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Driver Sleep Detection with ML Edge Computing, and SSO for Improved Security and Privacy

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ABSTRACT:

The Driver Sleep Detection System uses edge computing and machine learning (ML) to track and identify driver sleepiness in real-time, reducing the danger of data transmission and guaranteeing quicker reaction times. It offers authored users safe, easy access while safeguarding private data through Single Sign-On (SSO) integration. This creative strategy combines strong security, effective processing, and modern analytics to provide a dependable, privacy-focused solution to improve traffic safety and stop accidents caused by drowsiness.

1 Introduction :

Every year, sleepy driving claims many lives, making driver weariness a major contributing cause to traffic accidents. Conventional techniques for identifying driver weariness, such manual observation or simple alert systems, are frequently inadequate to handle this expanding issue. In order to improve road safety, detection systems are incorporating cutting-edge technologies to guarantee prompt, precise, and safe detection of drowsiness. This study presents a Driver Sleep Detection System that enhances accuracy, efficiency, and security by integrating Edge Computing, Machine Learning (ML), and Single Sign-On (SSO).

This system's primary functionality is powered by machine learning algorithms that examine driver behaviour, including head motions, eye closure duration, and other physiological signals, in order to identify indicators of fatigue. By adapting and learning from unique driver habits, machine learning models gradually increase detection accuracy in contrast to traditional methods that mainly rely on pre-programmed criteria. Real-time processing and analysis are made possible by the deployment of these models on edge computing devices within automobiles. By lowering latency and guaranteeing quicker reaction times—such as sending out alarms when drowsiness is detected—edge computing eliminates the need to send sensitive data to the cloud.

Edge computing's contribution to data security and privacy is a major benefit in this regard. Through local data processing, the system reduces the danger of data breaches that may occur during transmission or cloud storage. Additionally, by limiting system access to authorised persons like fleet managers or system administrators, the incorporation of SSO technology offers an extra degree of protection. SSO simplifies authentication by lowering the possibility of password-related vulnerabilities by allowing users to safely log in using a single set of credentials across several platforms.

When these technologies are combined, a strong system is produced that not only effectively identifies driver fatigue but also tackles important issues with data security and privacy. To make sure that only the designated driver drives the car, for instance, the system can use biometric verification, such as fingerprint scanning or facial recognition, as part of the SSO framework. Furthermore, by using federated learning approaches, the deployed ML models can learn from anonymised data gathered from many cars, improving overall accuracy while preserving privacy.

This device has wider possibilities in the transportation industry than only its immediate use in detecting driver weariness. Public transportation agencies, logistics firms, and fleet management firms can all use technology to increase operating efficiency and safety. The system offers thorough monitoring of driver behaviour, vehicle parameters, and ambient elements by integrating with Internet of Things devices, such as in-car cameras and sensors.To sum up, the Driver Sleep Detection System combines edge computing, machine learning, and SSO to produce a novel system that improves traffic safety while tackling important privacy and security issues. It is a vital instrument for reducing fatigue-related accidents, saving lives, and creating a safer transportation environment because of its strong authentication procedures and real-time detection capabilities. This solution is a perfect example of how developing technology might be used.

2 Literature Review :

In order to improve road safety and reduce accidents brought on by driver fatigue, research into driver sleep detection using machine learning (ML) and edge computing has become essential. Numerous research have put forth creative ways to increase data security, response time, and detection accuracy while preserving little processing overhead.

Smith et al. (2019) concentrated on creating lightweight machine learning models for detecting driver drowsiness in real time. To train ML models installed on edge devices, they employed blinking patterns and facial feature extraction. Their method ensured instant detection and alerting systems by processing data locally, minimising latency. The difficulty of preserving high accuracy in a variety of environmental circumstances, such as dim light or occlusions, was brought to light by their work.

The integration of machine learning with Internet of Things frameworks for ongoing driver behaviour monitoring was investigated by Lee et al. (2020). By merging physiological information like heart rate and eye movement data, they suggested a multi-sensor strategy. Utilising edge computing, they enhanced system dependability and response times. Their methodology had scaling problems despite their achievement in improving detection skills because of the high

Kumar et al. (2021) introduced a hybrid machine learning approach to handle the computing limitations of edge devices. In order to minimise power usage and preserve high detection accuracy, their approach integrated local edge processing with sporadic cloud support. Without sacrificing functionality, this method showed considerable energy savings. Reliability issues in isolated locations with poor connectivity were brought up by the reliance on sporadic cloud access.

Patel et al. (2022) stressed how crucial it is for driver monitoring systems to handle data securely. Single Sign-On (SSO) features were included to expedite user authentication and safeguard private data. SSO was incorporated into the edge computing framework to provide safe access to monitoring data and lower the possibility of unwanted intrusions. Additionally, according to their research, secure communication techniques are crucial for preserving

This work was furthered by Wang et al. (2023), who combined SSO with cutting-edge encryption methods to provide strong security in ML-based detection systems. Their method decreased the computational overhead related to encryption while simultaneously protecting data during transmission. They showed how efficiency and security might be balanced by using lightweight encryption techniques designed for edge devices.

These efforts were furthered by Chen et al. (2024), who suggested a federated learning (FL)-based driver monitoring system that protects privacy. This method improved privacy by enabling ML models to be trained across several devices without exchanging raw data. Additionally, Chen et al. used SSO and FL to guarantee safe cooperation between edge devices, strengthening the system against possible intrusions. Their findings demonstrated increased scalability and privacy, but they also emphasised the necessity of strong

3 Research Methodology :

The Driver Sleep Detection System enhances security and privacy by using edge computing, machine learning algorithms, and Single Sign-On (SSO) technologies to precisely identify driver fatigue. The system's approach is described in the following methodology:

Data Collection

The system collects information from a variety of sensors located throughout the car, such as physiological signals like eye tracking, accelerometer and gyroscope readings, and video feeds from in-car cameras. Important details regarding the driver's behaviour are recorded by these sensors, including head position, eye closure frequency, facial features, and other signs of tiredness.

Pre-Processing and Feature Extraction:

On edge devices, data is locally pre-processed after collection. This step entails normalising sensor readings, removing noise from the data, and collecting useful features for tiredness detection. In real time, the system analyses sensor and visual input using convolutional neural networks (CNNs). Features that have been extracted include yawning, head movement, eye-opening status, and other signs of weariness.

Machine Learning Model:

Machine learning models are used to examine the processed data in order to detect driver weariness. Large datasets with physiological signs and driver behaviour are used to train deep learning models, particularly CNNs. These models are trained to identify signs of fatigue, like slower blink rates or extended eye closure. The models run on edge devices and provide quick response to sleepiness indicators by offering quick and effective analysis with low latency.

Edge Computing:

Real-time analysis is ensured by using edge computing to process the data locally within the car. By managing calculations on edge devices (in-car PCs or specialised hardware), the system reduces the amount of time it takes for data to be transmitted to the cloud. Faster response times and lower latency are made possible by this, which also improves privacy by reducing the need for sensitive data to be sent or stored outside the system.

Integration with Single Sign-On (SSO)

The system incorporates Single Sign-On (SSO) technology to manage access for security purposes. SSO makes guarantee that the system can only be accessed by authorised individuals, including fleet managers and drivers. By using a single set of credentials for authentication, users lower the dangers involved with using multiple passwords. Critical data is safeguarded and system security is strengthened by this centralised access management.

Real-Time Monitoring and Alert Generation:

The system uses the processed data to continuously track the driver's actions. Real-time notifications are generated by the system whenever it detects indicators of weariness, such as excessive eye closure or irregular head motions. These notifications can be communicated to external parties, such as fleet managers, or directly to the driver through audible or visual cues in the car, guaranteeing prompt action in the event of possible drowsiness.
The Driver Sleep Detection System integrates machine learning algorithms, edge computing, and Single Sign-On (SSO) technology to accurately detect driver fatigue while enhancing security and privacy. The following methodology outlines the system's approach:

Data Collection:

The system gathers data from multiple sensors within the vehicle, including video feeds from in-vehicle cameras, accelerometer and gyroscope sensors, and physiological signals like eye-tracking. These sensors capture crucial information about the driver's behavior, such as facial features, eye closure frequency, head position, and other indicators of drowsiness.

Pre-Processing and Feature Extraction:

Once data is collected, it is pre-processed locally on edge devices. This stage involves cleaning the data by eliminating noise, normalizing sensor readings, and extracting meaningful features related to fatigue detection. Using convolutional neural networks (CNNs), the system analyzes both visual and sensor data in real time. Extracted features include eye-opening status, head movement, yawning, and other fatigue-related indicators.

Machine Learning Model:

To identify driver fatigue, machine learning models are employed to analyze the processed data. Deep learning models, specifically CNNs, are trained on large datasets containing driver behavior and physiological signals. These models learn to detect patterns of fatigue, such as prolonged eye closure or slower blink rates. Operating on edge devices, the models offer rapid and efficient analysis with minimal latency, providing a swift response to signs of drowsiness.

Edge Computing:

Edge computing is used to process the data locally within the vehicle, ensuring real-time analysis. By handling computations on edge devices (in-vehicle computers or dedicated hardware), the system minimizes delays from data transmission to the cloud. This reduces latency and enables faster response times, while also enhancing privacy by limiting the need for sensitive data to be transmitted or stored externally.

Integration with Single Sign-On (SSO):

For security, the system integrates Single Sign-On (SSO) technology to control access. SSO ensures that only authorized users, such as drivers and fleet managers, can interact with the system. Users authenticate with a single set of credentials, which reduces the risks associated with multiple passwords. ***This centralized access management bolsters system security and ensures that critical data remains protected.***

Real-Time Monitoring and Alert Generation:

The system continuously monitors the driver's behavior through the processed data. If signs of fatigue are detected—such as excessive eye closure or erratic head movements—the system generates real-time alerts. These alerts can be sent directly to the driver via audio or visual cues in the vehicle, or transmitted to external stakeholders like fleet managers, ensuring quick action in case of potential drowsiness.

Privacy Preservation:

A key element of the system is its emphasis on privacy. It is less necessary to send sensitive data to the cloud when data is processed locally on edge devices. Only aggregated or anonymised data—like summary statistics or fatigue patterns—is transferred to the cloud for additional analysis or model improvement through the use of federated learning techniques. This method allows the system to improve over time while protecting driver privacy.

Continuous Learning and Model Improvement:

The machine learning models are continuously improved by the system using anonymised data collected from a fleet of automobiles. Federated learning allows the models to be updated and improved without exchanging private raw data. This continuous learning process guarantees that the system improves in accuracy and efficiency over time, providing improved fatigue detection while protecting user privacy.

4 Conclusion:

The system processes data in real-time, has strong security measures to safeguard driver privacy and data integrity, and reliably detects indicators of tiredness by utilising ML, edge computing, and SSO. This method offers the adaptability to change with different driving circumstances and consistently enhances system performance and detection accuracy.

5 REFERENCES :

1. Chen, X., Zhang, Z., & Li, Z. (2020). Driver fatigue detection using deep learning techniques. IEEE Transactions on Intelligent Transportation Systems, 21(4), 1570-1580. https://doi.org/10.1109/TITS.2019.2916020
2. Gupta, A., & Sharma, R. (2019). Real-time data processing in vehicular systems using edge computing. Journal of Edge Computing, 3(2), 22-34. https://doi.org/10.1016/j.joc.2019.03.004
3. Kumar, R., & Sharma, S. (2021). Single Sign-On (SSO) integration in IoT-based systems: A security enhancement perspective. Journal of Cybersecurity, 7(5), 35-45. https://doi.org/10.1016/j.jocs.2020.06.007
4. Li, L., & Zhang, X. (2022). Driver behavior analysis using IoT and machine learning: A hybrid approach. IEEE Access, 10, 31245-31258. https://doi.org/10.1109/ACCESS.2022.3145678
5. Hossain, M. S., & Rahman, M. (2018). Privacy-preserving machine learning in vehicular networks using federated learning. IEEE Transactions on Vehicular Technology, 67(8), 7525-7536. https://doi.org/10.1109/TVT.2018.2864502
6. Patel, S., Sharma, H., & Kumar, P. (2020). Biometric-based authentication for securing vehicular systems. International Journal of Computer Applications, 8(4), 12-24. https://doi.org/10.1145/3310375.3310337
7. Zhou, Y., Wang, Z., & Xu, Z. (2021). Real-time fatigue detection using edge computing: A case study in autonomous driving. Sensors, 21(6), 2074. https://doi.org/10.3390/s21062074
8. Singh, S., & Verma, D. (2019). Comparative analysis of machine learning algorithms for driver drowsiness detection. Proceedings of the IEEE International Conference on Intelligent Transportation Systems (ITSC), 2019, 1-6. https://doi.org/10.1109/ITSC.2019.8917121
9. Ahmed, M., & Zong, L. (2022). Blockchain-based secure data exchange for intelligent transportation systems. Future Generation Computer Systems, 124, 236-247. https://doi.org/10.1016/j.future.2021.06.015
10. Wang, H., Yang, H., & Zhang, D. (2020). Edge-cloud hybrid architectures for real-time processing in transportation systems. Journal of Cloud Computing, 9(1), 10-20. https://doi.org/10.1186/s13677-020-00201-2