alert the driver.

5) WIRELESS WEARABLES METHOD

To avoid the disastrous road accidents, Warwick *et al.* [24] proposed the idea for drowsiness detection system using wearable Bio sensor called Bio-harness. The system has two phases. In the first phase, the physiological data of driver is collected using bio-harness and then analyzes the data to find the key parameters like ECG, heart rate, posture and others related to the drowsiness. In the second phase, drowsiness detection algorithm will be designed and develop a mobile app to alert the drowsy drivers.

6) DRIVER FATIGUE DETECTION SYSTEM

Chellappa *et al.* [25] presents the Driver fatigue detection system. The basic of the system is to detect the drowsiness when the vehicle is in the motion. The system has three components: external hardware (sensors and camera), data processing module and alert unit. Hardware unit communicates over the USB port with the rest of the system. Physiological and physical factors like pulse rate, yawning, closed eyes, blink duration and others are continuously monitored using somatic sensor. The processing module uses the combination of the factors to detect drowsiness. In the end, alert unit alerts the driver at multiple stages according to the severity of the symptoms.

7) HYBRID APPROACH UTILIZING PHYSIOLOGICAL FEATURES

To improve the performance of detection, Awais *et al.* [26] proposed the hybrid method which integrates the features of ECG and EEG. The method firstly extracts the time and frequency domain features like time domain statistical descriptors, complexity measures and power spectral measures from EEG. Then using ECG, features like heart rate, HRV, low frequency, high frequency and LF/HF ratio. After that, subjective sleepiness is measured to study its relationship with drowsiness. To select only statistically significant features, t-tests is used that can differentiate between the drowsy and alert. The features extracted from ECG and EEG are integrated to study the improvements in the performance using SVM. The other main contribution is to study the channel reduction and its impact on the performance of detection. The method measures the differences between the drowsy and alert state from physiological data collected from the driving simulated-based study. Monotonous driving environment is used to induce the drowsiness in the participants. The proposed method demonstrated that combining ECG and EEG improves the performance of system in differentiating the drowsy and alert states, instead of using them alone. The analysis of channel reduction confirms that the accuracy level reaches to 80% by just combining the ECG and EEG. The performance of the system indicates that the proposed system is feasible for practical drowsiness detection system.

IV. A COMPARATIVE STUDY OF DDT

Each drowsiness detection technique has its own pros and cons. Table 5 presents the advantages and disadvantage of each drowsiness detection technique discussed above. Non-intrusive drowsiness detection techniques are easy to use but do not provide accurate results. Behavioral parameters-based techniques are affected by illumination effects while vehicular parameters-based techniques are dependent upon the weather condition and geometric conditions of roads so sometimes become unreliable. Physiological parameters-based techniques give accurate results, but their intrusive nature needs to be resolved. Researchers are working to use physiological measures in a less- intrusive way with wireless devices. Sensors are placed on the drivers' body and signals are obtained wirelessly. The electrodes are also embedded on driving seat, seat belt, seat cover or steering wheel now a day to reduce the intrusiveness [27], [28]. Less-intrusive system decreases in accuracy as compared to intrusive physiological measures because of lesser direct

TABLE 5. Pros and cons of each technique.

Technique	Parameters	Pros	Cons
Behavioral parameters-based DDT	Eye blinking, Eye closeness ratio, Head movement, Yawning	Non-intrusive Easy to use	Effected by illumination, Lightening conditions
Vehicle parameters-based DDT	Steering wheel behavior, yaw angle, lane changing pattern	Non-intrusive	Effected by geometric characteristics of roads, Unreliable
Physiological parameters-based DDT	Heart rate, pulse rate, brain activity, respiratory rate, body temperature	Efficient, reliable	Intrusive

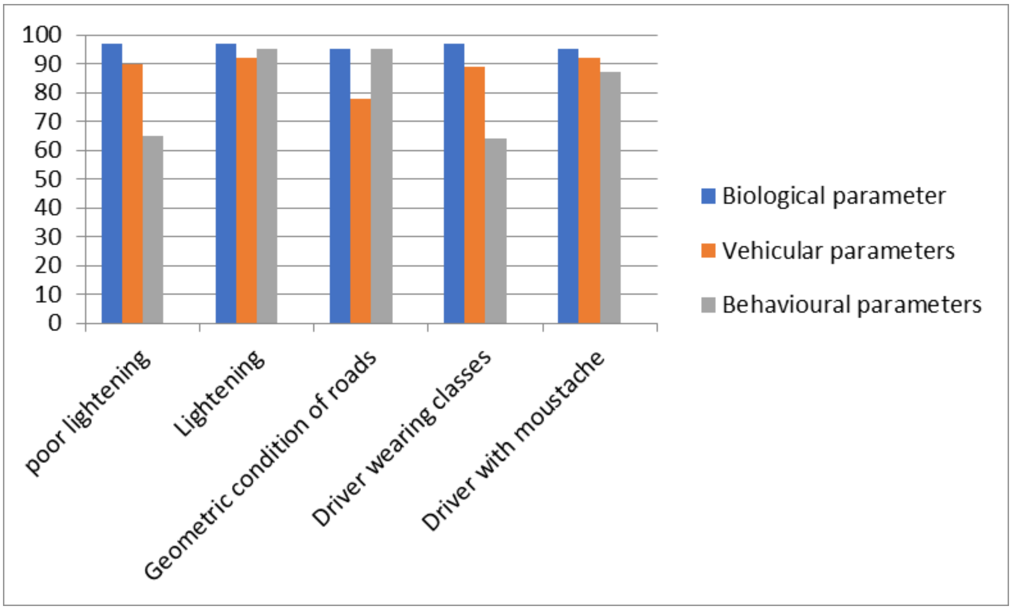

FIGURE 7. Comparative graph of DDT.

contact with the driver and errors in proper contact with electrodes in wireless communication. Still, there is a need to overcome the problems associated with physiological parameters-based detection techniques.

The detailed study of drowsiness detection systems based on behavior, vehicle and biological parameters, a comparative graph is generated in Figure 7. The efficiency of each drowsiness detection technique under certain circumstances is illustrated. The circumstances discussed here is poor lightening, proper lightening, and Geometric condition of roads, drivers with sun glasses and drivers with mustache. This analysis shows that biological parameters give stable and good results in such conditions, while the performance of behavioral parameters-based techniques reduce in poor lightening, driving with glasses and mustache. Biological parameters-based techniques are also reduced in efficiency in the bad geometric condition of roads.

V. HYBRID APPROACHES OF DDT

Physiological, behavioral and vehicular parameters for drowsiness detection can be used in combination with each other in such a way that one technique can reduce the limitations of others to increase overall accuracy of the system. A list of drowsiness detection system using hybrid parameters is listed in Table 6.

VI. CLASSIFICATION METHODS USED FOR DDT

Detail description of classification methods and their impact in drowsiness detection systems are discussed in detail. Pros and cons of each classification technique and comparative analysis of error rate in each of them is illustrated in this section of the systematic review paper. A detailed review of classification techniques, their pros and cons and later their graph-based comparison are discussed. Various types of machine learning classifiers are used for training data in the drowsiness detection system. Selection of appropriate classifier has strong impact on the efficiency of the system. Generally, SVM, HMM and CNN classifiers are used due to their high accuracy in drowsiness systems are compared to another set of classifiers such as KNN, HOG etc. Details of each of these three classifiers are discussed.

A. SUPPORT VECTOR MACHINE (SVM)

For classification and regression, SVMs are the supervised learning approaches. SVMs are firstly used for the selection of the training data set in a pre-defined form of data. In the

TABLE 6. Hybrid approaches of drowsiness detection.

Ref	Hybrid approach	Hybrid parameters	Method & Classifiers	Accuracy
[29]	Physiological, Behavioral and vehicular	Heart rate, BP, temperature, speed eyelid closure ratio	HRV color model, Fuzzy Bayesian network	94%-99%
[30]	Physiological and behavioral	Heart rate, Eye blinking duration	PSG, NASA lead method	Nil
[31]	Behavioral and vehicular	Eye status, lateral position, steering wheel angle	KSS, Neutral network, BPL algorithm.	87.78%-94.63%
[26]	Physiological and behavioral	Head movement, heart rate	Frame difference algorithm, R-peak detection algorithm	Nil
[32]	Physiological and behavioral	Heart rate, Eyelid closure ratio	PERCLOS, Burg method, Kruskal-Wallis test,	86%-96%

TABLE 7. Drowsiness detection systems using SVM.

Ref	Measure	Classifier	Description	Accuracy
[33]	Eye state	SVM	Based on the supervised learning approach.	98.4%
[34]	Eye state	Binary	Used binary method to detect the eye state	93.5%
[35]	Eye Closure	Harr Feature with SVMs	Uses the feature of the Haar algorithm with SVM's for the eye closure detection.	99.74%
[36]	Eye state	HOG and SVM	HOG is a feature extraction algorithm. SVM is used to detect the Current state of the eye.	91.6%
[37]	Eye Closure and Yawning	Binary SVM with linear kernel	Uses Binary SVM with linear kernel to detect the Eye closure and yawning.	94.5%

TABLE 8. Drowsiness detection systems using HMM.

Ref	Measures	Classifier	Description	Accuracy
[38]	EYE state	HMM	Used to detect the eye state information	99.7%
[39]	Eye blink	HMM	Used HMM to detect eye blinking rate	95.7&
[40]	Eye blinks	SVM and HMM	Detects drowsiness using eye blinking rate.	90.99%
[41]	Eye closure and other features	HMM and SVM	Detect the closures of the eye and some other features.	97%
[42]	Eye State	HMM	Used for the detection of the eye states.	95.9%
[43]	Eye state and head position	HMM	Eye state and head position are used for drowsiness detection	Nil

drowsiness detection, SVMs learns from the categorized data into the classified form of data. A number of measures are used in the detection of the driver drowsiness and the level of the driver drowsiness. A fully automatic system for the detection of the driver drowsiness is presented [33], Haar feature algorithm is used for the detection of the Eyes and face detection, SVMs is trained in the states like close, open eyes and to trigger the alarm. This framework is resulting in the accuracy of 100%, but its result is achievable in the lower frame rate, which leads us to the missed facial expression. A list of systems using SVMs classifiers are presented in Table 7.

B. HIDDEN MARKOV MODEL (HMM)

HMM is the statistical model used to predict the hidden state on the basis of observed state. In many applications, HMM is used like facial expression detection, gene annotation, modeling DNA, computer virus classification, and sequence errors. Table 8 lists the various features and approaches used by the HMM-based Downiness Detector. They proposed a new facial feature by detecting the change in the wrinkle by calculating the face intensity. IR (Infra-Red) webcam is used to eliminate changes for both day and night conditions. This system leads to the drawback because older people have a deeper wrinkle. Also, HMM technique is implemented for the tracking of eye based on color and its geometrical features, but the system fails to detect the face it driver is not looking forward and designed for the indoor conditions.

C. CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNN's are like a standard neural network that is additionally made from the neurons that incorporate with the learnable

TABLE 9. Drowsiness detection systems using CNN.

Ref	Measure	Classifier	Description	Efficiency
[44]	Visual Feature	CNN with SoftMax layer	Used voila and Jones algorithm with the CCN and SoftMax layer of the visual features.	78%
[45]	Eye gaze	CNN	Used voila and Jones algorithm with the CCN for the eye gaze.	98%
[46]	Eye State	MTCNN and DDDN	Used MTCNN and DDDN for the eye state detection	91.6%
[47]	Eye State	CNN	Used the Ada-boost and LBF and PERCLOS with CNN for the Eye State Detection	95.18%

TABLE 10. Pros and cons of classifiers.

Technique	Parameters	Pros	Cons
HMM	Probabilities, hidden states, eye state, head position, eye blinks, eye closure	Capture dependencies between the measurement, able to represent the variance of the appliance's power	Limited by the intrinsic structure
CNN	Eye state, visual features, eye gaze,	Accuracy in the image recognition	Slow to train, need lots of training data, high computational cost.
SVM	Eye Closure, Eye State, Eye Closure and yawning	Guarantees optimal, abundance of implementation, implicitly, good out-of-sample generalization.	Not suitable for large data set, less effective on nosier dataset

weights. CNN uses the layers of the spatial convolution that is considered best for the image, which show the strong correlations. CNN is used in many applications and proven itself successful such as image recognition, classification, and video analysis. CNN is firstly applied to Computer Visions by CUN and Yoshua but the best results are generated in 2012 for the object recognition shows the excellent results in Deep CNN. Representation learning is used in the proposed algorithm for the detection of driver drowsiness, here the Viola and Jones algorithm is used to detect the face. Firstly, the images are cropped in 48∗48 size image and then fed up to the outmost layer of the network contained the 20 filters, output is delivered to the SoftMax layer, but the system leads to failure because it does not consider the head pose. But another author achieved the more accurate result by using the 3D deep neutral network in which face is tackle by the combination of two more filters, the system works well even when the driver is changing the head. A list of CNN classifier-based drowsiness detection systems is listed in Table 9.

VII. COMPARATIVE STUDY OF CLASSIFICATION METHODS

Each of classifier has its own advantages and disadvantages. It is not necessary that each classifier will be suitable in every situation. Selection of appropriate classifier according to the system requirements is very significant for better efficiency and accuracy. Type of parameters for these classifiers and their pros and cons are discussed in Table 10.

A comparative analysis of test error rates of SVM, HMM, and CNN classification methods are illustrated. Lesser error rate leads to greater efficiency. Comparative analysis is presented in Figure 8. Comparative analysis of our study shows that HMM is more accurate as it has a lesser error rate as

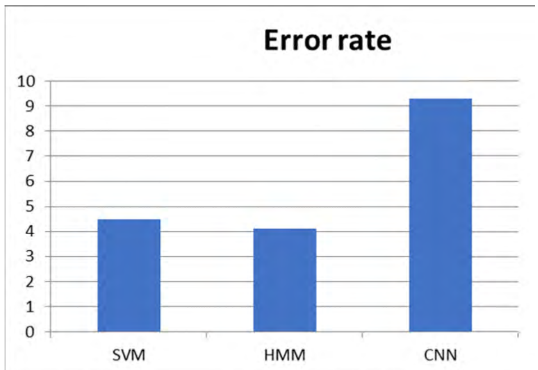

FIGURE 8. Comparative graph of classifiers.

compared to the other two. But SVM is easy to use, so it is most widely used classification method.

VIII. CONCLUSION

The main idea of this systematic review is to discover the state-of-the-art research in the drowsiness detection system. The systematic review provides details of behavioral, vehicular and physiological parameters-based drowsiness detection techniques. These techniques are elaborated in detail and their pros and cons are also discussed. The comparative analysis showed that none of these techniques provide full accuracy, but physiological parameters-based techniques give more accurate results than others. Their non-intrusiveness can be reduced using wireless sensors on the drivers' body, driving seat, seat cover, steering wheel, etc. Hybrid of these techniques such as physiological measures combined with vehicular or behavioral measures, helps in overcoming the problem associated with individual technique thus results in improved drowsiness detection results like the combination of ECG and EEG features achieves the high-performance results emphasizing the fact that combining the physiological signals improves the performance instead of using them alone.

The top supervised learning techniques have been presented. The pros and cons and comparative study of such techniques are discussed in detail. A comparative study of classifier shows different accuracy in various situations. However, SVM is the mostly commonly used classifiers which gives better accuracy and speed in most of the situations, but not suitable for large datasets. HMM shows a less error rate, but both CNN and HMM are slow in training and expensive as compared to SVM classifier.

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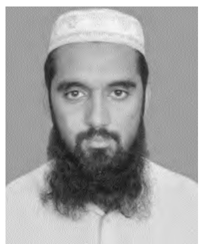

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