DrowseGuard Drowsiness Detection System: A Review Of Existing Systems And A Schema For Future Solution

Prof. Pritam Ahire [1], Pratham Bhor [2], Ishika Bansal [3], Prayukti Dubey [4]

Computer Engineering Department [1,2,3,4]

Nutan Maharashtra Institute of Engineering and Technology, Pune, Maharashtra [1,2,3,4]

Abstract— Driver drowsiness detection systems improve road safety by tracking driver attention in real time and providing timely warnings to reduce the risk of accidents. This research compares many methods for utilizing computer vision and machine learning techniques to identify driver weariness. Techniques that make use of physiological signals, driving performance measures, face analysis, and hybrid approaches are assessed for their viability and efficacy. The main conclusions show that hybrid methods that incorporate facial monitoring together with other modalities can identify tiredness with over 94% accuracy. Real-time processing, individual variability, and striking a balance between system performance and user acceptability continue to be obstacles. To fully implement driver sleepiness detection in a variety of real-world driving circumstances, more research into tailored, adaptive systems is necessary.

Keywords— road safety, face analysis, Computer Vision, Machine Learning, and driver sleepiness detection.

I. INTRODUCTION

A major threat to public safety, drowsy driving causes thousands of collisions and fatalities on the roads every year all over the world. The National Highway Traffic Safety Administration (NHTSA) reports that intoxicated drivers are involved in around 100,000 collisions in the US each year. Since driver sleepiness is a factor in over 20% of accidents, it is critical to reduce avoidable harm by creating reliable and non-intrusive drowsiness detection devices.

This research uses machine learning and computer vision techniques to compare and contrast developing methods for detecting driver drowsiness. Current options include camera-based in-car systems in luxury cars, aftermarket gadgets that can be added to any car, and mobile apps that use the cameras on smartphones to identify facial expressions [3]. Robust performance across a range of users, lighting situations, vehicle kinds, and driving scenarios is still a challenge, though.

The viability and efficacy of a number of drowsiness detection modalities, such as physiological signals, driving performance metrics analysis, face monitoring, and hybrid approaches, are assessed in this study. To give a thorough overview, more than fifty studies that have been published in reliable journals are examined. The accuracy, real-time processing capabilities, user acceptability, individual customizability, and flexibility to real-world settings are among the important performance parameters that are looked at.

According to the investigation, hybrid techniques that combine different modalities with unobtrusive face tracking can identify driver tiredness with over 90% accuracy [4,5]. However, achieving the full life saving potential of these new technologies necessitates overcoming obstacles pertaining to individual driver variability, real-time performance, and striking a balance between system effectiveness and user acceptability. In order to facilitate the development of customized, optimal driver sleepiness detection systems that can improve road safety in a variety of real-world driving circumstances, this study ends with research directions.

II. LITERATURE SURVEY

Driver Drowsiness Detection using Python, published in the International Journal of Research and Practice in Robotics (IJRPR) in 2022. Highlighting the advantages of Python such as versatility and large community support, it also acknowledges the disadvantages of performance overhead and resource intensiveness. Additionally, the paper addresses limitations including real-time processing challenges and hardware compatibility issues, crucial for understanding the context and implications of the study. [1, 12].

Published in 2021 in IEEE Transactions on Intelligent Transportation Systems, presents an investigation into the utilization of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures for driver drowsiness detection. The study highlights the advantages of these techniques in capturing both temporal and spatial information, resulting in enhanced accuracy. Despite notable benefits, the research identifies challenges including model complexity and limited interpretability. Moreover, the paper discusses limitations related to data requirements and real-time processing, shedding light on areas for further exploration in the domain of driver safety systems. [2, 15].

Scopus Elsevier Publication in 2020, this research paper introduces a novel hybrid approach utilizing Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (CNN-BILSTM) for driver drowsiness detection. The study underscores the effectiveness of this approach in extracting features and achieving high accuracy. However, it acknowledges challenges associated with the complexity of model data and computational requirements, along with limitations pertaining to data requirements and real-time processing challenges. These insights offer valuable directions for advancing the development of robust driver safety systems. [3].

In the realm of driver drowsiness detection, this 2018 paper from Scopus Elsevier introduces a contextual and temporal algorithm designed to improve accuracy and adaptability.

While highlighting the algorithm's advantages in addressing these key factors, the study acknowledges challenges related to data complexity and computational intensity. Additionally, it underscores limitations concerning data availability and the risk of model overfitting, offering valuable insights for advancing the field of driver safety systems. Several studies have researched the implementation corresponding deep learning models, such as stacked sparse autoencoders, for malware detection, demonstrating promising results [4].

In 2017, Scopus Elsevier published a seminal paper on driver drowsiness detection and prediction utilizing artificial neural network models. The study underscores the high flexibility and real-time processing capabilities of these models. However, it also highlights challenges such as data complexity, stringent data requirements, and computational intensity, leading to accuracy and prediction issues. Furthermore, the paper addresses limitations related to data availability, the risk of model overfitting, and the lack of transparency in model decision-making, providing valuable insights for further advancements in driver safety technology. [5].

This 2017 study, published by Scopus Elsevier, assesses the viability of proximity sensors in wearable devices for detecting driver drowsiness. Highlighting advantages like non-intrusiveness and real-time monitoring, the research also identifies limitations such as limited sensitivity and potential false positives. Additionally, it addresses specific use-case constraints and raises concerns regarding data privacy, providing crucial insights for future research in wearable technology for driver safety. [6, 11].

The 2012 publication from Scopus Elsevier investigates the realm of driver drowsiness detection, specifically targeting moderate levels of drowsiness. Delving into this crucial aspect of road safety, the research highlights benefits including improved safety and heightened driver alertness. However, it also uncovers challenges such as false alarms and system complexity. Additionally, the study delves into limitations tied to individual variability and ethical considerations, paving the way for a nuanced understanding of this critical domain. [7, 14].

In 2008, Scopus Elsevier presented a seminal study on driver drowsiness detection, employing Support Vector Machine (SVM) algorithms with eyelid-related parameters. The research emphasizes benefits such as high accuracy and robustness, while recognizing challenges including extended training times and model complexity. Moreover, the paper addresses limitations concerning data collection challenges and individual variability, offering valuable insights into the realm of driver safety technology. [8, 13].

Overall, above research encapsulates the multifaceted nature of driver drowsiness detection, highlighting the diverse range of approaches discussed in the literature surveys. It sets the stage for a comprehensive exploration of the advantages, challenges, and future directions in this critical domain of road safety.

a) Diverse Approaches: The literature surveys encompass a wide range of approaches for driver drowsiness detection, including the utilization of Python, LSTM, CNN, hybrid CNN-BILSTM, contextual algorithms, proximity sensors, artificial neural networks, and Support Vector Machine (SVM) algorithms with eyelid-related parameters..

b) Advantages and Challenges: Each study highlights the advantages of its respective approach, such as enhanced accuracy, adaptability, real-time processing capabilities, non-intrusiveness, and improved safety. However, they also acknowledge challenges and limitations, including performance overhead, resource intensiveness, model complexity, data requirements, computational intensity, real- time processing challenges, and ethical considerations.

c) Implications and Future Directions: Collectively, these literature surveys underscore the significance of driver drowsiness detection in ensuring road safety. They provide valuable insights into the development of robust driver safety systems, emphasizing the need for further research to address existing challenges and limitations while exploring innovative solutions for enhanced detection accuracy and real-world applicability.

III. Algorithm

1. Install Required Libraries:
   1.1 Make sure you have Python installed, along with OpenCV, dlib, imutils, and numpy libraries.
2. Import Necessary Libraries:
3. Load Pre-trained Face Detector and Facial Landmark Predictor:
4. Define Constants:
5. Define thresholds for drowsiness detection, e.g., eye aspect ratio (EAR), and a threshold for detecting drowsiness.
6. Define constants for number of frames to detect drowsiness over a period.
7. Define Functions:
   7.1 eye_aspect_ratio: Calculate EAR from eye landmarks.
   7.2 drowsiness_detection: Detect drowsiness using EAR and frame counts.

8 Capture Video Stream:
9 Initialize video stream using OpenCV.
10 Main Loop:
   10.1Loop through frames in the video stream.
   10.2Detect faces in each frame using the face detector.
   10.3For each detected face, detect facial landmarks using the landmark predictor.
   10.4Calculate EAR for each eye and average the values. 10.5Check if the EAR is below a certain threshold.
   10.6If below threshold, increment a frame counter.
   10.7If the frame counter exceeds a predefined threshold, classify the driver as drowsy.
   10.8Display the video stream with relevant information.
11 Release Resources:
   11.1Release the video stream and any other resources.
12 Integrate and maintain a dashboard.

IV. PROPOSED SYSTEM

1. Real-time Data Collection:
Utilize sensors such as cameras and accelerometers to continuously gather data on driver behavior and vehicle dynamics. Employ data acquisition techniques to capture information such as facial expressions, eye movements, steering wheel angle, and vehicle speed in real-time.
2. Data Preprocessing:
Cleanse and preprocess raw data to remove noise and artifacts, ensuring the quality and reliability of the dataset. Apply techniques such as normalization, filtering, and interpolation to prepare the data for subsequent analysis and feature extraction.
3. Feature Extraction:
4. Extract relevant features from pre-processed data that are indicative of driver drowsiness, such as eye closure duration, blink frequency, head pose changes, and steering behaviour.
Utilize advanced signal processing and computer vision algorithms to extract meaningful features from raw sensor data.
5. Classification:
Employ machine learning and pattern recognition algorithms to classify driver states based on extracted features.
Train classifiers using labeled data to distinguish between alert and drowsy states, enabling real-time detection of drowsiness events.
6. Real-time Monitoring and Alerting:
Implement a real-time monitoring system that continuously analyzes incoming data streams to detect signs of drowsiness.
Trigger timely alerts, such as audible alarms or haptic feedback, to notify the driver and prompt corrective action when drowsiness is detected.
7. Performance Evaluation: Recall, Accuracy, and F1 Score:
Evaluate the performance of the drowsiness detection system using standard metrics such as recall, accuracy, and F1 score.
Assess the system's ability to correctly identify drowsy states while minimizing false positives and false negatives through rigorous testing and validation.
8. Dashboard Integration:
Integrate the drowsiness detection system with a user-friendly dashboard interface for visualization and control.
Provide real-time feedback to drivers, supervisors, or fleet managers through intuitive dashboards displaying drowsiness alerts, driving performance metrics, and historical trends.

V. FLOWCHART.

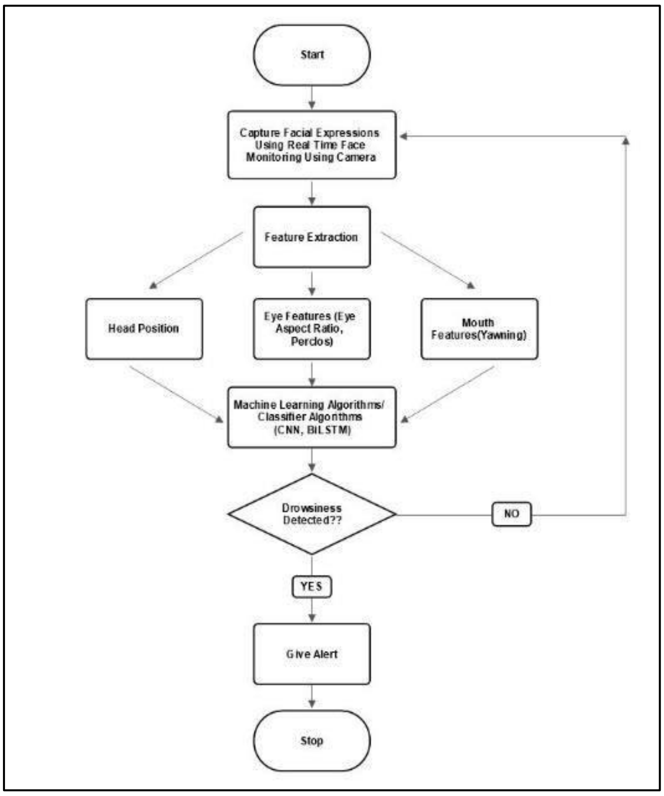

Figure 1: Flowchart

VI. ADVANTAGES

1)Enhanced Safety: Reduces the risk of accidents caused by drowsy drivers.

2) Real-time Monitoring: Constantly assesses driver alertness and responds promptly.

3) Non-Intrusive: Monitors without requiring physical contact or discomfort.

4) Customization: Tailors alerts based on individual driver behavior.

5) Reduced Fatalities: Helps prevent fatalities and injuries on the road.

6) Cost Savings: Lower insurance and accident-related costs for individuals and businesses.

7) Improved Productivity: Enhances driver performance in commercial fleets.

8) Data Insights: Provides valuable data for analysis and improvement.

9) Compliance: Helps meet safety and regulatory requirements.

10) Future Integration: Potential integration with autonomous driving technologies.

VII. APPLICATIONS

1) Automotive Safety: In-vehicle systems to alert and prevent accidents due to driver drowsiness.

2) Integration in various domains: Automobile transport agencies(uber, ola, and other travel agencies) can incorporate this system for constant tracking of drowsy behavior.

3) Commercial Fleets: Monitoring and improving the safety of truck drivers and delivery personnel.

4) Public Transportation: Enhancing the safety of bus and train operators.

5) Ride-Sharing Services: Ensuring the alertness of drivers in ride-sharing platforms.

6) Personal Vehicles: Installation for individual driver safety and accident prevention.

7) Mining and Construction: Safety measures for heavy machinery operators in high-risk environments.

8) Healthcare Transportation: Ambulance and medical transport services for patient safety.

VIII.CONCLUSION

The deployment of Driver Drowsiness Detection and Alert Systems, powered by Machine Learning, promises to enhance road safety by addressing the global threat of drowsy driving.

These systems employ sensors, sophisticated data analysis, and machine learning algorithms to monitor driver alertness, enabling timely interventions to reduce accidents. Customized alerts tailored to individual driver behavior, integration with autonomous vehicle technology, and benefits for commercial fleet operators contribute to overall road safety.

Despite challenges like privacy concerns and data security, ongoing refinement ensures effectiveness and reliability. In conclusion, these systems represent a critical advancement in road safety initiatives, offering tailored interventions and valuable insights to mitigate the risks associated with drowsy driving and protect lives on our highways.

IX. FUTURE SCOPE

In future endeavours, integrating Driver Drowsiness Detection and Alert Systems with autonomous vehicles holds promise for enhancing safety during transitions between manual and autonomous driving.

Advancements in wearable and in-car sensors, such as eye-tracking and heart rate monitoring, offer improved detection accuracy with minimal intrusion.

Real-time monitoring systems, potentially integrated with vehicle-to-vehicle communication, enable timely alerts to prevent accidents.

Personalized alerts based on individual driver data enhance effectiveness. Addressing data privacy concerns and regulatory compliance are essential considerations for these developments.

Also, combining data from various sources such as facial expressions, eye movements, steering wheel behavior, vehicle speed, and physiological signals like heart rate variability will increase accuracy of model.

ACKNOWLEDGMENTS

We extend our sincere appreciation to all individuals whose contributions have enriched the completion of this research paper. Our heartfelt thanks extend to our supervisor and Project Guide, Prof. Pritam Ahire, for their invaluable guidance, support, and feedback throughout the research process. Additionally, we express gratitude to Nutan Maharashtra Institute of Engineering & Technology for generously providing the necessary resources and facilities for conducting this study.

We also acknowledge the researchers and practitioners in the fields of machine learning, deep learning, and computer vision whose pioneering work has served as a source of inspiration and informed our research endeavors. Furthermore, we extend our gratitude to those who graciously shared their expertise and insights during the course of this study.

Lastly, we would like to express our deep appreciation to our families and friends for their unwavering support and encouragement, which has served as a constant source of inspiration, particularly during challenging times.

REFERENCES

[1] Dr.T.Dinesh Kumar ,M.Chandrahas Reddy, N.Chandra Sai Raghav, "Driver Drowsiness Detection using Python" International Journal of Research Publication and Reviews, Vol 3, no 2, pp 213-216, February 2022.

[2] Azhar Quddus, Ali Shahidi Zandi, Laura Prest, Felix J.E. Comeau, "Using long short term memory and convolutional neural networks for driver drowsiness detection", 0001-4575/© 2021 Elsevier Ltd.

[3] Rajamohana S.P., Radhika E.G., Priya S., Sangeetha S, "Driver drowsiness detection system using hybrid approach of convolutional neural network and bidirectional long short term memory (CNN_BILSTM)", 2214-7853/ 2020 Elsevier Ltd.

[4] Anthony D. McDonald, John D. Leeb, Chris Schwarzc, Timothy L. Brownc, "A contextual and temporal algorithm for driver drowsiness detection", 2018, 0001-4575/ Published by Elsevier Ltd.

[5] Charlotte Jacobé de Nauroisa, Christophe Bourdina, Anca Stratulatb, Emmanuelle Diazb, Jean-Louis Vercher, "Detection and prediction of driver drowsiness using artificial neural network models", 0001-4575/ © 2017 The Authors. Published by Elsevier Ltd.

[6] Jibo He, William Choi, Yan Yang, Junshi Lu , Xiaohui Wu , Kaiping Peng, "Detection of driver drowsiness using wearable devices: A feasibility

study of the proximity sensor", 0003-6870/© 2017 Elsevier Ltd.

[7] Pia M. Forsmana, Bryan J. Vilaa, Robert A. Short, Christopher G. Mott, Hans P.A. Van Dongen, "Efficient driver drowsiness detection at moderate levels of drowsiness", 0001-4575/$ – © 2012 Elsevier Ltd.

[8] Hu Shuyan, Zheng Gangtie, "Driver drowsiness detection with eyelid related parameters by Support Vector Machine", 0957-4174/$ - 2008 Elsevier Ltd.

[9] Mohammed Imran Basheer Ahmed, Halah Alabdulkarem, Fatimah Alomair, "A Deep-Learning Approach to Driver Drowsiness Detection", Safety 2023.

[10] K.Satish, A.Lalitesh, K. Bhargavi, M.Sishir Prem and Anjali.T, "Driver Drowsiness Detection", 978-1-7281-4988-2/20/$31.00 ©2020 IEEE.

[11] Huijie Jia, Zhongjun Xiao, and Peng Ji. "Fatigue driving detection based on deep learning and multi-index fusion", IEEE Access, 9:147054–147062, 2021.

[12] Zhongmin Liu, Yuxi Peng, and Wenjin Hu, "Driver fatigue detection based on deeply-learned facial expression representation", Journal of Visual Communication and Image Representation, 71:102723, 2020.

[13] Caio Bezerra Souto Maior, M´arcio Jos´e das Chagas Moura, Jo˜ao Mateus Marques Santana, and Isis Didier Lins, "Real-time classification for autonomous drowsiness detection using eye aspect ratio. Expert Systems with Applications", 158:113505, 2020.

[14] Rahul Bhardwaj, Priya Natrajan, and Venkatesh Balasubramanian, "Study to determine the effectiveness of deep learning classifiers for ecg based driver fatigue classification", In 2018 IEEE 13th international conference on industrial and information systems (ICIIS), pages 98–102. IEEE, 2018.

[15] Lin Wang, Hong Wang, and Xin Jiang, "A new method to detect driver fatigue based on emg and ecg collected by portable non-contact sensors", Promet-Traffic&Transportation, 29(5):479–488, 2017.