2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

DRIVER DROWSINESS DETECTION MODEL USING CONVOLUTIONAL NEURAL NETWORKS TECHNIQUES FOR ANDROID APPLICATION

[1] Mr. RAGHAVENDRA KARANAM,[2] B.Kusuma Sree,[3] D.Janani,[4] G.Anjali

[1]Assistant Professor, Department of ECE, Mallareddy Engineering College for Women, Hyderabad

[2,3,4,]Students, Department of ECE,Mallareddy Engineering College for Women, Hyderabad

ABSTRACT

Driver drowsiness, particularly microsleeps, poses a significant safety risk, making it a critical issue for automotive research and safety systems. Unlike speeding, which is an overt violation of traffic rules, drowsy driving can be much more insidious, as drivers often don't realize they are falling asleep. Addressing this, researchers have focused on detecting drowsiness and microsleep through various technological solutions. This paper presents an enhanced methodology for detecting drowsiness using a neural network-based approach, specifically leveraging Convolutional Neural Networks (CNNs) to classify drowsiness based on facial landmarks. Building on previous work that utilized a multi-layer perceptron (MLP) model for machine learning-based detection of drowsiness, the new approach improves upon accuracy and efficiency by incorporating facial landmark detection. These facial landmarks, which are detected through a camera system, serve as crucial features that are passed to a CNN for classification of drowsiness. This approach yields an accuracy rate of over 88% in categories where the driver is not wearing glasses and over 85% when driving at night without glasses. On average, the model achieves more than 83% accuracy across all categories tested. In addition to its impressive accuracy, the proposed CNN-based model offers significant advantages in terms of model size, complexity, and storage. Unlike traditional, heavier classification models, this CNN-based model is lightweight, with a maximum storage size of just 75 KB. This reduction in complexity makes it an ideal solution for real-time driver drowsiness detection, particularly for embedded systems and Android devices, where resource constraints are a concern. The model's simplicity, coupled with its high performance, ensures that it can be seamlessly integrated into driver monitoring systems, providing a practical and efficient solution for detecting driver drowsiness and enhancing road safety. The combination of facial landmark detection and CNN classification offers a robust and scalable approach to driver behavior monitoring, paving the way for the development of more accessible,

real-time drowsiness detection systems that can be deployed in a variety of automotive and mobile platforms. The proposed system demonstrates the potential for widespread application, especially for embedded and mobile devices, where ease of use and real-time performance are paramount. This paper contributes to the ongoing efforts to mitigate the dangers of drowsy driving, providing a reliable, low-latency solution that can be easily implemented in consumer and professional automotive systems.

I. INTRODUCTION

Drowsy driving is a significant contributor to traffic accidents, with the National Highway Traffic Safety Administration (NHTSA) reporting that approximately 2.5% of all fatalities in crashes are attributed to drowsy driving. In 2015 alone, over 72,000 crashes were linked to drowsy driving, a concerning statistic when compared to crashes caused by impaired driving, which is generally less frequent. Unlike intoxicated drivers, who experience slower reaction times, drowsy drivers are at risk of microsleeps, short episodes where they briefly lose awareness and cannot react in time to road hazards, such as lane departures or abrupt stops due to sudden braking. With nearly 1.4 million people dying in road accidents each year, making it the seventh leading cause of death globally, the automotive industry, research institutions, and governmental bodies are increasingly focusing on technologies that prevent such incidents. Modern automotive companies, including Mercedes-Benz and Tesla, have already developed advanced safety features such as variable cruise control, automatic braking systems, lane departure warnings, and assisted steering to

prevent accidents. Furthermore, Samsung's partnership with Eyesight is an example of using facial feature tracking to monitor a driver's attention, alerting them when they appear distracted or fatigued. However, these technologies are often proprietary and exclusive to high-end vehicles, leaving a gap in the market for more accessible and widespread solutions. With the rise of Android Auto and Apple Car integration in vehicles, drowsiness detection systems are now within reach of a much broader range of consumers. Many newer cars come equipped with these platforms, and even lower-end models are now including them. This presents an opportunity to develop cost-effective drowsiness detection systems utilizing embedded devices, such as smartphones, paired with the car's dashboard. These devices can enhance driver behavior monitoring by employing simple camera setups combined with state-of-the-art computer vision systems powered by deep learning algorithms. Microsleeps, which occur when a driver's eyes are closed for a brief period and they are not processing visual information, are particularly dangerous because the driver cannot react to immediate threats on the road. Although advanced sensors and radars in high-end vehicles can help avoid accidents by notifying the driver or even taking corrective action, it would be even more beneficial if the car could detect that the driver is fatigued and prompt them to take a break before microsleep occurs. A key challenge with current machine vision systems is that most algorithms are bulky, requiring specialized hardware to run efficiently, which is often not feasible on devices with limited computational power. This paper addresses this issue by proposing a deep learning-based drowsiness detection algorithm that is both lightweight and highly efficient, making it suitable for deployment on mobile or embedded devices. The algorithm is based on convolutional neural networks (CNNs) combined with facial landmark detection (D2CNN-FLD) to detect signs of drowsiness based on changes in facial expressions and eye movements. The simplicity and configurability of this approach enable it to be implemented easily on Android or iOS platforms, providing a cost-effective and scalable solution for real-time driver monitoring. The following sections of this paper are organized to explain the technical details of the proposed system. Section II presents a literature review of existing driver drowsiness detection systems, providing a foundation for understanding the advancements made in this area. Section III outlines the methodology behind the proposed drowsiness detection system, including a detailed explanation of the CNN and facial landmark detection technique. Section IV discusses the experimental results, comparing the proposed system's accuracy, efficiency, and performance against existing models. Finally, Section V concludes the paper, offering insights into the implications of this work and suggesting potential future research directions to improve drowsy driving detection technologies further.

II.METHODOLOGY

A) System Architecture

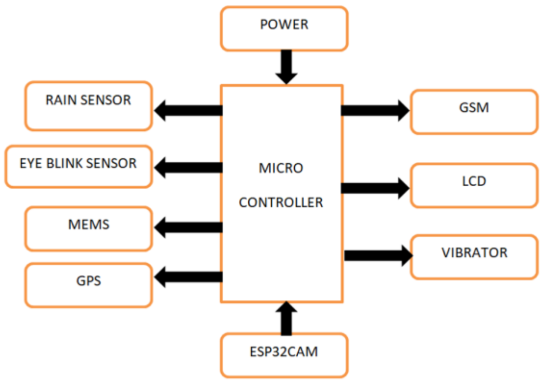

Fig1 .Block Diagram

A smartphone camera is used to capture the driver's facial features, particularly the eyes and facial expressions. The captured images are processed using CNN algorithms on the Android app, which analyze the driver's eye movements, blink patterns, and facial cues to detect signs of drowsiness. If drowsiness is detected, the system triggers real-time alerts such as sound alarms or vibrations to warn the driver. Data can also be sent to a cloud server for further analysis and tracking of drowsiness patterns over time.

B) Proposed Raspberry pi

The Raspberry Pi Pico is an affordable microcontroller board created by the Raspberry Pi Foundation. Unlike full-fledged computers, microcontrollers are small and have limited storage and peripheral options, such as the absence of devices like monitors or keyboards. However, the Raspberry Pi Pico is equipped with General Purpose Input/Output (GPIO) pins, similar to the ones found on Raspberry Pi computers, allowing it to connect with and control a variety of electronic devices. Introduced in January 2021, the Raspberry Pi Pico is based on the RP2040 System on Chip (SoC), which is both cost-effective and highly efficient. The RP2040 SoC includes a dual-core ARM Cortex-M0+ processor that is well-known for its low power consumption. The Raspberry Pi Pico is compact, versatile, and performs efficiently, with the RP2040 chip as its core. It can be programmed using either Micro Python or C, providing a flexible platform for users of various experience levels. The board contains several important components, including the RP2040 microcontroller, debugging pins, flash memory, a boot selection button, a programmable LED, a USB port, and a power pin. The RP2040 microcontroller, custom-built by the Raspberry Pi Foundation, is a powerful and affordable processor. It features a dual-core ARM Cortex-M0+ processor running at 133 MHz, 264 KB of internal RAM, and supports up to 16 MB of flash memory. The microcontroller provides a wide range of input/output options, such as I2C, SPI, and GPIO. The Raspberry Pi Pico has 40 pins, including ground (GND) and power (Vcc) pins. These pins are grouped into categories such as Power, Ground, UART, GPIO, PWM, ADC, SPI, I2C, System Control, and Debugging. Unlike the Raspberry Pi computers, the GPIO pins on the Pico can serve multiple functions. For instance, the GP4 and GP5 pins can be set up for digital input/output, or as I2C1 (SDA and SCK) or UART1 (Rx and Tx), though only one function can be used at a time.

C) Design Process

The design of embedded systems follows a methodical, data-driven process that requires precise planning and execution. One of the core elements of this approach is the clear separation between functionality and architecture, which is crucial for moving from the initial concept to the final implementation. In recent years, hardware-software (HW/SW) co-design has gained significant attention, becoming a prominent focus in both academia and industry. This methodology aims to align the development of software and hardware components, addressing the integration challenges that have historically affected the electronics field. For large-scale embedded systems, it is essential to account for concurrency at all levels of abstraction, impacting both hardware and software components. To facilitate this, formal models and transformations are employed throughout the design cycle, ensuring efficient verification and synthesis. Simulation tools are vital for exploring design alternatives and confirming the functional and timing behavior of the system. Hardware can be simulated at different stages, including the electrical circuit, logic gate, or RTL level, often using languages like VHDL. In certain setups, software development tools are integrated with hardware simulators, while in other cases, software runs on the simulated hardware. This method is generally more suited for smaller parts of an embedded system. A practical example of this methodology is the design process using Intel's 80C188EB chip. To reduce complexity and manage the design more effectively, the process is typically divided into four main phases: specification, system synthesis, implementation synthesis, and performance evaluation of the prototype.

APPLICATIONS

Embedded systems are being increasingly incorporated into a wide range of consumer products, such as robotic toys, electronic pets, smart vehicles, and connected home appliances. Leading toy manufacturers have introduced interactive toys designed to create

International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

lasting relationships with users, like "Furby" and "AIBO." Furbies mimic a human-like life cycle, starting as babies and growing into adults. "AIBO," which stands for Artificial Intelligence Robot, is an advanced robotic dog with a variety of sophisticated features. In the automotive sector, embedded systems, commonly referred to as telematics systems, are integrated into vehicles to offer services like navigation, security, communication, and entertainment, typically powered by GPS and satellite technology. The use of embedded systems is also expanding in home appliances. For example, LG's DIOS refrigerator allows users to browse the internet, check emails, make video calls, and watch TV. IBM is also developing an air conditioner that can be controlled remotely via the internet. Given the widespread adoption of embedded systems across various industries.

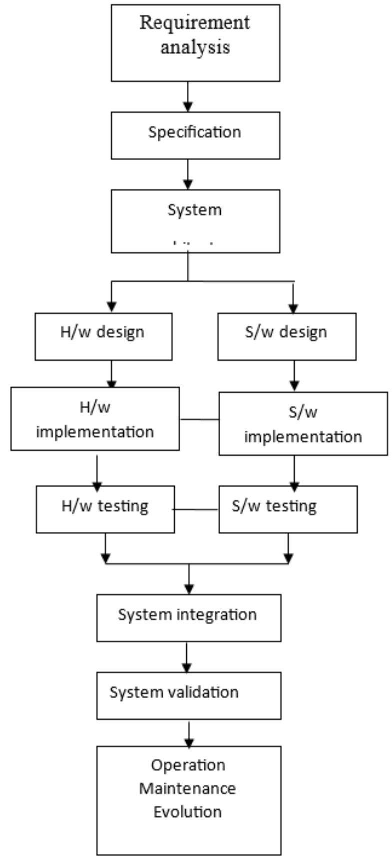

Fig 2. Embedded Development Life Cycle

III.CONCLUSION

This paper presents an improved drowsiness detection system based on Convolutional Neural Networks (CNNs) for real-time driver monitoring, with a focus on creating a lightweight and efficient solution for embedded systems while maintaining high performance. The system is designed to detect drowsy driving behavior by capturing images of the driver's face using a mobile device or embedded camera, detecting facial landmarks, and passing the data to a trained

CNN model for classification. The primary achievement of this work is the development of a compact yet highly accurate model, with an average accuracy of 83.33% across all categories, while keeping the model size under 75KB, ensuring that it can be easily deployed on devices with limited computational power. This makes the system ideal for integration into vehicle dashboards as part of advanced driver-assistance systems (ADAS), where it can alert the driver or intervene when signs of drowsiness are detected. Furthermore, the system can be incorporated into mobile devices, providing an accessible and portable solution for drowsy driving detection. The compact size of the model makes it suitable for real-time applications, ensuring quick processing without significant delays, which is critical for ensuring driver safety. Despite its strengths, there are certain limitations to this technology. One key challenge is the potential obstruction of facial features, such as when the driver wears sunglasses, which may impede facial landmark detection. Additionally, the system's performance can be affected by lighting conditions, especially in low light or high-glare environments, which may degrade the accuracy of facial feature detection. These limitations highlight areas for improvement in future iterations of the system, such as enhancing the model's ability to detect facial landmarks under various lighting conditions and improving its resilience to partial facial obstructions. Although the system performed well under controlled conditions, real-world scenarios may present challenges that need to be addressed for broader applicability. Further research could focus on incorporating diverse training data, such as different facial expressions, driving postures, and environmental conditions, to improve the model's robustness. Moreover, the use of more advanced facial detection algorithms could help mitigate issues related to obstructions or poor lighting. Despite these challenges, the current system represents a promising solution for detecting drowsy driving behavior with minimal computational resources, enabling its use in both mobile devices and low-cost embedded systems. As the technology advances, there is significant potential to improve its accuracy and usability. The system's integration into real-time driver-assistance systems could help prevent accidents caused by drowsy driving by providing early warnings or even triggering interventions, such as audible alerts, vibration warnings, or automated vehicle control to ensure driver safety. The lightweight and high-accuracy nature of this CNN-based model makes it a valuable tool in future automotive safety systems, offering a cost-effective and scalable solution to address the growing issue of driver fatigue. With further refinements, this technology could play a key role in preventing accidents caused by drowsy driving and enhancing road safety for all.

IV.FUTURE SCOPE

The future scope includes improving the accuracy and robustness of CNN algorithms, enabling them to detect drowsiness in various lighting conditions and across different face angles. Integration with 5G could allow for real-time data sharing with fleet management systems for monitoring drivers' conditions in commercial transport. Furthermore, the system could evolve to incorporate additional sensor data (e.g., steering wheel grip, heart rate) for more comprehensive monitoring. The app could be expanded to integrate vehicle control systems, offering automatic interventions (e.g., lane correction or speed reduction) in extreme cases of driver fatigue.

V.REFERENCES

[1] N. C. for Statistics and Analysis, "Crash Stats: Drowsy Driving 2015," October 2017. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/ Public/ViewPublication/812446

[2] M. Walker, Why We Sleep: Unlocking the Power of Sleep and Dreams. Scribner, 2017. [Online]. Available: https://books.google.com.qa/books? id=8bSuDgAAQBAJ

[3] W. H. Organization, "The top 10 causes of death." [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ the-top-10-causes-of-death

[4] M. Benz, "Mercedes benz safety - s class." [Online]. Available:https://www.mercedes-benz.co.uk/passengercars/mercedes-benz-cars/models/s-class/saloon-w222/safety/intelligent-drive.module.html

[5] Muze, "Eyesight." [Online]. Available: https://www.eyesight-tech.com/

[6] A. D. McDonald, J. D. Lee, C. Schwarz, and T. L. Brown, "A contextual and temporal algorithm for driver drowsiness detection," Accident Analysis & Prevention, vol. 113, pp. 25–37, Apr. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0001457518300058

[7] U. S. F. M. C. S. A. T. Division, “PERCLOS: A Valid Psychophysiological Measure of Alertness As Assessed by Psychomotor Vigilance,” October 1998.

[8] C. S. Wei, Y. T. Wang, C. T. Lin, and T. P. Jung, “Toward Drowsiness Detection Using Non-hair-Bearing EEG-Based Brain-Computer Interfaces,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2018.

[9] V. J. Kartsch, S. Benatti, P. D. Schiavone, D. Rossi, and L. Benini, “A sensor fusion approach for drowsiness detection in wearable ultra-low-power systems,” Information Fusion, vol. 43, pp. 66–76, Sep. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/ pii/S1566253517306942

[10] S. Tateno, X. Guan, R. Cao, and Z. Qu, “Development of Drowsiness Detection System Based on Respiration Changes Using Heart Rate Monitoring,” in 2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan, SICE 2018, 2018, pp. 1664–1669.

[11] A. Kamilaris and F. X. Prenafeta-Bold, “Deep learning in agriculture: A survey,” Computers and Electronics in Agriculture, vol. 147, pp. 70 – 90, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0168169917308803

[12] M. Tayab Khan, H. Anwar, F. Ullah, A. Ur Rehman, R. Ullah, A. Iqbal, B.-H. Lee, and K. S. Kwak, “Smart Real-Time Video Surveillance Platform for Drowsiness Detection Based on Eyelid Closure,” Wireless Communications and Mobile Computing, vol. 2019, pp. 1–9, 2019.