# AI-Based Systems for Autonomous Vehicle Driver Monitoring and Alertness

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## 1. Introduction

In this field, complex systems can be developed to ensure that driving a car is safe in a given area. In automated cars, there are two approaches: adapting advanced technology from automotive to adapt to a car, creating a platform-based multimedia sensor-based data acquisition and processing of all air commercial and experimental solutions. We focus on AI-based recognition where ML algorithms infer information from road, environment, e.g. as it has been done in recent years and used a camera system only by AI [1].

[2] [3]- Driving is an attention-demanding task that can be greatly impacted by various factors, including drowsiness, use of alcohol (Rizos and Hunt, 2017; Durosai and Wen, 2020), and poor vehicle conditions (Wang and Zohar, 2003). According to the National Safety Council (NSC), in 2020 42,060 people died in motor vehicle crashes in the US, which is the highest number since 2007 and almost an 8% increase (Road safety, 2020). The most frequent accidents are caused by disorientation, inadequate routing information, or loss of concentration, and are more likely to originate from one of several physiological phenomena. Factors that may lead to an accident include: a. Drowsiness, b. Alcohol and drugs, c. Emotions, d. Physical impairment. There are various solutions, from physiological (PCR) to automatic (emissions) early detection of driver fatigue / sleepiness, which can prevent accidents. The ability to predict drowsiness and ultimately sleep is very useful for additional vulnerabilities, such as monitoring system operators.

### 1.1. Background and Significance

In 2020, in the German-speaking area alone, 9 thriving Deep Tech companies were doing business, however the Das Batterieforum Deutschland continued to remark the supply chain challenges for batteries and the increase of bindingness intentions as of the raw material procurement in East Germany's mining area. This observation of the German-speaking market can also be concluded for the German and European market. In line with other partners, data-driven processes, connectivity and machine learning technologies for products (e.g. car, lithium battery) and related services (e-commerce) and manipulation / duplicate detection process were discussed in the future trend book. Financial support will be given to data-driven learning in the PRORETA program. For the future, key introduction to the vision of 2025 was presented which based on the data-driven process [3]. In this scenario environment, the differences to the Big Data market were illustrated, showing the particular strengths of Germany in this environment based on the data sovereignty aspect. Also, many other markets were indicated based on the target groups, e.g. buying new products, mobility, intelligent living / digitization, intelligent working / leisure, custom medicine and Data Science-as-a-Service.

[4] The rapid advancement of emerging technologies in the automotive industry is particularly noteworthy. Known challenges such as global supply chain disruptions and the on-going semiconductor crisis are expected to shift Six Mega-trends, namely the transition to zero-emission mobility, the development of connected and autonomous vehicles, the increasing share of E-commerce, the growing importance of cyber security, demographic changes, the increased need for health and comfort technologies in the interior. However, the CAKE project showed continuously increasing trunk sales for the automotive, chemical, and consumer goods industries, making it an interesting market segment for further consideration of megatrends [5]. Within the different megatrends the requirement for driver and other occupant monitoring subtopics are presented, e.g. stress and drowsiness detection and seat movements. The growing importance of next-generation vehicles and its impact on on-board sensors for occupant monitoring, systems and applications such as autonomous passenger cars (level 4, 5 of SAE) were also emphasized. These functionalities provide new solutions relevant for the improvement of human factors which is especially important in semi- and fully-autonomous vehicles.

### 1.2. Research Objectives

The furtherance of DMS algorithms are indispensable both for these systems and for preventing accidents in general. In the proposed system, the time data series $t(0)-t(n)$ were processed as a twoatrogram for input. By means of this transformation, the temporal order of the observed data. The performance of the system has proven to be outstanding both from the reliability and limitations point of view. Drowsiness bias recognition is not involved in the system. Given the importance of this analysis, further research could be focused on proposing more sophisticated methods of robust recognition of inattentional bias.

[4] [6]On highways, the probability that the driver's cognitive abilities are in some point lost is larger, and these tend to be preferred for the implementation of automation systems. If a person falls asleep and their vehicle runs off the lane, or the speed is inconsistent with road-traffic conditions, an accident can occur, sometimes with fatal consequences. This work proposes the use of different neural network types such as feedforward, convolutional, recursive, and long short-term memory (LSTM) networks. An extended person class was proposed assigning class 0 to non-drowsy epochs or if drowsy epochs had also occurred in its series, or assigning a class 1 (drowsy) if drowsy only appeared in the rest of its series. To evaluate the results, the co-fu-zzy index was used for a different set of data, and the alfa/foxtrot metric was used for time-series data. Results for the rest of the series were satisfying as well.

**2. State of the Art in Driver Monitoring Systems**

The benefits from these advancements emanate from the assumption that, even in scenarios where the driver is supervising an autonomously driving vehicle, the human operator is super attentive, super awake, fully aware of everything happening around her and can intervene, at incredibly short notice. Because these assumptions might not be applicable in practice, some authors are of the view that we may never have a truly "fully autonomous" system. The Society of Automotive Engineers (SAE) defined a standard for stages of driving automation. However, even vehicles at level 5 of autonomy require human supervision based on the new SOTIF (Safety of the Intended Functionality) standard aiming at a safety case for road vehicles. We identified the following driver states that cover the complete range of the human behavioral states and processes of interest in the context of driver aesthetic supervision as per ISO/TS 33019: Drowsy, Yawning, Sleeping under the influence, Sedated, The presence of Medication, Drugged, Drunk, High, Paralysed/numb or very fatigued, Near Missing. However, given the novelty and limited research in paradigms such as taking medication, being high and being under influence, the rest of the article focuses on the more well researched sleepiness and also for point of reference the driver states used commonly in the area of driver workload, drowsiness and driver monitoring.

[7] [6]Automobile safety has seen tremendous improvement due to ongoing research on automotive technologies like driver-assistance and autonomous driving systems. These technologies have the potential to reduce or eliminate human errors such as speeding, failure to maintain lane, and failure to yield that are the leading causes of automobile crashes. Moreover, these technologies can significantly benefit owners of vehicles by improving traffic throughput and safety, increasing fuel efficiency and allowing downtimes to be used for engaging in non-driving related work and entertainment. Since these advancements reduce the need for manual control by the drivers, they open significant opportunities for applications of intelligent systems that can monitor the driver and ensure that the driver is always attentive, awake and able to take-over manual control in case of a need. The English Oxford Living dictionary defines the term 'autonomous'; to mean: "Having the freedom to act independently"' or "Operating without human control or supervision". For the singular low frequency and high consequence situations e.g. parachute opening for life-saving, the demand for high safety levels has necessitated use of fully autonomous systems. The objective of this article is also to encourage focus of the research community towards the development of driver supervision systems that are capable of handling the full range of human behavioral states including fully autonomous systems and even systems with autonomous driving but for cases where a human, apart from being in the car, might potentially be under the influence of alcohol and drugs or when the driver shall be sleeping during the short time durations of vehicle maneuvering and the supervisor's main goal is to supervise automation or there isn't a potential or need for a take-over.

**2.1. Traditional Systems vs AI-Based Systems**

To effectively evaluate reliability and adequacy of the human observer during AVHMI, DMS performance evaluations should be undertaken [ref. 55c7f380-ac73-45f4-acc8-2f01d934ef63]. Specifically, many variables impacting the operation of driver monitoring systems were thoroughly analyzed in the articles qualified for this taxonomy. A cornerstone of these observations is the high degree of adaptivity and adaptability of AI-based systems, which outperform traditional systems. Here, the key concept of AVHMI operation may be the highly adaptive structures of both vehicular and subtending devices.

Research shows that as drivers gain trust in AV capabilities, their attention to driving may diminish due to automation complacency [6]. Introducing a non-invasive driver monitoring system can help detect inattention patterns and improve driver alertness. Despite the accumulated knowledge in this developing field, the technical requirements of different driving environments and the specific scenarios in AV/HMI remain unclear. The following topics derived from our systematic taxonomiy construction will provide a practical reference for researchers engaged in driver monitoring under AV operations. These findings suggest significant intersections between AI-based technology and DMS, particularly adaptive learning-based systems [8].

**2.2. Key Components of AI-Based Systems**

In the AI system, different inputs, data symmetry and age or an algorithm can cyclically select necessary features from the pre-trained deep learning model, which will be reliable in monitoring the driver's behaviour [9]. The deep learning model using artificial intelligence has the powerful capability for processing human's natural language signal, which depends on the many improved structure algorithm, like LSTM, RNN and SPHERE which was designed for detecting the discrete signal processing, also can move from clandestine sound to normal sound signal, which will be suitable for the auxiliary driver model. In real life, both adults and young people have been in a society with taking environmental factors in to consideration for adaptive network attack alarms. Establishing a driver's attention is given into real time is important for vehicles with driver warning system.

The AI-based systems for autonomous vehicle driver monitoring and alertness developed in recent years include different models of human behaviour and driving tasks, smart sensor design, signal processing algorithms, and advanced artificial intelligence [10]. Eye and drowsiness alertness detection have been a very popular research area among some researchers [11]. The system will be activated when the detection of the physiological signal changes on detected State and condition. In this line of research, Chen et al. construct a driver's fatigue and distraction model based on an eye state. Saleh and Alzubaidi proposed a deep learning model that could detect and track a set of facial landmarks, among which the lips, eyelids, and eyebrows are utilized to train a referential Driver State Monitoring (DSM) model. Since the appearance of the face is similar with eye mask when driver is wearing mask, it is easy to get misrecognition.

**3. Data Collection and Processing Techniques**

In terms of driver demographic data, the age group of the driver is the main consideration and during driving, the bridge system of the driver is also monitored.

(iii) Google trend data: The Goggle trend data of the last 10 years affect the driving psycho and alertness of the 1 year data collection driver.

(ii) Wireless Headband Acquisition System: For 25 participants, a wireless headband system was utilized to record brain (EEG, EOG), muscular (EMG) and EYE (ECG, EOG) bio signals (subject's blinks and eye movements) to develop an algorithm that predicts fatigue in advance.

(i) Vehicle speed and gear position: In vehicle safety, the vehicle speed plays a vital role to monitor the alert and drowsiness of the driver. The vehicle speed is one of the most important parameters to identify the vehicle category of whether it is a four-wheeler vehicle or two-wheeler vehicle.

What are the parameters used to detect the mood of the driver? The parameters are:

The physiological signals or body signal monitoring system is mainly Biosignal monitoring system (e.g. ECG, EEG, Hand gesture, EOG, Breathing rate) to get the analysis the drowsiness and mood of the driver. At the start of driving the collection of data is done when the body signals acquisition is processed. For the process of data gathering, a question comes in the mind.

[12] A real-time driving intelligence monitoring system for automotive environment is designed to understand the psychological and physiological states of the driver and detect any unusual behaviors, using non-intrusive and reliable approach [11]. For a full understanding of the driver's behavior, the system analyzes information about the driver's state and surroundings by integrating data from driver, vehicle and the road as shown in Fig. 2. Studied and evaluated section also contains various research work related to the safety and autonomous vehicle [13]. The vehicle contains ADAS sensors so the data from the vehicle is used to assess driver's attention. The driver's face and hands gestures with vehicle speed changes are the basic information which is used to detect the drowsiness, eyes closed, not on the road and hands not on the driving wheel. It is very important that driver is not sleepy or

busy in another activity during manual mode because the vehicle needs an immediate feedback from an active and attentive driver. The vehicle and the on-board sensors continuously give information about every second of the vehicle state and the environment around the vehicle with the help of acoustic, visual, touch, and coordinated stimuli for detecting some critical behaviors of the driver.

**3.1. Sensors and Data Sources**

Passive systems, installed in vehicle, cameras, advanced Driver-Assistance Systems (ADAS) systems and Radar and Lidars sensors are used and active systems, which are mainly made as wearables, inertial measurement units (IMU), Gimbal devices and wearable ECG systems are the types of driver monitoring and alertness systems. Artificial intelligence based driver monitoring and driver alertness methods are also implicit as a solution to follow, due to the ability to process high complex time-series data [2]. Often, sensors are used in the environmental car level in order to monitor the road condition, the pedestrians, the vehicles in front and back of the car and more characteristics of the road and its environment.

Various domestic and foreign sensors are used in autonomous driving systems and for monitoring and alertness instincts, it is important to extract driving-related features from different signals [14]. Generally, because of AI-based systems and also due to simplicity, multi sensor systems are used as the best solutions [15].

**3.2. Data Preprocessing and Feature Extraction**

To pre-process the data, frame the pre-training test scenario, eliminating sporadic movement. For the analysis, we utilized camera-based frontal monitoring and detection of the head region. In this 2D image feature, the face and facial area were pre-marked (eyes, mouth, face) using face recognition application programming interfaces (APIs) and then automatically resized using correlation interferometry to crop the head image. Based on the intersection over union (IoU) advance, the object detection automatically marked the facial area [6]. For data augmentation, pixel modifications (translation, re-shape, color modification, zoom, rotation, noise inset, occlusion inclusion) are also carried out to promote model training. The face and eye detection IOU were 0.05 and 0.3, respectively. In this 30 Hz resolution dataset, 45 Hz for the iris and the pupil signal and 120 Hz for audio signals were broadcast by our simulated VR driving model. When all files began to stream at the same time, the VR digital driving platform recorded the logs.

It is essential to pre-process the data and extract pertinent features before modeling state classification algorithms. Removing sporadic feature noise enabled by eye and head movement reduces the generalizability of the features and prevents model training. Saccadic movements are extensions of subject's noticeable visual evaluation when trying to achieve intelligence tasks such as driving in VR. Extracting those saccades and non-saccades necessary for demand sensing analysis [13].

**4. Machine Learning Algorithms for Driver Monitoring**

In a recent study, the driver's facial image data getting acquired using Web-Cam was used as an evaluation input [3]. Data is collected from two in-car datasets of pictures containing different kinds of lighting simulations (day and night). The in-car dataset 2 contains facial images of drivers both with and without facial masks. The model is designed to classify driving drowsiness into two classes: "alert" and "drowsiness". The model has achieved 99.22 % accuracy using GLDM feature extraction with existed ML classifiers. The machine learning algorithms like MLNN, SVM, KNN has acceptable results for EAUGRP feature extraction. The experiments conducted have obtained beneficial results by the classification of the patient's state from the facial images.

Deep learning algorithms have shown satisfaction in detecting the face, eye, and eye blink using a facial key data set. Given the significance of deep networks in detecting drowsiness, a state-of-the-art detection model is optimized by machine learning [16]. Machine vision and machine learning innovations are cost-effective as they need only a camera and no additional sensors [4].

**4.1. Supervised Learning Approaches**

The role of machine learning models in the safety, performance, and comfort features of vehicle communication services is discussed in Johannes et al.. Spatial Company designed a recognition algorithm for detecting the face position, intensity, and head movements of users while driving, focusing on the driver's Safety and Comfort features as well as face and scene detection [16]. The SVM is a popular approach for real-time driver's perceptive condition detection that is worked by Teixeira. The system based on driver's perceptive constant and data consist of a set of batch classifiers and reject classifiers and renew a reject classifier that is down voted by batch classifiers to next batch in every n frames to lower compensational cost or power consumption compared With other recent works Teixeira introduces a different ecosystem doing a combination learning together traffic monitoring and vehicle control rejecting, in which context he takes it as a general situation in which a driver is a state estimator.

Using supervised learning approaches, driver behavior is analyzed under different conditions [17]. Wang et al. proposed to use hidden Markov models (HMM) to predict driver actions in car-following scenarios under different congestion conditions, while multiple artificial neural networks (ANN) and principal component analysis (PCA) are used by Abuhav et al. to investigate the lane change behavior through a comprehensive data analysis. Reyes et al. further illustrated the power consumption and performance trade-off of using co-design strategies and different computing platforms of the machine and deep learning models in resource-constrained devices [18].

**4.2. Unsupervised Learning Approaches**

.Reflection models—reversible max pooling, Contextual attention mechanism, etc.—make anti-GAN (Adversarial Network), VAE-GAN, and Context encoder (ConGAI) systems good at visual quality, but their mutation character also makes their predictions less precise, requiring a too time-consuming pre-processing step. Although VAE-I3D performances better than the above systems in human abnormal prediction task, the scores are not too stable. Intrinsic evaluation of VAEGs algorithms does not seem to be good but it performs much better than I3DV. On brake event tracking tasks, our system is highly appreciated, compared to other prevailing systems such as PVA, when slight effects take place.

[4] The unsupervised learning approach is applied to abnormal event detection by using the concept of normalcy to understand the unusual behaviors while driving. It is widely adopted in various applications because of the lack of substantial annotation requirement in the training phase. There are two prominent strategies in this learning setting namely Gaussian distribution based and Convolutional Neural Network (G)AN or Variational Autoencoder (VAE) based techniques. An important application under the abnormal event detection category is driver alertness prediction which has gained significant interest over the years [19].

**4.3. Reinforcement Learning Techniques**

If a driver drowsiness or inattention is detected, a warning can be sent to the driver in different ways. This can be dash-mounted display, steering wheel haptic feedback, audio and light stimuli. In case the vehicle is equipped with vehicle-to-vehicle (V2V) communication systems , alert signals could be sent to the surrounding vehicles to prevent any possible dangerous situations.

Reinforcement learning started to be employed to design of less invasive driver monitoring systems aiming at preventing drowsiness without distracting the driver. The work of Thangaraj et al. aimed to detect driver's short- and long-term drowsiness using wearable electroencephalography (EEG) signals and a gyroscope in an automotive environment. In the context of the work, a two-directional Long Short-Term Memory Neural Network (LSTM) model was developed to generate top-view frame feature sequences from visual data, which then encode the time level dependencies in the lateral dataset entered into the forward and backward blocks. This model could be used as a multi-sensor fusion architecture to fuse the variables generated by the direct and lateral LSTM networks.

[20] [12]

**5. Challenges and Limitations**

Recommended carefully analyze AI-based and deep learning techniques as they have been explored for driver-activity monitoring and alertness detection, for instance, in [4]. An EOG- and EEG-signals-based system has been proposed, using a convolutional neural-network-based visual-attention mechanism with EEG signal processing to detect driver drowsiness. In this paper, the authors did not carry out a detailed description of algorithms. However, this study strongly highlighted the necessity of a comprehensive data-driven approach in the form of deep learning and AI to guarantee the best performance, stability, and compatibility for automotive driver-monitoring and alertness systems. This work also provides a tool to test the usability and challenges related to multimodal (for example, visual, aural, and haptic modalities) all-in-one automotive driver-monitoring and alertness systems. The proposed algorithm provided a valuable tool to fully develop an inexpensive 24/7 and user-friendly automotive driver-monitoring and alertness tool and to validate the system in the automotive driving setup. In addition, BCI-theory-based systems were given a promising approach to improve the performance of a vehicle, particularly with regard to achieving coordinated maneuvering and to Bioharness-ready application and functionality within automotive driver-monitoring and alertness systems. Based on multisensory processing particularly, artificial neural network algorithms have been developed with the automatic detection of driver activities, and a smart driver-attention-assurance algorithm in an automotive driving environment. There is considerable potential to directly incorporate electroencephalogram (in-ear EEG, Emgu, and other novel electrode-based systems) and EOG modules into future automotive driver-attention-preservation and driver-alertness systems to detect driver inattention and later drowsiness.

The review and critical analysis provided in this survey aim to explore the recent and significant advancements made in the field of AI-based systems for driver monitoring and alertness systems. For every system-based methodology the authors presented their architecture and working principle, and also, their achievement, in terms of the performance metrics used. The main idea was to review, analyze and critically discuss the developments made in this field.

**5.1. Privacy Concerns**

User acceptance of AVs equipped with DMS presents a unique set of challenges for the field of human–AV interaction (HAI). On the one hand, training drivers to use sophisticated automation features within an AV, such as the autopilot, could be a promising means of maintaining user engagement. Specifically, presenting drivers with a series of uDraw animations on the part of the screen that they are not attending to and requiring comprehensive responses to each from time to time could help to maintain the users' engagement with the autopilot. Such a method could be used to make drivers' level of alertness a function of their tendency to confront the uDraw animated characters. On the other hand, intelligent AVs should monitor driver attention and step in when they detect that it is insufficient. AVs could alert a driver who has shifted their gaze too often from the forward road view by attempting to direct the driver's gaze back toward that view using turns of the driver's seat or window tint.

[21] [6]Great advances have been made in driver monitoring systems (DMSs) for autonomous vehicles (AVs). DMSs monitor drivers' physical and cognitive states, aiming to decrease their cognitive workload and decrease the likelihood of accidents [2]. This provision is part of a

broader trend towards automating the driver task in AVs. However, user acceptance is a critical issue in this area.

**5.2. Real-Time Processing Constraints**

AI can be useful and efficient in transferring one module results to another one even in the case of novel algorithm but Algorithm robustness, perfectness and real time efficiency are other important constructs. Making sure that the module consisting of the AI Algorithm will work effectively, robustly and efficiently is very hard and needs to use new methodology in it. Synchronizing data from various sources, such as sensors, RSUs, and social media, poses a significant challenge in autonomous driving. The difference in data frequencies, such as the gap observed between cameras and LiDAR, complicates the synchronization process. These factors will increase the likelihood of failing in detection methods. Integration of all these modules has simultaneously been resulted main challenges. Owing to this, the maximum rate of execution for any module is not explained especially when the complexity improves.

Several papers [6], [11] have discussed different driver monitoring and alertness systems; however, in most of these systems there are at least some separate components which need to share the data in order to make the decision or issue an alert. A survey [22] has mentioned that making autonomous vehicles travel on streets is very easy for those who do not think deeply toward intelligence in general and more specifically toward roads as the complex changing environment. Decision making and implementation of them in the real time for intelligent agents such as autonomous vehicles are not easy because of numerous unknown conditions and possible simultaneous changes in their environment. The hardware platform also plays an important role. There are several constrains in the order of execution of the major functionalities and the upper bound must be well calculated to have the system working properly and robustly.

Key insights from the papers:

**6. Applications and Use Cases**

With advanced driver assistance systems (ADAS) and advanced automotive technologies, monitoring technologies are considered to be crucial for providing a better interface for safer and efficient vehicle operation. However, driver excitement, stress and concentration significantly affect driving behaviours and vehicle control performance. Therefore, for sole monitoring system contribution in enhancing vehicular operations, it is necessary for the driver to decide on their own if he has confidence in applying the assistive application. Therefore, this study demonstrates the application of monitoring and assessing individual driving style can significantly improve road safety. Customizing the Advanced Driver Assistance Systems (ADAS) features to meet the individual driver needs, expectations, abilities, and constraints is not only necessary to obtain the mentioned benefits from ADAS, but is the key to ADAS success.

Given the importance of driver's alertness in terms of monitoring system, a study of Tebruger conducted a series of driving simulator experiments, where the navigational control may be influenced by the availability of the alerting method. The authors pre-set four types of alerting systems: sound + red light on the dashboard, haptic feedback (vibrating belt), visual alert + haptic feedback, and sound. Results show that having systems with different modalities might enable the user to react more quickly to the alert stimuli. The study shows that the dual-modal system (with dynamic feedback) made the subjects react much more quickly than the other 3 types of single-modal alerting systems. This indicates that alerting effects could be improved using multiple modalities. However, the authors did not systematically compare the simultaneous effects of different modalities in detecting impending changes in route following on how passengers shaped the driver response.

### 6.1. In-Car Monitoring Systems

The design of such systems becomes more challenging as higher levels of automation are achieved. Since such driver monitoring systems (DMS) require the evaluation of the driver's active state and his/her ability to cognitively act against an emerging danger, arm net framework also provides key indicators for the controlled status of the driver. Moreover, a surprise element detection mechanism becomes in turn essential for monitoring the driver's vigilance. It helps in alerting either to wake up or handover controls to the driver in the case of autonomous vehicles. As being monitored continuously by the system, it is not surprising for the driver to enter a semi-automated state of driving. Such scenario impacts driving performance as well as the ability of the system to understand the mental state of the driver. An algorithm for the detection of the contemplated knowledge or idea of the driver is proposed in this case where, if the cognitive status indicates that the driver is not preparing for a take-over but thinking of something else, the rest action is prompted facilitated.

[23] The reliability of AI (Artificial Intelligence)-based systems to detect driver impairment, under both constrained and real driving conditions, is still under scrutiny. The highest level of autonomous driving (when the vehicle is operating on its own with no driver intervention), Level 5, is not yet realized. It is expected that antilethargy systems will be useful in this case, especially in providing the driver with stimulation while adapting to his/her profile and habits [3]. One essential component of an autonomous vehicle is the driver monitoring system (DMS), where the vehicle is required to monitor the driver to produce a competitive takeover strategy.

**6.2. Fleet Management Solutions**

Fleet management systems are focused on the complete management of the vehicles, with the main goal of reducing the maintenance, operational cost, and increase the overall productivity. To achieve these goals the fleet management system collects the information on the trip information, fuel reports, vehicle locations, speed, and the status of the onboard diagnostics (OBD) such as engine temperature, RPM, driving patterns, and the like [2]. The current commercial solutions for the driver monitoring systems are only used for driver identification and simple tracking at the specific commercial fleet companies. Most of these commercial solutions widely make use of GPS for the vehicle tracking, but they are not completely effective to prevent accidents and they are only used for the purposes of monitoring the driver. It is highly motivated to have a commercial system which collects the data using multiple sensors involved, having sensors such as IMU, GPS, camera, lidar, CAN, and OBDII. A commercial vehicle driver be individual who is driving the vehicle in a hiccup situation (in an unconscious state) and that few seconds of the delay may cause huge loss of human life occurred in the vehicle or to other and so it's mainly focus to detect such kind of abnormal driver behaviour detect which leads to unintentional accident.

Systems based on Artificial Intelligence (AI) are being increasingly researched in the vehicles to avoid road accidents by ensuring the active participation of the driver. As not all vehicle will be autonomous in the next decade and Vehicle-to-Pedestrian and Vehicle-to-vehicle communication systems are still not fully implement, DM is essential to periodically monitor the state of the driver to reduce the probability of distraction and drowsiness scenarios. These concepts reduce the probability of different accident typologies related to driver distraction and drowsiness such as single-vehicle off-road, hitting another vehicle from behind, lane departure, or crossing pedestrian or objects on the road, among others. Given the higher number of vehicles in a fleet, monitoring drivers within this context becomes a challenging task in practice.

**7. Future Directions and Emerging Trends**

Such systems could be trained from large drowsiness and driver monitoring databases to recognize drowsy behaviors promptly and accurately. Considering the complicated nature of visuo-vestibulomotor tasks, the implementation of three-channel EEG, after validating the performance of monocular eye-tracking and frontal face monitoring using a Portable Biological authentication system (BioPort), will lead to a real-time dual-level concurrent architecture. A small algorithm, for example, needs to discriminate drowsy from alert conditions clearly and concisely. While the accuracy and computational performance of the deep learning method were very good, in a subsequent investigation, the system was found to be susceptible to adverse environmental conditions, leading to severe changes in the collected videos [8].

[5] [10]One characteristic that valuable artificial intelligence models will need to exhibit is computational efficiency for deployment in large organizations. A fundamental principle of these intelligent models is also that the accuracy of their predictions must be superior to that of other existing methods, particularly those that use traditional machine learning algorithms, such as support vector machines and artificial neural networks. Moreover, the model will need to be binary-class classifications because the ultimate goal will be to assess the fatigue or mental status of an individual (e.g., alert or drowsy). Recently, deep learning economics have migrated from using conventional double-precision (64-bit) floating-point data types for both computation and memory to much more computationally efficient lower precisions, such as 16-bit and 8-bit mixed or integer quantizations. The deep neural model cannot be complex and computationally expensive but needs to be lightweight and embeddable in small embedded hardware, while meeting certain performance specifications.

**7.1. Multimodal Sensor Fusion**

Work by Kim and Kim used a diverse range of modalities such as speed, steering wheel angle, acceleration, and also collected data from blink detection, EEG and ECG. Additionally, efforts are also very much related to the Signal Processing of Data from Sensors for Decision Making in Autonomous Vehicles section of this Special Issue. Moreover, that in that specific sub-section two articles discussed advancements and new opportunities through signal processing for autonomous vehicles and kwon differently related to the vehicle control execution and signal fusion in the domain of vehicle-to-vehicle communication.

Integrating data from different sources has benefits in diverse areas including automotive safety and has long been considered the standard and basic methodology to assess and manage driver's alertness [24]. Inattention, for example, represents one of the major risk factors in road traffic collisions, and is also considered a significant issue for drivers in autonomous vehicles or during the presence of a co-active driving assistant [25]. Moreover, fatigue and drowsiness have long been recognized as an important contributing factor in traffic safety in general and for the autonomous driving domain, in particular, driver drowsiness remains a serious danger to traffic safety as the driver might underestimate the influence of drowsiness [26]. Kammler et all applied a range of different sensor technologies such as Electroencephalography (EEG), Galvanic Skin Response (GSR), and Photoplethysmography (PPG) in order to detect incidentally occurring dangerous driving situations.

**7.2. Edge Computing for Driver Monitoring**

[12] Transport networks are evolving and increasing progressively with the advent of sophisticated data acquisition and processing tools. The complicated composition of the data acquisition and processing architectures has flaws including intricate structures, fiasco to deal with unexpected issues under unsafe conditions, and reliance on the cloud for big data processing. Instead, providing mobile crowd-sensing systems with state-of-the-art machine learning models in artificial intelligence-capable technology has emerged as an alternative for in-vehicle systems for anomaly detection, a key step for enormous data processing due to its scalable, robust, and flexible architectures. Since artificial intelligence-based real-time traffic anomaly detection systems detect different types of anomalies and their relationship with the entire surrounding areas, they can lead towards safer and more efficient intelligent transport systems.[20] An algorithm based on the deep neural network architecture is proposed for detecting unusual driver behaviors in dash-camera recordings. For self-training of the architecture, the probability-based curriculum learning method deals with the issue of limited data. The attention model works to focus on critical frames and extract local evidence frames

as examples of unusual behaviors. Taking advantage of mutual information between visual and audio signals, both modalities have been used in a multi-modal fusion detection system. Results indicate the efficacy of the proposed architecture and considerable performance improvement over previous works.

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