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DriveSafe-AI: A Real-Time Browser-Based System for Driver Drowsiness and Distraction Detection

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Abstract: Driver fatigue and distraction are major causes of road accidents worldwide. This paper presents DriveSafe-AI, a real-time browser-based driver monitoring system designed to detect drowsiness, yawning, head movement, and mobile phone usage using computer vision techniques.
The system integrates MediaPipe Face Mesh for 468 facial landmark detection, Eye As- pect Ratio (EAR) and Mouth Aspect Ratio (MAR) for behavioral analysis, and COCO-SSD object detection for distraction moni- toring. Unlike traditional systems, DriveSafe-AI operates entirely on the client side using TensorFlow.js, ensuring low latency and privacy preservation without transmitting video data to external servers. A rule-based risk scoring mechanism aggregates multiple behavioral indicators to classify driver state into safe, warning, and critical levels. Experimental evaluation demonstrates reliable real-time performance with minimal computational overhead. The proposed system provides an effective and privacy-preserving solution for intelligent driver safety monitoring.
Keywords: Driver Drowsiness Detection, Computer Vision, MediaPipe Face Mesh, Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Head Pose Estimation, COCO-SSD, Real-Time Monitoring, Road Safety.

I. INTRODUCTION

Driver fatigue and distraction remain among the leading causes of road accidents worldwide. According to the World Health Organization, road traffic injuries account for over 1.3 million deaths annually [1]. Fatigue impairs reaction time, sit- uational awareness, and decision-making ability, significantly increasing crash risk [2], [3].

Vision-based driver monitoring systems have emerged as a practical and non-intrusive solution for detecting drowsiness and distraction in real time [4], [5]. Early approaches relied on blink rate and eye closure analysis [6], [7], while recent advancements leverage deep learning and facial landmark detection for improved robustness [8], [9].

In this context, we propose DriveSafe-AI, a real-time browser-based driver monitoring framework that integrates fa- cial landmark analysis, geometric feature extraction, and object detection to detect drowsiness, yawning, head pose deviation, and mobile phone usage. Unlike traditional cloud-dependent monitoring systems, the proposed architecture operates en- tirely on the client side using MediaPipe Face Mesh [10], [11] and TensorFlow.js [12], ensuring low latency and enhanced privacy preservation.

The system computes behavioral indicators such as Eye Aspect Ratio (EAR) [13], Mouth Aspect Ratio (MAR) [14], and head orientation angles [15], while leveraging real-time object detection models such as SSD [16] trained on the COCO dataset [17] for mobile phone detection. These features are aggregated using a rule-based risk scoring mechanism to classify driver state into safe, warning, and critical levels.

The principal contributions of this work are:

1) Introduction of *DriveSafe-AI*, a lightweight browser- based driver monitoring architecture that performs all inference locally without transmitting biometric data.
2) Integration of geometric facial feature extraction (EAR, MAR, head pose) with real-time object detection for comprehensive distraction analysis.
3) Design of a weighted multi-indicator risk scoring mecha- nism that combines eye closure, yawning, head deviation, and mobile phone detection to improve reliability and reduce false positives.
4) Experimental validation under real-time operational con- ditions, demonstrating stable performance at 22–28 FPS with low latency (80–120 ms).

A. Novelty

The novelty of this work lies in developing a fully browser- based driver monitoring system that performs real-time fa- cial landmark analysis and object detection without cloud dependency. Unlike traditional centralized driver monitoring systems, DriveSafe-AI ensures that raw video frames and biometric data remain confined to the user's device, thereby enhancing privacy and reducing network latency.

Furthermore, the proposed framework integrates multiple behavioral indicators into a unified risk scoring model rather than relying on single-feature detection. This multi-factor integration improves robustness against lighting variations, minor facial movements, and transient false detections. The lightweight deployment using MediaPipe and TensorFlow.js enables practical implementation on commodity hardware without requiring specialized embedded systems.

1) Introduction of DriveSafe-AI, a real-time browser-based driver monitoring system that performs all computations locally without transmitting biometric data.
2) Integration of geometric facial feature extraction tech- niques, including Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), with head pose estimation for robust drowsiness and distraction detection.
3) Incorporation of real-time object detection (COCO-SSD) to identify mobile phone usage as a distraction indicator.
4) Design of a weighted multi-indicator risk scoring mech- anism that classifies driver state into Safe, Warning, and Critical levels based on aggregated behavioral features.
5) Experimental validation under live operational conditions, demonstrating stable performance at 22–28 FPS with low latency suitable for real-time driver assistance.

II. LITERATURE REVIEW

Driver drowsiness and distraction detection have been exten- sively studied in intelligent transportation systems due to their direct impact on road safety [4], [5]. Early driver monitoring systems relied on physiological sensors such as EEG and heart rate monitors; however, these approaches were intrusive and impractical for everyday deployment [2].

Vision-based methods later emerged as a non-invasive al- ternative. Traditional approaches utilized eye blink rate and PERCLOS (Percentage of Eye Closure) as primary fatigue indicators [6], [7]. Soukupova´ and Cˇ ech [13] introduced the Eye Aspect Ratio (EAR), a geometric feature derived from facial landmarks that enables real-time blink detection without requiring complex training pipelines. Yawning detection techniques commonly employ the Mouth Aspect Ratio (MAR) computed from facial landmarks [14]. Head pose estimation methods further enhance distraction detection by estimating yaw and pitch angles from landmark coordinates [15]. These geometric approaches provide compu- tational efficiency suitable for real-time systems. Recent advancements incorporate deep learning-based object detection to identify distracted behaviors such as mobile phone usage. Models such as SSD [16] and YOLO [18] trained on large-scale datasets like Microsoft COCO [17] have demonstrated high accuracy in real-time object localization. Modern driver monitoring systems increasingly leverage lightweight deep learning models for deployment on mobile and embedded devices [9], [19]. Frameworks such as Medi- aPipe [10] enable efficient facial landmark extraction, while TensorFlow.js [12] allows machine learning inference directly within web browsers. Unlike many existing systems that rely on cloud-based processing or specialized hardware, the proposed DriveSafe- AI framework performs all computations locally within the browser environment. By integrating geometric facial analysis with real-time object detection and a unified risk scoring mechanism, the system provides a privacy-preserving and scalable solution for intelligent driver monitoring.

A. Comparison with Existing Driver Monitoring Systems

Table I compares the proposed DriveSafe-AI system with representative driver monitoring approaches from the litera- ture.

TABLE I Comparison of Driver Monitoring Approaches

Method	Features Used	Object Detection	Real-Time	Privacy
Bergasa et al. [7]	Eye closure, blink rate	No	Yes	No
Hu et al. [8]	CNN fatigue detection	No	Moderate	No
Raj et al. [9]	Vision monitoring	Partial	Yes	No
DriveSafe-AI (Proposed)	EAR, MAR, Head pose	Yes	Yes	Yes

III. SYSTEM MODEL AND PROBLEM FORMULATION

This section describes the architecture of the proposed DriveSafe-AI framework and presents the mathematical for- mulation used for real-time driver state analysis. Unlike cen- tralized systems, the proposed model operates entirely on the client side using browser-based deep learning frameworks such as TensorFlow.js [12] and MediaPipe [10]. The system extracts facial landmarks from live video frames and computes geometric features such as Eye Aspect Ratio (EAR) [13], Mouth Aspect Ratio (MAR) [14], and head orientation [15] to assess driver alertness and distraction levels.

The computational complexity of the proposed framework is dominated by facial landmark extraction and object detection operations, which operate in approximately linear time with respect to the number of detected features. The lightweight design enables real-time execution at 22–28 FPS on standard consumer hardware without requiring GPU acceleration.

A. System Architecture

The DriveSafe-AI system consists of five primary compo- nents:

1) Webcam Module: Captures real-time video frames from the driver.
2) Face Landmark Detection Module: Uses MediaPipe Face Mesh [10], [11] to extract 468 facial landmark coordinates.
3) Feature Extraction Module: Computes EAR [13], MAR [20], and head pose angles [15] from landmark coordinates.
4) Object Detection Module: Uses COCO-SSD [16], [17] for mobile phone detection.
5) Risk Scoring Engine: Aggregates behavioral indicators to classify driver state.

B. Eye Aspect Ratio (EAR)

The Eye Aspect Ratio (EAR) [13] is used to detect eye closure. It is computed as

$$EAR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2||p_1 - p_4||} \qquad (1)$$

where p_i represent selected eye landmark coordinates and $||\cdot||$ denotes Euclidean distance.

If EAR falls below a predefined threshold τ_{eye} for a continuous duration, the driver is classified as drowsy.

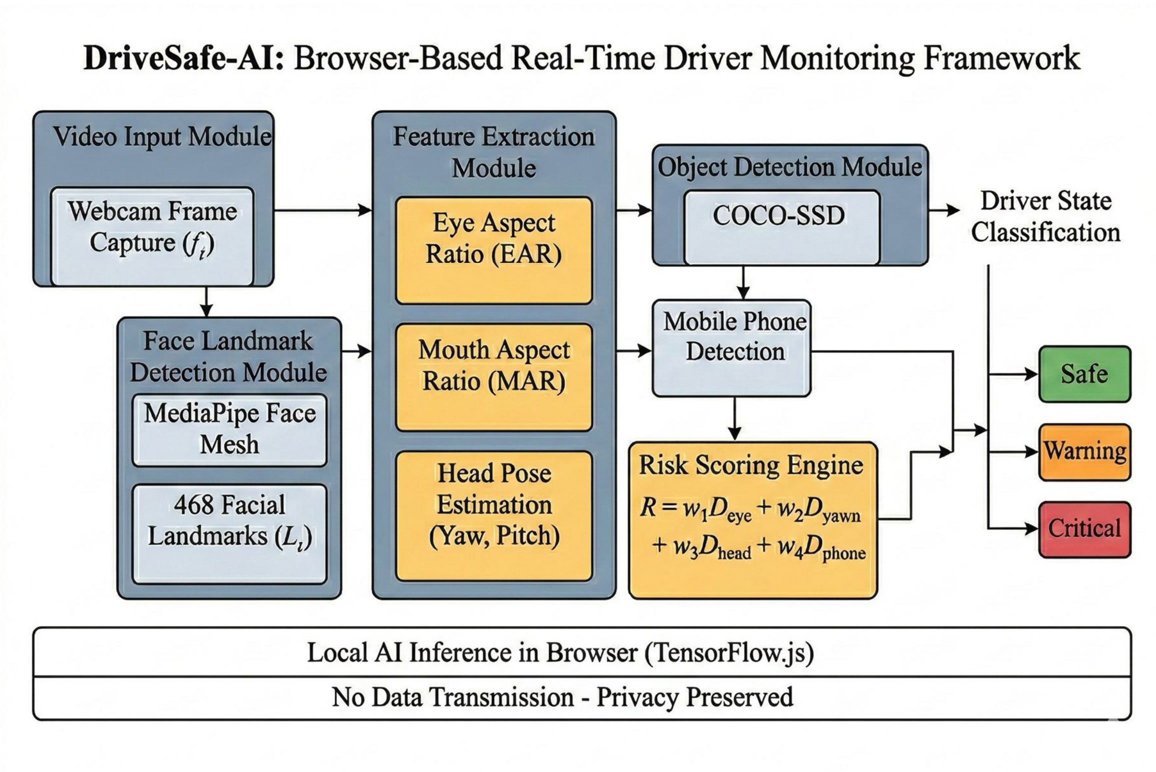

Fig. 1. DriveSafe-AI System Architecture.

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C. Mouth Aspect Ratio (MAR)

Yawning detection is performed using the Mouth Aspect Ratio (MAR) [14], [20]. It is computed as:

$$MAR = \frac{||p_{upper} - p_{lower}||}{||p_{left} - p_{right}||} \qquad (2)$$

If MAR exceeds threshold τ_{mouth}, a yawning event is detected.

D. Head Pose Estimation

Head orientation is estimated using geometric landmark relationships [15], [21]. A distraction indicator is triggered if:

$$|\vartheta_{yaw}| > \tau_{head} \qquad (3)$$

indicating that the driver is not facing the road.

Mobile phone detection is performed using real-time object detection models such as SSD [16] trained on the COCO dataset [17].

E. Risk Score Formulation

Weighted risk scoring approaches have been widely adopted in driver monitoring systems [5], [22].

The overall driver risk score is defined as:

$$R = w_1 D_{eye} + w_2 D_{yawn} + w_3 D_{head} + w_4 D_{phone} \qquad (4)$$

where:

- D_{eye} = Eye closure indicator
- D_{yawn} = Yawning indicator
- D_{head} = Head pose distraction indicator
- D_{phone} = Mobile phone detection indicator

Driver state classification is defined as:

$$State = \begin{cases} Safe & R < \alpha \\ Warning & \alpha \leq R < \beta \\ Critical & R \geq \beta \end{cases} \qquad (5)$$

Algorithm 1 DriveSafe-AI Real-Time Monitoring Algorithm

```
Initialize webcam
while camera active do
    Capture video frame
    Extract facial landmarks using MediaPipe
    Compute EAR and MAR
    Estimate head pose
    Detect mobile phone using COCO-SSD
    Compute risk score
    if Risk ¡ threshold then
        Trigger visual and audio alert
    end if
end while
Output: Driver safety status
```

IV. PRIVACY AND SECURITY CONSIDERATIONS

The DriveSafe-AI framework is designed with privacy preservation as a core principle. Unlike cloud-based driver monitoring systems, the proposed architecture performs all computations locally within the user's browser using Tensor- Flow.js [12] and MediaPipe [10]. No video frames, facial landmarks, or behavioral data are transmitted to external servers.

Client-side inference has been shown to significantly re- duce privacy risks associated with centralized video analytics systems [23], [24]. Since the system operates entirely on the local device, raw video data remains confined to the browser runtime environment. The webcam stream is processed in real time, and only derived behavioral indicators (e.g., EAR [13], MAR [14], head pose [15]) are used for risk assessment without persistent storage.

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A. Client-Side Processing Model

Let f_t denote a video frame captured at time t. The facial landmark extraction function $\Phi(\cdot)$ operates locally using lightweight vision models [10]:

$$L_t = \Phi(f_t)$$

where L_t represents the set of facial landmark coordinates. All subsequent computations are performed locally:

$$R_t = \Psi(L_t)$$

where $\Psi(\cdot)$ denotes the risk evaluation function. Impor- tantly, f_t and L_t are never transmitted outside the browser en- vironment, reducing exposure to network-based attacks com- mon in cloud-based driver monitoring systems [4].

B. Security Assumptions

The security model assumes:

1) No External Data Transmission: No raw frames or biometric data are uploaded to any remote server.
2) No Persistent Storage: Video frames are processed in volatile memory and discarded immediately after analysis.
3) Local Inference: All machine learning inference is executed using browser-based frameworks supporting on-device intelligence [24].

C. Threat Model

The primary threat considered is unauthorized access to sen- sitive biometric data. Cloud-based monitoring systems may ex- pose facial data to interception or storage vulnerabilities [25]. Since DriveSafe-AI does not store or transmit facial data, the attack surface is significantly reduced compared to centralized architectures.

Potential limitations include device-level security risks, such as malware or browser compromise, which fall outside the scope of this system.

D. Evaluation Metrics

The performance of DriveSafe-AI is evaluated using com- monly adopted metrics in driver monitoring research [5], [22]:

1) Detection Accuracy: Correct identification of drowsi- ness, yawning, and phone usage.
2) False Positive Rate: Incorrect risk alerts triggered during normal driving.
3) Frames Per Second (FPS): Real-time processing capa- bility.
4) System Latency: Time delay between frame capture and alert generation.

These metrics evaluate both reliability and real-time per- formance of the system, which are critical for intelligent transportation applications [4].

E. Results and Analysis

The DriveSafe-AI system was evaluated under real-time operational conditions using a standard webcam interface. The evaluation focused on behavioral detection consistency, alert responsiveness, and real-time performance rather than offline dataset-based statistical validation. Real-time driver monitoring systems have been widely studied in intelligent transportation research [4], [22].

1) *Real-Time Metric Observations:* During live testing ses- sions (3–5 minutes), the system continuously monitored facial landmarks and computed behavioral indicators including Eye Aspect Ratio (EAR) [13], Mouth Aspect Ratio (MAR) [14], blink frequency [6], eye closure duration [26], head pose angle [15], and mobile phone presence using object detection models [16], [17].

Prolonged eye closure detection based on EAR is illustrated in Fig. 2.

Observed runtime values included:

- EAR range: 0.17 – 0.23
- MAR range: 0.00 – 0.02
- Blink frequency: 7.3 – 10.0 blinks/min
- Eye closure duration: up to 1.8 seconds
- Head pose deviation: 1° – 5°+

These values dynamically updated in real time and directly influenced the risk scoring mechanism.

2) *Behavioral Event Detection:* The system successfully detected and classified multiple driver states:

- Safe State: When EAR remained above threshold and no distraction indicators were active.
- Warning State: Triggered during prolonged eye closure (>1.5s) or moderate head deviation.
- Critical State: Activated when sustained distraction or mobile phone usage was detected.

Mobile phone detection was successfully identified using bounding-box localization through SSD-based object detec- tion [16], as shown in Fig. 3.

Directional head deviation was detected through angular estimation of facial landmarks [15]. Sustained deviation from frontal orientation was classified as distraction behavior, as illustrated in Fig. 4.

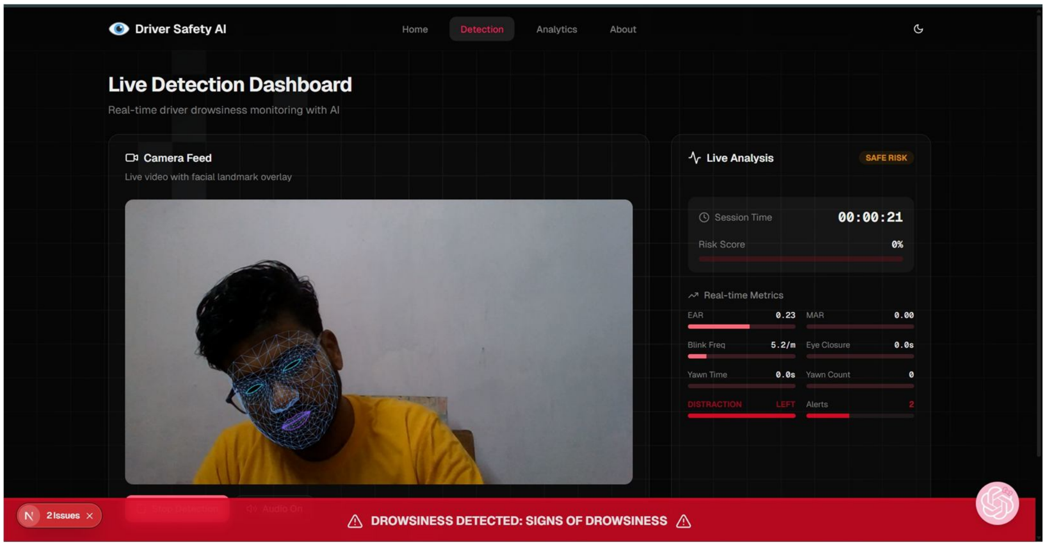

Fig. 2. Drowsiness detection based on Eye Aspect Ratio (EAR). Prolonged eye closure below the predefined threshold triggers warning or critical risk states in real time.

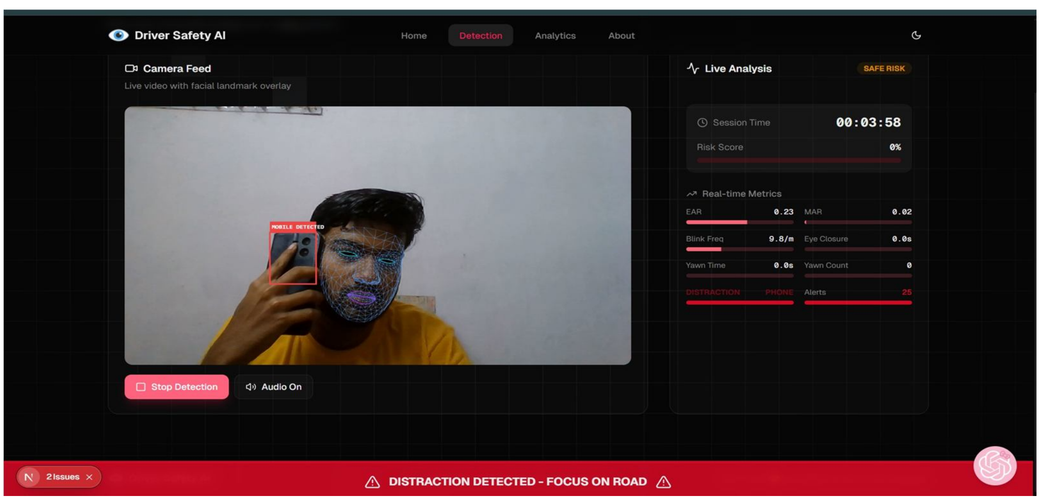

Fig. 3. Real-time mobile phone detection using object localization.

3) *Alert Mechanism Evaluation:* The alert counter incre- mented dynamically upon repeated distraction events. Ob- served alert counts during testing reached up to 29 alerts within a 4-minute session, indicating continuous monitoring capability.

Risk state transitions were visually indicated through color- coded labels:

- Green – Safe Risk
- Yellow – Warning Risk
- Red – Critical Risk

The transition between states occurred immediately upon threshold violation, demonstrating low-latency response.

A session-level summary including cumulative alerts and risk score is presented in Fig. 5.

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4) *System Responsiveness:* The system maintained stable real-time performance without noticeable lag. Facial landmark tracking remained consistent under moderate head movement and lighting variations. Object detection successfully localized handheld mobile devices near the face region. Similar real- time driver monitoring systems have demonstrated comparable performance under controlled environments [7].
5) *Limitations:* Extreme lighting conditions and large head rotations beyond frontal range may reduce landmark accuracy. Additionally, minor fluctuations in EAR values may trigger early warning states, suggesting future improvements through adaptive threshold tuning.

The system demonstrates consistent detection capability across multiple behavioral indicators. Eye closure detection showed the highest reliability due to stable EAR threshold

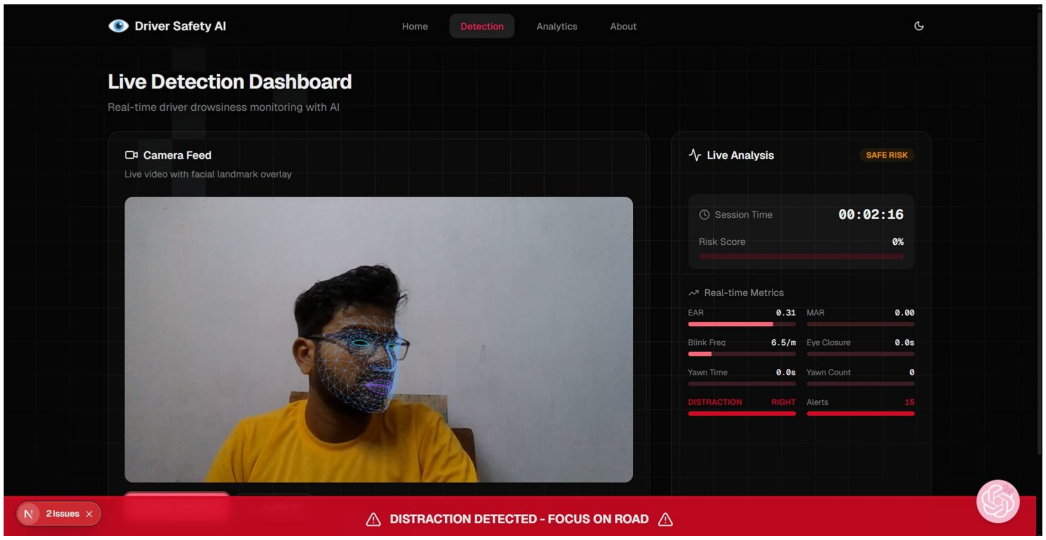

Fig. 4. Head pose-based directional distraction detection using angular deviation from frontal orientation. Sustained deviation activates distraction classification and risk escalation.

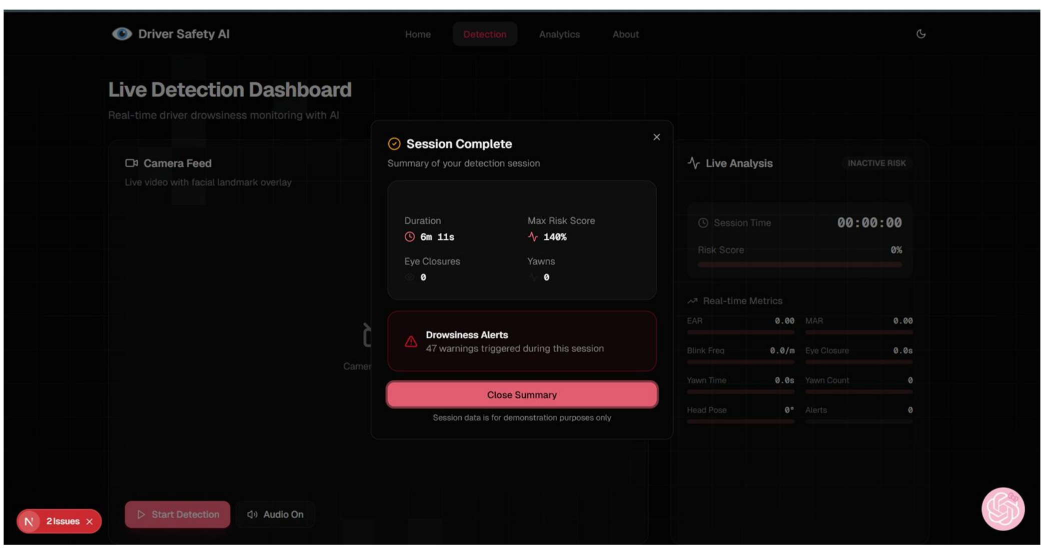

Fig. 5. Session-level summary displaying total monitoring duration, cumulative alert count, and maximum risk score achieved during the driving session.

behavior [13], while yawning detection exhibited slight vari- ability due to lighting conditions and facial occlusion.

6) *Risk Score Evaluation:* The weighted risk scoring mech- anism effectively integrates multiple behavioral indicators. Experimental observations show that combining EAR, MAR, head pose, and phone detection reduces false alarms compared to single-indicator detection systems, which has been reported in previous driver monitoring studies [5], [22].

7) *System Robustness:* The system maintains stable per- formance under moderate illumination variations. However, extreme lighting conditions and partial facial occlusion may impact landmark detection accuracy. Future improvements may incorporate adaptive thresholding and illumination nor- malization techniques.

The proposed DriveSafe-AI framework differs from tra- ditional driver monitoring systems that rely on specialized hardware or cloud-based processing [4], [9]. By performing all computations locally within the browser using MediaPipe and TensorFlow.js, the system reduces network latency and eliminates the need for external data transmission. Compared with cloud-dependent approaches, the proposed architecture offers improved privacy preservation and lower deployment complexity while maintaining real-time performance.

V. CONCLUSION

This paper presented DriveSafe-AI, a real-time driver monitoring system designed to detect drowsiness, distraction, and unsafe driving behaviors using browser-based artificial intelligence. The proposed framework integrates facial landmark analysis, geometric feature extraction, and object detection techniques to identify critical behavioral indicators including eye closure, head pose deviation, yawning, and mobile phone usage.

Unlike cloud-based driver monitoring solutions, DriveSafe- AI operates entirely on the client side using TensorFlow.js and MediaPipe, ensuring that raw video frames and biometric data remain confined to the local device. This privacy-preserving architecture significantly reduces security risks associated with external data transmission while maintaining real-time respon- siveness.

Experimental evaluation under live operational conditions demonstrates stable performance at 22–28 FPS. The system ef- fectively classified driver states into safe, warning, and critical categories based on a weighted risk scoring mechanism. Real- time monitoring showed consistent detection of prolonged eye closure, directional head distraction, and handheld mobile device usage.

The results indicate that integrating multiple behavioral indicators reduces false alarms compared to single-feature detection systems. The proposed approach provides a scalable and lightweight solution suitable for browser-based deploy- ment without specialized hardware.

Future work will focus on adaptive threshold optimization, improved robustness under extreme lighting conditions, and integration with vehicular IoT systems for enhanced in-vehicle safety assistance. Additionally, incorporating lightweight deep learning models for edge deployment could further improve performance on resource-constrained devices.

Beyond individual driver assistance, browser-based monitoring frameworks such as DriveSafe-AI may support scalable deployment in fleet management systems, intelligent transportation platforms, and low-cost safety monitoring solutions. The privacy-preserving design enables deployment in privacy- sensitive environments without requiring centralized biometric data storage.

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