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Driver Drowsiness Detection using Machine Learning

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Abstract: This article provides an overview of results based on sleepy driver behaviour using machine learning techniques. Faces contain information that can be used to interpret levels of sadness. There are many facial features that can be extracted from a face to infer sleepiness. These include blinking, head movement, and yawning. However, developing a sleepiness detection system that provides reliable and accurate results is challenging as it requires algorithms. In the past, methods of detecting drowsy drivers have been tested. Methods, including reference vector machines, complex neural networks and hidden Markov models in the context of drowsiness detection. In addition, meta-analysis was performed on 25 documents using machine learning methods to detect drowsiness. This method is a most widely used method for detecting drowsiness, but the aggregate neural network performs better when compared to the other two methods. Finally, this document lists publicly available datasets that can be used as a standard for drowsiness detection.

***Keywords:* Drowsiness Detection, SVM, CNN, HMM, E.A.R., dlib, EEG. EOG, ECG.**

I. INTRODUCTION

There is substantial statistics that sleepy driving is the leading cause of road traffic accidents worldwide. Driving for long periods of time can lead to accidents if you do not rest. South Africa has the highest number of fatalities among African regions, road accidents with deaths approximately 26.6% of the 1 million populations. In addition, 1,700 people died on the roads of South Africa in the 2016 holiday season alone, an increase of 5% over 2015. South African Transportation Minister released Statistics 2014-2015, which shows that 80% of road traffic accidents involve men between the ages of 19 and 34.In addition, Minister added that women are more likely to die in road accidents as passengers, especially on public transport. In addition, statistics show that the three main causes of road accidents in South Africa are distracted drivers (such as a driver on a mobile phone call), speeding and drunk driving .

These incidents have led researchers around the world to investigate early warning methods for drowsiness and warn. In addition, many countries and government officials are looking to implement solutions to improve driving safety.

Sleepiness or drowsiness can be described as a biological state in which the body transitions from a waking state to a state. At this stage, the driver may lose concentration and cannot perform actions such as avoiding a frontal collision or braking. There are clear signs that the driver is sleepy, for example:

- Yawning frequently.
- Failure to Open Eyes.
- Shake your head forward.
- Discoloration of the face due to blood flow.

Some studies recommend combating sleepiness by taking naps between trips, drinking caffeine (coffee, energy drinks, etc.), or driving with a company. There are several measures for determining the level of drowsiness of a driver. These measures can be divided into three categories:

I. Physiological measures
II. Funds-based measures and
III. Behavioural measures

In the first category, measurements are obtained by approximating conductor conditions by adding electronics to the skin, including an electroencephalogram (EEG), an electrocardiogram (ECG), and an electrooculography (EOG) were not widely adopted due to their practical limitations. . For the latter category, driver sleepiness is analysed based on the vehicle control system, which can include transitions, steering wheel dynamics, braking pattern and sensor, lane departure. Measuring a steering wheel usually gives better results than other methods for a car. Vehicle-based methods are non-invasive, but can be unreliable in accurately detecting drowsiness, as they depend on the nature of the road and the driver's driving skills. This category includes behavioural or computer vision scores, which are generally more reliable than the vehicle-based scores because they are people-oriented rather than vehicle-oriented. In addition, behavioural measures are more non-invasive and practical than physiological measures. Here, information is captured by the camera to detect small changes in the driver's facial expression. An ongoing assessment was undertaken to understand advances in driver drowsiness detection systems. All authors reviewed the use of head movements for detecting sleepy drivers. They cover general measures that can be used to detect driver drowsiness and provide a comparative analysis of different drowsiness detection systems, vehicle safety systems. This includes the analysis of sleepiness signals and the various methods used to measure these signals, with a number of modified driver drowsiness detection systems. An overview of the driver fatigue detection system was also provided. This paper focuses on methods that can be used to prevent road traffic accidents and sleep detection method. The rest of this document is organized as follows: Part II discusses the research that we did and motivation that we got to write this paper. Part III describes a general framework for detecting sleep drivers using machine learning techniques. Part IV provides an assessment of indicators used in sleep driving detection and decision methods. Section V provides meta-analysis results and lists publicly available datasets that can be used as a reference for the drowsiness detection task. Finally, there are findings in and conclusion in Section VI.

II. RESEARCH AND MOTIVATION

This section provides an introduction to methods currently available for detecting driver sleepiness, and details the problems. Visual tracking of objects is also an important problem in computer vision. sequence giving the initial state of the lens at the top of the frame. Lucas and Kanade suggest that tracking or positioning a moving target can be performed using the pixel ratio between adjacent frames of the video sequence and offset changes. This algorithm can only detect target with a moving average size between two frames. Using the new correlation filtering method in computer vision technology, the Total Minimum Output of Square Error (MOSSE) filter proposed by Bolm et al. can generate a stable correlation filter. Though the computational efficiency of MOSSE is high, the algorithm accuracy is low, and the can provide grayscale information for only one channel. With the correlation filter, Li and Zhu used a directional gradient histogram (HOG), color mapping functions, and thus a size adapted histogram to aid in object tracking. Danelljan et al. used HOG and a discriminant correlation filter to track. SAMF and DSST solved the problem of warping or expanding when tracked target was rotating. In addition, they solve the problem that the tracker cannot adaptively track an object, and therefore the operating speed is slow. After the successful execution of deep learning algorithm, some attempts try to participate in deep learning and therefore the correlation filter to track a moving target. Therefore, these algorithms cannot track an element in real time in a very real environment. The driving force behind the definition of basic approaches to the face was to obtain important data on areas of the eyebrows, eyes, lips and nose of the face. With the advancement of deep learning, this is the first test by Sun et al. To create DCNNs from CNN to distinguish facial cue points. This calculation only recognizes 5 key points on the face above, although its speed is very fast. To achieve accuracy for face key recognition methods, Zhou et al. Used FACE ++ to rationalize DCNN, in addition, can recognize 68 key points on the face, however this calculation combines the superior model and operations of this mysterious algorithm. Wu et al. proposed a Modified Convolutional Neural System (TCNN) based on the Gaussian Mixed Model (GMM) to enhance the various CNN layers. In any case, the power of TCNN is based on outrageous information. Kowalski et al. Introduced Deep Sorting System to identify key points on the face, he prioritized over different calculations. Unfortunately, DAN requires huge models and complex dependencies. To meet prerequisites for real-time performance, we used dlib to recognize face key points.

III. PROCEDURE FOR DETERMINING DRIVER DROWSINESS

Behavioural methods measure drowsiness using a vehicle camera to monitor facial features such as eye conditions, vehicle movement, etc., head, blinking and yawning rates. Most researchers follow a general procedure to extract facial features from a camera. Once these characteristics are obtained, additional processing is applied to determine the sleepiness level , typically using machine learning techniques such as support vector machines (SVMs), neural networks (CNNs), or Hidden Markov Models (HMMs). These methods are trained using labelled functions and outputs to build models that can be used to predict sleepiness. The hardest part of the process is finding a large dataset that includes the expected differences between races and different skin pigments, which are particularly challenging due to the security and privacy concerns of publishing these race datasets for academic and commercial use.

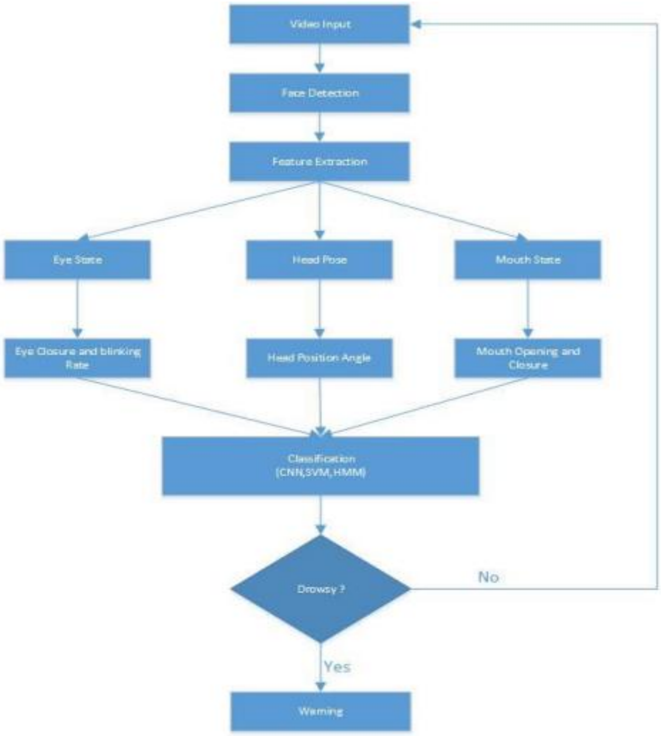

Figure 1: Process of Driver Drowsiness Detection

The figure-1 shows the general structure used for most methods for detecting driver drowsiness. Facial features commonly extracted from the driver's face include the following:

3.1 Eye proximity analysis:

Eye condition is an important characteristic is widely used to determine driver drowsiness. Sleepiness includes eye closure rate (PERCLOS) and eye contraction rate (EAR). The EAR is the ratio between the height and width of eyes and was introduced in by Soukupova and Cech in 2016. In contrast, PERCLOS closes at percent over a period of time. The main difference between the two is that the EAR classifies the ratio of the eye as it decreases, while the PERCLOS classifies the eye as open or closed.

3.2 Blink rate:

Blink rate measurement methods use blink rate to measure drowsiness. The normal frequency of flashes per minute is approximately 10. When the driver is asleep, the frequency of flashes will decrease.

3.3 Analysis of yawning:

Yawning can be caused by fatigue or boredom, in drivers it shows that they can doze off while driving. The methods can measure the width of the driver's mouth to determine the characteristics of yawning in drivers by tracking the 's mouth shape and the position of the corners of the lips.

3.4 Facial analysis:

This method uses combinations of facial features to detect drowsiness in drivers. This includes features such as forehead wrinkles and extreme head poses.

The following sequence of steps in the figure above suggests a typical procedure for determining sleepiness. The steps are as follows:

Capture Video: This is the step in which video frames from the camera or smartphone are split into a series out of images. The video is filmed in such a way that only of the driver's faces is captured.

Face Recognition: The second stage is usually aimed at detecting faces in the image frames. Viola and Jones is the most widely used algorithm for determining the driver's face in an image. However, with CNN, the entire image is typically fed to on a network with many filters and auto-retrieved features.

Object Extraction: When face detection is applied, the functions are usually extracted using various methods such as Landmark Location, Histogram Orientation (HOG), and Sample Local Binary (LBP). Feature Analysis: The extracted features can then be processed such as PERCLOS or EAR for eye analysis or mouth-based methods for yawning detection.

Classifier: The classification stage consisted of classifiers used to make decisions about driver sleepiness. If the classifier detects an indication of drowsiness based on weighted parameters, warning is triggered prompting the driver to rest.

These operating methods have some limitations as the performance of the system is affected by lighting conditions, camera movement, and the frame rate used to take the photographs of the driver's face. Changes in lighting can often be corrected with infrared (IR) cameras.

IV. MEASURES AND TECHNIQUES FOR DETECTING SOMENUS

Different studies have used different measurements to detect faces and extract details from video transmissions. This is due to the lack of a standardized dataset that could be used as a reference. Thus, it is difficult to compare approaches simply by assessing the reported accuracy. Machine learning methods for classifying different levels of sleepiness are currently being discussed along with a review of measurements making up driver's sleepiness detection system.

4.1. *Support Vector Machine (SVM)*:

The SVM is a supervised learning method for classification and regression. SVM was first introduced by Boser, Guyo and Vapnik in 1992. SVM tries to find a hyperplane that splits the training data into predefined classes. In the area of sleepy drivers, SVM is primarily used to learn how to classify different driver states based on data tagged. A lot of work has been done to leverage SVM's sleep detection capabilities. Various scores were used as metrics to measure the sleepiness level of drivers using SVMs. A comparison of these indicators is presented in Table I, and the approaches are briefly described below.

Author	*Year*	*Measure*	*Classifiers*	*Frame per second(fps)*	*Accuracy %*
G. J.AL-Anizy et al. [26]	2015	Eye closure	Haar features with SVM	60	99.74
M. Sabet et al. [27]	2012	Eye state	SVM	25	98.4
L. Pauly and D. Sankar [34]	2015	Eye state	HOG and SVM	5	91.6
A. Punitha et al. [35]	2014	Eye state	SVM	15	93.5
B. N. Manu [36]	2016	Eye closure and Yawning	Binary SVM with Linear kernel	15	94.58

Table 1: SVM technique for Drowsiness Detection

The authors proposed a fully automated system able to detect sleepy drivers. The SVM was trained to detect open or closed eyes and trigger alarm. Likewise, proposed a system that can also detect sleepy and absent-minded driver. Here, Viola and Jones algorithms are used to detect faces and a colour histogram with local binary (LBP) samples plotted for cross-frame face tracking. The system achieved 100% accuracy in face detection, but the system is likely to suffer from this approach as the low frame rate can be achieved, which can result in loss of facial expressions.

4.2. B. Hidden Markov Model (HMM):

HMMs are a statistical version used to make predictions about hidden states primarily based totally on discovered states described with the aid of using probabilities. HMMs were developed in the late 1960's and early 1970's with the aid of using Leonard Baum and colleagues. Today, HMMs have a considerable use in programs such face expression recognition, gene annotation, modelling DNA collection errors, and pc virus classification. Table II indicates the variety of capabilities and techniques used with the aid of using HMM-primarily based totally drowsiness detectors, however Zhang et al. and Choi et al. overlooked statistics required for comparing their findings and aren't blanketed on meta-evaluation stage. The authors of proposed a brand new facial function with the aid of using adjustments in wrinkles detected by calculating the nearby edge depth at the face. They used an Infra-red (IR) digital digicam to do away with illumination adjustments and permit for operation in both day and night time situations. Unfortunately, this machine can yield fake outcomes whilst is used on older humans due to the fact they have deeper wrinkles. In contrast, applied HMM strategies for eye monitoring primarily based totally on colour and geometrical capabilities. For illumination elimination, authors used a two level Lloyd-max quantization meant to be strong to illumination adjustments. Unfortunately, this machine is designed for indoor situations and it fails to come across the face if the driving force isn't going through forward.

Author	Year	Metric	Classifiers	Frame per second(fps)	Accuracy %
Zhang et al. [31]	2015	Eye state	HMM	N/A*	95.9
A. Bagci and R. Ansari [33]	2004	Eye state	HMM	3	99.7
Pan et al. [37]	2007	Eye Blink	HMM	25	95.7
I. H. Choi et al. [21]	2016	Eye state and Head position	HMM	16–20	N/A*
E. Tadesse et al. [38]	2014	Eye closure and other features	HMM and SVM	20	97
Y. Sun et al. [39]	2013	Eye blinks	SVM and HMM	61	90.99

Table 2: Driver Drowsiness Detection through HMM

4.3. Convolutional Neural Network (CNN):

The CNN is similar to a conventional neural network, which also consists of neurons, including training weights. The CNN uses spatial complexity classes corresponding to the images showing strong spatial correlations. CNN has proven successful in areas such as image recognition, video analysis, and classification. Obviously, in 2012, when deep accumulation neural networks showed excellent results in recognizing objects. Table III provides an overview of CNN methods based on the detection of drowsiness. Proposed an algorithm for detecting drowsiness of drivers using representative training. Here, the popular Viola and Jones algorithms were used for face recognition. The images were cropped to 48 * 48 square images and fed to the first level of the network of 20 filters. The entire network consists of two layers. CNN output is passed to softmax for classification. The system does not account for head position changes and may lead to errors. However, all authors used deep 3D neural networks to obtain more accurate results. Here, the face is tracked using a combination of the kernelized correlation filter with the Kalman filter to effectively track the face. The selected areas of the face are then converted to 3DCNN, which is then processed. Magnification is converted to a gradient for classification. This system works great even when the controller changes head position.

Author	Year	Metric	Methods	Classifiers	Accuracy %
F. Zhang et al. [46]	2017	Eye state	AdaBoost, LBF and PERCLOS	CNN	95.18
K. Dwivedi et al. [44]	2014	Visual features	Viola and Jones algorithm	CNN with softmax Layer	78
A. George and A. Routray [47]	2016	Eye gaze	Viola and Jones algorithm	CNN	98.32
B. Reddy et al. [48]	2017	Eye state	Eye state and mouth	MTCNN and DDDN	91.6

Table 3: CNN Technique for Driver Drowsiness Detection

V. PROPOSED SYSTEM

The proposed HOG- Linear SVM system, targets to successfully identify the sleepy driver and wake him up immediately by sounding an alarm. This system needs a camera to capture the live running video of the driver behind the wheel. This video series is analysed for sleepiness in the driver.

5.1. Initial camera setup:

The first step in the system is to install the camera in front of the driver so that we can successfully capture the driver's face for further processing. The camera must be configured in such a manner that it is not intrusive, that is, the does not interfere with the driver on the road, and the must be properly positioned so that the face is clearly captured and thus provides accurate results. The Raspberry Pi can be used to integrate components into such a system, but since the Raspberry Pi comes with little RAM, the entire load to do all system operations, rendering the GUI, and handling the build process for activity would be too much. If dlib is compiled on Raspberry Pi, an error message will be displayed. But in this can be fixed if we update our Raspberry Pi system to request maximum memory and update the paging file to size. The camera can also connect to a standard laptop. Once this hardware configuration is complete, we can proceed to sleep detection algorithm to determine which drivers are running sleepy through the video stream from camera.

5.2. Face recognition:

The next step is to detect the controller's face displayed in the video stream. For face detection we use histogram-oriented gradients (HOG) function, which uses the gradient address distribution as a function that is more accurate and faster than other algorithms. Gradient Histogram (HOG) Image Descriptor and Linear Support Vector Machine (SVM) can be used to train high-precision object classifiers or in specific studies of Human Detector. In this case, we will configure it to work for face recognition. The principles followed by the face descriptor HOG is that the look and shape of a local object can often be very well characterized by a local distribution of gradients or face directions, even if the exact gradients or the position of the edges are not known. In practice, this can be accomplished by dividing the image window into -Small spatial areas ("cells"), for each of which a local one-dimensional histogram of gradient directions or edge directions on cell pixels is accumulated. The combined inputs of plot form a view. For better light invariance, shadows, etc. It is also useful to normalize contrasts of local responses before using them. This can be successfully achieved by dividing the local "energy" histogram into slightly larger regions of space. ("Block") and use the result of this to normalize all the cells in the blocks of normalized descriptors will be named as histogram-oriented gradient (HOG) descriptors. By covering the detection window with a dense (actually overlapping) mesh of HOG descriptors and using their Feature vector included in the standard based on linear SVM window classifier gives us detection sequence person. See Figure 2.

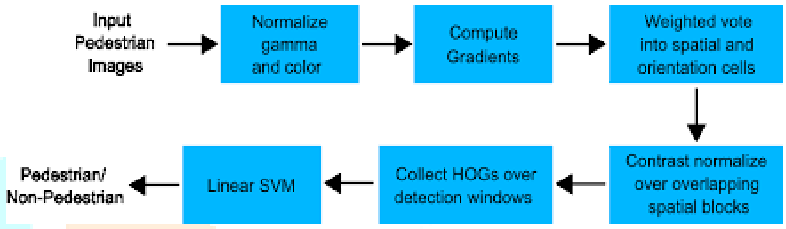

Figure 2: HOG and Linear SVM

5.3. Detection and Extraction of Facial Traces:

The next step after successfully detecting faces is to recognize facial landmarks and retrieve desired facial landmarks. There are many ways to find facial landmarks, but most methods work with marking and locating areas such as the right eyebrow, left eyebrow, right eye, left eye, nose, mouth, and jaw with a set of regression trees. This detection algorithm is part of the dlib library. This method works by manually assigning specific coordinates (x, y) to areas around of each face structure and using this set of trained face landmarks in the image. This detector is available in the dlib library, which estimates the position of 68 (x, y) coordinates specific to each individual face structure. The 68 coordinates of facial landmarks can be shown in the following figure. Render 68 face coordinates of waypoints we can locate and extract the eye areas with the method using the defined face indices for areas of the left and right eyes. The right eye can be accessed using coordinates [36.42] and the left eye can be accessed using coordinates [42.48]. These indices are part of the 68-point iBUG 300w dataset [21]-[23], in which a face landmark detector is available from the trained dlib library. Regardless of which dataset is used, if the shape predictor is trained on exactly input training data, the same dlib structure can be used. The 68 facial landmark is shown in the figure 3.

Figure 3: 68 Facial Landmark Coordinates

5.4. Eye Aspect Ratio (E.A.R) Computation:

To detect if the driver‘s eye is closed or not, and to also successfully differentiate between standard eye blinks and eyes being closed during a state of drowsiness, we make use of an algorithm that uses a facial landmark detector. We compute a single, scalar quantity called eye aspect ratio (E.A.R) that reflects whether the eye is closed or not. For each video frame, the landmarks of the eye regions are found, and the Euclidean distance using the height and width of the eye is calculated, which is the eye aspect ratio (E.A.R).

$$EAR = \frac{||p2 - p6|| + ||p3 - p||5}{2||p1 - p4||}$$

Where p1, p2, p3, p4, p5, and p6 are the 2D landmark locations, depicted in the Figure.

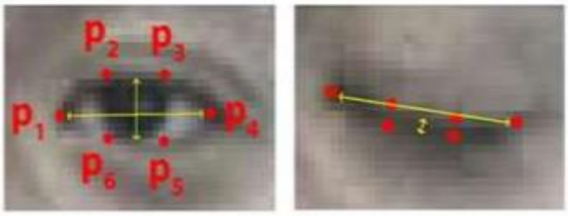

Figure 4: Automatically Detected Open and Closed eyes with Landmark p(i)

5.5. Sleepiness Assessment and Counter Measures:

After successfully calculating the E.A.R, we can use these values to assess the driver's sleepiness. The E.A.R value remains constant when the eyes of conductor are open, but begins to decrease to a value of near zero when the eyes begin to close. The E.A.R. is independent of head and body position. So, using these results, we can classify the eye condition as open when E.A.R is zero or close to 0, otherwise the state is determined to be closed. The last part is to decide whether or not to sound the alarm. The average duration of human blinks is 100400 milliseconds, so if driver is asleep, its blink time exceeds. In our system, threshold is set to 5 seconds, and if it is crossed, signal is issued and a warning appears.

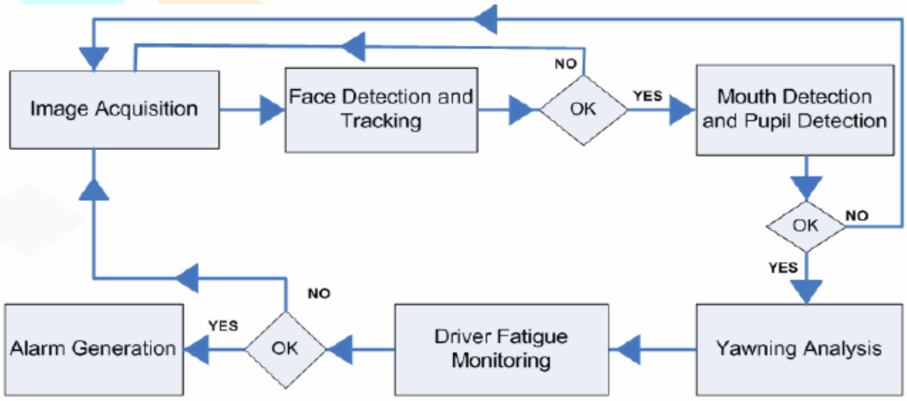

Figure 5: Driver Drowsiness Detection Block Diagram

VI. META ANALYSIS

Although much work has been done to the date, there is yet significant room for improvement in the driver sleepiness detection system. It is therefore not easy to compare the two. In addition, the datasets used to test these systems tend to be limited and often collected in a controlled environment, which can lead to failures in scenarios in the real world. In an attempt to ensure a fair comparison, meta-analyses were performed using 25 articles collected for this literature review. The articles collected mainly used classification accuracy to compare system performance. A performance score of shows that CNN returns more accurate results than SVM and HMM. The SkillingsMack nonparametric test was performed with a Chisquare value of 6.66, a significant p = 0.035709, which indicates that there is a difference in performance between the tests performed.), ZJU Blink Database, Yawn Detection Dataset (YawnDD), EyeChimera, and NTHU drowsy driver detect video datasets. Below figure shows the squared precision obtained for each method, with raw data and associated databases. CNN seems to be superior to other approaches, but comparing HMM and SVM is difficult due to lack of data. It should be noted that these trials are based on published samples, which may bias or favour the methods proposed in the reported literature. Among all documents, SVM is the most widely used classifier, followed by CNN and HMM. It is understood that there has been a rise in sleepy driving use of CNN since 2012, along with an increase in deep learning elsewhere machine vision.

VII. CONCLUSION

There are many behavioural and machine learning techniques that can be used to detect driver sleepiness. This article provides an overview of approaches to detecting driver sleepiness using machine learning methods and discusses a range of characteristics and metrics used for classification. The main purpose of these systems is to detect a slight change in the driver's facial expression, which contains information about drowsiness. While there are different methods that can be used to measure sleepiness (behavioural, physiological, and vehicle-based), this review focuses on the behavioural approach as they are non-invasive, work over a wide range of lighting conditions, and not necessarily change media . This article discusses machine learning methods such as SVM, CNN and HMM. Unfortunately, it is very difficult to compare these approaches as there are currently a limited number of normalized datasets to do so. In an attempt to correct this, a meta-analysis was carried out. This analysis highlights the effectiveness of CNN outperforming other approaches, but also shows that is required for large datasets and tests for detecting drowsiness. Further work will focus on the creation of dataset, which includes a range of different races, in order to make a more reliable comparison of sleepiness.

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