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Drowsiness, Fatigue and Poor Sleep's Causes and Detection: A Comprehensive Study

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ABSTRACT Drowsiness/sleepiness is a serious issue that needs to be addressed for improvement in the safety of road driving. Past statistical data on road accidents has shown enormous increases in car crashes due to drowsy/sleepy feelings. This study comprehensively summarizes all aspects of the drowsy state and its effects during car driving: its symptoms, causes, preventive actions, car accident statistics, sleep stages, and the behavioral, physiological and neural activation changes occurring during wakefulness and in the drowsy state. It considers drivers' behavioral data and corresponding methodologies for its analysis, the biomedical signals of the human body (including neuronal signals in the forms of electrical and hemodynamic responses), and their use for drowsiness detection. All of the existing methodologies, their uses and pros and cons, are comprehensively summarized. A detailed survey of the data published by neuro-imaging methodology-, physiological signal- and behavioral methodology-based studies in addition to studies using electro-mechanical installed sensors are statistically and theoretically summarized. Additionally, the neuronal activity occurring during the drowsy and awake states are analyzed, and the important contributions of fNIRS, fMRI and EEG in this context are discussed in detail. Differing existing drowsiness-detection systems installed in popular car brands also are reviewed. Finally, the remaining challenges and future suggestions for drowsiness-detection systems are summarized as well.

INDEX TERMS Drowsiness, fatigue, functional near-infrared spectroscopy, functional magnetic resonance imaging, electroencephalography.

I. INTRODUCTION

Car driving in a drowsy state or with attention distraction is a serious problem that results in large numbers of cars crashes each year [1], [2]. Such crashes lead to great loss of life as well as countless injuries and disabilities [3]. The statistical data on car crashes available at the national highway and traffic safety departments of many countries shows the alarming figures of 1.4 million deaths and up to 50 million minor or serious injuries [4]. The Highway and Traffic Safety Administration (USA) has estimated that around 100,000 car crashes are due to drowsiness, sleepy feeling or fatigue [1], [3], [4]. **Figure 1** plots the highway car crash data for the last 25 years in the USA. Sleep is a neuro-biological need of healthy humans [5]–[7]. In general, sleepiness/drowsiness can be defined as slow and gradual loss of the human brain's processing efficiency [8]–[10]. Thus, during the drowsy stage, there is a load on the human brain that renders difficulty in the performance of tasks that would be easily done in the alert stage. The gradual loss in efficiency results from malfunction of the cortical network for decision-making [8], [11]. Such situation leads in cutting off complex network performing their jobs based upon visual, hearing and sensing etc. Therefore, an increase in the global level of coherence of cortical electric activity which indicates the drowsiness [12]–[14].

Drowsiness is associated with a gradual decrease in response time, less vigilant behavior, deficiency in processing of available information and errors in short-term memory. The driver's drowsy state or sleepy behavior results in loose control of his car, which later might collide with either other moving vehicles or certain stationary objects [3], [10]. Several researchers and car manufacturers are working hard to develop methodologies that can be used to prevent such

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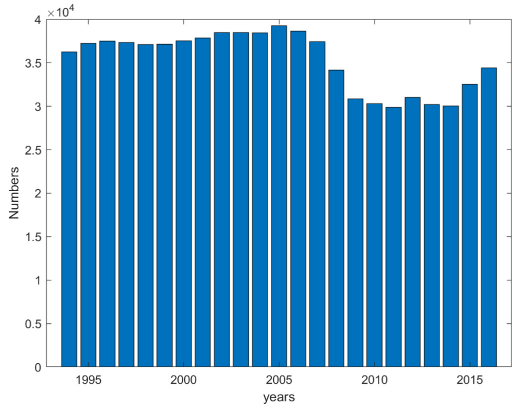

FIGURE 1. Total number of car accidents per year as observed by National Highway Traffic Safety Administration (NHTSA), USA.

accidents [2]. There are two possible ways to avoid accidents. The first is the use of preventive measures, by which a driver is monitored, and an alarm is displayed to advise him/her to stop the car during a dangerous mental stage. The second is the abnormal situation in which a driver is deemed to be asleep and car systems automatically control the vehicle to avoid accidents until it can be safely stopped. Cortical-activity-related signals are nothing but measures of chemical ion change/signaling. These chemical ion changes can be measured through positron emission tomography (PET), or by blood oxygen level dependent (BOLD) function via functional magnetic resonance imaging (fMRI) [15]–[17], the hemodynamic-related signal detected by functional near-infrared spectroscopy (fNIRS) [18]–[20], and indirect measurement of electrical activity by electroencephalography (EEG) [13], [21]. These cortical-activity-measuring techniques were initially used to compare main signals during activity and resting states and, thereby, to characterize externally applied stimuli [22], [23]. However, it is a well-established fact that substantial electric and metabolic activity exists in the brain even during the resting state of wakefulness [12].

Over the years, researchers have developed methodologies to predict or indicate the drowsy state prior to a collision [8], [24], [25]. Generally, these methodologies can be categorized into three main streams: vehicle-based sensors that predict a drowsy or unusual state [26]–[29]; observation of driver-behavioral data [30], [31], and measurement of drivers' physiological signals [32]–[35]. Vehicle-based sensing may be done by steering wheel data, steering wheel angle, the applied pressure pattern on an acceleration paddle, lane-position indication by an external visual sensor, and/or a pressure sensor installed inside of the driver's seat [36]–[38], among other means. The behavioral aspects of a driver may be determined by continuous recording through a camera installed in the dashboard to observe eye-closure time, eye-blinking frequency, movement and pose of the head, yawning and eye openings, etc., [36], [39]. Similarly, physiological data on a driver can be observed to detect the drowsy state. These signals include heart rate, the time delay between each heartbeat, ECG signals, respiration rate, pulse pattern, etc., [26], [40]. In addition to these measurements, nowadays, cortical signals are also an indicator of different brain conditions, especially the drowsy state [12], [17], [19], [24], [40]–[44].

TABLE 1. Car crashes site information in cases of driver's drowsiness/sleepiness.

S. No	Symptoms of Drowsy Car Crashes
1	No breaks applied, or no safety measures were taken to avoid accident at the scene
2	Timing of accidents: late night or afternoon time when we feel at low energy
3	Only single vehicle drifts
4	The crash or accident seems to be severe with no evidence of any attempt to avoid it.
5	The accident occurs at high speed.
6	Only one person is in the car
7	The driver was not drunk.

Accidents that result due to the drowsy state of drivers have certain common features that traffic safety personnel normally observe. These features include but are not limited to (1) driving during late-night hours (2:00 AM to 6:00 AM) or after mid-afternoon (3:00 PM to 5:00 PM); (2) driving on highways/expressways; (3) drifting of only one car; (4): young drivers; (5) non-application of brakes; (6) one person only is in the car; (7) lack of safety measures at accident sites; (8) blood-alcohol level of the driver being over the limit for safe driving; (9) vehicle drifting from the road or colliding with another vehicle [29], [45]–[49]. Table 1 summarizes the symptoms observed of car crashes resulting from a driver's drowsy state.

II. DROWSINESS AND ITS CLINICAL SYMPTOMS

A comfortable and good level of sleep is a crucial part of body health. Sleep is defined as a specific time span reserved for the rest of the human body and cortical functions to reduce body and mental fatigue for healthy functionality [8]. It is logical that during sleepiness/drowsiness, the consciousness of the brain is partially suspended [8], [29]. It is very difficult to measure the sleep time required for healthy functionality of the brain and human body and more specifically the specific time of each stage of sleep [12], [50]. The National Sleep Foundation (NSF; USA) recommended that a new-born baby needs 14-17 hours (h) of sleep, that infants require 12-15 h, toddlers 11-14 h, preschoolers 10-13 h, primary-school-going children 9-11 h, teenagers 8-10 h, young adults 7-9 h, adults 7-9 h, old people 7-8h∗. A pictorial view of sleep requirements is provided in **Figure2**.

Normally rapid eye-movement (REM) sleep, on average, accounts for 20- 25% of total sleep time. Sleep deprivation/drowsiness at any time of day is one of the symptoms indicating an inadequate duration of sleep [8]. Such symptoms are dominant during the late hours of the day and the early morning [29]. Alcohol and drugs worsen sleep deprivation/drowsiness symptoms, and caffeine/tea has less effect in overcoming sleep deprivation than is commonly supposed. The drowsiness feeling that occurs during daytime

TABLE 2. Symptoms, causes and reduction strategies for drowsy state.

Drowsiness		
Causes	**Symptoms**	**Reduction strategies**
Poor sleep	• Fatigue	Short sleep (nap)
Disturbing Light Inter Vision	• Restless-leg syndrome	Coffee
Acoustic noise	• Eye pressure	Shower
Anxiety and tension	• Headache	Temperature reduction
Lack of oxygen	• Eye blinking with unusual frequency	Fresh oxygen
	• Head nodding	
	• Yawning	
	• Pressure on shoulder	

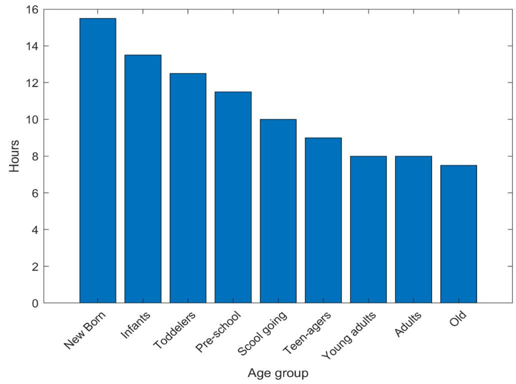

FIGURE 2. Sleep requirements by age group for healthy functionality of daily life.

is caused by several factors [26], [29]. The first and most important factor is poor sleep quality. Insomnia is one cause of poor sleep quality. It is characterized by a person's unsuccessful efforts to sleep that last for more than one-half hour. Also includes periodic disturbances during sleep. Another fundamental reason for poor sleep quality is an uncomfortable sleeping environment. It includes uncomfortable light, acoustic disturbances, etc. In addition, inadequate breathing flow, with an insufficient amount of oxygen, can be a cause of restless sleep that results in a drossiness state during daytime.

Table 2 summarizes drowsiness symptoms and causes. Pressure on the eyes, fatigue and headache, and restless-leg syndrome are major indications of the drowsiness state. Drowsiness can be overcome by 15- 20 minutes of sleep (a nap), a cup of coffee, a shower, and other means.

III. SLEEP CLASSIFICATION AND STAGES

The sleep/drowsiness process can be divided into four stages of sleep [12], [51]. These stages are termed as stage 1, stage 2, stage 3 and stage 4. The first three stages are part of non-rapid eye movement (NREM), and the final stage is named rapid eye movement (REM) in the literature [52]. **Stage 1:** During stage 1 the body feels fatigue and tends to relax, and this may cause jerks and abrupt changes in body position. The drowsiness level in stage 1 can easily be disconnected/disrupted by external stimulation of low intensity. Mostly, stage 1 is related to the alfa range of an EEG signal. The patterns and characteristics of the cortical signal during stage 1 are similar to cortical activity related to someone who is relaxing. The later stages of stage 1 produce further low-frequency signals in the range of theta waves [53]. **Stage 2:** In this stage, the slow movement of the eye balls starts to be discontinuous; this is the first stage of NREM. It is not easy to stay awake by low-intensity external stimulation. There are two characterizing features during this stage, namely, sleep spindles and k-complexes [54]. During stage 2, the body tends to move into a deep/further-relaxation mode with dominating theta wave activity including bursts of spikes in electrically measured signals known as sleep spindles. Thus, sleep spindles are high-frequency cortical-electrical signals that exist in the form of low-frequency waves. Similarly, k-complex is a very low-frequency pattern with relatively high amplitude signals, and is often measured in stage 2. **Stages 3 &4:** These stages are referred as deep sleep with relatively low-frequency waves less than 4 Hz with relatively high amplitudes [7], [8]. The frequency of waves in these stages are those of delta waves [11]. A human is less effected by external stimulation during this stage. **REM Sleep**: This stage of sleep is referred to as rapid eye movement sleep (REM). The cortical signals observed in this stage are very similar to those measured during wakefulness [55]. This is commonly known as dreaming sleep, and all muscles are paralyzed with the exception of those that are related to the respiratory system, cardiopulmonary system, etc. Sleep deprivation or drowsiness symptoms prevailing for longer times are associated with negative consequences for the human body and functionality. Table 3 below shows the systems and frequencies of cortical signals, biological processes and physiological signals during each stage of sleep.

IV. EVALUATION OF DROWSINESS/FATIGUE AND SLEEP LEVEL

It is very important to analyze and evaluate the level of drowsiness. The literature shows that there exist several methods and strategies that can be utilized to measure drowsiness levels. The details of these methods are given below.

A. EPWORTH SLEEPINESS SCALE

Dr. Murray Johns (Melbourne, Australia) developed a method of assessing average sleep and drowsiness levels [56]. This method consists of a simple questionnaire having eight questions with numeric answers in the range of 0-3. A cumulative score of eight answers is divided among five groups: normal

TABLE 3. Sleep stages and corresponding biomedical information.

Name	Stage	Frequency	Features	External Stimulation	Eye Movement	Biological symptoms*	Clinical Name
NERM	1	Alfa, Theta	NA	Effective	Non-rapid	HR (D) Temperature (D) Yawning (I) Eye blink (I) HRV (I) Respiration frequency (D)	Orthodox sleep
	2	Theta	NA	Slight	Slow non-rapid		
	3	Delta	K-complexes Sleep Spindles	Less	Non-rapid, tends to increase		
	4	Delta					
REM	Dream	Stage 1	Similar to awake state	Not effective	Rapid		Paradoxical sleep

* D: decrease, I: increase

sleep (0- 5), higher normal sleep (6- 10), mild-excessive sleep (11-12), moderate-excessive sleep (13- 15), and severe excessive sleep (16- 24) [57]. This is the most utilized method for analysis of drowsy/sleep stages, especially during day-time [56].

B. MULTIPLE SLEEP LATENCY TEST

This test is based on the fact that persons who fall sleep quickly are considered to be drowsier [58]. This test measures small intervals of sleep-oriented situations throughout a day [59], [60]. On the basis of sleep stages, it is concluded that a person is drowsy, if he falls asleep within five minutes [61]. The multiple sleep latency test (MSLT), which measures the ability to fall asleep under soporific conditions, is the current gold standard for quantifying daytime sleepiness [62].

C. STANFORD SLEEPINESS SCALE

The Stanford sleep detection system consist of seven statements through which a person's level of wakefulness is evaluated [63], [64]. A subject chooses a single number from a list by evaluating personal symptoms mentioned in that list [65], [66].

D. KAROLINSKA SLEEP TEST

This is a similar test to the Sandford sleepiness scale. A subject rates his/her current feeling by choosing a number from a list of levels 1-9, depending upon the closest situation mentioned in each level [67]. The Karolinska Sleep Test (KST) stages are divided into "very-alert", "very-sleepy", "fighting-sleep", and "an effort to remain awake" based on nine-steps [68]. It has already been validated against physiology and performance measures [69].

E. ELECTROCARDIOGRAM (ECG)

In this methodology, a human subject's heart rate is evaluated [70], [71]. There are two possible procedures. In the first one, heart rate is measured. It is a well-established fact that during sleep stages or drowsiness, the heart rate starts to decrease [72]. It is important to mention, too, that reduction of heart rate is also observed at nighttime while driving during late hours. The second procedure entails detection of heart rate variability, i.e., the time interval between pulses [73], [74]. The previous literature shows that the heart rate variability of an awake person manifests high-frequency signals, whereas sleep-deprived or drowsy persons show low-frequency heart rate variability [75]–[77]. Respiration rhythm is another important parameter that can be a potential discriminatory feature for the drowsy/alert states. According to the literature, the frequency of the breathing pattern decreases during the drowsy state.

F. ELECTRO-OCULOGRAM (EOG)

This method estimates alertness level based on eye movement [78]. Specifically, it measures the electrical signal representing the potential difference between the cornea and retina of a subject's eye [79], [80]. In this method, an electrode is placed near the end of each eye and another is placed at top of the eye. Later, signals are classified for eye movement. In cases of a slower rate of eye movement than is normal, the subject is declared to be in the drowsy state [81]. Several studies in the past have utilized this methodology to access the drowsy state with accuracy [78]–[82].

G. HEAD MOVEMENT

It is a well-established fact that during the sleepy/drowsy state, the human body starts to feel relaxed due to fatigue caused by work load [83]. Thus, the head movements of normal and drowsy persons will have different characteristics [84]. A drowsy person will show head nodding, means to say, sudden changes of head position. This condition can be measured using visual or motion sensors. This method has been shown to be a potential choice for detection of drowsy stages [83]–[87].

H. JAW MOVEMENT

It is common practice for a wakeful person to inhale air with ordinary movement of the jaw [88],whereas a tired person will open up the jaw much more widely [89]. This can easily be measured through a simple camera that operates based on a pattern recognition methodology. Several studies in past have experimented with human subjects and animals for detection of sleep symptoms [88]–[92].

I. EYE BLINKING

Eye blinking is another discriminatory feature for detection of alertness [93]. It can be observed in several ways. One of them is to detect the opening of the eyelids. It is common that during fatigue situations, the gap between eyelids tends to decrease. Similarly, another way could be to measure eye-blinking frequency. A drowsy-state person tends to manifest a high eye-blinking frequency as compared with an awake person [93]–[95].

V. NEUROLOGICAL EVIDENCE OF DROWSINESS

Technological development has enabled humans to measure cortical signals indicative of different brain states [96]. These findings can be helpful for avoidance of car crashes and prediction of brain states much earlier than the points at which collisions happen [19], [29], [51]. fNIRS, EEG and fMRI, being non-invasive methodologies, are useful for such investigations [37], [97]–[101]. Among them, EEG and fNIRS are at competitive positions due to additional advantages of portability, low cost, and acceptable temporal and spatial resolutions [96], [102], [103]. In past, different sensors have been utilized by car manufacturers to detect and indicate drivers' drowsiness state. Nonetheless there are still many car crashes due to drowsy feelings. Therefore, several researchers have initiated efforts to find and predict drowsy states using neuro-activation data. EEG-based drowsiness/sleep-related findings have been published most frequently in the past 50 years. Also, the symptoms of drowsiness and their corresponding effects on the hemodynamic response have begun to be more closely scrutinized. We have analyzed the published data of drowsiness/sleep/fatigue studies and found very interesting results. **Figure 3** summarizes the details of published articles related to drowsiness/sleepiness and fatigue based on EEG, fNIRS and fMRI. All the statistics presented in Figure 3 is collected through Web of Science by putting different keywords. The keywords used for search are EEG + drowsiness, EEG + sleep, EEG + fatigue, fMRI + drowsiness, fMRI + sleep, fMRI + fatigue, fNIRS + drowsiness, fNIRS + sleep and fNIRS + fatigue, A relative-percentage analysis of the published results also is presented in **Figure 4**. They show that most of the drowsiness-related studies presenting neuronal-activation-based findings have been based on EEG.

A. FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (FNIRS)-BASED FINDINGS

Ahn et al. (2016) [40] evaluated the neuro-physiological correlates of drivers' mental conditions. This study compared well-rested individuals with sleep-deprived persons using eight-channel fNIRS in addition to EEG and biological signals. The authors found that the dHbO of the well-rested controls was higher than that of the sleep deprived. The dHbR of both groups showed much closer patterns. The authors

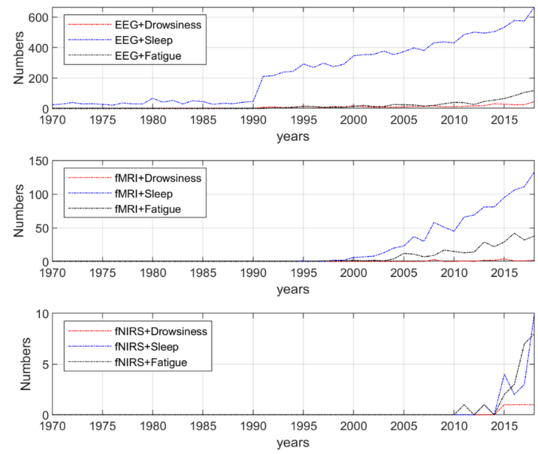

FIGURE 3. Publication record for drowsiness, sleepiness and fatigue according to neuro-imaging modalities.

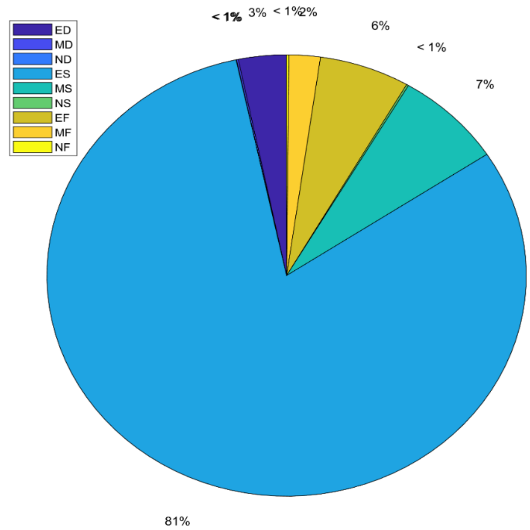

FIGURE 4. Percentages of published articles addressing drowsiness (D), sleepiness (S) and fatigue (F) according to EEG (E), fMRI (M) and fNIRS (N).

also calculated driving-condition level scores to discriminate well-rested and sleep-deprived persons. Khan et al. (2015) [19] implemented linear discriminate analysis (LDA) to detect drowsiness by utilizing eight different features from optical data with different windows of 0∼15 seconds. Their results suggested that mean accuracies of 83.1% to 84.9% could be achieved by using these features: mean HbO, signal peak, and sum of peaks. The authors have divided the scanning area into three regions, concluded that, on average, dHbO has a relatively higher concentration during the drowsy state. Li et al. (2018) [116] evaluated 13 individuals ina seven-hour driving simulation test by observing optical signals from the pre-frontal cortex. They found that a specific area therein showed increased dHbO and dtHb as the time of driving increased. Nugyun *et al.* [5], [97] analyzed fNIRS and EEG signals in addition to biological signals to discriminate drowsy and awake states. They utilized classical LDA and found that dHbO and the beta power in the frontal lobe were significantly different during the two states. They found that the mean values of the awake and drowsy states for dHbO were 0.019 and −0.017, respectively, and for dHbR, were −0.003 and 0.005, respectively. Borragen et al. (2018) [117] analyzed mental fatigue using trans-cranial current stimulation (tDCS) and observed cortical oxygenation changes by fNIRS in the frontal cortex. They concluded that tDCS, in comparison with the sham condition, failed to counteract cortical-fatigue-related changes, whereas tDCS combined with induction of cortical fatigue shifted the inter-hemispheric oxygen level in the post-training resting state. In an interesting study by Liu et al. (2014) [110], a positive correlation between drowsy state and pre-frontal activation was found by experimenting with a simulated environment in which a speed-control driving task was performed. The level of drowsiness was evaluated through a five-item Likert-type questionnaire. An increase in pre-frontal activation was observed via fNIRS during the drowsy state. Cai et al. (2017) [118] investigated fatigue level using fNIRS by parietal-occipital scanning. They found a spatial correlation between the occipital cortex and binocular depth perception. Chuang et al. (2018) [119] investigated four different regions, namely the parieto-occipital, motor-right, motor-left and frontal cortex, to discriminate the drowsy state. They concluded that there was a significant increase in dHbO power in those regions during the deviation periods. In an interesting work by Karageorghis et al. (2018) [134], the authors found that music behaves as a potential candidate for prevention of internal fatigue-related hemodynamic signal measured through fNIRS. Mehta and Rhee (2017) [135] analyzed social stress and its effects on pre-frontal cortex HR signals by experimenting with 60 adults and children based on motor tasks. The results suggested that aging results in decreased force-steadiness with a significant increase in bilateral pre-frontal cortex activity. In an earlier work, Mehta et al. (2015) [136] concluded that stress fatigue has different patterns for fat/obese people than for people of normal BMI. It could therefore be concluded that obese persons must be more careful while driving because they may have drowsy feeling much quicker than non-obese people. A very important study by Muthalib et al. (2013) [120] investigated mental fatigue in relation tothe motor- and pre-frontal cortices by stimulation via trans-cranial direct-current stimulation. The pre-frontal cortex was scanned through fNIRS while for the motor cortex, tDCS was applied. They found higher activity in the pre-frontal cortex during task failure irrespective of the tDCS-application conditions. Ochi et al. (2018) [121] presented results for pre-frontal activation in a hypoxic environment based on an analysis of15 healthy subjects performing a color word strop task both before and after a 10-minute moderate-intensity exercise. They concluded that hypoxic exercise reduces left-dorso-lateral pre-frontal cortex activity. Such conditions could be related to the enclosed environment of a car during a long drive. Rhee and Mehta (2018) [122] presented results showing that females have more motor fatigue than males based on an analysis of obese and non-obese persons. Richter et al. (2018) [123] analyzed pre-frontal cortex hemodynamic signals under visual fatigue. Their findings suggested that hemodynamic activity during visual fatigue is influenced by time. Xu et al. (2017) [42] analyzed the functional connectivity for a long driving simulation task coupled with mental calculation tasks in order to investigate fatigue. They concluded that the pre-frontal and motor cortex are closely connected during mental fatigue. Harrivel et al. (2013) [18] analyzed functional neuro-imaging data to discriminate alertness and rest periods. The authors defined two regions: one related to high levels of task engagement, called the task-positive region, and the other related to low levels of engagement, called the task-negative region. The authors claimed that for the first time, it was possible to detect, through fNIRS, a negative correlation between HR activity in the key areas of the task-positive and task-negative regions. These methods could be helpful for monitoring of attention/alert states using fNIRS. Bu et al. (2018) [137] effectively showed that wavelet phase coherence (WPC) and the wavelet amplitude of dHbO are discriminatory features for analysis of poor-quality sleep. They analyzed 15 poor-quality sleep (PQS) individuals in comparison with 14 healthy controls, having scanned their pre-frontal, sensory motor and occipital lobes using fNIRS. They found that the WPC values of PQS were lower than those of the healthy individuals. This finding suggests that individuals could be scanned before long driving to avoid any drowsiness condition in cases of poor sleep. Chaung et al. (2018) [119] tested16 individuals in an event-related lane-departure experiment of 1 hour duration. The results indicated that dHbO increased while the driver was fighting fatigue. Table 4 summarizes the work done to detect drowsiness by utilizing fNIRS and the corresponding contributions.

B. FUNCTIONAL MAGNETIC RESONANCE IMAGING (FMRI)-BASED FINDINGS

The characterizing feature for any cortical imaging devices are temporal and spatial resolutions [96]. Functional magnetic resonance imaging (fMRI) has better spatial resolution than EEG or fNIRS [104]. However, at the same time, it entails a huge setup, making it unsuitable for any portable job [105]. Additionally, regular analysis of a driver's drowsiness state by fMRI is very difficult. On the other hand, the findings of fMRI can be beneficial to any brain-state analysis seeking to localize specific brain areas showing response under sleepy/drowsy and alert/awake conditions [16]. Also, fMRI data's correlation with EEG and fNIRS data offers a great potential for clearer and more concrete findings for those two latter modalities [12], [106]. In this context, Allen et al. (2018) [125] analyzed the connectivity patterns of brain networks during eyes-open and eyes-closed states. Several existing methodologies have been used to explore functional connectivity and its usefulness for understanding and characterizing brain states responsible for particular tasks [107]. Allen et al. (2018) [125] suggested that it is very important to analyze drowsiness level in both eyes-closed and eyes-open states, and indeed, the authors

TABLE 4. Summary of fNIRS-based neurological findings related to drowsiness, fatigue and sleep stages.

Reference, Year	Modalities	Task	Condition	Subjects	Methodology	Contribution	Results
[40], 2016	fNIRS, EEG, EOG, ECG	Simulated driving	Well-rested (ER) Sleep deprived (SD)	10 males One female	Features	Driving condition level score	Ave. HR (SD: 61.8 WR: 69.9) Ave. Classification: 75.9 HbO WR dominates HbO SD in pre-frontal cortex.
[19], 2015	fNIRS	Simulated driving	Ten hours sleep deprivation at night	13 (males)	8 features with different time windows	Combination of different features and time windows	Classification with window 0~5: 83.1, 0~10: 83.4, 0~15: 84.9
[116], 2018	fNIRS	7 hours driving simulation	Preliminary voluntary attention experiments Go/NoGo	13	Attention test score (Accuracy/RT)	Degradation in attention test score correlated with driving time	Increase in dHbO and dtHB as time of driving increases
[97], 2017	fNIRS, EEG, EOG, ECG	Simulated driving	Oval shape driving path with four curves	10 males 1 female	LDA, time-series analysis	LDA	dHbO and beta power were discriminatory features in frontal lobe EEG and fNIRS accuracy: 79.2±sd
[117], 2018	fNIRS, tDCS	TloadDback task	30 digits and 30 letters /block	22	Pre- versus post-task subjective fatigue and sleepiness scales	tDCS current stimulation effects	Trans-cranial DCS (as compared to a sham condition) over left prefrontal cortex failed to counteract CF-related modifications. Increased COE or decreased oxygenation
[1118], 2017	fNIRS	Slow event-related paradigm	Static RDS pairs	7 males 6 females	NIRS-SPM and data analysis with statistical parameters	Hemodynamic response elevation during stereopsis	dHbO increase was observed in occipital cortex under binocular depth perception
[119], 2018	fNIRS, EEG	Simulated driving	Lane-deviation events (LDE)	16	fNIRS data transformation to frequency domain	Neural activation increases during fatigue and subjects responded in LDE with fatigue as well	Increase in dHbO at frontal cortex during fatigue
[120], 2013	fNIRS, tDCS	Isometric contraction task	Sham treatment of 50 min. after task failure	15 males	fNIRS signal	Hemodynamic increases as fatigue level increases	Increase in dHbO at prefrontal cortex until task is failed.
[121], 2018	fNIRS	Color word Stroop task	Normoxic and hypoxic	13 males 1 female	Inter-trial mean of differences	Hypoxic conditions results in negative effects	In hypoxic condition, SpO_2 decreases after task
[122], 2018	fNIRS	Handgrip motor fatigue	Voluntary exhaustion	59 adults (30 non-obese 29 obese)	dHbO averaged in eight regions	Pearson correlations and Fisher's z-scores to evaluate correlation strength.	No obesity or sex di□erences were found.
[123], 2018	fNIRS	Vergence Stimulation	With or without mental load	20	Linear mixed model analyses	fNIRS data is effective to analyze supervisory oculo-motor-control tasks	ΔHbO and ΔHbT increases at onset of control, cognitive control, convergence load and combined conditions.
[124], 2015	fNIRS, EEG EMG, HR,HRV	Intermittent handgrip exercises and Stroop Color Word and 1-Back tests	Voluntary exhaustion	11 females	fNIRS signal	HR increased over time, HRV unaffected.	ΔHbT remained stable over time and across tasks
[42], 2017	fNIRS	Simulated driving	Mental calculation	14	Wavelet coherence (WCO) and wavelet phase coherence	Four frequency intervals	Low WCO-level was found in intervals 1 and 3 in prefrontal area, whereas interval 4 in motor area.
[18], 2013	fNIRS, fMRI	Multi-source interference task	Distracter digits	3 males 2 females (fNIRS)	Hemodynamic response function model	Task-positive and task-negative networks	Negative correlation corresponds to activities in task-positive and task-negative regions.
[20], 2016	fNIRS, fMRI	Attention task	Multiple sources of interference	4 males 3 females	Six different fNIRS data processing methods	Higher state prediction accuracy when noise filtered with adaptive model	Prediction accuracy: Static regression (72%) Non-stationary model (84%)
[7], 2018	fNIRS	Auditory and visual stimuli	Awake and sleepy condition	91 infants	fNIRS data analysis and statistical testing	Experimenting with infants for analysis of auditory and visual stimulus.	The response to same stimuli in sleepy stage was different. Functional connectivity was higher during sleep than in awake state.

showed that –the two states respond in common and also manifest different connectivity patterns from those associated with EEG-spectral signatures. In another study, Tagliazncchi and Laufs [108] and Tagliazncchi *et al.* [109] analyzed functional connectivity under the sleep and awake conditions. Their findings indicated an increase in network modality during the N3 sleep stage in comparison with the alert/awake state. Haimovici analyzed brain network connectivity patterns during wakefulness. They observed that the clustering of dynamic functional connectivity upon short time windows reflected fluctuation in wakefulness. This report validated the previous findings of increased modularity during non-REM sleep. Horavitz *et al.* [12] investigated different levels of consciousness (i.e., alert state)under light-sleep and drowsy conditions. They found a significant increase in BOLD-signal fluctuations in the visual cortex in addition to other cortical areas, though the visual cortex fluctuations were the most significant. For the drowsy state, meanwhile, they observed a correlation with the default mode network (DMN). Their findings suggests that DMN and primary sensory cortices activities do not require a level of consciousness. Drummond *et al.* [55] observed increased pre-frontal activation during the drowsy state by experimenting with a divided-attention task utilizing fMRI. Ong et al., (2015) [127] analyzed spontaneous eye-closure activity. Such activity is frequently adopted by individuals insleep-deprived conditions. The authors observed concurrent and extensive hypnagogic co-activation of the visual, auditory and somatosensory cortices and DMN as well. Since spontaneous fluctuations of the eye are indicative of the drowsy state, visual auditory and DMN could be scanned through portable devices for determination of sleep-deprived drivers and fatal accidents could be avoided. Poudel et al. (2014) experimented with 20 healthy humans in the well-rested condition (i.e., they were not sleep deprived). The participants were put through a 50-minute driving task. All of the experiments were recorded through a camera. The visual recordings showed micro-sleep behaviors of around 70% of the subjects. The fMRI recording during the experiments suggested increases/decreases of activity patterns in different brain regions. Thalamic posterior-cingulate and occipital cortex activities were observed to be decreased, whereas frontal, posterior and parietal activities were found to be increased, during short intervals of sleep recorded through the camera. Stern et al. (2011) [6] analyzed the source localization and function of vertex sharp transient, which is a marker of the

TABLE 5. **fMRI-based previous studies for detection of drowsiness/ sleep stages.**

Reference, Year	Modalities	Task	Condition	Subjects	Methodology/tool	Contribution	Results
[125], 2018	fMRI, EEG	Eyes-open and Eyes-close	Eye-link 1000 eye-tracker	25	K-mean clustering of correlation using Spatial independent component analysis	Distinct functional network connectivity	There exist common and different connectivity patterns during eyes-open and -closed states.
[16]2008	fMRI, EEG, ECG	Eyes-closed	Without falling sleep	15	Linear correlation analysis	Correlation variation between heart rate and fMRI data	High correlation areas are different from default network and a negative correlation b/w heart-beat-interval and alfa band power.
[126], 2017	fMRI, EEG	Sleep and awake	Evening time and stages of sleep	58 (sleep) 16 (wake)	Statistical parameter mapping (SPM)	Discrete patterns related to sleep and awake states.	Method to identify sleep in resting states without EEG.
[12], 2008	fMRI, EEG	Sleep and awake	1 min awake followed by sleep	9 males 5 females	IDL and SPM2	Fluctuations during drowsy states.	Visual cortex observed significant increase in BOLD signal fluctuations during light sleep.
[127], 2015	fMRI	Rest-awake (RA)/ sleep-deprived (SP)	8:00 AM and 6:00 AM	24 (successful)	SPM2 and FSL	Transition from drowsy state to light-sleep	Co-activation of visual, auditory and somatosensory cortices with DMN.
[128], 2014	fMRI, EEG, Camera	Tracking Task	Continuous tracking 2-D random target	10 males 10 females	FSL	Neural activity during micro-sleeps	Transient decrease in thalamic, posterior-cingulate, and occipital regions and an increase in frontal, posterior-parietal, and para-hippocampal response during short sleep sessions.
[6], 2011	fMRI, EEG	Awake/ sleep with SP	Late morning and mid-afternoon	2 males 5 females	FEAT and FSL	Vertex sharp transient (VST)	VST localization in primary sensory-motor cortex. VSTs different from sleep-spindles
[129], 2007	fMRI, EMG	Finger abduction force and reaction time	1 week apart sessions	7 males 8 females	SPM2	Cortical response related to motor-fatigue	Increase in cortical activity as fatigue
[55]	fMRI	Divided attention task	Normal sleep and total SD (TSD)	7 males 6 females	AFNI	Total sleep deprivation	Brain regions showed higher response in TSD in comparison with normal sleep.
[130], 2018	fMRI	Psycho-motor vigilance task (PVT)	With 40 hours SD and 40 hours short sleep sessions	14 males 17 females	SPM8	Difference in sleep-deprived states and with short naps	Circadian and sleep homeo-static processes impact on vigilant attention

NREM sleep stage in EEG data. The simultaneous recording of EEG and fMRI showed that the primary sensory cortex is responsible for sharp transient ejection. The drowsy feeling could also be the result of motor fatigue. Duinen et al. (2007) [129] comprehensively analyzed the relation of fatigue with cortical activation. Their observation showed an increase in motor and bilateral orbito-frontal activation with increasing motor activity in cases of fatigue. However, the activation clusters were small. The brain stem is involved in the control of several important brain functions that operate the human body. These functions include respiration rhythms, heartbeat, and sleep cycles, among others. It is difficult to record functional data of the brain stem through fMRI, since its location is very close to major arteries adjacent to pulsatile cerebrospinal fluid-filled spaces [41]. Thus, alternatively, indirect measurement or some network activation can be analyzed through fMRI during sleep or drowsy feelings. Sleepiness behavior and cortical responses vary over the course of the 24 hours of each day, depending on sleep conditions, work load, and, specifically, cardiac pulsations. Maire et al. (2018) [130] experimented with healthy individuals by performing a psychomotor vigilance task in fMRI under two conditions. The first one is sleep deprivation based on40 hours of no sleep, which group was deemed the high sleep pressure group. The second group, deemed the low sleep pressure group, was allowed 40 hours of a multiple nap-protocol. The sleepiness level was evaluated on the Karolinska sleepiness scale. The experimental data suggested that cardiac and sleep homeostatic processes impact upon vigilant attention. Table 5 summarizes the work done to detect drowsiness by utilizing fMRI, along with the corresponding contributions.

C. ELECTROENCEPHALOGRAPH (EEG)-BASED FINDINGS

In 2002, Tejero and Chóliz [9] studied should the effects of constant speed and periodically varying speed on the alertness of drivers in a motorway driving experiment. They recorded EEG activity from 11 subjects in a 40-45 kph driving experiment. The results of their analysis showed that periodic speed modifications can be a way to stay alert, whereas driving at a constant speed, which tends to bore drivers to certain degrees, may cause fatigue and drowsiness. Eoh *et al.* [11] studied the drowsiness/fatigue in eight subjects in a simulated driving experiment. Fifty minutes of 8-channel EEG data and subject behavioral data obtained by camera was recorded and analyzed. Three frequency bands, namely theta, alpha and beta, were utilized in terms of their mean power, ratio indices and burst activity to analyze the sleepy states of the subjects. The results showed that the alpha, beta, index beta/alpha and index (alpha+ theta/beta) were significantly different as the drivers' state was converted from alert to drowsy. Pal et al., 2008 [51] proposed an unsupervised method to detect changes in the alert state of drivers. They suggested that in the alert state, PSD from the theta and alpha bands at channel Oz follows a multivariate normal distribution, which can be used to drive alert model of each subject by using a small amount of EEG data. Then, this model was used to analyze the deviation in PSDs to determine whether the driver is in the alert state or the drowsy state. In another study, Yeo et al., 2009 [13], the authors used the SVM classifier to detect the alert and drowsy states of drivers. Twenty young participants were participated in a simulated driving task to acquire EEG signals. Features were extracted by calculating the PSD of the delta, theta, alpha and beta bands. For each frequency band, four features, namely dominant frequency, average power of dominant peak, center of gravity frequency, and frequency variability, were calculated using PSD values. Finally, SVM was used to classify the alert and drowsy states of drivers. The results suggested that SVM can achieve a classification accuracy of 99.3%, indicating that it can be successfully used to classify alert and drowsy states. Simon et al., 2011 [52] proposed an algorithm that uses a few seconds of EEG data to detect alpha spindles (short narrowband bursts in the alpha band) by measuring peak frequency, amplitude, and duration. They tested their algorithm on signals generated both synthetically and acquired under real-life driving conditions. They then compared the results of their algorithm with the conventional alpha power criterion. Statistical analysis revealed significant increases from the first to the last driving section for the alpha spindle parameters. Another study, Liu et al., 2013 [111] used a single-channel wireless EEG system to detect the drowsy state of drivers by incorporation of music to reduce the chances of becoming drowsy. Data acquired from 20 male and 20 female subjects were decomposed into four different frequency bands to calculate PSD features for the classifiers. An integrated classifier consisting of SVM, ANN and kNN was used to achieve an average accuracy of 81.3% in detection of the drowsy state. In a later study, Gurudath et al., 2014 [112], the authors developed a drowsiness detection algorithm by combining discrete wavelet transform and K-mean clustering. EEG data acquired from a driving simulator experiment was decomposed into different frequency bands using discrete wavelet transform. The mean, median, variance, standard deviation and mode were calculated for each band and provided as features to the K-mean clustering algorithm for classification. Roy et al. (2014) [21] proposed an ICA and adaptive thresholding-based algorithm to detect eye blinks using EEG data only, whereas most of the comparable studies have used EOG signals to do so. They suggested that this algorithm can be used to detect the mental fatigue of drivers. They acquired data from 11 subjects for a working memory task. The results of their analysis suggest that their algorithm can achieve a true detection rate of 89%, while the correlation of their results with the results from EOG signals was 0.81. Li and Chung (2014) [14] hypothesized that there is a linear relationship between EEG activity in the occipital cortex (specifically the O2 location) and eye-closure degree. They analyzed EEG data from 30 subjects, and their results suggested that alpha power at O2 increases with increased drowsiness, whereas beta power decreases with increased drowsiness. Their proposed model achieved 87.5 and 70.0% accuracy for the male and female subjects, respectively. In a subsequent work, Li and Chung (2015) [53], developed a Bluetooth-based low-power-consumption system to detect early drowsiness of drivers. They combined EEG data with head movement data to increase the SVM-based alert/drowsy classification accuracies. Data from six subjects who had participated in a simulated driving exercise yielded 96.24% accuracy when EEG data is used with head movement, as compared with 82.71% when only EEG data was used. Gharagozlou et al., 2015, [131], analyzed the fatigue caused to drivers using a virtual reality simulator. Twelve healthy male car drivers participated in an overnight study. They analyzed the initial and final 10 minutes of recordings by calculating the PSD and FFT in the alpha frequency band. The results showed that there was a significant difference in the absolute alpha power between the initial and final stages; moreover, the increase in the alpha power in the final section of driving indicated the onset of fatigue. Hajinoroozi et al., 2016 [50], proposed a channel-wise convolution neural network with a restricted Boltzmann machine algorithm for classification of drivers' different states. EEG data from 37 subjects acquired during a virtual-reality-based driving simulator experiment were used in this study. The results showed that the proposed algorithm achieved 76.72% cross-subject accuracy and outperformed other algorithms such as SVM and DNN. Yang et al. 2018 [54], proposed a two-layer algorithm by analyzing the behavioral data and EEG signals acquired from 52 participants in a simulated driving experiment. In the first layer, 14 features were extracted from the behavioral data acquired from the simulation software. Five categories of driving behavior were obtained based on the driving data and the following procedure: first, K-means was used to form two clusters of base driving features, respectively the driving style and stability. Then, SVM and SVM recursive feature elimination were applied for feature selection and extraction. Finally, the driving-behavior types were classified using K-means. In layer two, EEG features extracted from different frequency bands were classified using the kNN classifier. The results suggested that their methodology can achieve an average classification accuracy of 69.5%, and a maximum accuracy of 83.5%. Chen et al., 2018 [132] proposed a novel brain-networks-based approach to detect drowsiness. EEG signals from 15 male subjects were acquired in a simulated driving task. They calculated phase lag index (PLI) values for different frequency bands to assess the functional connectivity between different pairs of channels and to construct a minimum spanning tree by connecting electrodes in descending values. The results of their statistical analysis showed that the PLI values in the delta band tend to increase as the subject's state transitions from altered to drowsy. In their subsequent work [113], the alert and drowsy states of drivers were analyzed by a proposed combined minimum spanning tree and synchronization likelihood-based functional brain network approach. Features extracted from these were transferred to four well-known classifiers, from which the K-Nearest-Neighbors classifier achieved a maximum average accuracy of 98.6%. Recently, Wang et al., 2018 [114] used dry EEG to evaluate two methodologies based on PSD and sample entropy to detect drivers' fatigue in real-life driving. To do so, they acquired EEG signals from 10 subjects in a simulated driving experiment. The results of their analysis suggested that PSD scores increase with increased mental fatigue, whereas sample entropy scores decrease with increased mental fatigue. However, they observed that PSD is more robust and more effective than sample entropy to detect mental fatigue while driving. In another study, Wang et al., 2018 [44], the authors developed a single-channel-EEG-based method to detect driver fatigue by combining four features, three base classifiers and three ensemble algorithms. They tested EEG data acquired from 12 subjects in a simulated driving task for different combinations of features, classifiers and ensemble algorithms. The results of their analysis suggested that Channel T6, feature fuzzy entropy, and classifier-gradient-boosted decision tree with 500 boosting stages achieved the best results, boasting an average accuracy of 91.1%. Zhang et al., 2018 [115] studied driver drowsiness using EEG to find the optimal recording locations. Twenty-two subjects were used for recording of EEG signals from the Fp1, Fp2, T3 and T4 locations in a simulated driving experiment. The PSD was calculated for the delta, theta, alpha and beta frequency bands. The results suggested that delta band activity increases, whereas theta and alpha activity decreases in the drowsy state as compared to the alert state. They further suggested that changes at the T3 and T4 locations were much larger than changes at Fp1 and Fp2. Barua et al. 2019 [24] studied sleepiness during driving using EEG and EOG. They recruited 30 drivers to drive in the alert and sleepiness states within a simulated driving scenario. Three conditions, namely alert, somewhat sleepy, and sleepy, were analyzed. EEG features were extracted by calculating PSD for the different frequency bands, whereas blink duration was used as the feature from EOG. Four different classifiers were used to classify the multistate and binary state (alert vs. sleepy) conditions, from which SVM achieved maximum accuracies of 79 and 93%, respectively. Table 6 summarizes the work done to detect drowsiness by EEG and the corresponding contributions.

VI. AUTOMOBILE-INSTALLED DROWSINESS DETECTION SYSTEMS

The previously available data on road accidents indicated that around 25% of road accidents on highways/expressways are caused by drowsy feeling, fatigue symptoms, etc. This statistic showed that drowsiness causes more accidents even than drunk driving. Therefore, car manufacturers are working hard and financially supporting research to develop an intelligent system installed in automobiles that not only alerts drivers under drowsy conditions but also responds automatically and intelligently to avoid accidents and collisions. Toyota has developed a specific system to respond in cases of driver inattentiveness, namely, ''Toyota Safety Sense''. This system has two main features. The first one is a pre-collision detection system that guards against frontal collisions by indicating visual and audio alarms to drivers, and, in cases where the driver does not respond within a pre-defined time period, the system declares him to be in a drowsy state and automatically applies breaks to avoid collision. The second feature of this system is correct lane alertness. In this hardware, a front-installed camera continuously detects the lane markers, and if the car deviates from those lanes, audio and visual beepers are displayed in the dashboard to correct the steering wheel position. In cases where the driver does not respond to these indications, the system declares the driver to be in a drowsy state and automatically adjusts the steering. Hyundai has installed a ''Driver Attention Warning'' system. This system is based on the signal received from the wheel's position in a particular lane and time of driving. By analyzing the angle of torque applied to the steering wheel, the movement of the car in the lane and the time of driving, the system determines the pattern of driving and, if necessary, declares the driver un-attentive by displaying a coffee cup signal and sounding an audio alert.

Mercedes' ''Attention Assist System'' determines the driver's condition through a specific sensor installed in the steering wheel in addition to observing the acceleration of the car, breaking patterns, the condition of the road and driving time, etc. In contrast with other cars, which utilize visual sensors to monitor facial expressions and specifically the eye patterns representative of the driver's current state, Mercedes has installed its specific steering sensor. The overall system continuously observes the driver's driving patterns during a particular trip and generates a driver's profile with certain thresholds. If the system detects a significant variation in comparison with the generated profile, the Attention Assist System declares the driver in the fatigue stage and generates an alert or warning sign and beep. Ford has installed a ''Driver Alert System'' that is based upon lane assist data. A pinhole camera installed behind the dash rearview mirror continuously visualizes the moving patterns of the car and decides whether the vehicle is staying inside a lane. In cases where the driver is deviating from a specific lane, the system generates a vibration in the steering wheel to alert the driver and declare him to be in a drowsy state; and if the driver does not respond within predefined time, the system adjusts the steering wheel to avoid deviation. Bosch has developed a ''Driver's Drowsiness detection system'' that determines the drowsy state of a driver by analyzing steering movement, and, if necessary, alerts him to apply the brake paddle. This is easily done by analyzing the car's steering angle and the velocity profile of that angle. Nissan has installed a ''Drowsiness-Detective Alert'' system that determines the drowsy state of a driver by analyzing the steering profile for a few minutes of driving. This system makes a model of the driver's behavior based upon steering wheel movement patterns (it is common practice for drivers to slightly adjust and correct the steering wheel while driving under specific road conditions). If the driver is in a drowsy state, he will deviate from the model/observed data pattern and stop following those particular characteristics, and/or he will slow the pace of the pattern. In such situations, the dashboard of the car displays a coffee cup notification to alert the driver and to avoid any fatal accident. BMW has installed a ''Driver Assistance System'' that provides lane assistance, lane-departure warnings and lane-change warnings based upon visual data gathered through specific cameras installed at certain locations in the car. Table 7 summarizes the sensors installed by car manufacturers to detect drowsiness state and their working principles.

VII. RESEARCH CHALLENGES AND FUTURE RECOMMENDATIONS

Drowsiness/sleepiness is a vital state of the human body that is essentially required for healthy functionality. However, in some cases, among which, obviously, is car driving, drowsiness/sleepiness leads to devastating results. A recently

TABLE 6. Drowsiness/sleep-related findings in electrical signals of neuronal activity.

Study	Year	Sub	Experiment	Method	Brain area	Contribution
[9]	2002	11	Motorway driving experiment	PSD	O2-P4	Driving at constant speed causes fatigue
[11]	2005	8	Simulated driving	Relative Power	Multiple	Alpha, beta and their indices have differences
[51]	2008	13	Virtual-reality-based driving	PSD	Multiple	PSD from theta and alpha band at channel Oz follows the multivariate normal distribution
[13]	2009	20	Simulated Driving	PSD-SVM	Multiple	SVM can be used to detect drowsy state
[52]	2011	55	Real-life driving	Different parameters	Multiple	Alpha spindles-based criteria to detect drowsiness
[111]	2013	40	Simulated driving	PSD-SVM-ANN-kNN	Fp1	Listening to music can reduce the chances of getting drowsy
[112]	2014	NA	Simulated driving	DWT-K-mean clustering	Multiple	Drowsiness detection algorithm
[21]	2014	11	Working memory task	ICA and adaptive thresholding	Frontal and fronto-central	Blink detection using EEG
[14]	2014	30	Simulated driving	Power spectrum analysis	Occipital	Linear relationship between EEG activity in the O2 and eye-closure degree
[53]	2015	6	Simulated driving	Relative power-SVM	Occipital	Drowsiness detection system
[131]	2015	12	Virtual reality simulator	PSD-FFT	Multiple	Significant difference in the absolute alpha power between initial and final stages
[50]	2016	37	Virtual reality simulator	Convolutional neural network	Multiple	Proposed algorithm for classifying different states
[54]	2018	52	Simulated driving	K-mean and SVM	Multiple	Proposed two-layer algorithm for analyzing driver's behavioral data and EEG signal
[132]	2018a	15	Simulated driving	Phase lag index values	Multiple	Proposed an approach based on brain networks to detect drowsiness
[113]	2018b	15	Simulated driving	K-Nearest-Neighbors classifier	Multiple	Proposed a combined minimum spanning tree and synchronization likelihood-based functional brain network approach
Wang et al., [114]	2018a	10	Simulated driving	PSD and sample entropy	Multiple	Use of Dry EEG
Wang et al., [44]	2018b	12	Simulated driving	Multiple algorithms	Multiple	Channel T6, feature fuzzy entropy, and classifier gradient boosted decision tree with 500 boosting stages achieved best results
[115]	2018	22	Simulated driving	PSD	Frontal-Temporal	Delta band activity increases whereas theta and alpha activity decreases in the drowsy state
[24]	2019	30	Simulated driving	PSD-blink duration EOG-SVM	Multiple	SVM achieved maximum accuracy with 79% in multistate and 93% in binary state

published article [133] have summarized some of methods frequently used for drowsiness detection and possible applications with certain classifiers. In this article we have targeted brain signals and their respective response changes during drowsy feeling in addition to separately analyzing each method and corresponding pros and cons. Researchers have endeavored to alert drivers during the drowsy state so that unwanted and devastating circumstances may be avoided. At the same time, car manufacturers have been exerting prodigious effort to develop drowsiness detection systems and accident prevention mechanisms that not only accurately detect the drowsy state of a driver but also take automatic preventive action to avoid accidents. Still, though, there is no such system available that offers high accuracy. For example, lane-detection systems have some limitations: lane deviation is possible in overtaking and to avoid objects/obstacles. Similarly, installed steering sensors depend upon the accuracy of classification/detection algorithms, which cannot be 100%. In addition, false detection and deliberate changes in steering profiles, due to some other factors, are also possible. For example, eye blinking, eye-opening time, head nodding, and jaw movement, etc., could also be the results of some other clinical symptoms of certain diseases. Additionally, sun- and eyeglasses could also be restricting factors by which eye-based drowsiness detection systems could fail. Skin temperature and heart rate might result from the temperature inside the car cabin. In such conditions, the cortical-measured signal indicating drowsy state is a potential candidate. However, equipment like fMRI is not suitable, since it requires a huge setup and is not easy to apply for an experiment. On the other hand, it is of great potential importance, as some very important insights into brain functionality can be gleaned from this device's data. As for fNIRS,its portability and economy make it a promising candidate for drowsiness detection. Its drawback is the un-comfortable feeling of the NIRS optodes positioned continuously over the pre-frontal cortex. EEG on the other hand, with its high temporal resolution, is the most frequently used biomedical system for drowsiness detection. Its specific data features, k-complexes and sleep spindles are concrete evidence of drowsy feelings. However, continuous installation of EEG electrodes on a driver's head is a difficult task.

The present authors believe that a drowsiness detection system could be designed by utilizing a multi-modality

TABLE 7. Sensors installed by car manufacturers to detect drowsy feelings.

S. NO	Sensor	Working principles
1	Camera	Lane detection Object detection Head nodding Eye blinking Eye-opening measures Fuzzy logics Yawning
2	Steering wheels sensors	Pattern of driving Applied torque Steering wheel profile Steering angle Velocity profile
3	Breaking sensor	Model-based approach
4	Pressure sensor	Driver's seat

approach. For example, a steering sensor plus a dashboard camera could be employed for continuous monitoring of eye-blinking patterns, head nodding, and yawning, etc., in addition to a driving seat pressure sensor. A system with multi-sensor data could result in much closer and accurate estimation of drowsy/sleep feelings. In addition to this, highway police can utilize an fNIRS/EEG system to monitor driver at specific times. Additionally, as a simpler and easy option, self-evaluations in the form of drowsiness detection questionnaires could also be filled out by drivers at certain check points.

VIII. CONCLUSION

This paper reviews drowsiness causes, systems, as well as its preventive methodologies and neuronal activation states. It is concluded that most of research work in brain signal based drowsiness detection is done though EEG. Additionally, no drowsiness detection and alert systems of cars are hundred percent reliable. Therefore, multimodality approach could be helpful and much accurate.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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