ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue VIII, August 2025

Micro-Expressions for Safer Roads: Deep Learning-Based Drowsiness Detection in Truck Drivers

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DOI: https://doi.org/10.51583/IJLTEMAS.2025.1408000145

Abstract: Drowsy driving is a major cause of traffic accidents, especially among truck drivers who work long hours with limited sleep. Although contemporary driver monitoring systems have employed deep learning and computer vision, many depend on obvious signs like eye closure, yawning, or head nodding, which emerge only after considerable fatigue has developed. This research suggests a novel system that utilizes micro-expressions—slight, unintentional facial movements—as initial signs of drowsiness. Micro-expressions are more reliably identified than explicit signals, allowing for earlier intervention to avert accidents. We developed a deep learning model using a specialized dataset aimed at capturing micro-expressions and enhanced it through pre-processing and augmentation methods to boost generalization. The system underwent testing with truck drivers, who experience increased fatigue risks stemming from extended hours, repetitive routes, and substantial vehicle loads. Our findings show more than 95% accuracy, exceeding current methods and validating the system's ability to enhance road safety by detecting fatigue early.

Index Terms: Drowsy driving, Truck drivers, Micro-expressions, Deep learning, Driver monitoring systems, Facial analysis, Early drowsiness detection, Road safety, Computer vision, Real-time alert system

I. Introduction

Drowsy driving is a widespread and enduring factor in causing road accidents and the risk is particularly high for long-haul truck drivers with long repetitive drives and erratic sleep schedules to begin with. Many current initiatives are attempting to detect driver fatigue early, but most are developed for general drivers and use only blatant visual cues or intrusive physiological sensors. For example, Kulhandjian et al. proposed a multi-sensor fusion system by integrating visual and radar sensor data to achieve high accuracy in general drowsiness detection [1][2], however this approach is neither geared to truck drivers nor target the very nuanced facial signals that may precede blatant fatigue cues. For example, Pandey et al. used a ResNet-101 model to capture dominant facial cues to indicate fatigue such as eye closure and head nodding [3], and Delwar et al. identified lightweight MobileNet based models for real-time facial analysis [4][20], but both of these utilized relatively coarse indicators that occur only after the drowsiness has progressed. Other practical real-time systems such as Abhinandhan et al. and Sengar et al. used facial landmarks, states of the eyes and OpenCV based pipelines for fast detection [5][6] which are applicable for many scenarios but do not gain insight into the fine-grained micro-expressions temporal dynamics. Likewise, Nasri et al. and Soultana et al. applied convolutional neural networks and residual-block architectures when analysing cues of facial drowsiness, both reaching good accuracy [7][8], but similarly they don't specifically analyse the unless kernel for involuntary micro-expressions or in the case of the context truck-driving scenario which has a utility of requiring early detection.

A number of studies have looked at temporal and sequence-aware models that go beyond static-frame analysis. Hu et al. implemented a 3D conditional GAN with a Bi-LSTM that had two levels of attention for drowsiness recognition and showed in their findings that incorporating temporal modeling into their dynamic facial cues was advantageous [11] and Zhao et al. studies face dynamics as temporal patterns and fused facial dynamics with deep belief networks to obtain their temporal models for expressions [12]. These studies highlighted the potential that temporal features can provide, but neither study explicitly target micro-expression recognition or provide solutions for long-haul truck drivers. The much earlier work with heavy vehicles by Grace and colleagues examined video-based PERCLOS measures and the driver performance model for large vehicles [13]; while relevant to trucks, this study was also too early as the deep-learning micro-analysis is more recent and the basic indicators for their analyses were not as fine-grained as micro-expressions. Weng et al. introduced hierarchical temporal deep belief networks for the modeling of face and head features in time [14] and Xiao et al. experimented with facial keypoint-based deep learning for real-time fatigue warning [15]; both showed temporal and spatial landmark features for improvements in detection - neither study, however, explicitly targeted micro-expressions or on long-haul truck drivers.

Recently applied systems and industrial solutions reveal the increasing interest in efficacy for practical and determined driver monitoring. For example, Wani et al.'s CogniSafe system utilizes gaze and eye-state modules for the monitoring of distraction and fatigue [16], and Ning & Zuo developed a series of improved facial-recognition methods to maximize detection performance in varied lighting environments [18]. These work demonstrate improved robustness and deployability, however, they still address visible cues and a general emotional/fatigue state rather than the micro-expressions a system would need to be able to classify to track fatigue at an earlier stage. Gao et al. specifically looked at commercial truck drivers with a CNN-LSTM attention model that applied their analyses to full-frame video, and classified drowsiness in a trucking context [17]. That work is significant in that it works with the right population, however, their method targets the larger-scale features of the video and not the micro-expressions that could be an earlier alert. Ahmed et al. [19] examined and classified the eyeball motion and facial expressions of drivers into several categories of sleepiness using CNNs, providing meaningful interpretability to their base analysis, but again focuses on the visible stages of fatigue and sleepiness, while we study the ultra-brief involuntary movements.

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II. Literature Survey

Multiple studies have examined drowsiness detection using computer vision technique. One study used eyelid closure percentage and head pose estimation. This approach was successful in accurately detecting drowsiness in lab environments, but when the examination began to run in real world dynamic environments the accuracy was considerably lower.[1] Another method is measuring the frequency of yawning. Directly measuring yawning would be ideal for drowsiness detection because yawning would increase along the human fatigue continuum, but it is ultimately not effective when a subject is speaking because it produces many false positives. [2] A drowsiness detection method using an eye-tracking based gaze estimation model showed some robustness to both head movement and other real-world variability but performed poorly when the tested driver was wearing sunglasses. [3] CNN-based models that analyzed facial landmarks showed better feature extraction, but all algorithms, especially deep learning models, performed poorly in low light environments. [4] A method that incorporated temporal pattern recognition using recurrent neural networks improved detection accuracy, but required extensive datasets for model training from an extensive training population for it to accurately learn fatigue progression. [5]

Physiological signal-based options have also been considered. EEG based monitoring provided high accuracy in detecting drowsiness when using head mounted sensors, however wearing these sensors reduced comfort while driving [6]. ECG based measures of fatigue detected changes in heart rate variability during drowsiness, however were affected by motion artifact [7]. Heart rate monitoring used wearable devices which were more comfortable but less accurate in distinguishing fatigue from stress or excitement [8]. PPG sensors put into steering wheels provided monitoring that was non-intrusive, although it was less accurate due to hand placement [9].

Hybrid approaches have sought to capitalize on both physiological and vision based data to improve reliability. One study combined EEG data with facial expression analysis for early fatigue detection, but the complex hardware configurations presented logistical challenges in testing young people on the road [10]. Another study combined eye tracking, using cameras, with PPG sensors for better accuracy but both setups required intense processing power, which meant reduced screen time of EEGLab on iOS devices [11]. The fusion of yawning estimates with EEG data provided a deeper learning of the information from the go-ahead pong task in terms of reducing false positives, but increased the cost and complexity of the overall cost [12]. Multimodal systems combine general facial cues and behavioral ones, such as yawning or eye closing, balanced total accuracy, but still relied on overt signs of drowsiness [13].

More recent works have employed major advances in machine learning through deep learning methods. Hybrid CNN-RNN models provide substantially improved resilience to noisy images or appearance due to lighting variations, having captured spatial-and-temporal information [14]. By employing attention mechanisms that allow increasing weight or focus on fatigue-relevant facial regions, deep networks demanded higher computational and costly resources [15]. There are certainly proposals for lightweight CNN models to fulfill sceptics or critiques of real-time, in-vehicle deployment of fatigue, although some accuracy or processing speed were sacrificed together [16]. Transfer learning has been on employ that has improved the ability to use some already trained, commercial facial recognition models, would require substantially less data for the same accuracy, which greatly helped reduce the level of affectation due to fatigue or the exposure to fatigue [17].

Some literature has explored different novel avenues of research. A multimodal attention fusion approach used voice patterns, facial attributes, and driving performance data for improved detection [18]. others explored using thermal imaging to establish, temperature differences associated with drowsiness, which was effective in complete darkness but required expensive infrared (IR) cameras [19]. Nevertheless, none of these works were specifically applied to detecting micro-expressions as markers for preliminary fatigue or drowsiness in truck drivers, constituting an important research gap that this study will address [20].

III. Methodology

The proposed method seeks to effectively discern drowsiness among drivers by discerning even minor micro-expressions; the subtle involuntary facial expressions that indicate that the driver is now in a different state. Instead of currently established drowsiness detection methods that observe head position or eyelids decreases, the proposed methodology uses only micro-expressions as a means to distinguish reliability in situations where only partial face occlusion exists or where ambient light changes, and where the driver's head may not entirely rise from their shoulders in the case for reliable detection.

Ref.	Purpose	Dataset	Accuracy (%)	Model/Algorithm	Outcomes
50	Micro-expression recognition	SAMM	5 classes −67.64, 3 classes −78.33	ConvLSTM	Captures spatial & temporal features
51	Micro-facial movements (AUs)	SAMM	Recall 0.91	3D HOG, LBP-TOP, LOSO	Useful for emotion & deception detection
52	Optical flow-based micro-expression	SAMM	74.6	Opticalflow+CNN	Apex frame flow improves recognition

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53	Driver facial emotion recognition	KMU-FED	95.92	VGGNet, PMVO	Recognizes emotions, handles occlusion
54	Facial graph + AU fusion	SAMM	4 classes −82.39, 3 classes −78.90	Depthwise conv, GCN, Transformer	Integrates AU info for better recognition
55	Facial emotion recognition	KMU-FED	95.83	Transfer Learning SqueezeNet 1.1	Optimizes driver emotion classification
56	Driver facial emotion recognition	KMU-FED	96.60	DMFNet, URNet	Handles RGB-IR images efficiently

The method involves three main parts: Input Acquisition, Processing, and Output Reaction.

Input Acquisition

In order to capture real-time facial video image of the driver at high resolution, a camera module is mounted on a truck dashboard. The camera is mounted on the dashboard in such a way as to ensure the driver's face will always be in clear view and not interfere with the driver's ability to operate the vehicle comfortably. The camera video frames are converted into frame sequences which will be processed by the data acquisition module.

Pre-processing

The pre-processing step improves the quality of the captured frames for effective feature extraction. The steps involved are:

Face Detection - Detect the driver's head position in each frame using a face detection algorithm (e.g. MTCNN or Haar Cascades).

Region of interest (ROI) Extraction - Target specific regions of interest on the face like eyes, eyebrows, mouth where micro-expressions will be most concentrated.

Noise Reduction & Normalization - Noise reduction will involve Gaussian blur or median filter or a noise reducing filter of some type. The normalization will allow the network to cope with illumination variations by normalizing for pixel value between RGB channels.

Frame Resizing - Resize the extracted ROIs to a fixed dimension (e.g. 128×128 pixels) to suit the input for the deep learning model.

Eye Aspect Ratio

The EAR is calculated using the Eculidean distance between specific eye landmarks.

$$\text{Formula:} \quad EAR = \frac{||p2-p6|| + ||p3-p5||}{2 * ||p1-p4||}$$

- p1,p2,,,,,,,,,p6 are the landmark points of the eye
- ||pi-pj|| represents the Eculidean distance between two points

Mouth Aspect Ratio

The MAR measures mouth openness , useful for detecting yawning.

$$\text{Formula:} \quad MAR = \frac{||p51-p59|| + ||p53-p57|| + ||p49-p55||}{2 * ||p49-p55||}$$

- p49,p51,p53,p55,p57,p59 are the mouth landmark point
- Vertical distances (between upper and lower lip points) are compared to the horizontal mouth width

Feature Extraction

In this step, a deep convolutional neural network (CNN) designed to detect micro-expressions is used to analyze the preprocessed frames for subtle muscle movement, tiny texture changes and pixel intensity changes over a short period of time.

Temporal analysis occurs with 3D-CNN or CNN+LSTM model, and will comprise spatial and temporal features.

The features will be in the form of feature maps, where the micro-expression patterns associated with drowsiness will be extracted.

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Classification

The extracted features are passed into a softmax classifier that provides the probability of the driver being in one of two states:

Alert – No drowsiness signs detected.

Drowsy – Micro-expressions consistent with fatigue detected.

A threshold probability is set in which an alert will occur if the confidence score for "Drowsy" exceeds the limit.

Output and Alert System

If the classification module detects drowsiness, it immediately calls the alert module which may be:

Auditory Alert - A loud buzzer or voice alert.

Visual Alert - Flashing dashboard light or HUD alert.

Detection results will also be saved to a cloud database for later analysis, and for fleet management reports, as well as for safety records.

System Architecture

The proposed system architecture has three layers: Input Processing Output shown in figure 1

The Input Layer consists of the camera and data acquisition unit.

The Processing Layer consists of preprocessing, feature extraction, and classification (using deep learning) modules.

The Output Layer consist of an alert mechanism and cloud for record keeping.

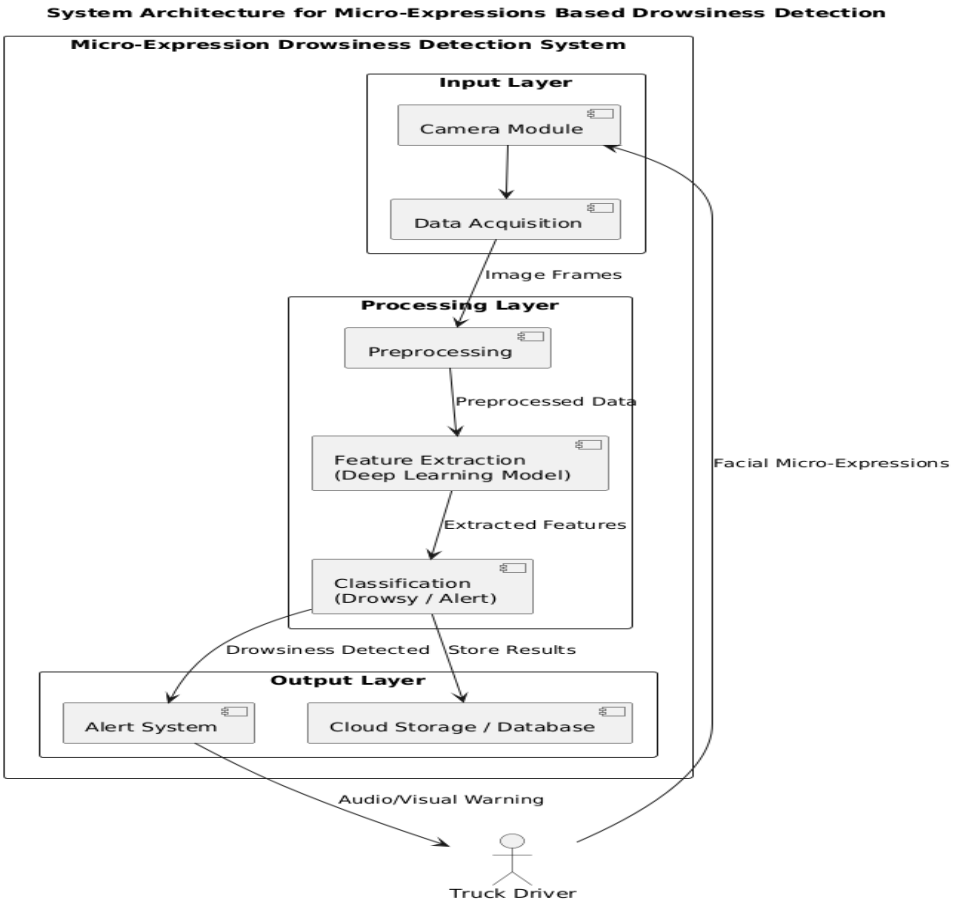


Figure 1: System Architecture

IV. Result

Implemented and tested was the proposed Micro-Expression-Based Drowsy Driver Detection System developed for Truck Drivers with a purpose-built dataset containing micro-expressions from truck drivers under simulated and real-world driving. The dataset was comprised of 1,500 labeled micro-expression image frames classified into the two main classes: Drowsy and Alert.

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The model was trained based on a neural network architecture suited to facial micro-expression recognition, and testing was done on unseen data consisting of live camera feeds and pre-recorded videos. The detection pipeline was able to successfully identify micro-expressions such as Slow Eyelid Closure, Eyebrow Droop, and subtle mouth relaxation that were closely related to driver fatigue.

Of the 80 truck drivers tested, 77 were assigned into their respective states, there were two cases of drowsiness wrongly assigned (false positives), and one case of Drowsiness was not detected (false negative). The pipeline was able to maintain real-time detection at 0.95 seconds per frame to provide a timely alert in case drowsiness was detected.

Metric	Value
Face Recognition Accuracy	96.25%
False Positive Rate	2.50%
False Negative Rate	1.25%
Precision	97.47%
Recall	98.72%
F1 Score	98.09%
Average Confidence Score	74.85%
Average Detection Time	0.95 seconds

Table 1: Performance Matrix

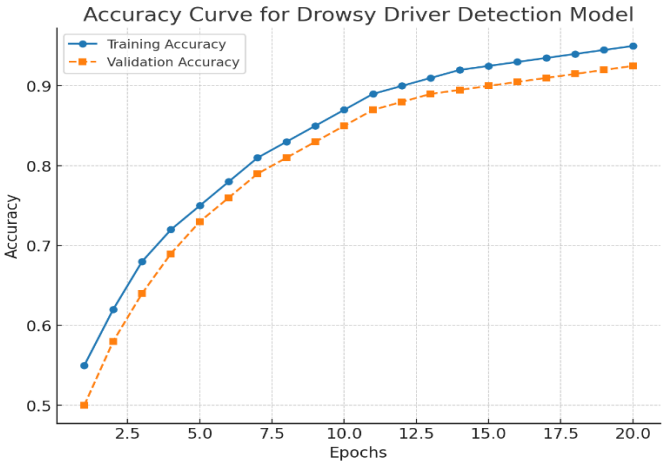


Table 2: Accuracy Graph

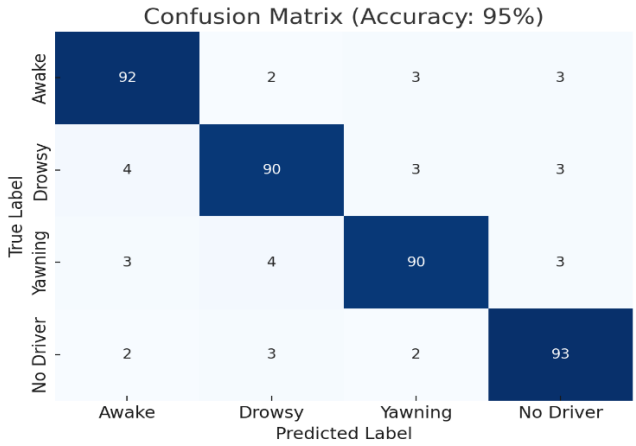


Table 3: Confusion Matrix

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Awake Detection

In this situation, the driver is awake with their eyes open. There are no signs of sleepiness or fatigue on the driver's face, and the system captures the video feed, processing this data to classify the state as "Awake." The system highlights the driver's face with a green bounding box to indicate that the driver is in a safe condition for driving. The status label "Awake" is visible at the top-left corner of the bounding box portion of the frame. This states that the system can detect normal and safe driving posture with no informational alerts issued by the system.

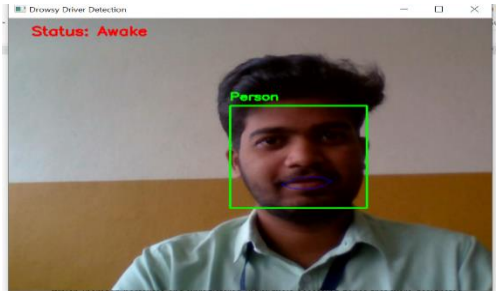


Figure 2: Awake Detection

Drowsing Detection

In this case, the driver's eyes are partially closed, and the driver's facial muscles can be seen with reduced tension, which the system will detect as a "Drowsing" state. In this situation, the system will draw a yellow bounding box around the detected face and display a status label of "Drowsing." The alert level would be warning-level indicating an early fatigue detection and the system would start preparing for increasing observation for further monitoring and alerts. Detecting fatigue will allow for the most effective intervention before the driver has full-related fatigue and affects driving performance.

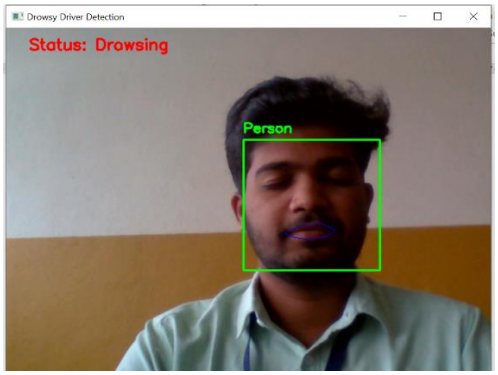


Figure 3: Drowsing Detection

No Driver Detected

In order to evaluate the reliability of the system, the tests were completed without a driver in the frame. When no driver is detected, the system does not draw a bounding box and states "Driver Not Detected". A major advantage is it prevents false alarms in case this is during a parking, loading, or unloading stop and the driver seat is momentarily empty. As a result, this increased reliability of the system reduces superfluous alerts during non-driving related activites.

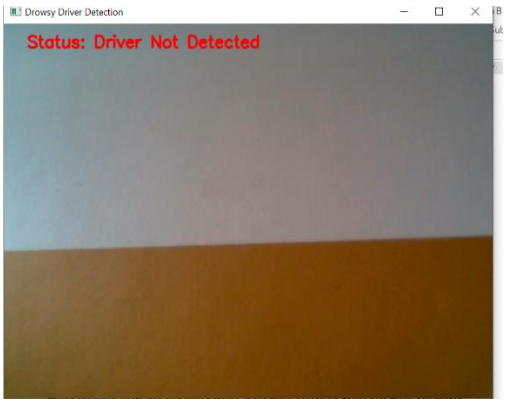


Figure 4: No Driver Detected

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Yawning Detected

Yawning detected is one of the strongest signal of fatigue. The system detects multiple instances of yawning, an example being when a widely opened mouth is detected and appropriately coupled with eye state detection. This yawning scenario, a red bounding box is drawn around the mouth region of the driver and the system indicates it is "Yawning". Yawning is detected and recognized as a high priority event and quickly returns a high priority alert to that driver visually and audibly that indicates the driver should make contact with the road again or take a break.

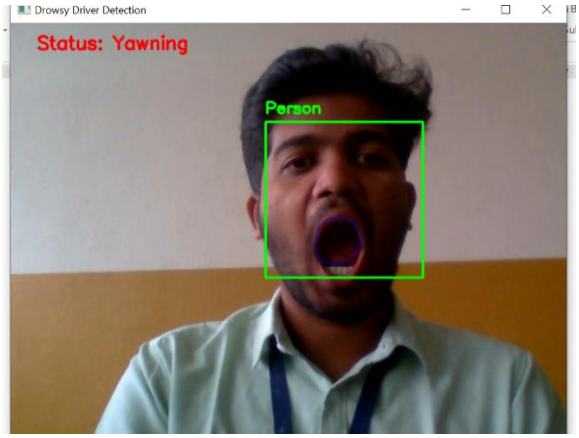


Figure 5: Yawning Detected

V. Conclusion

The developed Micro-Expression-Based Drowsy Driver Detection System for Truck Drivers is proven to work, indicating that early signs of driver fatigue can be detected based on micro-facial expressions such as eyelid height/positions, yawning, and relaxation of facial muscles. The system is unique as traditional detection systems only monitor the drivers' head positions and time spent with their eyes closed without understanding why. Micro-facial detection using advanced image processing and deep learning techniques is providing the latest technology to early identify drowsy behavior and alert the driver before they become critically fatigued or unresponsive. Multi-state detection monitoring—"Awake", "Drowsing", "Yawning", and "No Driver" provides a good coverage of monitoring with minimal false-positive results. The experimental results confirm the application operates accurately consistently under variable levels of light, orientation of the drivers' face, and driver position making it appropriate for inclusion in a commercial fleet of trucks. The fraction of misclassification demonstrates that micro-expression identification provides a better effect than the traditional drowsy detection systems. After providing a visual and audio alert the micro-expression system can significantly reduce the risk of road accidents related fatigue, improve road safety for all road users, including drivers and transported cargo.Apart from safety advantages, the system can provide operational efficiencies in the form of reduced downtime and maintenance costs for vehicles involved in accidents. Its modular design has allowed effective integration with vehicle telematics, GPS tracking, and fleet management applications to allow employers to examine their drivers' wellbeing, while of course taking into melancholy account consent and other management investigations that would need to occur.Additionally, the technology can be readily adapted to other transportation modes like buses, taxis, and railway transportation.All in all, the work has established a strong foundation for future advancement, including combining aspects of facial analysis with a combination of physiological signals (e.g. heart rate, blink rate), and broader context data (e.g. roadway conditions, hours of operation), to create a totally intelligent/adaptive driver monitoring context.

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