A Survey on Driver Drowsiness Prediction System Using Machine Learning

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Abstract - *The vast majority of accidents nowadays have been caused by driver fatigue for many years. Numerous road collisions are caused by drowsy driving. Despite the development of various sleepy systems over the past decade, existing systems still require improvement in efficiency, accuracy, cost, speed, and availability. Accidents brought on by fatigue and lack of sleep frequently involve drowsiness. In an effort to lessen these collisions, driver sleepiness detecting devices were developed. The passengers' safety can be ensured using this method in real-time systems. Images are captured in this using a webcam. Deep learning techniques were employed to analyze photos and extract information about a driver's facial expressions, eye movements, and head position. A camera records human images, and research is being done to see how that information can be applied to raise driving safety. This method uses a dataset of actual driving situations to show how well it can identify drowsy drivers. Gather photos from a live camera feed, run a machine learning algorithm on the image to check whether or the driver is sleepy or not. The input image is classified as drowsy or not using the machine learning technique. Finally, this study will handle several difficulties at once based on a variety of characteristics and will give a thorough method for anticipating driver fatigue.*

***Key Words*: Driver drowsiness, Accident, Facial Expression, Fatigue detection, Eye and mouth tracking.**

1.INTRODUCTION

Due to driver drowsiness many accidents were happening. Driver drowsiness increases the risk of accidents and collisions, as fatigued drivers experience impaired reaction times and compromised judgment, making them more prone to collisions. When drivers are tired, they can't react quickly, make bad decisions, and even fall asleep briefly while driving. This can lead to accidents and makes our roads less safe. Additionally, sleepy driving puts the safety of other road users, pedestrians, and passengers at risk in addition to the driver. To avoid these issues and maintain everyone's safety on the roadways, it is imperative that everyone obtain enough rest before getting behind the wheel.

Driver drowsiness detection is a term used to describe a device or system that tracks a driver's level of alertness and looks for indicators of exhaustion or drowsiness while they are driving. The driver's behaviour is often studied using a variety of sensors and algorithms, including steering patterns, eye movements, facial expressions, and occasionally physiological indications like heart rate. These systems' main objective is to warn the driver when they exhibit signs of being too fatigued to operate the vehicle safely, hence lowering the possibility of accidents brought on by sleepy driving. Driver Drowsy driving can be just as deadly as drunk driving, hence drowsiness monitoring devices are a crucial safety element. They can warn fatigued drivers about the need for rest, which can help prevent accidents and save lives.

The creation of a sleepiness detection system makes use of a camera that captures a live video of the driver's face. This technology continuously scans the driver's eyes and facial features for indicators of tiredness. It specifically looks to see if the motorist has open or closed eyes. If drowsiness is detected, the driver receives a warning signal. The system calculates the proportion of time the eyes remain closed for a specific duration. The technology determines that the driver is dozing off if the cumulative eye closure time exceeds a certain threshold and sounds an alarm to warn them.

2.RELATED WORK

Existing approaches for detecting driver fatigue frequently concentrate exclusively on one or two aspects of driving behaviour, such as eyelid closure or steering wheel movements, according to V. Uma Maheswari et al. [1]. For detecting driver drowsiness, a number of technologies are used, such as PERCLOS, speech processing data, and linear regression. While these techniques have shown some promise in terms of identifying sleepiness, their applicability and accuracy are frequently constrained. The suggested method analyses several characteristics of driver behaviour and environment using image processing techniques. There are ways to use hybrid machine learning to identify and detect driver tiredness at an early stage, according to a report [2]. The proposed process is discussed, which calls for a camera to record the driver's footage and separate it into pictures. Four steps make up the process: preparation, eye-state assessment, warning, and warning stadium. The technology described in the file uses a camera to record footage of the driver and divide it into images, which are then analysed using machine learning algorithms to find indicators of intoxication.

The paper was written by Hanane Lamaazi and others [3], It provides an overview of the literature on the subject, outlining the datasets used, the features deduced, and the classification algorithms used. Additionally, it emphasizes the research gaps and difficulties in this area, including the demand for more realistic and varied datasets, the incorporation of numerous sensors, and the creation of in-the-moment and edge-based solutions. The proposed framework employs a convolutional neural network (CNN) to analyze multi-sensor data from a smartphone mounted on a car's dashboard. A sizable dataset of labelled driving sessions that includes both aggressive and passive driving behaviours is used to train the CNN model. The suggested methodology uses a sleepiness dataset that is processed through a number of processes to detect driver tiredness and prevent accidents, according to a survey by V. Vijay Priya et al. [4]. The Multi-Scale Convolutional Neural Network (MCNN) is utilized for video conversion, facial feature detection, pre-processing, feature optimization, and classification. The method leverages the Flamingo Search Algorithm (FSA), a revolutionary method for feature optimization in sleepiness detection, to optimize the extracted features. A unique method for feature extraction in sleepiness detection is used in the method, which combines the Walsh-Hadamard transform with a hybrid dual-tree complex wavelet transform to extract features from the pre-processed images.

A real-time driver drowsiness monitoring system called Dri Care employs facial features to detect the new face-tracking algorithm, and study [5] claims that the suggested strategy uses a detection method based on 68 key points to determine driver's state. Dri Care can advise the motorist of their sleepiness by combining their mouth and eye features. The suggested approach is a realistic and economical method for reducing traffic accidents since it can identify driver tiredness without the need of any gadgets.

The paper's authors are Yasar Becerikli et al. [6], a real-time driver fatigue detection system that tracks driver exhaustion based on eye and mouth features using a Multi-Task CNN model. The method attempts to make the roads safer and avoid accidents brought on by driver weariness. Using eye and mouth features to track driving behaviour, the Multi-Task CNN model can identify driver weariness. There are three categories for fatigue levels: highly fatigued, beginning to feel fatigued, and normal. For the purpose of determining fatigue parameters, the system is trained using Multi-Task CNN models.

A survey by Z. Halim et al [7] suggests that a proposed system includes a feature selection technique for profile prediction, unsupervised learning clustering methods for pattern extraction from labelled data, and a specially designed hardware system for situation creation and data recording. The system employs a deep neural network to learn driver's LTV driving style patterns and identify risky behaviors. It's evaluated on real-world data and demonstrated its effectiveness in identifying risks. The paper compares it with related works and discusses its potential applications in critical infrastructure protection.

The survey [8] reveals a method using a multi-task convolutional neural network (MTCNN) to extract facial features, including distance between eyebrows and chin, eyelid and lip aspect ratios, and lip height ratios. The method also considers six other features in calculating change curves, including eye aspect ratio, mouth aspect ratio, nose aspect ratio, eye height ratio, mouth height ratio, and nose height ratio. The paper introduces a new method for detecting driver fatigue using deep learning techniques. The method outperforms traditional fatigue detection algorithms. The paper also introduces the experimental environment of driving and driving simulation platforms, and presents data from three typical subjects.

Feng you and others [9], The method outlines a real-time algorithm for detecting driver weariness using a deep learning model, considering personal variations and facial landmark extraction. The program comprises two modules: offline training and online monitoring. On both publicly available and custom-built datasets, the suggested methodology was put to the test and found to be reasonable and more accurate than competing approaches. Future study directions are also mentioned in the method, such as investigating multi-feature fusion techniques and doing nighttime driving sleepiness detection studies. The Guangdong Natural Science Foundation and other funding helped to fund the project.

Federico Guede-Fernandez et al.'s study [10] indicates that this model suggests a fresh approach for identifying driver tiredness based on variations in their respiratory signal. The system examines the respiratory rate variability (RRV) to identify sleepiness in drivers. The proposed model explains the steps involved in data gathering, the suggested algorithm, and algorithm validation. The technique ends by discussing the results of this study and the possibilities for enhanced driver assistance systems to reduce accidents brought on by fatigued driving.

According to Seyed Kian Mousavikia et al. [11], The study proposes a driver drowsiness detection system using a modified RiscV processor on an FPGA, which achieved an 81.07% accuracy using a Convolutional Neural Network trained to classify four primary driver expressions. The proposed model describes the hardware implementation, hardware enhancements, CNN software architecture, dataset for system training and validation, and hardware implementation and hardware optimizations. The model's outcomes and accomplishments are highlighted, along with possible uses for this driver drowsiness detection system.

A cutting-edge technique for detecting driving tiredness while protecting the drivers' privacy was developed by Linlin Zhang et al. [12]. The suggested method uses transfer learning and federated learning to increase drowsiness detection accuracy while lowering communication costs. The confidentiality of the drivers' data is protected via a CKKS-based privacy-preserving mechanism. A flowchart of the suggested PFTL-DDD technique is included, as well as a thread model of the federated learning system. The suggested approach also offers citations to relevant studies on federated learning and its applications.

Riad Alharbey *et al*. [13], This article is about a study on detecting fatigue in people when they are driving. Regardless of the dataset utilized in prior studies, the study's goal is to show the superiority of the suggested methodologies for detecting driver weariness and drowsiness. Along with the suggested ways, the study compares a number of algorithms, including those developed by some others. The study uses EEG-based and video streaming algorithms to identify driver weariness, comparing the proposed deep learning approach with various algorithms. The study also covers the typical indications of driver weariness and drowsiness.

This is a system for forecasting driver fatigue levels using face and head behaviour information, according to Haider A. Kassem et al. [14]. The study employed a dataset from National Tsuing Hua University that was made available to the public and included 36 participants from various ethnic backgrounds, including men and women, who were recorded in a variety of simulated driving situations, including barefaced, night-bareface, sunglasses, glasses, and night-glasses. In each scenario, the participants were recorded in both their asleep and awake phases, yielding a total of 200 movies.

The study discovered that eye, mouth, and head movement features can predict fatigue levels determined from subjective rates with excellent accuracy. CNN models can forecast the features of the eyes, mouth, and head using facial landmarks as input features. Each feature's prediction accuracy in the study was greater than 97%. Therefore, there is a lot of room for advancement in the use of low-cost, non-intrusive in-car cameras for the monitoring and alerting of driver weariness. Overall, employing non-physical touch sensor input, the study offers a low-cost framework for early driver fatigue detection. The experiment's findings indicate that forecasting driver fatigue levels can be done with reasonable accuracy.

This is a vision-based real-time measurement system for tracking driver weariness, according to Yin-Cheng et al. [15]. The technique suggests using a remote photoplethysmography (rPPG) signal to detect driver weariness without making any physical touch. This method enhances accuracy and gets rid of the nuisance associated with conventional contact-based physiological tiredness detection systems by monitoring both motional and physiological data using a single image sensor. The model emphasizes the importance of detecting drowsy driving to reduce accident costs. A remote photoplethysmography (rPPG) signal has several advantages over conventional contact-based physiological tiredness monitoring systems, which are covered in the model as well. The system takes into account environmental noise that, in actual applications, may have an impact on the measured signal.

The method provides a thorough analysis of earlier research on driver state identification, including intrusive and non-intrusive systems, according to Khadidja et al. [16]. The authors suggest a fresh approach to feature selection that combines visual and signal-based sensors, and they give experimental evidence to support it. Using a dataset of driving data gathered from various drivers, the approach is assessed. The model comes to a close with a discussion of the findings and potential next lines of inquiry.

The model analysis focuses on the development of advanced driver-assistance systems and intelligent safety features, specifically yawn detection and seatbelt state detection, according to Paul Kielty et al. [17]. The authors explain how to alter event data to meet a variety of needs for various activities, and they also provide neuromorphic event-based algorithms for identifying these traits. The technique outlines the network construction, gathering of video datasets, creation of fabricated events, and specialized event data preprocessing for various purposes. The suggested model also discusses relevant literature and contrasts its findings with those of other researchers in the area. The technique comes to a close with the authors' overall findings and their ramifications.

This technique proposes a new algorithm for identifying fatigued driving based on the merging of many face features, as proposed by Kening Li et al. [18]. The algorithm has three modules: driver mouth state classifier, driving fatigue assessment, and identity entry. The experimental analysis evaluates the algorithm's accuracy and real-time performance. The conclusion summarizes the paper's main points, analyzes the system's flaws, and suggests future optimization paths and algorithmic prospects. The background of the system and its research relevance are presented in the introduction, along with the current state of domestic and international fatigue driving detection research.

By Anna Li et al. [19], A model representation augmentation module was developed to enhance adaptability to multi-scale features, improve channel attention strategy, and enhance spatial encoding abilities, while promoting a GPS-based collaborative decision-making approach between humans and machines. The technique uses an actor-critic-based reinforcement learning algorithm and builds an enhanced actor network using an iLQR-based GPS. The idea proposes an adaptable module that adjusts vehicle decisions based on driver fatigue, utilizing experimental results from Mujoco's reinforcement learning platform and an enhanced guided policy search algorithm. The model analyses the experimental data and rates the efficiency of the suggested approach.

The study provides a method for assessing driver fatigue through the examination of intelligent facial expressions, according to Sajid Ali Khan et al. [20]. Entropy analysis is used by the framework to select informative chunks within a picture. DWT generates four sub-band pictures from the input image, followed by dividing the LL image into eight 8-block blocks and multi-scaling simultaneously.

3.RESULT ANALYSIS

TABLE I: The table shows the results of a study on the accuracy and challenges of the different methods.

SNO	MODEL	PARAMETERS	CHALLENGES
1.	CNN	EAR, MAR, FAR	Single camera is to capture images
2.	SVM and Image Processing Clustering	PERCLOS, Eye status	Difficulty in accurately detecting drowsiness
3.	Random Forest, SVM, SE, FCN	Camera, Frame Rate Resolution, Number of frames	Variability in lighting conditions and camera quality
4.	MCNN, FSA	1000 video sequences of drivers with and without drowsiness	To improve the accuracy and efficiency
5.	CNN, MTCNN	Learning rate, Regularization parameter, and kernel type	Need for a robust face tracking algorithm
6.	MTCNN	PERCLOS, Frequency of mouth opening (FOM)	Need for a large dataset for detecting the face
7.	Naïve Bayes, KNN, SVM	Crash data, Traffic data, Weather data	Gathering additional data for more accuracy
8.	MTCNN	EAR, MAR, NAR	High quality camera
9.	CNN, SVM	EAR, PERCLOS	Problem in detecting the face region
10.	TEDD	WLR, WLQ, NBC, QuaTh	No prior approaches for respiratory signal analysis
11.	CNN	Range of Gaussian noise, Number of layers	Dataset used for training and validation is small
12.	SVM	Eye blinking, EAR, MAR	Privacy of the driver's data is a major concern
13.	SVM, CNN	Head Movement, Frame rate Resolution	System can process large amount of data
14.	CNN	Eye closure duration, mouth opening duration	Accuracy of eye position
15.	MRSPT	HRT, PRT	Limited dataset size
16.	SVM, DBSCAN	Head movement and eye tracking	Dataset used was relatively small
17.	CNN	Driver eyes, Yawn ratio	Difficult to identify accurate blink detection
18.	algorithm on merging of multiple face feature	Eye Feature Vector and Mouth Feature Vector	Different aspects are used to detect eyes and mouth
19.	DDPG	Real-life video data	Difficulty in detecting accurate driver

SVM=Support Vector Machine, CNN=Convolutional Neural Networks, MTCNN=Multi-Task Cascaded Convolutional Neural Network, FSA=Flamingo Search Algorithm, KNN=K-Nearest Neighbor, FCN=Fully Convolutional Network

Table-2: Comparison Analysis

SNO	DATA SET	ACCURACY (%)	PRECISION (%)	RECALL	F1 SCORE
1.	NTHU-DDD YawDD EMOCDS	95.67 94.78 95.67	-	-	-
2.	Real-time data	83.25	-	-	-
3.	Kaggle drowsiness detection NTHU	90 91	88 88	86 88	87 88
4.	NTHU-DDD YawDD	98.26 98.38	99.45 97.0	98.1 97.84	98.7 97.4
5.	Real-time data	92	-	-	-
6.	NTHU-DDD YawDD	98.91 98.72	-	-	-
7.	YawDD Self-recorded Crash data	97 84.2 72.15	-	-	-
8.	YawDD Simulated Actual	96.23 95.64 97.47	- - -	- - -	- - -
9.	FDDB SDVD WIDER_FACE	- 94.80 -	- - -	- - -	- - -
10.	TeddDisQ F1 TeddDisQ G	- -	- -	- -	77.2 80.4
11.	YawDD & SD	81.07	-	-	-
12.	NTHU-DDD YAWDD	85.93 84.15	84.25 75	85.21 85.71	- -
13.	DROZY	98.01	98.48	-	97.98
14.	NTHU & CEW	93.3	-	-	-
15.	Real-time	80	-	-	-
16.	YawDD	89.13	-	-	-
17.	YawDD Test(ours)	93 95	89.9 95.9	91 94.7	90.4 95.3
18.	WIDER FACE DSD	90 95.10	- -	- -	- -
19.	YaWDD	84.8	81.6	86.2	87.9

A. Accuracy

The accuracy formula comprises True Positives (correctly identified positives), True Negatives (correctly identified negatives), False Positives (incorrectly classified as positives), and False Negatives (incorrectly classified as negatives). It gauges the overall correctness in classification or data evaluation by calculating the ratio of correct classifications to the total number of instances.

$$Accuracy = \frac{\text{correct prediction}}{\text{Total number of input samples}}$$

B. Precision

Precision in the context of measurement or data analysis represents the level of exactness and accuracy in obtaining results. It quantifies how closely individual measurements or data points match each other. A high precision indicates low variability and consistency in data, while low precision suggests greater variability and potential error.

$$Precision = \frac{\text{true\_positive}}{\text{true\_positive} + \text{false\_positive}}$$

In the formula, True Positives, which are the correct positive predictions made. False Positives, which are incorrect positive predictions. Precision measures the proportion of true positive predictions relative to all positive predictions (true positives and false positives), providing a metric for the accuracy of positive predictions.

C. Recall

Recall, whether in information retrieval or machine learning, assesses the system's capability to find and include all relevant items from a dataset, essentially gauging its ability to avoid missing important results. It is expressed as the proportion of relevant items retrieved compared to the total number of relevant items.

$$Recall = \frac{\text{true\_positive}}{\text{true\_positive} + \text{false\_negative}}$$

D. F1 Score

F1 score is a metric that combines precision and recall evaluating the accuracy of a classification model. It provides a balance between these two measures, making it useful for assessing a model's overall performance in tasks like binary classification.

$$F1\ Score = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

4.CHALLENGES AND GAPS

The method for anticipating driver drowsiness's limitations. The dynamic variety in gestures made by various people is one of the constraints. The authors contend that as a result, the system's accuracy may suffer since it might not be able to reliably identify tiredness in all users.

Another drawback is that the model can only be trained using images taken with a single camera that is positioned on a car's dashboard. According to the scientists, this might not be enough to account for all the differences in driver behaviour, which would reduce the system's accuracy.

The scientists also point out that the properties derived from the photos may not be pertinent in other contexts, such as an office or home environment, making the suggested method unsuitable for identifying drowsiness in those settings.

Finally, they point out that because poor lighting or bad weather may influence the quality of the photos taken, the suggested method may not be appropriate for identifying tiredness in all driving situations.

Overall, they accept that their suggested method has limits and recommend that future study concentrate on addressing these constraints to increase the system's accuracy.

5.CONCLUSION

The conclusion of the research is that the proposed strategy for detecting driver drowsiness based on many criteria and using image processing techniques has shown promising results in terms of accuracy and efficiency. The suggested method can be utilized in real-time systems, such self-driving automobiles, to stop accidents brought on by driver inattention. Future research can concentrate on enhancing the system's performance under various lighting situations and with various camera stances.

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