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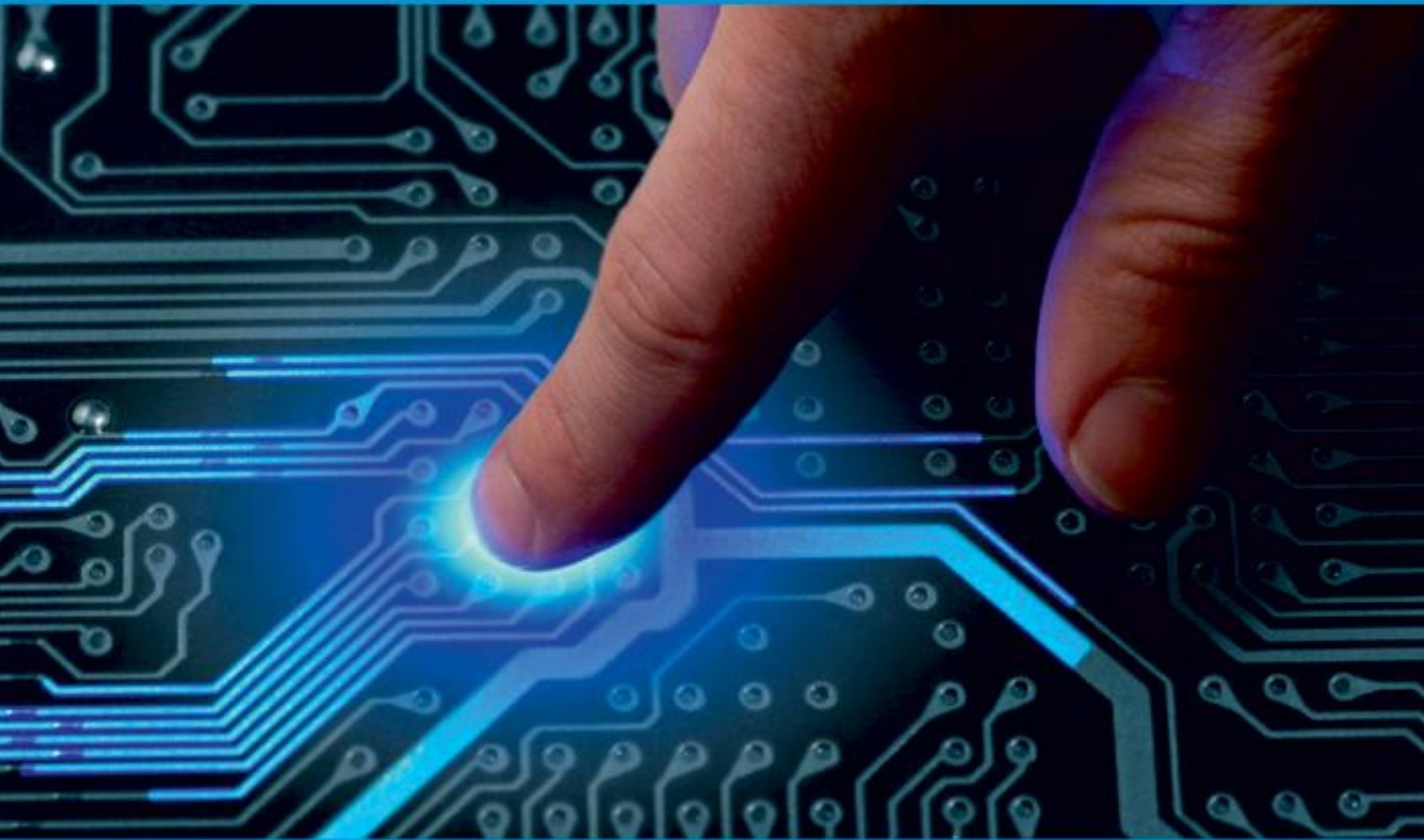

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Driver Distraction Detection Using Machine Learning

Bhoomika Y[1], Mr. Arun Kumar K L[2]

PG Student, Dept. of Master of Computer Applications, Jawaharlal Nehru New College of Engineering, Shivamogga, India

Assistant Professor, Dept. of Master of Computer Applications, Jawaharlal Nehru New College of Engineering, Shivamogga, India

ABSTRACT: Drunk driving accounts for about 20% of traffic fatalities, with drowsiness and weariness among the major contributors. Due to long workdays, shift work, sleep apnoea, or demanding jobs, driver weariness is a serious problem in rural single-vehicle collisions. One of the main causes of the 1.25 million road accident fatalities each year is distracted driving. This study uses a dataset for identifying driver distractions and employs a genetically weighted ensemble of convolutional neural networks to detect distractions with 90% accuracy. The study looks at the influence of visual cues on distraction detection and finds that in real-world situations, a simplified version of the approach obtains a classification accuracy of 84.64%. To lower traffic accidents and fatalities, information technologies to identify driver distraction and inattention must be developed. Currently, driver weariness is the only particular reason that road vehicle distraction detection technologies can identify. Despite the rising automation of driving brought on by advanced support systems, human drivers will continue to supervise vehicle automation for a longer period of time. This research evaluates the available scientific literature on techniques for detecting driver attention and incorporates those strategies into a comprehensive framework. Using sensors, measured data, calculated data, computed events, inferred behavior, and inferred distraction type, the framework visualizes the whole detection information chain.

I. INTRODUCTION

Accidents can result from being sleepy or drowsy, with tiredness being a contributing factor in 30–40% of accidents. With the use of vision-based equipment, technological improvements have made it simpler to identify distractions and tiredness. The driver's visage and important landmarks are analyzed using facial detection, eye location, and blinking patterns. A webcam is used to identify fatigue by analyzing face characteristics and eye location using custom image processing. The driver will be warned by an alarm if the eyes are closed for a predetermined amount of time.

Transport and safety officials are gravely concerned about the growth of distracted driving. The incidence of accidents brought on by distracted driving has grown due to the widespread usage of cellphones and other electronic gadgets. In order to identify and reduce driver distractions in real-time, scientists and engineers have resorted to machine learning. To correctly identify distracted driving, machine learning algorithms examine data sources including photos, videos, sensor inputs, and vehicle telemetry. These algorithms may be included into intelligent cars and advanced driver assistance systems (ADAS), delivering timely alerts and interventions that will eventually prevent accidents and save lives.

II. RELATED WORK

Here we have selected few key literatures after exhaustive literature survey and listed as below:

Arefnezhad et al[1], With the use of neurofuzzy, support vector machine, and particle swarm optimization techniques, created a non-interfering sleepy tiredness detection system using vehicle steering data.

Mutya et al[2], In order to alleviate tiredness, created a steering wheel algorithm that combines CNN for accurate classification and low false detection rates with image-based or pictorial steering movements.

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Budak et al[3], AlexNet, VGGNet, and wavelet transform methods were used by to create a sleepy alert system employing EEG methodologies. To warn drivers of drowsiness, the system evaluates sleepiness using brain indication signals, cameras, and sensors. It then uses machine learning techniques.

Hayawi and Aleed et al [4], A technique for detecting sleepiness was created by utilizing the Heart Rate Variability (HRV) output from EEG devices.

Song et al[5], Using EMG sensors, a human-machine interface, and a system to detect eye, muscle, and skin movement, created a system to detect driver weariness.

Ma et al[6], created a useful application for recognizing driver drowsiness based on facial expression. To track face movement and identify sleepiness using a fuzzy inference method, the system makes use of deep learning and AdaBoost classifiers. However, the accuracy is reduced when drivers are wearing glasses.

Kinage and Patil[7]. An eye blinking sensor-based method for tiredness detection was proposed by For alarm messages and position monitoring, a GPS and GSM device are integrated with a vibration sensor, heart rate measurement sensor, and other sensors.

III. PROBLEM STATEMENT

The goal of driver distraction detection is to create a system that accurately pinpoints instances of driving while distracted, which can result in collisions or lower traffic safety. To identify possible distractions, the system examines elements such as the driver's eye movements, head position, facial expressions, and vehicle sensors. It must discriminate between typical driving behavior and unsafe practices like chatting on a cell phone, eating, drinking, or using in-car technology. The ultimate objective is to deliver prompt notifications or actions to reduce hazards and enhance traffic safety. The objective is to decrease accidents brought on by inattentive or distracted driving and improve the safety of drivers, passengers, and pedestrians by precisely recognizing and managing driver distractions.

IV. DESIGN AND IMPLEMENTATION

Dlib is an independent component-based open-source C++ software library intended for contract and component-based engineering. It is a piece of open-source software distributed under the terms of the Boost Software License.

HOG is a feature descriptor used in computer vision and image processing to identify objects. It counts the occurrences of gradient orientation in certain regions of an image, much as edge orientation histograms and scale-invariant feature transform descriptors. HOG employs overlapping local contrast normalization on a dense grid of uniformly spaced cells to improve accuracy.

A common problem in computer vision is object detection, which involves locating and identifying areas of interest in pictures. The YOLO model, created by Joseph Redmon and colleagues in 2016, is well-known for its quickness and accuracy. It has gone through multiple revisions, with YOLO v7 being the most recent. This article compares YOLO v7 to different object identification systems and analyzes its distinctive properties.

Because of its accuracy and speed, the YOLO method for real-time object recognition has become popular. It has several uses, including those related to traffic lights, people, parking meters, and animals. This article describes the algorithm and focuses on its practical uses.

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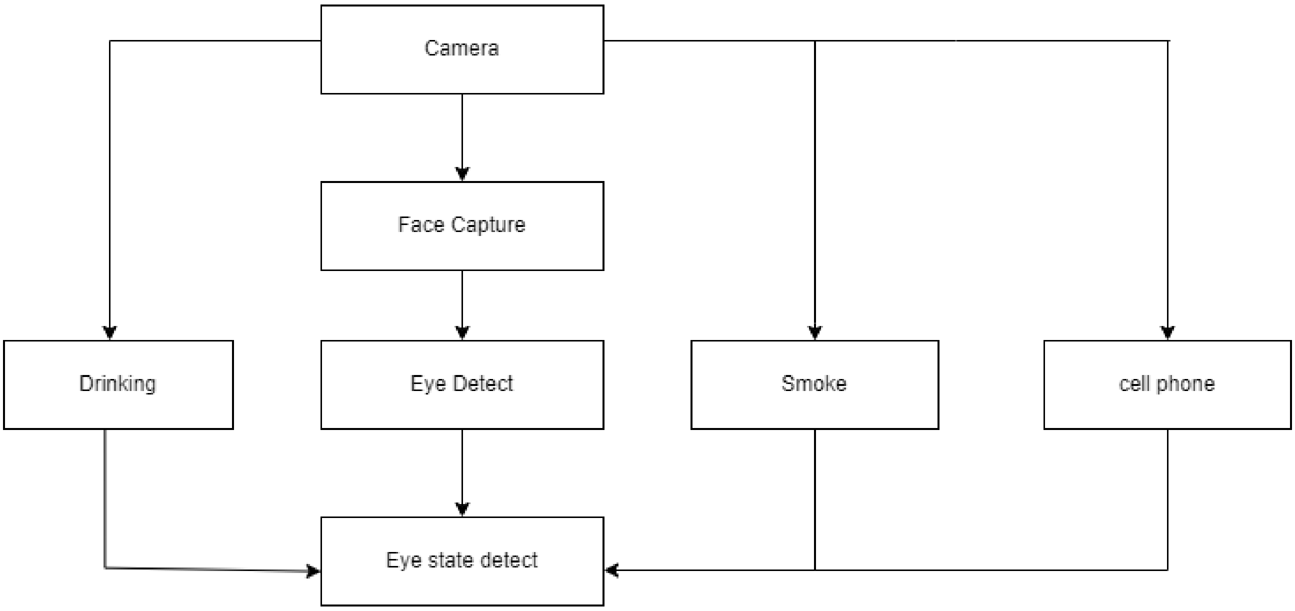

Figure 1: Flow chart of the system

The Fig.1 shows the flowchart of the Driver distraction detection.

1.**Face Detection:** Dlib is an independent component-based open-source C++ software library intended for contract and component-based engineering. It is a piece of open-source software distributed under the terms of the Boost Software License.

2.**Facial landmark extraction:** The emergency stopping capabilities of smart cars may not always be successful, and driver weariness is a key contributing factor in auto accidents. Computer vision models can recognize symptoms of fatigue or preoccupation in the faces of drivers, causing alarms to go out if they fail to pay attention, so preventing accidents. Computer vision is more straightforward and less intrusive than built-in movement tracking systems and wearable ECG tracking devices, which can both carry out comparable tasks. While MobileNetV2 architecture can detect driver drowsiness in video streams without landmark identification, it takes more training time than neural networks for this purpose. Neural networks can detect sleepiness in drivers' faces utilizing facial landmark inputs.

Typically, a mix of computer vision techniques and machine learning algorithms is used to extract face landmarks using machine learning. Combining facial detection and facial landmark localization is one common strategy.
A generic how-to for extracting face landmarks using machine learning is provided below:

A dataset of facial photographs and the related ground truth annotations for facial landmarks should be gathered. The face expressions, positions, and lighting in this dataset ought to be varied.
Apply a facial detection technique to find the faces in the input images, such as Haar cascades or a deep learning-based face detector.

3.**Eye Tracking:** A potential approach for hands-free, seamless contact is eye-gaze-based interaction, which enables persons with weak motor abilities to use computers without using their hands. This method is especially useful when dealing with limitations and difficulties brought on by the environment, such as secondary chores, minor injuries, or the lack of a keyboard. By avoiding touching shared gadgets, you may help stop the spread of infectious illnesses. To determine a person's present location, eye tracking technologies detect a person's eye movements and locations.

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4.**Eye blinking:** Eye blinks are monitored using an infrared sensor. It is composed of two parts. the sender and the receiver. The transmitter continuously emits infrared rays that are directed towards the eye. The receiver is watching for variations in the reflected waves that indicate an eye blink. An increased production is anticipated if the eye is closed. If the eye is open, there won't be much of an output.

5.**Drinking , Smoking and Cell phone detection :** When utilizing machine learning to detect driver distraction, drinking detection entails finding situations in which the driver is partaking in alcohol-related activities while driving a vehicle .Machine learning-based smoke detection for detecting driver distraction focuses on locating situations where the driver is smoking while operating a vehicle. To detect instances of distracted driving while using a mobile phone, machine learning is used in driver distraction detection.

Data collection: Collect a diverse dataset of images or videos that contain drivers smoking or not smoking. Ensure that the dataset includes a wide range of lighting conditions, driver appearances, and smoking behaviors.

Data Preparation: Resizing the photos, normalizing the pixel values, and dividing the dataset into training and testing sets are used to preprocess the acquired data. To improve the robustness of the model, take into account enhancing the data by adding random transformations such as rotations, flips, and brightness modifications.

Feature extraction: Extract useful details from the preprocessed photos that can capture smoking habit characteristics. Commonly employed for this purpose are convolutional neural networks (CNNs). Transfer learning may be used by using the learned representations of pre-trained CNN models like VGG, ResNet, or Inception.

Training: Utilize the retrieved features and accompanying labels (smoking or not smoking) to train a classification model. Support Vector Machines (SVM), Random Forests, or more sophisticated models like deep neural networks are some of the most well-liked techniques for training machine learning models. Try out several algorithms and hyperparameters to determine which model performs the best.

Evaluation: Utilize the testing set and performance indicators like accuracy, precision, recall, and F1 score to assess the trained model. This process enables evaluation of the model's potency in smoking behavior detection.

Deployment: Include the trained model in a real-time system that can analyze video streams or pictures taken by an in-car camera. Apply the model to successive frames or photos while keeping an eye out for smoking by the driver. If the model notices smoking, the driver may be informed or given a warning as necessary.

V. RESULT ANALYSIS

Fig 1:Facial landmark detection

Finding certain spots of interest on a person's face or other objects is the goal of the computer vision problem known as landmark detection, often referred to as facial landmark detection or keypoint detection. Identifiable

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facial characteristics including the eyes, nose, mouth, and eyebrows correspond to these landmarks, sometimes referred to as keypoints or landmarks. Applications like face analysis, emotion identification, facial expression tracking, virtual reality, and augmented reality all depend heavily on landmark detection.

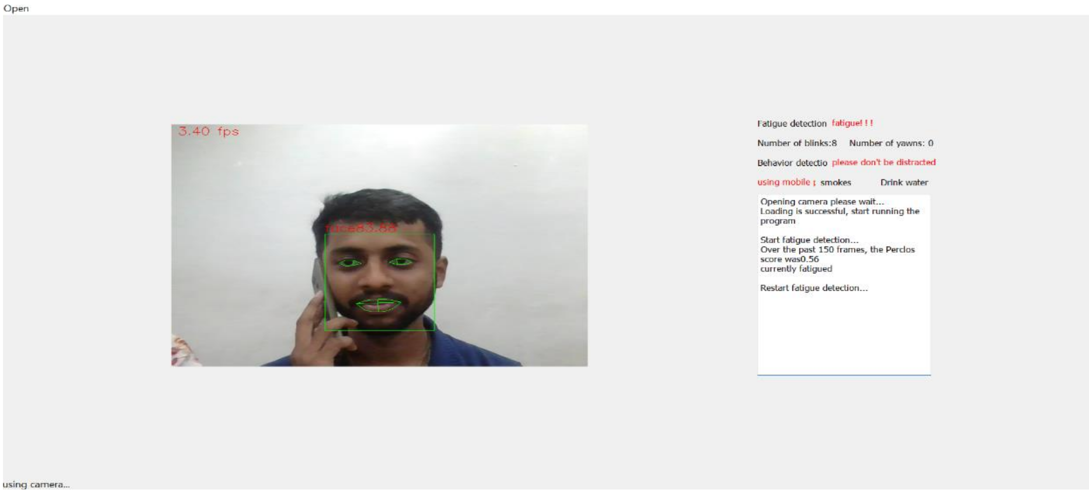

Fig 2: Mobile usage detection

Mobile usage detection refers to the process of identifying and analyzing how a mobile device is being used by a user. It involves monitoring and understanding the activities performed on a mobile device, such as app usage, screen time, internet browsing, calls, and messages. Mobile usage detection can be valuable in various contexts, including user behavior analysis, digital wellness, parental control, and mobile app optimization.

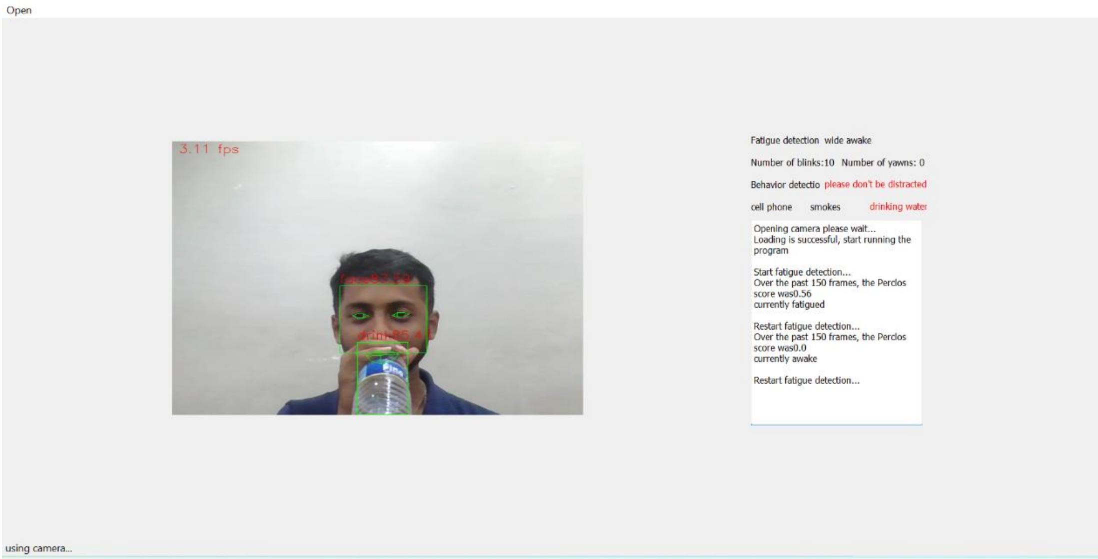

Fig 3: Drinking detection

The act of ingesting alcoholic drinks while operating a vehicle is referred to as "drinking in driver distraction. It is a risky activity that seriously reduces a driver's cognitive and physical capabilities, increasing the likelihood of collisions and injuries. Driving while intoxicated is a significant contributor to traffic deaths and is illegal in the majority of jurisdictions.

Drinking while driving reduces a driver's ability to pay attention, concentrate, and respond quickly. Reduced judgment, poorer eyesight, decreased coordination, longer response times, and a decreased capacity to focus are just a few of the physical impacts of alcohol.

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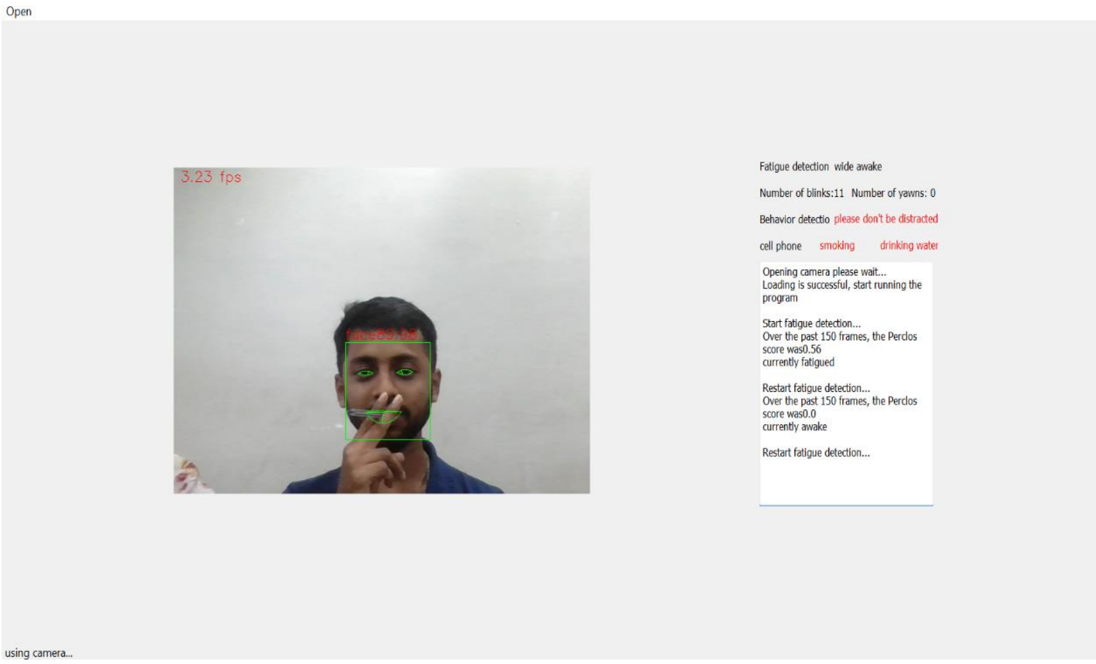

Fig 4: Smoking detection

The act of smoking while driving a vehicle, such as cigarettes, cigars, or e-cigarettes, is referred to as driver distraction. It is seen as a distracting habit that might impair the driver's focus, bodily coordination, and response time, increasing the likelihood of collisions. When a motorist smokes as a kind of diversion, their focus and concentration are distracted from the road, which can result in potentially dangerous scenarios.

VI. CONCLUSION AND FUTURE WORK

Using a publicly available dataset, this research provides a vision-based approach for identifying distracted driving postures. The model achieves 90% classification accuracy using a genetically weighted ensemble of convolutional neural networks. Real-time accuracy may be maintained with a simpler model using AlexNet. The accuracy of the categorization is increased by the detection of faces, hands, and skin, but in real-time circumstances, their performance overhead is larger. A better face, hands, and skin detector should be developed in the future, employing manual labeling and Fast-RCNN training to locate faces and hands simultaneously.

In order to identify the three primary categories of distraction—manual, visual, and cognitive—the scientific literature on distracted driving is reviewed in this research. Driver distraction techniques are integrated into a complete framework. The framework describes each step in the process of distraction detection, including sensor data gathering, data processing, behavior inference, and distraction type inference. Researchers looking at driver distraction detection technologies and practitioners working in the transportation industry can both benefit from this review. By assisting researchers in categorizing their own methodologies or expanding them to incorporate more characteristics for greater distraction detection, the framework might inspire future research projects.

Future systems may use a number of data sources, such as audio analysis, gaze tracking, and physiological signals, to improve the accuracy and robustness of their distraction detection capabilities. The speech patterns and stress levels of drivers can be considerably improved by this integration of many modalities.

Vehicle processing is made possible by advances in edge computing and hardware, which reduce dependency on the cloud and allow for quicker, real-time data analysis, resulting in prompt alarms and actions.

For safety-critical applications like driver attention monitoring, future systems will concentrate on explicable AI algorithms to increase confidence and comprehension of the technology. They will also use ways to continuous learning, allowing models to develop over time and handle new distractions and difficult situations better.

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