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A Convolutional Neural Network – Based Fatigue Alert System

Dr. V.Mathumitha, Bhupathi Pavan Kalyan, Budidha Ajay, Chappi Chakresh I,

Boppudi Veeraiah Chowdary

Associate Professor, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai, India

B. Tech Students, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai, India

ABSTRACT: Drowsiness detection is a critical application in various fields, particularly in transportation, where driver fatigue is a major cause of accidents. This project aims to develop a simple yet effective system for detecting drowsiness using machine learning techniques. The system leverages computer vision and machine learning algorithms to analyse facial landmarks and eye closure patterns in real-time. We utilize a pre-trained facial feature extraction, focusing on key indicators such as eye aspect ratio (EAR) and head position. The data collected is processed and classified to distinguish between alert and drowsy states. The model is trained on a dataset of annotated facial images, which include both drowsy and non-drowsy conditions. The system's performance is evaluated through accuracy, precision, and recall metrics, demonstrating its potential as a low-cost solution for enhancing safety in vehicles and other settings

KEYWORDS: 1.Driver Alertness 2. Image Processing,Pattern Recognition 3. Human Behavior Monitoring 4. Face Detection 5.Eye Blink Detection 6.Sleepiness Detection, 7.Deep Learning,8. Non-Intrusive Monitoring, 9.Safety Enhancement, 10.Fatigue Prevention.

I. INTRODUCTION

Drowsiness is a significant factor contributing to accidents, particularly in the transportation sector. With the increasing demand for safety in vehicles and workplaces, detecting signs of fatigue in individuals has become a critical area of research. Traditional methods of drowsiness detection, such as subjective self-reporting or physiological measurements are often intrusive and impractical for real-time applications.

This project addresses the challenge of drowsiness detection by leveraging machine learning techniques, specifically Convolutional Neural Networks (CNN) and Haar Cascade classifiers, to create a non-intrusive, real-time monitoring system. The system analyzes facial features, such as eye movements and blink rates, to detect early signs of drowsiness. By processing video input through a camera, the system can accurately identify patterns associated with fatigue and provide timely alerts to prevent potential accidents

The integration of CNN for feature extraction and Haar Cascade for face detection ensures that the system is both efficient and effective, capable of operating on minimal hardware. This makes the solution accessible for a wide range of applications, from enhancing driver safety to monitoring worker alertness in various industries. The project's aim is to develop a reliable, general-purpose drowsiness detection system that can be easily implemented in real-world scenarios, contributing to improved safety and well-being across multiple domains.

II. LITERATURE REVIEW

Due to the rise in traffic accidents, there is an urgent need to reduce driving mistakes, particularly driver fatigue or drowsiness. Many algorithms have been developed to detect fatigue and alert drivers, but challenges remain in achieving high detection accuracy and minimizing the time required for alerts. These factors are critical for reducing

traffic accidents. video recordings of driver behavior, have been used to develop fatigue detection techniques. This paper introduces two approaches: one utilizing machine learning classifiers for EEG signals and the other employing deep learning models for video streams. The Support Vector Machine (SVM) classifier achieves up to 98% accuracy, while the Convolutional Neural Network (CNN) reaches 99% accuracy. Experimental results show that both algorithms provide the highest detection accuracy and Shortest Testing Time (TT) compared to other recent fatigue detection methods, making them effective solutions for improving driver safety.

A CNN-based fatigue alert system uses Convolutional Neural Networks to detect signs of drowsiness or fatigue, typically from facial features like eyes and mouth in real-time video. Studies have shown high accuracy using CNNs, often achieving **90–95% accuracy** in controlled conditions. Challenges include handling poor lighting, occlusion, and the need for diverse training data

III. METHODOLOG

The proposed drowsiness detection system can be broken down into several key modules, each responsible for a specific aspect of the system's functionality. Below are the primary modules:

1. Data Acquisition Module:

Objective:

Capture live video feed from a camera (e.g: webcam) to monitor the user in real-time.

Components:

Camera Interface: Connects and streams video from the camera.

Frame Extraction: Captures frames from the video feed for processing.

2. Face Detection Module:

Objective:

Detect the user's face and key facial features within the captured video frames.

Components:

Haar Cascade Classifier: Uses pre-trained Haar Cascade models to identify and localize the face, eyes, and mouth within each frame.

3. Pre-processing: Converts frames to grayscale and performs necessary image preprocessing for better detection accuracy

4 . Drowsiness Detection Module:

Objective: Analyze the extracted features using a Convolutional Neural Network (CNN) to determine the user's state of alertness.

Components:

CNN Model: A pre-trained CNN processes the extracted features (eye aspect ratio, mouth openness, etc.) to classify whether the user is drowsy or alert.

Thresholding: Applies predefined thresholds (e.g., prolonged eye closure) to make a final decision on drowsiness.

5. Alert/Notification Module:

Objective: Generate alerts if the system detects signs of drowsiness.

Components:

Audio/Visual Alerts: Triggers alarms (e.g., sound, vibration, visual cues) to alert the user when drowsiness is detected.

IV. IMPLEMENTATION

The implementation of a CNN-based fatigue alert system begins with collecting data, either through real-time video capture or by using labeled datasets like NTHU-DDD or YawDD, which include various facial expressions related to

drowsiness. The next step is preprocessing, where facial landmarks such as eyes and mouth are detected using tools like OpenCV, Haar cascades, or MTCNN. These regions of interest are then resized and normalized for input into the CNN model. A suitable CNN architecture—either custom-built or pretrained like VGG16 or MobileNet—is used to classify images into "fatigued" or "alert" categories. The model is trained on the dataset using techniques like data augmentation to handle different lighting conditions and head poses. Once trained, the model is integrated into a real-time system that continuously processes video frames from a camera. If the system detects signs like closed eyes for a certain duration, frequent blinking, or yawning, it flags the user as fatigued. Based on these predictions, an alert mechanism is triggered—such as a buzzer, audio message, or visual warning. For real-world deployment, the system is optimized using lightweight CNNs or converted to formats like TensorFlow Lite for faster processing on edge devices. This makes the system suitable for integration in vehicles or workplace environments to improve safety and performance.

V. RESULTS AND CONCLUSION

Due to the rise in traffic accidents, there is an urgent need to reduce driving mistakes, particularly driver fatigue or drowsiness. Many algorithms have been developed to detect fatigue and alert drivers, but challenges remain in achieving high detection accuracy and minimizing the time required for alerts. These factors are critical for reducing traffic accidents. video recordings of driver behavior, have been used to develop fatigue detection techniques. This paper introduces two approaches: one utilizing machine learning classifiers for EEG signals and the other employing deep learning models for video streams. The Support Vector Machine (SVM) classifier achieves up to 98% accuracy, while the Convolutional Neural Network (CNN) reaches 99% accuracy. Experimental results show that both algorithms provide the highest detection accuracy and Shortest Testing Time (TT) compared to other recent fatigue detection methods, making them effective solutions for improving driver safety

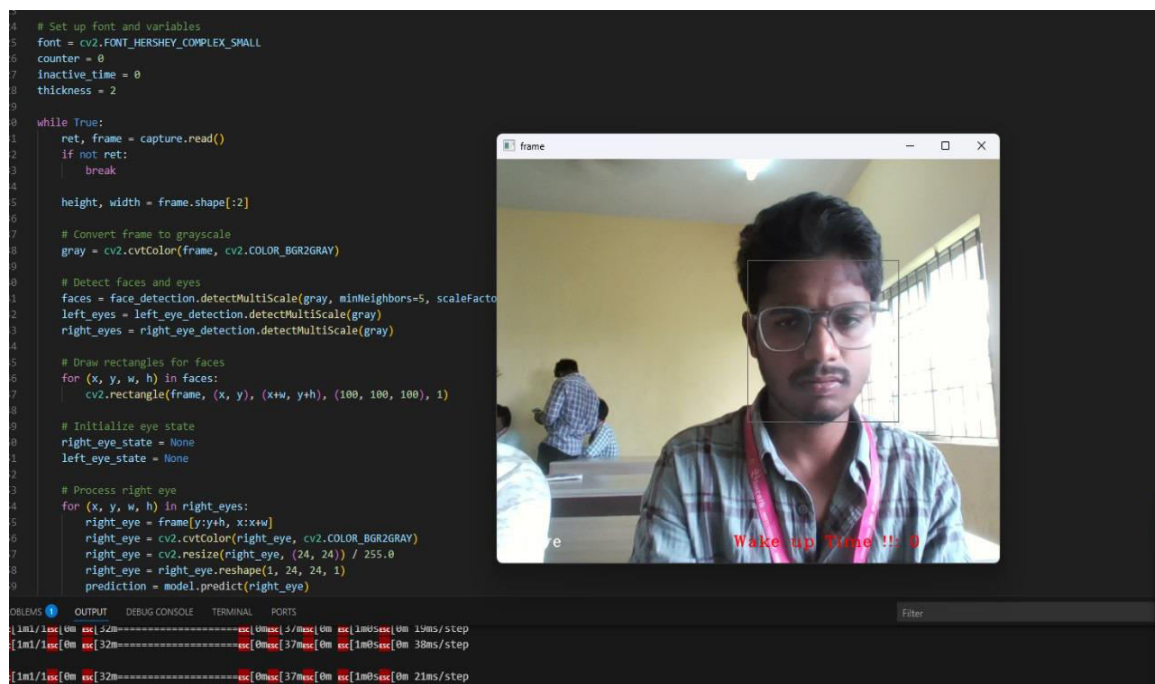


Fig 3: wake up time Demo

VI. SYSTEM ARCHITECTURE

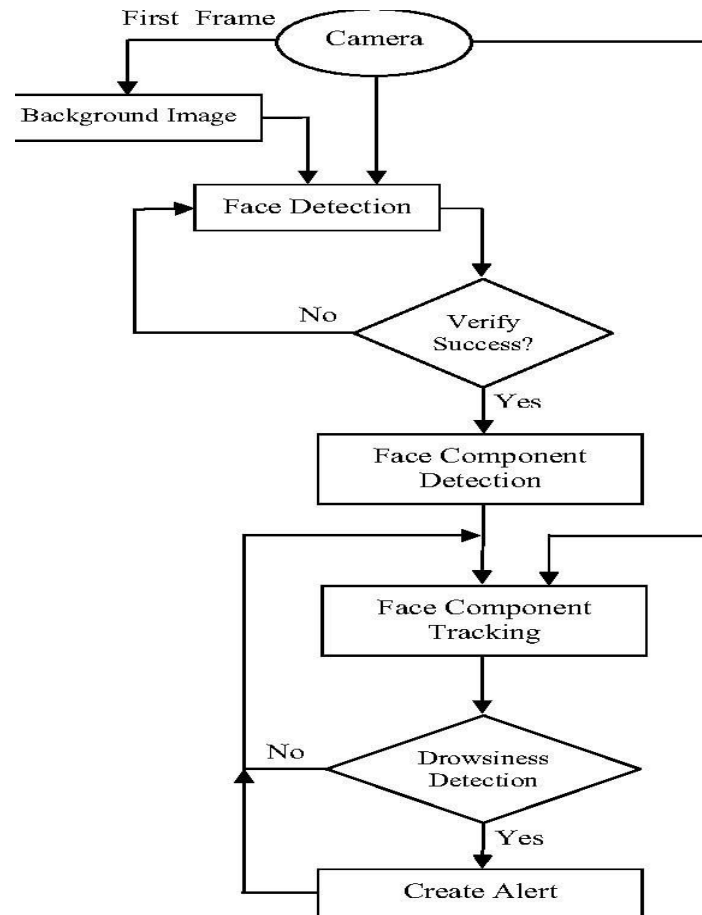


Figure 1. The proposed system flowchart.

Fig(): System architecture

VII. CONCLUSIONS & FUTURE SCOPE

1. Non-Intrusive and User-Friendly:

The system operates using a standard webcam, eliminating the need for wearable sensors, which are often uncomfortable and intrusive. This makes it more accessible and easier to deploy across various environments.

2. Real-Time Detection:

The integration of Haar Cascade classifiers enables rapid face and feature detection, while the CNN effectively analyzes these features to detect drowsiness in real-time. This capability is critical for applications such as driver monitoring, where timely alerts can prevent accidents.

3. Cost-Effective Implementation:

By utilizing commonly available hardware and open-source software, the system is cost-effective, making it suitable for widespread deployment in both consumer and industrial settings.

4. Scalability and Versatility:

The modular architecture of the system allows it to be easily adapted and scaled for different use cases, including monitoring in vehicles, workplaces, and even personal health applications.

5. Balance of Accuracy and Efficiency:

The combination of Haar Cascade for quick detection and CNN for detailed analysis ensures a good balance between accuracy and computational efficiency, making the system robust yet lightweight.

Future Scope

While the proposed system provides a solid foundation for drowsiness detection, there are several areas for further research and development to enhance its effectiveness and applicability:

1. Improved Accuracy with Advanced Models:

Future iterations could explore the use of more advanced deep learning architectures, such as Recurrent Neural Networks (RNNs) or attention-based models, to improve the system's accuracy in detecting subtle signs of drowsiness.

2. Integration with IoT and Smart Devices:

The system could be integrated with Internet of Things (IoT) devices to create a connected ecosystem that not only detects drowsiness but also communicates with other systems (e.g., vehicle control systems) to take preventive actions automatically.

3. Multi-Modal Drowsiness Detection:

Incorporating additional data sources, such as physiological signals (e.g., heart rate, skin conductance) or environmental factors (e.g., ambient light, temperature), could enhance the robustness of the system, making it more reliable in diverse conditions.

4. Personalized Drowsiness Detection:

Future versions could incorporate machine learning models that adapt to individual users, taking into account personal behavioral patterns and physiological characteristics to improve detection accuracy.

REFERENCES

- [1] National Crime Records Bureau (NCRB), Ministry of Home Affairs, and Government of India. (Oct. 2021). Accidental Deaths and Suicides in India. [Online]. Available: https://ncrb.gov.in/sites/default/files/ADSI_2020_FULL_REPORT.pdf
- [2] World Health Organization. (2011). Mobile Phone Use: A Growing Problem of Driver Distraction. [Online]. Available: https://www.who.int/violence_injury_prevention/publications/road_traffic/distracted_driving_en.pdf
- [3] M. Ramzan, H. U. Khan, S. M. Awan, A. Ismail, M. Ilyas, and A. Mahmood, "A survey on state-of-the-art drowsiness detection techniques," *IEEE Access*, vol. 7, pp. 61904_61919, 2019, doi:10.1109/ACCESS.2019.2914373.
- [4] A. Dasgupta, D. Rahman, and A. Routray, "A smartphone-based drowsiness detection and warning system for automotive drivers," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 11, pp. 4045_4054, Nov. 2019, doi:10.1109/TITS.2018.2879609.
- [5] C.-T. Lin, R.-C. Wu, S.-F. Liang, W.-H. Chao, Y.-J. Chen, and T.-P. Jung, "EEG-based drowsiness estimation for safety driving using independent component analysis," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 52, no. 12, pp. 2726_2738, Dec. 2005, doi:10.1109/TCSI.2005.857555.
- [6] Y. Cui, Y. Xu, and D. Wu, "EEG-based driver drowsiness estimation using feature weighted episodic training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 11, pp. 2263_2273, Nov. 2019, doi:10.1109/TNSRE.2019.2945794.
- [7] Y. Jiang, Y. Zhang, C. Lin, D. Wu, and C.-T. Lin, "EEG-based driver drowsiness estimation using an online multi-view and transfer TSK fuzzy system," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1752_1764, Mar. 2021, doi:10.1109/TITS.2020.2973673.
- [8] W. Zhang, B. Cheng, and Y. Lin, "Driver drowsiness recognition based on computer vision technology," *Tsinghua Sci. Technol.*, vol. 17, no. 3, pp. 354_362, Jun. 2012, doi: 10.1109/TST.2012.6216768.
- [9] M. A. Tanveer, M. J. Khan, M. J. Qureshi, N. Naseer, and K.-S. Hong, "Enhanced drowsiness detection using deep learning: An fNIRS study," *IEEE Access*, vol. 7, pp. 137920_137929, 2019, doi: 10.1109/ACCESS.2019.2942838
- [10] Maraju, P. K. (2024). Advancing synergy of computing and artificial intelligence with innovations challenges and future prospects. *FMD Transactions on Sustainable Intelligent Networks*, 1(1), 1-14.
- [11] B.-G. Lee and W.-Y. Chung, "Driver alertness monitoring using fusion of facial features and bio-signals," *IEEE Sensors J.*, vol. 12, no. 7, pp. 2416_2422, Jul. 2012, doi: 10.1109/JSEN.2012.2190505.

- [12] M. Kahlon and S. Ganesan, "Driver drowsiness detection system based on binary eyes image data," in Proc. IEEE Int. Conf. Electro/Inf. Technol.(EIT), May 2018, pp. 209_215, doi: 10.1109/EIT.2018.8500272.
- [13] M. H. Alkinani, W. Z. Khan, and Q. Arshad, "Detecting human driver inattentive and aggressive driving behavior using deep learning: Recent advances, requirements and open challenges," IEEE Access, vol. 8, pp. 105008_105030, 2020, doi: 10.1109/ACCESS.2020.2999829.
- [14] C. Zhang, X. Wu, X. Zheng, and S. Yu, "Driver drowsiness detection using multi-channel second order blind identifications," IEEE Access, vol. 7, pp. 11829_11843, 2019, doi: 10.1109/ACCESS.2019.2891971.
- [15] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, and A. Sengur, "An effective hybrid model for EEG-based drowsiness detection," IEEE Sensors J., vol. 19, no. 17, pp. 7624_7631, Sep. 2019, doi: 10.1109/JSEN.2019.2917850.
- [16] W. Deng and R. Wu, "Real-time driver-drowsiness detection system using facial features," IEEE Access, vol. 7, pp. 118727_118738, 2019, doi: 10.1109/ACCESS.2019.2936663.
- [17] M. Omidyeganeh, A. Javadtalab, and S. Shirmohammadi, "Intelligent driver drowsiness detection through fusion of yawning and eye closure," in Proc. IEEE Int. Conf. Virtual Environ., Hum.-Comput. Interfaces Meas. Syst., Sep. 2011, pp. 1_6, doi: 10.1109/VECIMS.2011.6053857.



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