Enhancing Road Safety: A Multi-Modal Drowsiness Detection System for Drivers

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***Abstract*—Driver drowsiness is a major contributing factor in road accidents, emphasizing the need for enhanced detection measures to improve car safety. This paper describes a multi-modal fatigue detection system that uses data from an internal camera, a front camera, and vehicle factors to reliably assess driver alertness. The technology outperforms traditional methods in terms of detection accuracy by utilizing powerful machine learning algorithms. Simulation and real-world tests show considerable improvements in reliability and performance. This integrated strategy offers a promising alternative for reducing the dangers associated with driver weariness and improving overall traffic safety.**

Keywords—Component; fatigue detection; drowsiness monitoring; ADAS

I. Introduction

The rising number of traffic accidents due to driver drowsiness poses a significant threat to worldwide vehicle safety. Drowsiness decreases reaction times, alertness, and decision-making abilities, potentially leading to serious consequences. According to World Health Organization study, drowsy drivers cause up to 30% of road accidents [1]. Despite advances in car safety systems, detecting and reducing driver drowsiness remains a major concern. Existing systems frequently rely on a single data source, such as driver monitoring cameras or vehicle behaviour analysis, which may not provide a complete picture of the driver's state.

This study overcomes this limitation by creating a multi-modal sleepiness detection system that combines data from an interior camera, a front camera, and a variety of vehicle factors. The inside camera catches the driver's facial expressions and eye movements, which provide direct indications of weariness. The front camera detects the vehicle's position relative to road markings and other cars, providing contextual information about the driving environment. Furthermore, vehicle data, such as steering patterns, speed variations, and lane deviations, contribute to a thorough evaluation of driver behavior and potential sleepiness signs.

By combining these disparate data streams, the proposed system intends to improve the accuracy and reliability of sleepiness detection, thus enhancing overall traffic safety. This paper describes how the integrated system was designed, implemented, and evaluated. It begins with an overview of sleepiness labeling and monitoring technologies, followed by data collection and specification in accordance with norms and regulations. Next, the system architecture and feature extraction algorithms are given. The report also explains the detection algorithms used to process data and generate alerts, as well as the system integration and real-time operation techniques.

The system's performance is confirmed by simulation and real-world testing, which show considerable gains in detection accuracy over typical single-modality systems. The findings highlight the system's potential to improve automobile safety and enable better driving experiences. Finally, the consequences of these findings for vehicle safety are examined, and ideas for further research are suggested.

II. Instrumentation and Data Collection

A. Drowsiness Labeling

Drowsiness is classified in a variety of ways, including subjective and objective measures. The Karolinska Sleepiness Scale (KSS) is the most commonly used tool. Participants rated their drowsiness on a scale of 1 (very awake) to 9 (extremely drowsy, fighting sleep). The KSS is known for its simplicity and rigorous validation, making it a dependable tool in both research and therapeutic settings. Another popular subjective measure is the Stanford Sleepiness Scale (SSS), which asks people to score their sleepiness on a scale of 1 (feeling active and vital) to 7 (no longer fighting sleep, sleep onset imminent) [2].

Other scales are the HFC Drowsiness Scale, Epworth Sleepiness Scale (ESS), Johns Drowsiness Scale (JDS), Observer Rating of Drowsiness (ORD), and Subjective Drowsiness Rating (SDR). The HFC sleepiness Scale, ORD, and SDR use external labelling methods, in which an observer assesses the subject's sleepiness based on observable behaviors and physical indications. In contrast, the ESS is a self-administered questionnaire that assesses an individual's proclivity to fall asleep in a variety of scenarios, providing a total score indicative of general daytime drowsiness. The JDS is unique in that it relies on physiological signs, such as eye movements, blink rate, or brain activity, to objectively quantify drowsiness.

The KSS was chosen as the major instrument for sleepiness labelling in this study because of its ease of use and solid validation record. The KSS allows participants to easily and reliably self-assess their state of drowsiness, giving a strong and trustworthy indicator to support the study's aims.

B. Drowsiness Monitoring

Driver sleepiness detection strategies include a wide range of physiological [3], behavioral [4], and vehicle-based approaches [5], each with differing levels of intrusion and accuracy. Physiological approaches such as electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and electrooculography (EOG) are highly accurate because they detect early signs of drowsiness. In this study, ECG data will be collected with self-reported participant assessments to provide precise baseline measures of sleepiness levels in a controlled environment. This combination provides an excellent paradigm for evaluating drowsiness using both subjective and objective inputs.

The fundamental goal of this research is to combine behavioral and vehicle-based detection algorithms to increase overall accuracy and solve edge circumstances that may be difficult for a single modality. Eye movements, facial emotions, and head position are among the indications used in behavioral analysis. Although these procedures are less physically intrusive than physiological measures, their relationship with monitoring raises issues about psychological intrusiveness. Typically, behavioural detection uses cameras and deep learning algorithms to diagnose sleepiness states based on data including blink duration, blink frequency, percentage of eyelid closure (PERCLOS), yawning, and head posture. Eye movement-based tests are especially effective because of their high association with tiredness.

Vehicle-based approaches are used in addition to behavioural detection to capture driving information such as lane position, steering wheel movements, acceleration patterns, and pedal usage. Steering wheel movement and lane-keeping performance are commonly investigated measurements, with conflicting results about their relative accuracy in diagnosing drowsiness. Vehicle-based procedures are most effective in locations with clear road markings and favorable weather conditions, but they are often less dependable than physiological or behavioral measures when used alone.

The combination of behavioral and vehicle-based methods takes advantage of the strengths of both approaches. Behavioural methods provide extensive, real-time insights into the driver's state by continuously monitoring facial and ocular traits, whereas vehicle-based methods provide a practical, non-intrusive way of evaluating driving performance. By combining these modalities, the proposed method improves the resilience and diversity of sleepiness detection while balancing accuracy, intrusiveness, and practicality. This hybrid technique is intended to provide a comprehensive solution fit for real-world applications, effectively tackling a wide range of scenarios and edge cases.

C. Data Collection

To improve data collecting for sleepiness detection, a comprehensive technique was used to gain a holistic picture of driver alertness. ECG was used to monitor participants' heart rate and heart rate variability, providing important information about their physiological status. Participants used the KSS to self-report their sleepiness levels, allowing subjective fatigue ratings to be correlated with physiological data.

Front and interior cameras were carefully placed to capture the vehicle's position in the lane, as well as facial expressions, eye movements, and head posture, allowing for thorough behavioral analysis. Furthermore, vehicle data were tracked via the Controller Area Network (CAN) technology, which captured crucial driving metrics like steering wheel movements, lane deviations, and pedal usage. The obtained data is utilized to train the model, validate it, and calculate the system's performance.

D. Norms and Regulations

To maintain safety and dependability, drowsiness and distraction detection systems in the automotive sector must meet high standards. Euro NCAP (European New Car Assessment Program) [6] is a major regulatory body that provides rigorous methods for evaluating the performance of advanced driver assistance systems (ADAS). Euro NCAP evaluates these systems on their ability to detect and reduce risks associated with driver fatigue and distraction, which plays an important part in establishing vehicle safety ratings. These studies include extensive assessments of the system's response to real-time sleepiness signs, accuracy in detecting distractions, and overall reliability under varied driving scenarios.

Furthermore, the European Union's General Safety Regulation 2 (GSR2) mandates all new vehicles to have driver monitoring devices that can identify both tiredness and distraction [7]. GSR2 requires that these systems meet high precision, reliability, and user data protection standards in order to improve road safety.

We created software and system requirements in accordance with the automobile safety standard ISO 26262 [8] and the applicable regulation. Furthermore, we measured performance and validated it in accordance with the defined requirements and applicable norms.

III. Operational Decision Model

A. System Architecture

The suggested multi-modal sleepiness detection system is intended to use the strengths of several data sources to deliver a complete assessment of driver weariness. The system architecture is separated into four major components: data collecting, processing, analysis, and alarm production. Each component is critical to guaranteeing the accuracy and reliability of the sleepiness detection procedure. Fig. 1 depicts the major components of our multi-model driver drowsiness detection system (DDAS):

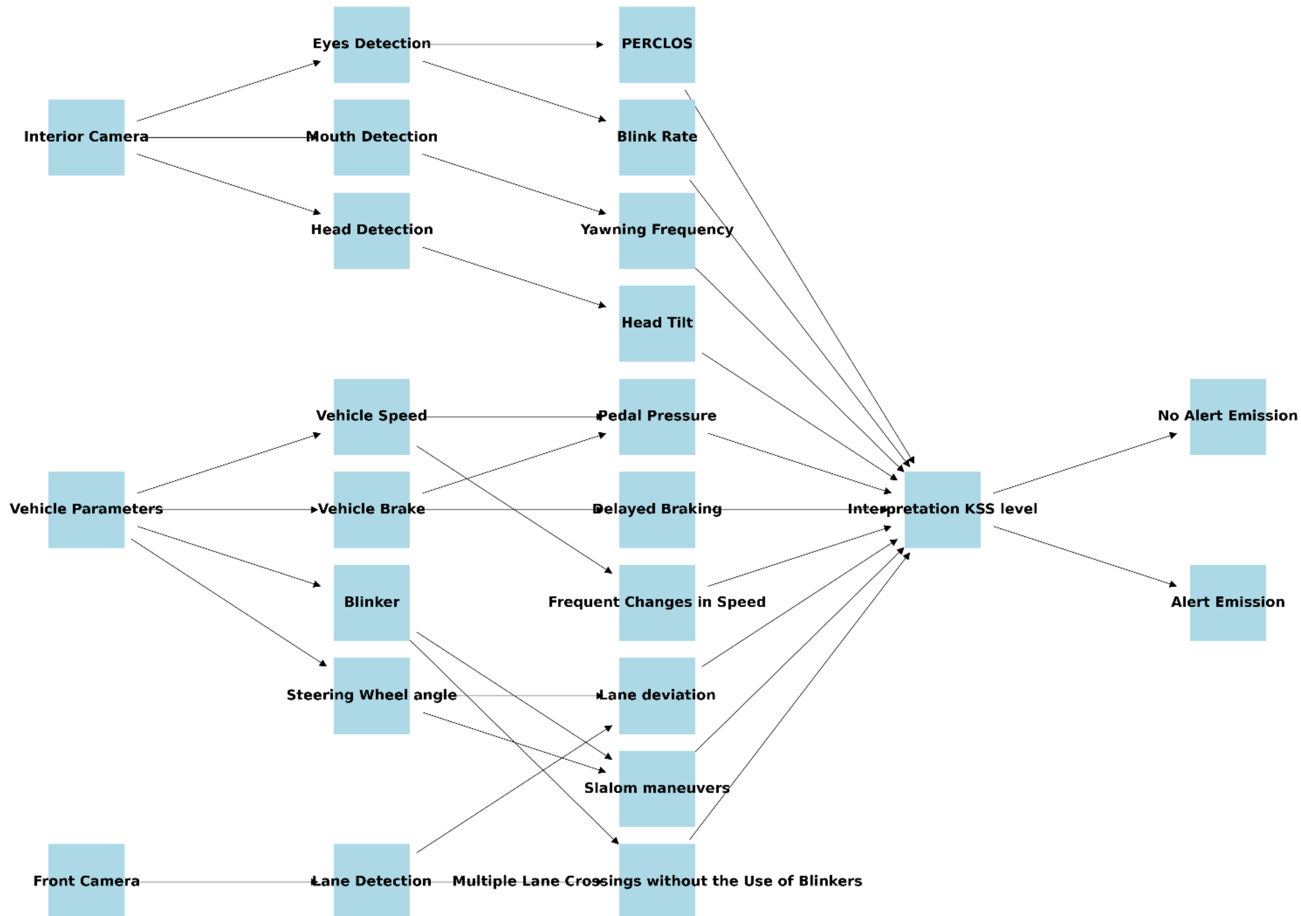

Fig. 1. Multi-modal driver drowsiness detection system framework.

The data acquisition device uses three basic sources: an internal camera, a front camera, and vehicle parameters. The interior camera is set up to capture the driver's facial expressions and eye movements. The front camera, positioned behind the rearview mirror and facing the road, captures real-time imagery of the road ahead. Vehicle parameters are obtained from the CAN network.

Data processing entails extracting and identifying unique properties from each data source. The internal camera identifies face landmarks such as eyes, mouth, and head orientation. These traits are identified and tracked using methods such as facial recognition and feature point detection. The front camera identifies lane markers and the vehicle's relative distance to the lane, while line detection algorithms track lane deviations and headway distance. Meanwhile, the vehicle parameters subsystem gathers information on steering wheel movements, speed variations, brake pedal pressure, and acceleration patterns.

The data analysis unit examines the retrieved features to determine the driver's state. Blink frequency, duration of eye closure (PERCLOS), and yawning frequency are all examples of fatigue indicators in interior camera footage. High blink rates and prolonged eye closures are clear signs of tiredness. The data from the forward-facing camera is utilized to calculate lane deviation frequency, time-to-lane crossing, and headway. Frequent lane drifting, crossing lines, without indicating and maintaining a low headway distance can all indicate a lack of attention. Vehicle parameters are examined to identify slalom motions, speed abnormalities, and erratic braking. Sudden steering wheel movements, irregular speeds, and abrupt brakes all indicate driver weariness or inattention. To process these features and identify drowsiness-related patterns, an advanced machine learning technique called support vector machine (SVM) is used. These models are trained using annotated datasets to distinguish between normal driving behavior and indicators of weariness.

When drowsiness is identified, the system issues relevant alerts to the driver. These alerts include both voice notifications and visual cautions on the dashboard. These warnings are intended to catch the driver's attention and encourage them to take a rest.

B. Features Extraction and Decision Making

1) Lane detection and deviation: The front camera identifies lane deviations, indicating irregular driving behavior.

The video stream is preprocessed to determine the road's region of interest (ROI), then edge detection is performed using the Canny edge detector:

$$G(x, y) = (\sqrt{(G_x^2 + G_y^2)}$$

where, G (x, y) is the gradient magnitude at pixel (x, y), and G_x, G_y are horizontal and vertical gradients, respectively. The identified edges are converted into line segments using the Hough Transform:

$$\rho = x \cos\theta + y \sin\theta$$

where (x, y) are edge points in the image, ρ is the perpendicular distance from the origin to the line, and θ is the line's angle.

Lane position deviations are measured as the Standard Deviation of Lane Position (SDLP):

$$SDLP = \sqrt{(\frac{1}{n}\sum_{i=1}^{n}(\rho_i - \bar{\rho})^2}$$

where ρ_i is the lateral position of the vehicle at time i, and $\bar{\rho}$ is the average lane position across the observation window [9].

2) PERCLOS (Percentage of Eye Closure): PERCLOS quantifies the proportion of time that the eyes are closed during an observation session:

$$PERCLOS = \frac{N_{closed}}{N_{total}}$$

Where:

The term N_{closed} = Number refers to the number of frames with an Eye Aspect Ratio (EAR) below the threshold, which indicates closed eyes.

N_{total} is the total number of frames captured during the observation time.

The Eye Aspect Ratio (EAR) for each frame is determined as:

$$EAR = \frac{dist(p_2,p_6)+dist(p_3,p_5)}{2.dist(p_1,p_4)}$$

Where:

$p_1, p_2, \ldots, p_6$ = Coordinates for eye landmarks [10].

3) Blink rate: Blink rate is the number of blinks per minute, calculated as:

$$\text{Blink Rate} = \frac{N_{blinks}}{T} \times 60$$

Where:

N_{blinks} = Number of detected blinks during the observation period.

T = Duration of the observation period in seconds [11].

4) Yawning frequency: Yawning frequency refers to the number of yawns each minute:

$$\text{Yawning Frequency} = \frac{N_{yawns}}{T} \times 60$$

Where:

N_{yawns} is the number of yawns identified throughout the observation time.

T represents the duration of the observation period in seconds. [12]

5) Head tilt: Head tilt angle (θ) is measured by measuring the vertical and horizontal distances between specified facial landmarks:

$$\theta = \arctan\left(\frac{dist(p_{\text{nose}}, p_{\text{chin}})}{dist(p_{\text{eye\_corner\_left}}, p_{\text{eye\_corner\_right}})}\right)$$

Where:

p_{nose} = Landmark for the tip of nose.

p_{chin}= Chin landmark.

$p_{\text{eye\_corner\_left}}$ and $p_{\text{eye\_corner\_right}}$ = Landmarks for the outer corners of the left and right eyes [13].

6) Slalom: To identify slaloming using steering wheel angle (α(t)), examine the rate of change ($\dot{\alpha}(t) = \frac{d\alpha}{dt}$) for sudden adjustments. Calculate the frequency of oscillations (f_{steer}) using the Fourier Transform of α(t).

we calculate the amplitude of oscillations ($A_{steer} = \frac{1}{T}\frac{d\alpha}{dt}\int_{t_0}^{t_0+T}|\alpha(t)|\,dt$) to reflect the magnitude of steering changes. A composite Slaloming Index (SI) comprises the following metrics:

$SI = w_1 . f_{steer} + w_1 . A_{steer}$

High SI values indicate slaloming without using the blinker, indicating erratic steering that could be attributed to fatigue [14].

7) SVM-Based model

a) Feature vector: The feature vector x combines all necessary parameters for detecting tiredness:

x = [PERCLOS, Blink Rate, Yawning Frequency, Head Tilt, Pedal Pressure, Delayed Braking, Frequent Change in Speed, Lane Deviation, Slalom Maneuver, Multiple Lane Crossings without Blinker]

b) SVM decision function: The SVM decision function is defined as follows:

$$f(x) = w\cdot + b$$

Where:

$W = [W_1, W_1, \ldots, W_{10}]$ Weight vector for the features.

b: Bias word.

f(x): A decision score that indicates the possibility of drowsiness.

Classification Rule

The categorization choice depends on the sign of f(x):

Y = sin f(x)

Where:

Y = +1 indicates Non-Drowsy.

Y = −1 indicates Drowsy.

c) Mapping to KSS level: The decision score f(x) is mapped to the KSS level use the mapping function g(f(x)):

$$K = g(f(x))$$

Where:

KSS levels range from 1 (high alertness) to 9 (high drowsiness).

d) KSS-based decision outcomes: The system action is based on the KSS level K:

$$\text{State} = \begin{cases} No\ Alert, if\ K < 7 \\ Alert, if\ K \geq 7 \end{cases}$$

e) SVM training objective: The SVM is trained by minimizing the following objective function:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$$

subject to:

$$y_i(\text{w}.\ x_i + \text{b}) \geq 1\text{-}\ \xi_i, \qquad \xi_i \geq 0$$

The regularization parameter C is used to balance the trade-off between maximizing margin and minimizing misclassification errors.

ξ_i: Slack variables for misclassified data points [15][16].

C. Operational Phases of DDAS

1) Initialization of DDAS: The DDAS is activated under the following conditions: the engine is turned on, the driver is present with the door closed and the seatbelt buckled, and no malfunctions are identified in the monitored parameters.

2) Learning phase: The DDAS learning phase occurs once every driving session, assuming the sleepiness function is engaged. This phase begins immediately upon system activation and lasts one minute, during which the system assesses the driver's sleepiness level. If a driver change is detected, the system resets and begins a new learning period. After completing the learning phase, the system moves on to the monitoring phase.

3) Monitoring conditions: The learning phase is reset every time the vehicle is started or a driver change is detected. To accurately detect tiredness, the vehicle must travel at a minimum speed of 50 km/h.

4) Monitoring phase: Following the learning phase, the DDAS enters the monitoring phase, which continues until the engine is turned off. During this phase, notifications are disabled in certain situations, such as when the vehicle's speed falls below 50 km/h. The technology continuously detects the driver's fatigue level.

IV. Validation and Performance Analysis

A. Simulation Based Result

The proposed DDAS's performance was evaluated through a series of video simulations that analyzed video footage acquired during the data collecting phase to detect sleepiness occurrences based on predetermined thresholds and metrics. To evaluate the system's usefulness and accuracy, a confusion matrix was created, which provided a detailed breakdown of the system's classification.

The video simulations included a diverse collection of lighting conditions, face angles, and subject sleepiness levels. The system's outputs were recorded and compared to the ground truth labels. The system's overall detection accuracy was assessed to be 92%, proving its capacity to discern between drowsy and alert states. In particular, the system properly identified alert states (True Negatives) in 94% of cases while accurately detecting drowsiness (True Positives) in 86%. However, it misidentified alert states as drowsy (False Positives) in 8% of cases and failed to detect drowsiness (False Negatives) in 6%. Fig. 2 displays the confusion matrix based on a huge dataset injected:

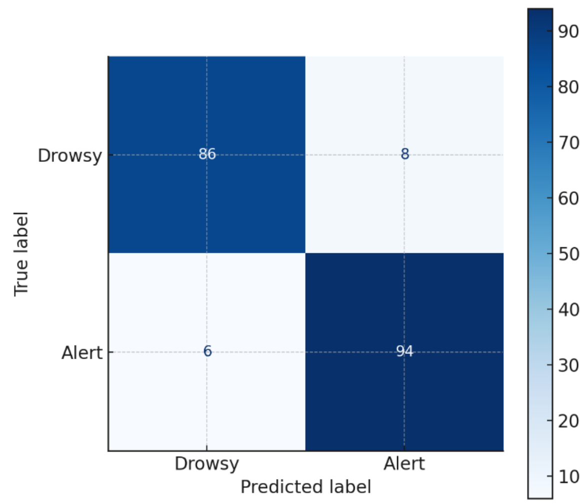

Fig. 1. DDAM confusion matrix.

The system demonstrated great sensitivity in identifying drowsiness, which is crucial for timely intervention and accident avoidance. The relatively low False Negative rate demonstrates its effectiveness in reducing unnoticed drowsiness. However, the False Positive rate, while acceptable, implies that further refinement in feature extraction and threshold tweaking could help eliminate unwanted warnings, hence improving user experience.

The system's performance was further tested under difficult conditions. Due to limited visibility of facial landmarks in low-light conditions, accuracy dropped somewhat to 88%. Under severe angles, accuracy remained stable at 90%, thanks to improved preprocessing and feature normalization. During rapid head movements, there was a modest decrease in True Positive detection, indicating an area for improvement in motion compensation.

B. Real-Condition Testing

Real-world testing in operating settings was carried out to validate the suggested sleepiness detection system. The technology was placed in a vehicle and tested with drivers doing typical driving tasks. The scenarios included changing lighting (daylight, dusk, and night), different road surroundings (urban and highway), and dynamic driver behaviors. During these experiments, the system tracked and evaluated the driver's facial expressions, blinking patterns, and head movements to detect drowsiness in real time. The real condition testing findings are reported in the confusion Table I below:

TABLE I. REAL TIME DRIVING RESULTS

Predicted \ Actual	Drowsy	Alert
Drowsy	TP: 82%	FP: 12%
Alert	FN: 10%	TN: 88%

The system had an overall detection accuracy of 85%. It recognized drowsiness (True Positives) in 82% of cases and accurately identified alert states (True Negatives) in 88% of cases. However, it misclassified alert states as drowsy (false positives) in 12% of cases and failed to detect tiredness (false negatives) in 10% of cases.

C. Results, Discussion and Future Work

The testing findings show that the suggested DDAS works reliably under both simulation and real-world settings. The system's exceptional sensitivity in detecting drowsiness provides quick intervention, which is crucial for avoiding accidents. Furthermore, the comparatively low False Negative rate demonstrates its usefulness in reducing undetected drowsiness, an important feature of driver safety systems. The system's overall accuracy, especially in difficult settings like low light and severe facial angles, demonstrates its durability and adaptability to real-world applications.

These favorable results suggest that the system meets the safety and performance requirements stipulated in the GSR2 regulatory frameworks and Euro NCAP standards. Compliance with these standards demonstrates the system's ability to greatly improve driver safety and reduce traffic deaths. Its capacity to identify tiredness with high reliability is consistent with the growing emphasis on integrating advanced driver monitoring systems into vehicle safety regulations.

While the system worked effectively, there is still room for improvement. Future work should focus on lowering the False Positive rate in order to improve the user experience and reduce unwanted notifications. Advanced techniques, such as deep learning-based facial analysis, multi-modal data integration, and feature extraction method improvement, may improve system performance. Furthermore, further field testing with a more diversified driver population would help generalize the system's usefulness across different demographics and driving circumstances.

The positive results demonstrate the system's suitability for real-world deployment, assuring compliance with international safety standards while providing a dependable solution for improving driver safety and contributing to the growth of intelligent vehicle technology.

V. CONCLUSION

This study introduces a multi-modal detection system that combines interior and front cameras with vehicle parameters to improve drowsiness detection accuracy. Using powerful machine learning, the system achieves 92% accuracy in simulations and 85% in real-world tests, consistently diagnosing fatigue under varied settings.

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