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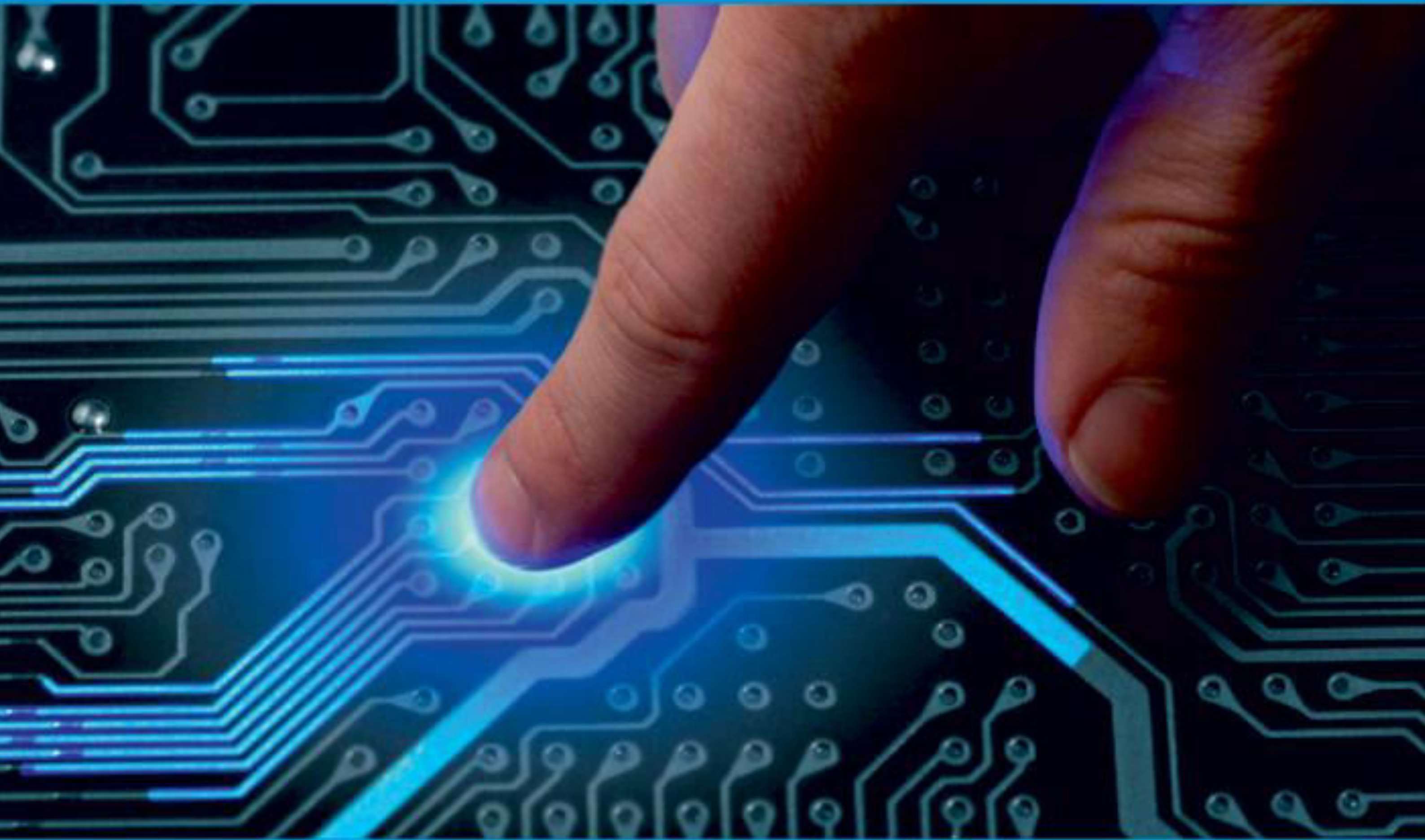

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A Survey on Driver Drowsiness Detection System and Road Safety Application

Niraj Bansal, Mrunalini Hibare, Om Sakhare, Rushiraj Kudapane, Prof. Rashmi Kale

Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

Professor Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

ABSTRACT: As road safety continues to be a critical concern worldwide, the development and implementation of driver drowsiness detection systems and road safety applications have gained significant attention. This survey paper provides a comprehensive overview of these systems and their impact on enhancing road safety. In simple terms, we explore how technology can help prevent accidents caused by drowsy drivers.

We delve into the various approaches and technologies employed in detecting driver drowsiness, from physiological sensors to machine learning algorithms. Notable methods include eye tracking, steering behaviour analysis, and EEG-based systems, with an emphasis on their effectiveness and practicality.

Additionally, we discuss the real-world applications and implications of these systems in improving road safety. By analysing relevant statistics and studies, we highlight the significant reduction in accident rates and fatalities associated with the deployment of drowsiness detection technology.

Through this survey, we aim to provide a clear understanding of the current state of driver drowsiness detection systems, their advantages, limitations, and their profound impact on road safety.

KEYWORDS: Driver Drowsiness Detection, Road Safety, Machine Learning, Real-time Alert System, Vehicle Safety.

I. INTRODUCTION

Every day, millions of people around the world rely on automobiles as their primary mode of transportation. However, as convenient as driving can be, it comes with a significant responsibility: ensuring road safety. One of the most critical factors affecting road safety is driver drowsiness, as drowsy driving can lead to accidents, injuries, and even fatalities. In this survey paper, we explore the fascinating world of Driver Drowsiness Detection Systems (DDDS) and their applications in enhancing road safety.

Drowsy driving is a common problem, and according to the National Highway Traffic Safety Administration (NHTSA), it contributes to thousands of accidents each year in the United States alone [1]. The consequences are severe, with the potential for loss of life and significant economic costs. Fortunately, technology has evolved to provide innovative solutions to combat driver drowsiness and improve road safety.

Driver Drowsiness Detection Systems are a class of technology that leverages various sensors and algorithms to monitor a driver's behaviour, physiology, and environment. These systems can detect signs of drowsiness, such as erratic steering, changes in facial expressions, or even physiological indicators like heart rate and eye movement. Once detected, these systems can trigger alerts to wake up the driver or take control of the vehicle, preventing potential accidents.

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This survey paper aims to provide a comprehensive overview of the different techniques, methods, and technologies used in DDDS. We will also explore their road safety applications, highlighting their effectiveness in mitigating the risks associated with drowsy driving. Additionally, we will delve into real-world implementations and success stories of DDDS across various vehicles and road safety initiatives.

As we delve deeper into the world of driver drowsiness detection systems, we will discover how these technologies are playing a crucial role in making our roads safer and reducing the human and economic costs of drowsy driving incidents.

II. LITERATURE SURVEY

The purpose of this systematic review paper is recognition and categorization of the best possible techniques, measures, tools and classification methods for drivers' drowsiness detection. The systematic reviews help to recognize what we know in the concerned domain. All the data gathered from primary studies is categorized. Once the systematic review of empirical studies is done, we gather relevant information and identify the research gaps in the existing research studies [2]. The population of systematic review consists of research papers relevant to drowsiness detection.

Acharya et al. (2011) developed a drowsiness detection system that utilizes image-based techniques. This system incorporates recent trends and evaluation studies. The approach involves tracking facial features, monitoring eye closure, and assessing the driver's head position and movement [3].

Bao and Wu (2016) proposed an intelligent system for real-time drowsiness detection, leveraging hybrid image processing techniques. Their method combines eye tracking, facial feature analysis, and head pose estimation to provide early warning of driver drowsiness [4].

Lee and McGehee (2007) re-examined the role of eye glance in driver distraction and the importance of monitoring biometric data. They emphasized the value of eye-tracking devices and wearables in assessing drowsiness levels, such as detecting microsleeps based on eye behaviours [5].

Li et al. (2018) introduced a real-time drowsy driving detection system reliant on biometric sensors. By tracking blink frequency and duration, they successfully identified driver drowsiness. The method provided a nonintrusive and efficient way of monitoring driver alertness [6].

Khan et al. (2019) conducted a comprehensive review of driver drowsiness monitoring systems, emphasizing their commercial potential. The survey discussed various machine learning and deep learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for driver drowsiness prediction and alert generation [7].

Zheng et al. (2016) introduced a real-time nonintrusive monitoring and prediction system for driver fatigue using machine learning techniques. This method combined physiological signals, vehicle data, and environmental factors to assess driver drowsiness [8].

Gozalvez et al. (2011) explored the role of vehicle-to-infrastructure (V2I) communications in preventing drowsy driving accidents. They discussed the integration of drowsiness detection systems with V2I networks, allowing for real-time data exchange with roadside infrastructure to provide timely warnings to drivers [9].

Daamen and Hoogendoorn (2014) studied the impact of intelligent speed adaptation on drivers' sleep duration. They examined V2I applications that adjust vehicle speed based on the driver's drowsiness level, contributing to safer road conditions [10].

Memon et al. (2019) offered an extensive discussion on the challenges and future directions for driver drowsiness detection systems. Their review encompassed issues related to real-world deployment, privacy concerns, and standardization in drowsiness detection technology [11].

Carvalhais and Nadais (2018) identified challenges in applying these systems in real-world conditions. Their work emphasized the need for further research in areas like multi-modal sensor fusion, robustness, and adaptability of

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drowsiness detection systems [12]. But before we go further, we must understand the reasons and factors causing drowsiness and distractions.

1. FACTORS CAUSING DROWSINESS

Drowsiness is a state of feeling sleepy or tired, which can lead to reduced alertness and impaired cognitive function. Drowsiness can be caused by various factors, including sleep deprivation, sleep disorders, medication, alcohol, and fatigue.

Sleep deprivation is a common cause of drowsiness, and it can be caused by a variety of factors, including work schedules, lifestyle, and medical conditions. People who work long hours or night shifts are more likely to experience sleep deprivation, which can lead to drowsiness while driving. Lifestyle factors such as staying up late, watching TV, or using electronic devices before bedtime can also contribute to sleep deprivation.

Sleep disorders such as sleep apnea and narcolepsy can also cause drowsiness. Sleep apnea is a condition in which a person's breathing is interrupted during sleep, leading to poor sleep quality and daytime drowsiness. Narcolepsy is a neurological ailment that reasons immoderate sunlight hours sleepiness and unexpected sleep attacks [13].

Medications which includes antihistamines, antidepressants, and sedatives can reason drowsiness as a facet effect. These medications can impair cognitive function and reduce alertness, making it difficult to stay awake while driving [14].

Alcohol consumption can also cause drowsiness, and it is a major cause of road accidents. Alcohol is a depressant that slows down the central nervous system, leading to reduced cognitive function and impaired judgment. Even small amounts of alcohol can cause drowsiness and impair driving ability [13].

Fatigue is another common cause of drowsiness, and it can be caused by physical or mental exertion, stress, or boredom. People who are fatigued may experience reduced alertness, impaired cognitive function, and slower reaction times, making it difficult to stay awake while driving [14].

2. FACTORS CAUSING DISTRACTIONS

Distractions while driving can be a major cause of road accidents. Distractions can be caused by various factors, including mobile phones, music players, and other electronic devices, eating, drinking, and smoking while driving, and external distractions such as billboards, roadside attractions, and other vehicles.

Mobile phones are a major cause of distraction while driving. The use of mobile phones while driving can lead to reduced cognitive function, slower reaction times, and impaired judgment. Texting while driving is particularly dangerous, as it requires visual, manual, and cognitive attention, taking the driver's attention away from the road.

Music players and other electronic devices can also cause distractions while driving. Adjusting the volume, changing the song, or searching for a playlist can take the driver's attention away from the road, leading to reduced alertness and impaired cognitive function.

Eating, drinking, and smoking while driving can also cause distractions. These activities require manual and cognitive attention, taking the driver's attention away from the road. Eating and drinking can also cause spills, which can lead to reduced visibility and impaired driving ability.

External distractions such as billboards, roadside attractions, and other vehicles can also cause distractions while driving. These distractions can take the driver's attention away from the road, leading to reduced alertness and impaired cognitive function [15].

III. METHODOLOGIES

1. Driver Drowsiness Detection Algorithms

Here in this section, we will see some of the machine learning models used to detect the driver's drowsiness and they are as follows:

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1.1 Support Vector Machine

The proposed method starts by capturing real-time video of the driver's face using a digital camera. The video is captured in terms of frontal face, and frame by frame extraction is carried out from that video.

The frames captured during low lighting conditions and at night usually have low contrast and low brightness, making it difficult to detect facial expressions of the driver. Therefore, image processing techniques are applied to enhance the frames using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve drowsiness detection. CLAHE is a technique that enhances the contrast of an image by dividing it into small regions and applying histogram equalization to each region.

The next step is to extract facial landmarks and cues from the video frames. A facial landmark predictor inside the dlib library is used to localize key points of the face region. The predictor uses a 68 landmark point model based on histogram of oriented gradients (HOG) and linear classifier. The eye aspect ratio, mouth opening ratio, and yawning frequency are calculated based on the detected facial landmarks. The eye aspect ratio is the ratio of the distance between the vertical eye landmarks to the distance between the horizontal eye landmarks. The mouth opening ratio is the ratio of the distance between the upper and lower lip landmarks to the distance between the nose and chin landmarks. The yawning frequency is the number of times the mouth is opened beyond a certain threshold.

Drowsiness is detected based on the values of the eye aspect ratio, mouth opening ratio, and yawning frequency using adaptive thresholding. Adaptive thresholding is a technique that adjusts the threshold value based on the local image characteristics. Machine learning algorithms are used offline to improve the accuracy of drowsiness detection. The proposed system uses a Support Vector Machine (SVM) classifier to classify the driver's state as drowsy or alert [16].

1.2 AdaBoost Classifier

The proposed algorithm for face detection and landmark detection uses a combination of MCT AdaBoost for face detection and LBF regressor for accurate face landmark detection, tailored for real-time operation on embedded devices. In the video query process, an image frame from the camera is captured and pre-processed with Gaussian filtering to reduce noise. The MCT AdaBoost classifier is applied to detect faces. The MCT feature is robust to varying lighting conditions.

To enhance efficiency, a two-stage cascade classifier approach is employed. The first stage consists of three-pixel position weak classifiers with high weights, effectively filtering out non-face objects. The second stage includes the remaining weak classifiers and confirms the presence of a face in the region passed by the first stage classifier. Additionally, a Correlation Filter is used to track objects and recover from detection misses, helping to ensure reliable face detection.

Within the detected face region, the algorithm identifies facial landmarks, utilizing a set of 68 landmarks from the 300-w dataset. Landmark detection is achieved through regression with Local Binary Feature (LBF), involving local binary feature mapping and global linear regression using random forests.

Furthermore, the system determines eye states (closed or open) by calculating the eye aspect ratio (EAR) based on landmarks in the eye region. Drowsiness is assessed using PERCLOS (Percentage of Eye Closure), representing the proportion of time the eyes remain closed.

In essence, this algorithm combines robust face detection with accurate landmark localization, and it includes mechanisms for tracking and addressing detection misses, making it suitable for efficient operation on embedded devices, particularly for tasks like monitoring eye states and drowsiness [17].

1.3 Convolutional Neural Network

The proposed system for detecting driver drowsiness and fatigue is built upon the utilization of deep learning algorithms, with a primary focus on two key models: the Convolutional Neural Network (CNN) and the Multilayer Perceptron (MLP). These algorithms are central to the project's mission and contribute to its effectiveness in identifying drowsiness in drivers.

In the initial phase, known as the "Collection and Pre-processing of Data," the system faces the challenge of acquiring a suitable dataset. After an extensive search, the researchers discover a relevant dataset provided by the University of Texas, Arlington. This dataset contains 180 videos, each averaging around 10 minutes in duration, featuring a total of 60 participants. To ensure the dataset's quality and relevance, the videos are pre-processed by resizing them. This step lays the foundation for further analysis.

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The next critical step involves "Extracting Features" to identify key facial attributes associated with driver drowsiness. Various mathematical formulas are applied to calculate ratios such as the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Pupil Circularity, and the Mouth Aspect Ratio over Eye Aspect Ratio (MOE). These ratios are instrumental in monitoring eye and mouth movements, which are indicative of drowsiness.

"Feature Normalization" is introduced to reduce the impact of variations in facial expressions and lighting conditions. This ensures that the features used for drowsiness detection remain consistent and reliable. Feature normalization is performed by comparing the facial landmarks to the baseline established using the first three frames of each participant.

The dataset is then divided into training and testing sets, with a 77.27% split in "Splitting Dataset for Training and Testing." This separation allows the model to be trained effectively and evaluated with rigor.

The heart of the system lies in "Applying Classifiers." Deep learning classifiers, specifically MLP and CNN, are employed to predict driver drowsiness based on the extracted features. These classifiers play a pivotal role in the accurate identification of drowsiness.

Finally, the system evaluates the performance of the classifiers using various "Performance Parameters." These include confusion matrices, F1 score, sensitivity, precision, and specificity. Additionally, the Receiver Operating Characteristic (ROC) curve is employed to visualize the trade-offs in model performance. By assessing the model's ability to predict true positives and true negatives, the system ensures a comprehensive evaluation of its effectiveness in detecting driver drowsiness.

In summary, the project's workflow intricately combines deep learning algorithms, data collection, pre-processing, feature extraction, normalization, dataset splitting, and classifier application. The use of diverse performance metrics and visualization tools allows the system to address the crucial issue of driver drowsiness comprehensively, contributing to enhanced road safety [18].

1.4 Multi-Scale Convolutional Neural Network

In this study, the feature extraction model uses a hybrid dual-tree complex wavelet transform with Walsh-Hadamard transform to extract features from images. The extracted features are optimized and used for classification to detect drowsiness in drivers. The pre-processing step is performed with the cross-guided bilateral filter to eliminate unwanted distortion or improve the features in the image for further processing. Key frame selection is used to estimate facial landmarks, which are then used in the pre-processing step. The pre-processed feature images are optimized using the Flamingo search algorithm and MCNN for the detection of drowsy and non-drowsy states.

The FSA algorithm is used to select the optimal point features for the detection of drowsiness in drivers. The FSA algorithm comprises three features with the MCNN-based classification. The MCNN architecture model comprises the convolution, max-pooling, and classification layers. The Flamingo search algorithm is used to optimize the features in the images based on the characteristics of the flamingo, such as local communication, identification of higher food areas, and computation of position based on foraging and migration behaviours The process of optimizing the pre-processed feature images using the Flamingo search algorithm and Multi-Scale Convolutional Neural Network (MCNN) for the detection of drowsy and non-drowsy states. The goal of this process is to select the optimal point features for the detection of drowsiness in drivers.

The Flamingo search algorithm is used to optimize the features in the images based on the characteristics of the flamingo, such as local communication, identification of higher food areas, and computation of position based on foraging and migration behaviours. This algorithm is applied to the MCNN model to select the optimal point features for drowsiness detection.

The Feature Selection Algorithm (FSA) is then applied over the MCNN for classification. The FSA algorithm comprises three features with the MCNN-based classification. The MCNN architecture model comprises the convolution, max-pooling, and classification layers.

The pre-processed feature images are optimized using the Flamingo search algorithm and MCNN for the detection of drowsy and non-drowsy states. The optimal point features for the detection of drowsiness in drivers are estimated with the FSA applied over the MCNN for the classification of Drowsy and Non-drowsy [19].

2. Road-Safety Applications

Here in this section, we will see some of the road safety applications that were designed to help drivers overcome distractions and help them being safe. And they are as follows:

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2.1 Sprint's Drive First

If the car i in driving mode, you should be, too. The FREE Drive First app from Sprint sends calls to voicemail and silences email and text alerts when a vehicle reaches 10 mph. Exit and 911 emergency buttons on the home screen of a locked device allow users to override the application only for Sprint customers, while allowing access to three key contacts and three mobile applications, such as GPS navigation or music apps. It also blocks text message alerts and auto-responds to the message sender that the driver is currently unavailable.

2.2 FleetSafer

Employees who use mobile phones or tablet computers to text, email, and browse the web while driving are not only a danger to themselves, but they also pose a significant risk and liability to their employer. FleetSafer is software for corporate fleets that automatically promotes safe, legal and responsible use of mobile devices while driving. FleetSafer Mobile is an application for commercial fleets, available for Blackberry, Windows, and Android mobile devices. The software automatically locks the phone during driving to prevent calls, texts, and e-mails. It also sends auto-reply messages to incoming texts and e-mails. Customizable and flexible to enforce most corporate distracted driving policies, FleetSafer Mobile can be triggered either by telematics, Bluetooth, or GPS systems.

2.3 DriveSafe.ly

DriveSafe.ly™ is a mobile application that reads text (SMS) messages and emails aloud in real time and automatically responds without drivers touching the mobile phone. DriveSafe.ly is the solution to texting while driving. DriveSafe.ly is a mobile application created by iSpeech that reads text messages and e-mails out loud in real-time and automatically responds without drivers touching the mobile phone. Price per phone is $79.90 annually or $7.99 per month.

2.4 Textecution

Textecution is an application developed for the T-Mobile G1 Google phone that restricts the user's ability to text message while driving. It is estimated that 46% of teens text message while driving, a potentially dangerous behavior. Once Textecution recognizes that the phone is traveling faster than 10 mph, it disables the phone's texting features so text messages cannot be sent or received. The app is available for Android devices for a one-time cost of $9.99.

2.5 Cellcontrol

Cellcontrol™ is liberating for the driver and delivers peace of mind to the drivers loved ones. With Cellcontrol™, inappropriate interaction with a mobile device is simply not permitted. The ability to text while driving, read or post to Facebook or Twitter, take a selfie, play a game, SnapChat or you name it is limited to a pre-defined policy of what can or cannot be done with a mobile device when the vehicle is in motion. Cellcontrol™ enables customized "policy-zones" – allowing passengers the freedom to use mobile technology, while the driver-zone is protected. Instead of using GPS to determine vehicle movement, Cellcontrol leverages Bluetooth-enabled technology that directly integrates with the vehicle's onboard diagnostics to determine motion and implement policy. Compatible with more than 1,000 devices, Cellcontrol disables more than the cell phone; it also prevents distracted driving from other mobile devices, including laptops and tablets, which may tempt drivers to take their eyes off the road.

2.6 KyrusFleet

KyrusFleet™ disables texting and other distracting applications on cell phones and other mobile devices, preventing use when driving. KyrusFleet™ engages Safe Mode instantly when the vehicle starts moving but permits full phone use when the vehicle comes to a stop. Your system administrator, in accordance with company policy or local laws,

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can configure specific protection settings. The system administrator can configure specific settings based on company policy. KyrusFleet does not track employee location, read text messages, scan emails, web traffic, or monitor phone calls or record driving behavior [20].

IV. CONCLUSION AND FUTURE WORK

In conclusion, the use of machine learning models plays a crucial role in driver drowsiness detection systems. These models are employed in real-time video analysis to monitor facial landmarks, eye aspect ratios, mouth opening ratios, and yawning frequency to determine a driver's state as drowsy or alert. These technologies enhance road safety by providing early warnings to prevent accidents caused by drowsy driving.

Moreover, various road safety applications have been developed to combat distractions and promote safe driving practices. These apps, including Sprint's Drive First, FleetSafer, DriveSafe.ly, Textecution, Cellcontrol, and KyrusFleet, serve as powerful tools to mitigate the risks associated with mobile device usage while driving. By silencing alerts, sending auto-reply messages, and even disabling certain features, these applications contribute to reducing distracted driving and enhancing road safety.

Collectively, the combination of advanced driver drowsiness detection algorithms and road safety applications demonstrates the potential to significantly reduce accidents and fatalities on the road, ultimately making our highways safer for all.

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