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A Review of Recent Advancements In The Detection Of Driver Drowsiness

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ABSTRACT
This paper overviews the literature on detecting driver drowsiness using behavioral metrics and machine learning approaches. Faces provide information that can be utilized to deduce sleepiness levels. Many facial features can be derived from the face to determine the level of tiredness. Eye blinks, head motions, and yawning are examples of these. The construction of a sleepiness detection system that produces reliable and accurate results, on the other hand, is a complex endeavor that necessitates precise and robust algorithms. In the past, various strategies for detecting driver drowsiness were investigated. The new advent of deep learning necessitates re-evaluating these algorithms' accuracy in detecting tiredness. As a result, this research examines machine learning techniques such as support vector machines, convolutional neural networks, and hidden Markov models in the context of drowsiness detection. Finally, this work provides a list of publicly available datasets that can be utilized as sleepiness detection benchmarks.

1. INTRODUCTION

Despite recent road and vehicle design advancements for driver safety, the total number of major automotive accidents has recently increased. According to data from the National Highway Traffic Safety Administration (NHTSA), 56,000 sleep-related vehicle collisions injure more than 40,000 Americans yearly [1]. According to the Sleep Research Center (UK). Several research studies have provided various estimations of sleep deprivation's impact on traffic accidents. Driver distraction or inattention is also a significant issue for safe driving [2]. In conclusion, driver inattention and sleepiness are critical contributors to traffic accidents. If you do not take breaks when driving for long periods, you can end up in an accident. These tragedies have prompted academics worldwide to look at techniques for detecting and alerting sleepiness early on. Furthermore, several countries and government leaders are focusing on putting measures in place to increase driving safety. Drowsiness, often known as sleepiness, is a biological state in which the body is transitioning from an awake to a sleeping state. A motorist may lose attention at this point and be unable to perform steps such as avoiding head-on crashes or braking on time. There are several telltale symptoms that a motorist is sleepy, including yawning continuously, inability to keep eyes awake, tilting the head forward, changes in facial color owing to blood flow, and Leaving street lanes repeatedly [3]. On the other hand, ways to combat fatigue, taking naps between journeys, ingesting caffeine (coffee, energy drinks, etc.), or driving with an assistant partner [4].

Researchers have recommended several strategies for detecting these indicators of tiredness as soon as feasible to avert accidents. These measures are divided into four categories [5]:

- Image-based measures are obtained by analyzing the driver's movements and facial expressions with a camera.
- Biological-based measures, which are related to the driver's bio-signals and can be recorded by placing special sensors on the driver's body
- Vehicle-based measures rely on monitoring the vehicle's behavior and movement.

- Hybrid-based measures, which combine two or more of the above measures.

This article explains how to apply machine learning approaches to create accurate and reliable recommendations for driver sleepiness detection systems.

2. THE MEASURING OF DRIVER DROWSINESS

To ensure safe driving, a reliable driver monitoring system must be built, informing the driver if he or she is tired or inattentive. We will talk about how to assess tiredness in this section.

The term "drowsy" means "prone to falling asleep." Compared to a normal condition, a sleepy driver who falls asleep behind the wheel has a lower level of attentiveness. A motorist may fall asleep for a few seconds and be completely unaware of it. This is referred to as micro-sleep. Micro-sleep can last anywhere from a few seconds to 30 seconds or even longer. This is enough time to stray from one's lane and collide with a tree or another vehicle. As a result, the driver's sleepiness level, which happens when the driver switches from awake to sleepy, should be monitored.

We must extract driver behavior information as well as driving behavior information to determine the driver's level of tiredness. Visual and non-visual information combine to make up driver behavior data. Eye closure, blinking, yawning, head position, and facial expression are visual traits [6, 7]. The frequency of eye blinking and the extent to which the eyelids open are good indicators of weariness [6]. Heart, pulse, and brain activity are examples of non-visual elements. Driver sleepiness is detected by physiological markers such as the electrocardiogram (ECG), electromyogram (EMG), electro-oculogram (EoG), and electroencephalogram (EEG)[8-10]. Deviations from lane position, vehicle speed, steering movement, and pressure on the accelerator pedal, among other things [11, 12].

3. PROCESS FOR DETECTING DROWSINESS IN DRIVERS

To determine drowsiness levels, behavioral approaches employ mounted cameras in the automobile to analyze face traits such as eye state, head movement, blinking rate, and yawning.

Most researchers use a standard procedure to extract face characteristics from a video stream. Following the collection of these characteristics, machine learning techniques such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Hidden Markov Models are used to estimate the amount of sleepiness (HMM).

These strategies are used to train models that can predict sleepiness using characteristics and tagged outputs. Finding an extensive dataset covering the predicted diversity among races and skin colors is the most challenging component of this approach because of the security and confidentiality difficulties that occur when publishing datasets for academic and commercial use. This is a challenging task. Figure 1 depicts a similar foundation for most techniques for detecting driver sleepiness.

The following facial traits are frequently derived from a driver's face from the Analysis of eye closure, the driver's eye condition is an important aspect commonly used to identify tiredness. The Percentage of the eye closure (PERCLOS) and eye aspect ratio are two methods for determining the amount of sleepiness (EAR).

Soukupova and Cech established EAR in 2016 [13], which is the ratio between the height and breadth of the eye. PERCLOS, on the other hand, is the Percentage of eye closure over time. The main distinction between the two is that EAR categorizes the eye's ratio as it declines, whereas PERCLOS categorizes whether the eye is open or closed.

On another side, The frequency of eye-blinks is used to evaluate drowsiness in methods that measure the blinking rate. The blinking rate lowers when the driver is tired. The average blink rate per minute is around ten. We can also use yawning as caused by exhaustion or boredom, which might suggest that a motorist is about to fall asleep behind the wheel. By tracking mouth shape and position of lip corners, methods can detect yawning tendencies in the driver by measuring the width of the mouth [14]. Finally, we can useed Facial expression analysis which this method uses a combination of many facial features to identify tiredness in a driver. This includes traits like forehead wrinkles and exaggerated head postures [15].

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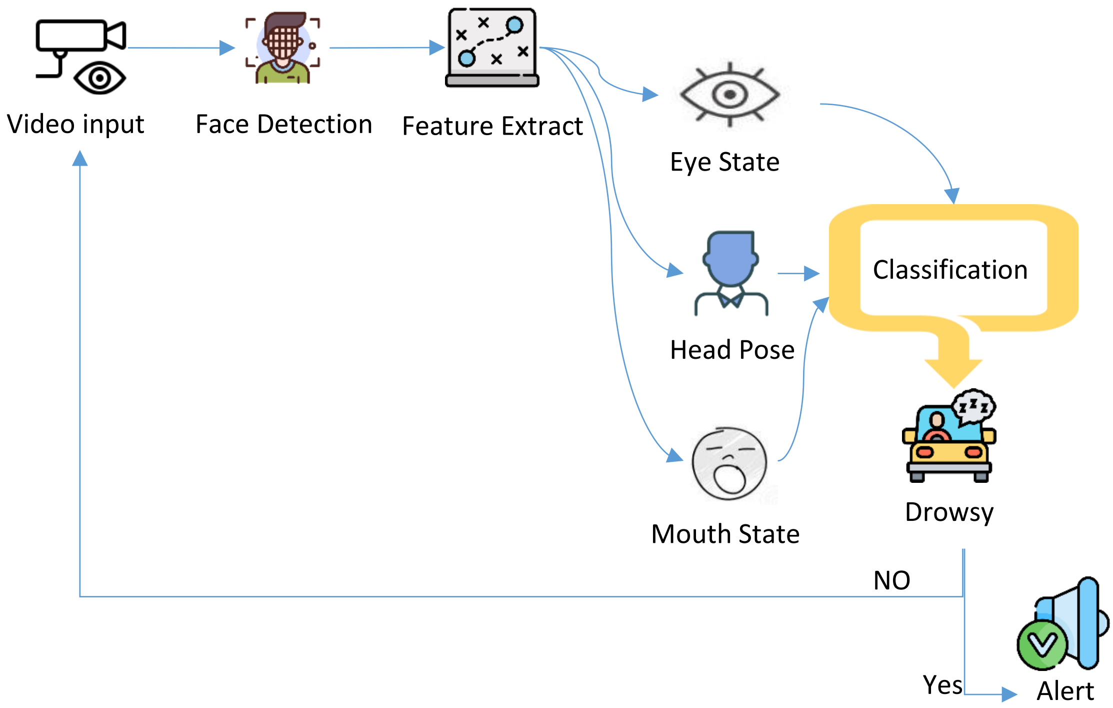

Figure 3-1 : Process for detecting driver drowsiness.

4. MEASURES UTILIZED FOR DETECTION OF DROWSINESS.

Researchers analyzed driver reactions and vehicle driving behaviors in an attempt to detect different degrees of tiredness. We present an overview of the four frequently used metrics stated in the above introduction section, in this part.

Figure 2 shows a driver drowsiness detection system's main block structure and data flow that may use any of the four measurements stated above. The target characteristics are retrieved from the collected signals using an appropriate sensing device once the data is obtained.

This phase is crucial since it streamlines the system's input by removing useless data and retrieving the necessary ones. Some plans may use feature transformation or dimensionality reduction to project the data into a different domain, making it easier to analyze or reducing the computational load. The fourth phase uses multiple feature selection techniques, such as backward or wrapper feature selection approaches, to choose the best features that correspond to sleepiness. After then, in the training phase, machine learning (ML) or deep learning is employed to create a model that is used to categorize the driver's state. In the testing phase, the trained model is used to identify the driver's degree of tiredness and, if necessary, take action, such as activating an alarm or advising the driver to take a break.

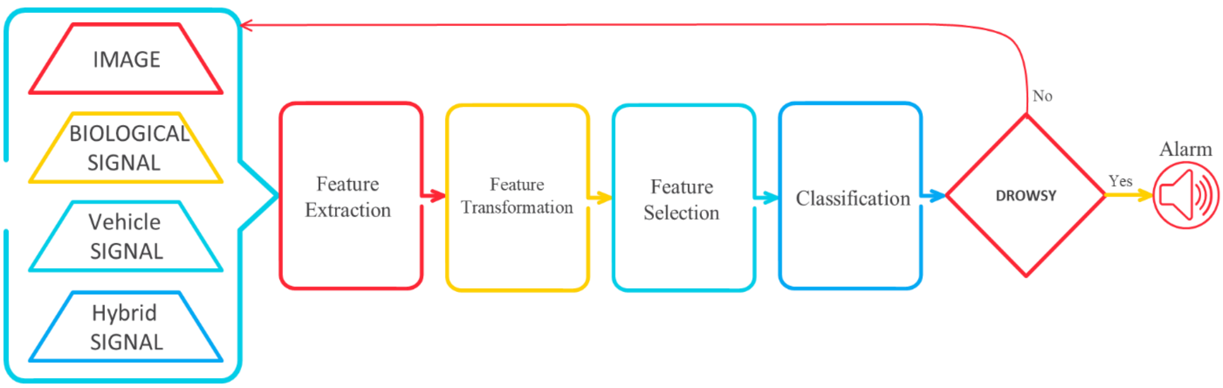

Figure 2 Data flow from drowsiness detection systems for drivers.

4.1. Measures based on images

Some sleepiness signals are apparent, and cameras or visual sensors can capture them. The driver's facial emotions and movements, particularly his head movements, are among them. These signals are referred regarded as visual or image-based measures [16] in the literature. We refer to them as image-based measures in our work to emphasize that these measures frequently result in features derived from images or videos. It's also worth mentioning that image-based measurements are a subgroup of physical [17] or behavioral [5] measures.

Body motions acquired from movies or motion sensors such as gyroscopes and accelerometers are referred to as physical and behavioral metrics [18, 19].

The National Tsing Hua University Drowsy Driver Detection public dataset of the National Tsing Hua University Computer Vision Lab [20] is a commonly used dataset among Image-based Drowsy Driver Detection systems. Because of the numerous circumstances and sleepiness aspects, it covers, this dataset has grown in popularity. The collection contains recorded videos for 36 participants of various ethnicities and includes training, assessment, and testing datasets. It also takes into account situations where the driver is wearing sunglasses or glasses, day and night lighting conditions, and a range of simulated scenarios, such as Normal driving, Yawning, Slow blink rate, Falling asleep, And bursting out laughing.

4.2. Measures based on biology

Many biological signs, including brain activity, heart rate, breathing rate, pulse rate, and body temperature signals, have been utilized to identify the driver's tiredness [17]. These biological cues, also called physiological measurements [5], be more accurate and dependable than other methods for identifying sleepiness. This precision is due to their capacity to detect early biological changes in the case of tiredness, notifying the driver before any physical indicators of fatigue manifest.

The EEG signals reveal the actions of the brain. They are an excellent source of knowledge about brain physiology. EEG data can reflect changes in a drowsy driver's brain activity, allowing for early identification of tiredness; therefore, this method has gotten much attention in recent years.

4.3. Measures based on the vehicle

This strategy is based on the analysis and tracking of driving patterns. Every driver develops their driving style. As a result, a sleepy driver's driving behaviors may be separated from those of an awake driver. Due to the difficulties of adequately detecting sleepy driving state traits, vehicular-based metrics are the least researched methodologies [8]. As a result, numerous researchers [24,113,114] integrate this metric with image-based or biological measurements.

Steering wheel angle (SWA) and lane departure are the two most commonly discovered vehicle-based measurements used to detect driver tiredness. Tracking lane curvature, location, or curvature derivative can be used to detect a lane departure. Angle sensors linked to the steering wheel can be used to measure the SWA. However, data gathered may change from one approach to the next.

4.4. Measures based on the Hybrid

A hybrid Drowsy Driver Detection system extracts drowsy characteristics using an image-and biological-and vehicle-based data, aiming to create a more robust, accurate, and reliable Drowsy Driver Detection System. there are the recently proposed hybrid Drowsy Driver Detection systems such as Driver assistance system based on image- and vehicle-based features, Biomedical and motion sensors, EEG signals' spectral, head movement, and blink analysis, Drowsy Driver Detection using image-, biological-, and vehicle-based features fusion, Combined EEG/NIRS Drowsy Driver Detection system, Drowsy Driver Detection using EEG, EOG, and contextual information, and Drowsy Driver Detection with a smartphone.

5. TECHNIQUES FOR DROWSINESS DETECTION

Various methods for recognizing a face and extracting information from a video stream have been employed in various research. Regrettably, most of these research employ different datasets, which may favor their methods. The absence of consistent datasets that can be used as a benchmark is the reason behind this. As a result, comparing techniques based only on stated accuracies is difficult.

Machine learning algorithms for classifying different levels of tiredness, as well as a review of metrics that make up a driver drowsiness monitoring system, are now reviewed.

5.1. Support Vector Machines (SVM)

SVMs are classification and regression supervised learning algorithms [21, 22]. Boser, Guyo, and Vapnik were the first to present SVMs in 1992 [23]. SVMs look for a hyperplane that divides training data into pre-defined categories. SVMs are utilized mainly in driver sleepiness to learn to categorize distinct states of the driver using labeled data.

Much work has gone into attempting to use SVMs to identify tiredness. SVMs have been used to determine a driver's tiredness level using various measurements as features.

The authors of [24] presented a wholly automated approach for detecting driver sleepiness. The Haar feature method [24] was employed for face detection and eye extraction. After that, an SVM was trained to distinguish between open and closed eyes and sound an alert. Similarly, [25] presented a technique for detecting driver inattention and tiredness. Face identification was made using the Viola and Jones technique, and color histograms containing Local Binary Patterns (LBP) were employed to follow the face over frames. Face identification accuracy was 100 percent; however, the technology's low frame rate might result in missing facial emotions.

Also the authors of [26] presented a technique for detecting Eye closure and Yawnin using Binary SVM with Linear kernel. The accuracy was 94.5 percent.

5.2. Hidden Markov Model (HMM)

Hidden Markov models (HMM) are statistical models used to produce hidden state predictions based on observable states described by probability. Leonard Baum and associates [27] created HMMs in the late 1960s and early 1970s. Face expression recognition, gene annotation, modeling DNA sequence mistakes, and computer virus classification are just a few of the areas where HMMs are used nowadays [28, 29].

Using changes in wrinkles identified by estimating the local edge intensity on the face, the authors of [30] presented a new facial characteristic. They employed an infrared (IR) camera to minimize lighting variations and allow operation at any time of day or night. Unfortunately, this method might produce erroneous findings when used on older adults with deeper wrinkles. on the other hand, color and geometrical cues were used to construct HMM approaches for eye tracking. The authors utilized a two-level Lloyd-max quantization for illumination removal that was designed to be resilient to variations in illumination [31]. Unfortunately, because this device is meant for indoor use, it will not identify the driver's face if he or she is not facing forward. Also the authors utilized Eye closure and other features in 20 Frame per second to construct HMM and SVM approaches, the system had a 97 percent accuracy rate [32].

5.3. Convolutional Neural Network (CNN)

Convolutional Neural networks (CNN) are comparable to traditional neural networks in that they are built up of neurons with learnable weights. CNN's employ spatial convolutional layers best suited for pictures with significant spatial correlations. Image identification, video analysis, and classification have been effective with CNNs [33]. Yann Le Cun and Yoshua Bengio were the first to use CNNs in computer vision [34]. However, it was not until 2012 that deep convolutional neural networks exhibited great results in object recognition [35] that the exceptional performance of CNNs in computer vision became clear.

[36] suggested a representation learning-based system for detecting driver sleepiness. The faces were detected using the well-known Viola and Jones method. Images were reduced to 48*48 squares and sent into the network's first layer, including 20 filters. There are two tiers throughout the entire network. For classification, the CNN's output was transferred to a softmax layer. As a result, this approach may fail since it does not account for changes in head posture. So, the authors of [37] employed a 3D deep Neural Network to acquire more accurate findings. A combination of a Kernelized Correlation filter and a Kalman filter [37] is used here for robust face tracking. The extracted facial areas are then sent into a 3D-CNN, which is subsequently classified using a gradient boosting machine. This method functions well even if the driver's head position changes [36]. While the authors utilized Eye gaze to detection drowsy through Viola and Jones algorithm in CNN's Classifiers to obtain accurcy around to 98.32% [38].

6. CONCLUSION

Due to technological advancements in IoT, sensor miniaturization, and artificial intelligence, the drowsiness detection field has significantly improved over the last decade. This report provided a comprehensive and up-to-date assessment of driver sleepiness detection technologies established in the previous 10 years.

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It has detailed and classified the four primary techniques for creating Drowsy Driver Detection systems, depending on the types of suggestive sleepiness characteristics used. The four categories are image, biological, vehicle, and hybrid-based systems.

A study of approaches to driver sleepiness detection using machine learning algorithms was also included in this research. This study examines machine learning techniques such as SVM, CNN, and HMM. These systems' principal purpose is to detect a little shift in a driver's facial expression that carries sleepiness information. The construction of a sufficient dataset encompassing various races will be the focus of future studies to make more valid sleepiness comparisons.

REFERENCE

1. N. H. T. S. Administration, "Traffic Safety Facts 2006: A Compilation of 28 Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates 29 System, pp 50," ed: National Highway Traffic Safety Administration National Center for …, 2006.
2. Y. Liang, Detecting driver distraction. The University of Iowa, 2009.
3. U. S. D. Center, "Drowsy Driving," 2017.
4. D. A. R. Eric Suni, "Drowsy Driving," 2022.
5. M. Ramzan, H. U. Khan, S. M. Awan, A. Ismail, M. Ilyas, and A. J. I. A. Mahmood, "A survey on state-of-the-art drowsiness detection techniques," vol. 7, pp. 61904-61919, 2019.
6. Q. Ji, Z. Zhu, and P. J. I. t. o. v. t. Lan, "Real-time nonintrusive monitoring and prediction of driver fatigue," vol. 53, no. 4, pp. 1052-1068, 2004.
7. S. Abtahi, B. Hariri, and S. Shirmohammadi, "Driver drowsiness monitoring based on yawning detection," in 2011 IEEE International Instrumentation and Measurement Technology Conference, 2011, pp. 1-4: IEEE.
8. A. Sahayadhas, K. Sundaraj, and M. J. S. Murugappan, "Detecting driver drowsiness based on sensors: a review," vol. 12, no. 12, pp. 16937-16953, 2012.
9. M. Akin, M. B. Kurt, N. Sezgin, M. J. N. C. Bayram, and Applications, "Estimating vigilance level by using EEG and EMG signals," vol. 17, no. 3, pp. 227-236, 2008.
10. A. Kokonozi, E. Michail, I. Chouvarda, and N. Maglaveras, "A study of heart rate and brain system complexity and their interaction in sleep-deprived subjects," in 2008 Computers in Cardiology, 2008, pp. 969-971: IEEE.
11. C. C. Liu, S. G. Hosking, and M. G. J. J. o. s. r. Lenné, "Predicting driver drowsiness using vehicle measures: Recent insights and future challenges," vol. 40, no. 4, pp. 239-245, 2009.
12. K. Torkkola, N. Massey, and C. Wood, "Driver inattention detection through intelligent analysis of readily available sensors," in Proceedings. The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No. 04TH8749), 2004, pp. 326-331: IEEE.
13. B. Reddy, Y.-H. Kim, S. Yun, C. Seo, and J. J. I. C. Jang, "Real-Time Eye Blink Detection using Facial Landmarks," 2017.
14. M. S. B. Zainal, I. Khan, H. J. R. J. o. A. S. Abdullah, Engineering, and Technology, "Efficient drowsiness detection by facial features monitoring," vol. 7, no. 11, pp. 2376-2380, 2014.
15. I.-H. Choi, C.-H. Jeong, and Y.-G. J. A. S. Kim, "Tracking a driver’s face against extreme head poses and inference of drowsiness using a hidden Markov model," vol. 6, no. 5, p. 137, 2016.
16. J. D. Fuletra, D. J. I. J. o. R. Bosamiya, I. T. i. Computing, and Communication, "A survey on drivers drowsiness detection techniques," vol. 1, no. 11, pp. 816-819, 2013.
17. G. Sikander and S. J. I. T. o. I. T. S. Anwar, "Driver fatigue detection systems: A review," vol. 20, no. 6, pp. 2339-2352, 2018.
18. L. B. Leng, L. B. Giin, and W.-Y. Chung, "Wearable driver drowsiness detection system based on biomedical and motion sensors. In 2015 IEEE SENSORS. 1–4," ed: IEEE, 2015.
19. A. Mehreen, S. M. Anwar, M. Haseeb, M. Majid, and M. O. J. I. S. J. Ullah, "A hybrid scheme for drowsiness detection using wearable sensors," vol. 19, no. 13, pp. 5119-5126, 2019.
20. C.-H. Weng, Y.-H. Lai, and S.-H. Lai, "Driver drowsiness detection via a hierarchical temporal deep belief network," in Asian Conference on Computer Vision, 2016, pp. 117-133: Springer.
21. A. Ben-Hur and J. Weston, "A user’s guide to support vector machines," in Data mining techniques for the life sciences: Springer, 2010, pp. 223-239.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2657 - 2663
https://publishoa.com
ISSN: 1309-3452

22. S. R. Sain, "The nature of statistical learning theory," ed: Taylor & Francis, 1996.
23. B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in Proceedings of the fifth annual workshop on Computational learning theory, 1992, pp. 144-152.
24. G. J. AL-Anizy, M. J. Nordin, and M. M. J. A. J. A. S. Razooq, "Automatic driver drowsiness detection using haar algorithm and support vector machine techniques," vol. 8, no. 2, pp. 149-157, 2015.
25. M. Sabet, R. A. Zoroofi, K. Sadeghniiat-Haghighi, and M. Sabbaghian, "A new system for driver drowsiness and distraction detection," in 20th Iranian Conference on Electrical Engineering (ICEE2012), 2012, pp. 1247-1251: IEEE.
26. B. Manu, "Facial features monitoring for real time drowsiness detection," in 2016 12th International Conference on Innovations in information technology (IIT), 2016, pp. 1-4: IEEE.
27. L. E. Baum and T. J. T. a. o. m. s. Petrie, "Statistical inference for probabilistic functions of finite state Markov chains," vol. 37, no. 6, pp. 1554-1563, 1966.
28. T. S. Prasad and N. R. Kisore, "Application of Hidden Markov Model for classifying metamorphic virus," in 2015 IEEE International Advance Computing Conference (IACC), 2015, pp. 1201-1206: IEEE.
29. B.-J. J. C. g. Yoon, "Hidden Markov models and their applications in biological sequence analysis," vol. 10, no. 6, pp. 402-415, 2009.
30. T. Nakamura, A. Maejima, and S. Morishima, "Driver drowsiness estimation from facial expression features computer vision feature investigation using a CG model," in 2014 International Conference on Computer Vision Theory and Applications (VISAPP), 2014, vol. 2, pp. 207-214: IEEE.
31. A. M. Bagci, R. Ansari, A. Khokhar, and E. Cetin, "Eye tracking using Markov models," in Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004., 2004, vol. 3, pp. 818-821: IEEE.
32. E. Tadesse, W. Sheng, and M. Liu, "Driver drowsiness detection through HMM based dynamic modeling," in 2014 IEEE International conference on robotics and automation (ICRA), 2014, pp. 4003-4008: IEEE.
33. U. J. T. d. s. b. Karn, "An intuitive explanation of convolutional neural networks," 2016.
34. A. Vision et al., "The Handbook of Brain Theory and Neural Networks," 1998.
35. A. Krizhevsky, I. Sutskever, and G. E. J. A. i. n. i. p. s. Hinton, "Imagenet classification with deep convolutional neural networks," vol. 25, 2012.
36. K. Dwivedi, K. Biswaranjan, and A. Sethi, "Drowsy driver detection using representation learning," in 2014 IEEE international advance computing conference (IACC), 2014, pp. 995-999: IEEE.
37. X.-P. Huynh, S.-M. Park, and Y.-G. Kim, "Detection of driver drowsiness using 3D deep neural network and semi-supervised gradient boosting machine," in Asian Conference on Computer Vision, 2016, pp. 134-145: Springer.
38. A. George and A. Routray, "Real-time eye gaze direction classification using convolutional neural network," in 2016 International Conference on Signal Processing and Communications (SPCOM), 2016, pp. 1-5: IEEE.