Drowseguard Drowsiness Detector: Python Implementation Employing Deep Learning And Computer Vision

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**—** In 2021, a report from the Ministry of Road Transport and Highways Transport Research Wing underscored the alarming toll of road accidents, which claimed the lives of 1,53,972 individuals and injured 3,84,448. The majority of those affected were drivers aged between 18 and 45 years. Additionally, a CDC survey revealed that approximately 1 in 25 adult drivers reported experiencing drowsiness and even falling asleep while operating a vehicle within the past 30 days. The devastating consequences of these accidents highlight the urgent need for effective preventive measures. Transportation companies employing overnight drivers face particularly heightened risks, as nighttime driving often leads to severe fatigue and drowsiness. Consequently, automakers are increasingly implementing driver drowsiness detection systems. While existing systems, such as those employed by Toyota and Audi using ECG machines, have drawbacks like discomfort, there's a growing interest in advanced solutions based on machine learning and deep learning. Proposed systems aim to assess driver fitness and alert them based on fatigue levels, utilizing technologies like webcams for facial monitoring. By implementing such systems on a broader scale and at a manageable cost, the potential to significantly reduce the rate of road accidents is substantial. Moreover, platforms like OLA and Uber could leverage performance analysis modules to monitor drivers' fitness levels and mitigate risks associated with drowsiness effectively.

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

I. Introduction

A significant concern for public safety is the prevalence of drowsy driving, which contributes to thousands of collisions and fatalities worldwide each year.

Data from the National Highway Traffic Safety Administration (NHTSA) indicates that approximately 100,000 collisions annually in the US involve intoxicated drivers. Driver sleepiness is cited as a factor in over 20% of accidents, underscoring the urgent need for reliable and non-intrusive drowsiness detection devices.

Various methodologies, including physiological signals analysis, facial monitoring, and hybrid approaches, have been explored to address this issue. Recent studies have shown promising results, with hybrid techniques combining different modalities and unobtrusive face tracking achieving over 90% accuracy in identifying driver tiredness.

However, challenges such as individual driver variability, real-time performance, and balancing system effectiveness with user acceptability remain significant hurdles to fully realizing the life-saving potential of these technologies. Thus, further research is needed to develop customized, optimal driver sleepiness detection systems capable of enhancing road safety across diverse driving conditions and addressing the complexities of real-world scenarios.

II. Literature Survey

Many publications shows effective and famous methods and algorithms for driver drowsiness detection.[17, 18].The paper in International Journal of Research and Practice in Robotics discusses Python-based Driver Drowsiness Detection, noting its versatility and community support, but also highlighting performance overhead and real-time processing challenges.[1, 10, 14, 9] Additionally, an IEEE Transactions on Intelligent Transportation Systems article from 2021 explores LSTM and CNN architectures for driver drowsiness detection, emphasizing their ability to capture temporal and spatial information, while also noting challenges like model complexity and data requirements.[2, 12].

Two recently published papers shed light on use of machine learning, OpenCV and use of image recognition in healthcare domain and enhancing quality of image using new complex technologies. [19, 20].

2020 Scopus Elsevier publication introduces a CNN-BILSTM hybrid approach for driver drowsiness detection, emphasizing its feature extraction effectiveness but acknowledging challenges in model complexity and real-time processing.[3, 11] A 2018 Scopus Elsevier paper presents a contextual algorithm for driver drowsiness detection, highlighting its accuracy improvements and adaptability, while recognizing challenges like data complexity and computational intensity.[4, 15].

A seminal 2017 Scopus Elsevier paper on driver drowsiness detection and prediction using artificial neural networks underscores their flexibility and real-time processing capabilities, alongside challenges like data complexity and accuracy issues.[5, 6, 13].

A 2012 Scopus Elsevier publication investigates driver drowsiness detection targeting moderate levels of drowsiness, highlighting benefits such as safety improvements and driver alertness, despite challenges like false alarms and system complexity.[7]. Finally, a 2008 Scopus Elsevier study presents driver drowsiness detection using SVM algorithms [8].

2023 paper published in IJARCCE gives a comparative analysis of all methods that can be used for driver drowsiness detection.[16].

Overall, these literature surveys highlight the critical importance of driver drowsiness detection in ensuring road safety. They provide valuable insights into the development of robust driver safety systems, underscoring the necessity for further research to address existing challenges and limitations while exploring innovative solutions to enhance detection accuracy and real-world applicability.

III. System Design

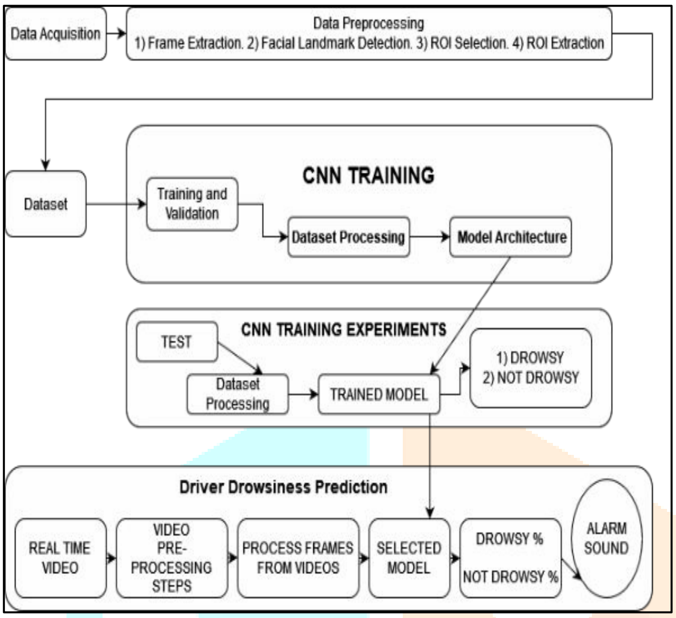

Figure 1. Design of System

1. Components:
   10.1. Data Collection: Utilize OpenCV for accessing camera feeds and capturing frames.
   10.2. Data Processing: Employ NumPy for efficient numerical operations on image data.
   10.3. Analysis: Utilize computer vision techniques from OpenCV for tasks like facial recognition and feature extraction.
   10.4. Alert Generation: Implement logic to trigger alerts based on analysis results.

2. Data Sources:
   2.1. Camera Feeds: Streams of images captured by onboard or external cameras.
   2.2. Physiological Monitors: Additional sensors measuring factors like heart rate variability or eyelid closure.

3. Data Processing:
   3.1. Pre-processing: Use OpenCV for tasks like resizing, normalization, and noise reduction.
   3.2. Feature Extraction: Extract relevant features from images, such as facial landmarks or eye closure patterns, using OpenCV functionalities.

4. Analysis Techniques:
   4.1. Machine Learning: Train models using libraries on extracted features.
   4.2. Computer Vision: Apply techniques like 68 facial landmark detection DAT File using OpenCV's built-in functions.

5. Integration:
   5.1. Utilize Python's modular structure to integrate different components seamlessly.

6. Dashboard Creation:
   6.1. Develop real-time dashboards using libraries like Matplotlib or Polly for visualization.
   6.2. Update dashboards dynamically with new data using event-driven programming paradigms.

7. Scalability:
   7.1. Design the system to leverage parallel processing capabilities of libraries like OpenCV for handling large volumes of data efficiently.
   7.2. Utilize cloud-based solutions for scalability and resource management.

8. Adaptability:
   8.1. Implement adaptive algorithms that adjust to individual drivers' behaviour using reinforcement learning or adaptive filtering techniques.

9. Alert Mechanisms:
   9.1. Integrate alert generation logic with system components, triggering alerts based on predefined thresholds or conditions.
   9.2. Utilize libraries like Pygame or Tkinter for creating auditory or visual alerts.

10. Evaluation:
   10.1. Define metrics for evaluating system performance, such as accuracy, precision, and recall.
   10.2. Conduct comprehensive testing using datasets with ground truth labels to assess the system's effectiveness.

IV. FLOWCHART

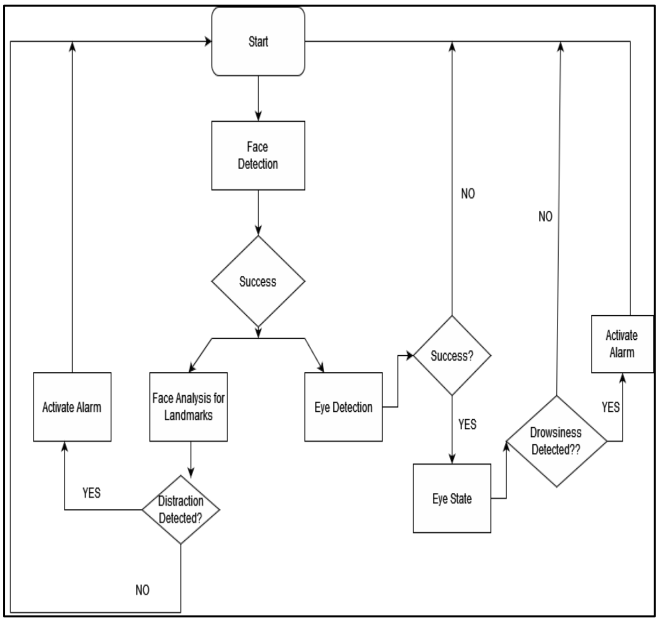

Figure 2. Flowchart

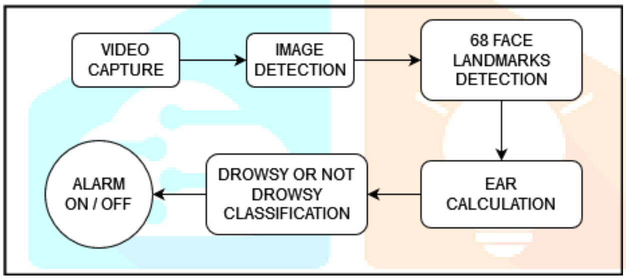

Figure 3. Real Time System Implementation

V. ALGORITHM

1) Input Frame: This represents a single frame or image captured by the system, likely from a camera monitoring the driver's face.

2) Sequence: It indicates that a sequence of frames or images is being processed in real-time to track changes in the driver's condition.

3) Detect Faces: The system first identifies and locates the driver's face within the captured frame.

4) Detect Eyes: Once the face is detected, the system further identifies and localizes the eyes within the face.

5) Deep Features Representation of Eyes: Similar to the mouth, deep features related to the driver's eyes are extracted, providing information about the eye state.

6) Calculate Feature with VGG-eyes: Another set of features, possibly more detailed or specialized, is calculated from the driver's eyes using the VGG (Visual Geometry Group) deep learning model.

7) Fatigue Feature Fusion Model: This model likely combines various features, including those from the eyes and mouth, to assess the driver's fatigue level.

8) Eye State Model: Similar to the mouth state model, this model processes the deep features from the eyes to determine their state, such as whether the eyes are open or closed.

9) Drowsiness: This represents the final output, where the system makes a determination regarding the driver's drowsiness state, signaling whether the driver is at risk of falling asleep while driving.

10) Emergency Alert to his Network - To create an emergency alert message for network transmission, use the Common Alerting Protocol (CAP) format. Include essential details like the sender, date and time, alert type, scope, urgency, severity, and specific information about the emergency event. This structured approach ensures that the message is clear and actionable for recipients.

11) Update Dashboard: The described architecture suggests a sophisticated system that leverages deep learning models to analyze facial features, detect driver fatigue, and ultimately assess drowsiness. The fusion of features from the eyes and mouth allows for a comprehensive evaluation of the driver's condition, enhancing the accuracy of drowsiness detection.

VI. MATHEMATICAL MODEL

We make use of Euclidean distance to compare feature vectors. For Performance Measures, we use parameters like Precision, Accuracy, Recall and F1 Score.

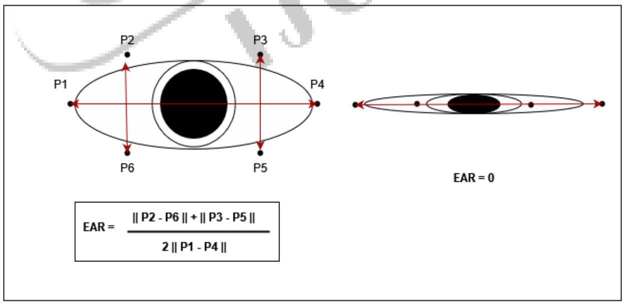

Figure 4. Euclidean Distance Calculation.

VII. PERFORMANCE EVALUATION

The confusion matrix is a valuable tool for assessing the accuracy and effectiveness of an algorithm. It provides a detailed breakdown of the algorithm's classifications, including true positives, false positives, true negatives, and false negatives, offering insights into its performance.

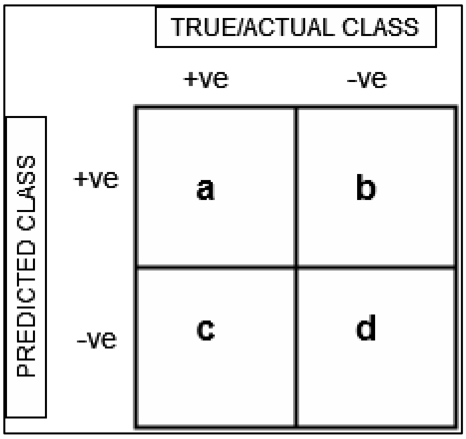

Figure 5. Confusion Matrix

In above diagram,
a = True Positive,
b = False Positive
c = False Negative
d = True Negative.

- True Positive: Correctly identified positive instances.
- False Positive: Incorrectly identified negative instances as positive.
- False Negative: Incorrectly identified positive instances as negative.
- True Negative: Correctly identified negative instances.

1. Accuracy score = (d+a)/(a+b+c+d).
2. Precision score = a/(b+a) .... (Predicted Yes).
3. Recall score = a/(b+c) .... (Actual Yes).
4. F1_score = (2*Recall*Precision) / (Recall + Precision).

After calculation, we get approx. 94% accuracy.

VIII. RESULT

Figure 6. shows the state where the driver is fully active, and the Euclidean distance calculated is above the threshold and hence, the driver is classified into fully active state.

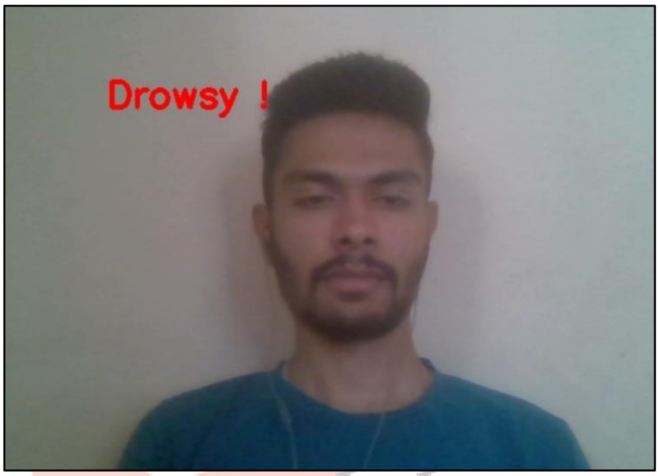

Figure 7. shows drowsy state of the driver, as the EAR calculated by algorithm is below threshold mentioned for drowsiness level.

Figure 8. is a state where the driver is completely asleep, as the EAR calculated turns out to be zero, hence, falling in sleepy category.

The model captures instances and states in real time and integrates it with a live dashboard, which maintains all history related to driver during the entire journey, displaying the states where the driver was active, drowsy and sleeping. This dashboard can be viewed by the administrator of the form of by a third person or a third party software in future.

IX. 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.

X. CONCLUSION

In conclusion, Driver Drowsiness Detection and Alert Systems driven by Machine Learning offer a promising solution for improving road safety against drowsy driving risks. These systems use sensors, data analysis, and machine learning to monitor driver alertness, intervening promptly to prevent accidents.

Customized alerts based on individual behavior enhance effectiveness, while integration with autonomous vehicle technology boosts overall road safety. Fleet operators benefit from improved driver safety, reducing accident costs and insurance premiums. Real-time dashboards provide insights into driver behavior, enabling proactive accident prevention.

Addressing privacy and security concerns is crucial for public trust, while ongoing refinement is necessary to maximize effectiveness and reliability, ultimately safeguarding against drowsy driving hazards. Overall, these systems represent a critical advancement in road safety through machine learning and data analytics.

XI. FUTURE SCOPE

In envisioning the future of drowsiness detection systems, enhanced sensing technologies are key. Picture next-gen systems with advanced sensors like contactless heart rate monitors, high-resolution infrared cameras, and eye-tracking sensors. These sensors work together to monitor physiological signals and facial movements accurately, ensuring continuous vigilance against drowsiness.

Integration of advanced machine learning techniques is crucial. Imagine systems using deep learning architectures like CNNs and RNNs, trained on vast datasets to predict drowsiness precisely. For example, a deep neural network can analyze facial micro expressions, heart rate variability, and driving performance metrics to assess drowsiness accurately.

For real-time adaptability, systems could adjust alerting mechanisms based on context. In urban areas, gentle alerts may be prioritized to prevent startling, while on highways, more assertive alerts may be needed.

Integration with autonomous vehicles is another frontier. Systems could detect fatigue and transition to autonomous driving mode, allowing drivers to rest safely. Data privacy and security are vital, with encryption and onboard processing safeguarding sensitive information.

Integration with smart infrastructure shows promise for further enhancing road safety.

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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.

[16] Sayali Alex Dive, Gaurav Prashant Pande, Soumitra Yatin Sathe, Satyajit Sirsat, "Driver Drowsiness Detection Methods: A Comparative Study", International Journal of Advanced Research in Computer and Communication Engineering, DOI: 10.17148/IJARCCE.2023.12337.

[17] Q. Massoz, T. Langohr, C. François and J. G. Verly, "The ULg multimodality drowsiness database (called DROZY) and examples of use," 2016 IEEE Winter Conference on Applications of Computer Vision (WACV), Lake Placid, NY, USA, 2016, pp. 1-7, doi: 10.1109/WACV.2016.7477715.

[18] Trutschel, U., Sirois, B., Sommer, D., Golz, M. and Edwards, D., 2011, June. PERCLOS: An alertness measure of the past. In Driving Assesment Conference (Vol. 6, No. 2011). University of Iowa.

[19] Pritam Ahire , Predictive and Descriptive Analysis for Healthcare Data, A Hand book on Intelligent Health Care Analytics - Knowledge Engineering with Big Data " https://www.wiley.com/en-us/Handbook+on+Intelligent+Healthcare+Analytics%3A+Knowledge+Engineering+with+Big+Data-p-9781119792536 Published by Scrivener Publishing, Wiley Group,2021.

[20] Pritam Ahire , "To Detect The Number Plate By Enhancing The Image", JETIR, ISSN-2349-5162, Volume 10, Issue 5, May 2023.