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Enhancing Driver Stress Detection through Multimodal Integration of Eye Tracking and Physiological Signals

Tri Agung Widayat[1], Quirina Ariantji Patrisia Mintje[2], Sri Yanthy Yosepha[3]
Politeknik Penerbangan Medan, Indonesia[1]
Akademi Penerbang Indonesia Banyuwangi, Indonesia[2]
Universitas Dirgantara Marsekal Suryadarma, Indonesia[3]
Correspondent : chila3838@gmail.com [1]

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ABSTRACT: Driver stress poses significant risks to traffic safety, impairing attention, decision-making, and reaction time. Traditional monitoring methods often lack sensitivity. This study proposes and validates a novel multimodal framework that integrates synchronized eye-tracking and physiological data to significantly enhance the sensitivity and real-time accuracy of driver stress detection, addressing limitations of earlier unimodal approaches. Thirty licensed drivers participated in simulated driving tasks under baseline and stress-induced conditions. Eye-tracking metrics (pupil diameter, fixation duration, blink rate) and physiological signals (heart rate, skin conductance, heart rate variability) were collected. Data were synchronized and analyzed using Linear Discriminant Analysis (LDA) and other machine learning models to classify stress conditions. Under stress, pupil dilation increased by 20%, blink rate rose by 35%, and gaze spread narrowed, indicating visual tunneling. Physiologically, heart rate increased by 17%, skin conductance by 31%, and HRV decreased by 19%. The combined multimodal model achieved 91.4% classification accuracy, outperforming unimodal approaches. These results align with previous research showing that multimodal systems provide more reliable stress detection by integrating visual and autonomic markers. The findings highlight the system's potential for real-time applications in Driver Monitoring Systems (DMS). Multimodal integration of eye-tracking and physiological signals enhances the sensitivity and reliability of driver stress detection. This approach offers a foundation for intelligent, adaptive DMS capable of improving road safety. Future work should focus on real-world validation and ethical implementation strategies. These findings demonstrate that multimodal integration provides a more comprehensive understanding of driver stress through complementary visual and autonomic indicators. The proposed framework forms a foundation for intelligent, adaptive Driver Monitoring Systems (DMS) capable of real-time stress recognition and proactive safety intervention.

Keywords: Driver Stress, Eye Tracking, Physiological Monitoring, Multimodal Integration, Driver Monitoring System, Cognitive Workload, Real-Time Classification.

INTRODUCTION

Driving is a complex activity requiring continuous cognitive engagement, situational awareness, and rapid decision-making. The presence of cognitive stress during driving can significantly compromise performance and safety. As modern traffic environments grow more demanding, there is a rising need to understand how stress affects driver behavior and to develop technologies that can detect and respond to stress in real time.

Cognitive stress has been shown to alter attentional control, impair reaction time, and increase the risk of traffic incidents. Shi et al. (2019) found that stressors such as multitasking or complex navigation divert cognitive resources from essential driving tasks. As a result, behaviors such as speed variability, reduced lane-keeping ability, and slower hazard recognition are observed more frequently under cognitive load. This finding emphasizes the importance of integrating cognitive monitoring into safety systems to mitigate the adverse effects of stress on driver behavior.

One promising solution for real-time cognitive state monitoring is eye-tracking technology. Eye-tracking systems measure visual behaviors such as fixation duration, saccades, blink rate, and pupil dilation all of which correlate with levels of cognitive workload and stress. According to Wu et al. (2021), under cognitive load, drivers exhibit altered gaze behavior, including narrowed visual attention and increased blink frequency. Gabrielli et al. (2024) demonstrated that eye movement patterns alone could predict stressful driving conditions with substantial accuracy. These visual cues offer a non-intrusive, real-time proxy for mental state assessment, making eye-tracking a valuable component in driver monitoring systems.

Nevertheless, eye-tracking in isolation may not capture the full spectrum of stress responses. Stress is inherently multifactorial, manifesting through both psychological and physiological pathways. Physiological markers such as heart rate (HR), galvanic skin response (GSR), and heart rate variability (HRV) are increasingly used in stress detection research. Studies by Dogan et al. (2022) report that during acute stress episodes, HR and GSR levels increase while HRV decreases, reflecting autonomic nervous system arousal. These physiological signals have been effectively used to infer emotional states in high-risk operational settings and are now being explored for driver stress detection.

The integration of eye-tracking with physiological sensors forms a multimodal approach that enhances the robustness of stress detection. Nweke et al. (2019) point out the limitations of unimodal systems, which are often unable to discern subtle or context-dependent emotional changes. By contrast, multimodal systems that synthesize data from multiple channels provide a more comprehensive and nuanced understanding of driver state. Such integration enables adaptive systems that can respond more appropriately to driver needs in real-time environments.

Recent advances in artificial intelligence and sensor technologies have further propelled the development of driver monitoring systems (DMS). Liu et al. (2023) demonstrate that machine learning algorithms can analyze multimodal data including facial expressions, driving patterns, and physiological metrics to detect fatigue, distraction, and stress with high accuracy. These systems are increasingly embedded in modern vehicles, offering new possibilities for proactive safety interventions.

Multimodal integration also plays a critical role in driving simulations and human factors research. According to Feng et al., (2022), combining data from cameras, biometric sensors, and telemetry in simulated environments offers granular insights into driver behavior under various stressors. This integration facilitates better driver training and the development of resilient user interfaces and automation systems.

Despite these advancements, challenges remain. Factors such as individual variability in stress response, environmental influences, and calibration difficulties can affect measurement reliability. To be effective, multimodal systems must address these issues through improved modeling, personalization, and validation in real-world settings.

This study proposes a multimodal stress detection framework combining eye-tracking and physiological data to classify driver stress more accurately. Building on prior findings, it hypothesizes that such integration will outperform unimodal approaches in classification accuracy. The study also aims to assess the relative contribution of visual versus physiological indicators and to explore the feasibility of implementing these systems in adaptive DMS technologies.

The novelty of this work lies in its synchronized use of visual and physiological cues within a controlled driving simulation to construct a predictive model for stress detection. Unlike previous unimodal or sequential approaches, this framework emphasizes simultaneous multimodal data fusion to enhance predictive accuracy and practical applicability for real-time driver monitoring.

METHOD

This study employs a multimodal experimental design to assess stress detection in drivers by integrating eye-tracking and physiological data. The methodology incorporates principles from validated simulation protocols and machine learning frameworks to ensure scientific rigor and real-world applicability.

Participants

Thirty licensed drivers (aged 21–45) were recruited with balanced representation across gender. All participants had normal or corrected vision and no history of neurological or cardiovascular disorders. Participants provided informed consent and were briefed on potential psychological stress during simulation.

Experimental Design

The experiment was conducted using a high-fidelity driving simulator capable of reproducing real-world scenarios with visual, auditory, and kinesthetic feedback. Two conditions were designed: a baseline driving session under relaxed conditions and a stress-inducing session involving time pressure, simulated hazards, and cognitive load via secondary tasks (e.g., Stroop test). The order of condition exposure was randomized to control for sequence effects, consistent with Lee & Winston (2016).

Data Acquisition Tools

- Eye-Tracking: A Smart Eye Pro system (120 Hz) recorded fixation duration, blink rate, pupil diameter, and gaze distribution.
- Physiological Sensors: Heart rate (HR), galvanic skin response (GSR), and heart rate variability (HRV) were measured using validated wearable devices.
- Logging & Synchronization: All data were timestamped using a unified logging system to ensure alignment across modalities(Ahmad et al., 2020).

Measurement Baseline and Stress Validation

Baseline metrics for each parameter were recorded during an initial relaxation phase. Stress induction was validated through both physiological markers (increased HR and GSR, decreased HRV) and self-report assessments of perceived stress. The use of defined baseline states allowed deviations during stress conditions to be interpreted with higher specificity (Ahmad et al., 2020).

Data Preprocessing and Feature Extraction

Data streams were filtered and aligned to eliminate artifacts. Key features extracted included:

- Eye: mean fixation duration, blink frequency, pupil dilation amplitude, gaze spread
- Physiology: HR peaks, GSR slope, RMSSD (for HRV)

Feature selection (e.g., fixation duration, HRV, GSR slope) was grounded in cognitive workload theory, where visual attention and autonomic nervous system reactivity are key dimensions of stress manifestation during driving. These features were standardized and structured into multimodal datasets for classification, ensuring theoretical and empirical relevance in stress modeling

Machine Learning Analysis

A Linear Discriminant Analysis (LDA) classifier served as the primary model, benchmarked against Support Vector Machines (SVM) and Random Forests. Ensemble models were evaluated for robustness (Gao & Kasneci, 2022). Feature selection was guided by correlation matrices and recursive feature elimination.

Deep learning models (e.g., feedforward neural networks) were piloted on larger datasets to assess generalizability. Training included 10-fold cross-validation and stratified sampling to control for participant-specific bias. Performance metrics included accuracy, precision, recall, and AUC.

Ethical Considerations

Participants were fully informed of the study's aims and provided written consent. Simulated scenarios were designed to evoke stress without causing trauma. Data were anonymized and stored in compliance with institutional review board (IRB) guidelines.

This methodological framework integrates validated experimental design principles and advanced analytics, ensuring reliability, replicability, and real-world relevance for stress detection in driver monitoring systems.

RESULT AND DISCUSSION

This chapter presents the empirical findings from the multimodal stress detection study, integrating eye-tracking and physiological data. Results are structured around three main domains: eye-tracking responses, physiological responses, and classification accuracy using machine learning techniques.

Eye Tracking Responses

Pupil dilation significantly increased under stress, consistent with findings by Brouwer et al. (2017) who reported that increased visual processing demand and cognitive workload lead to measurable pupil expansion. Participants showed an average increase of 20% in pupil diameter during high-stress driving scenarios.

Contrary to some previous findings, fixation duration in this study decreased by 47% under stress. Ma et al. (2020) observed longer fixations with greater workload, the discrepancy here may reflect scenario design, where participants were forced to rapidly shift attention, limiting fixation duration. This supports the possibility of divergent gaze strategies under different task pressures (Han et al., 2023).

Blink rate increased by 35% under stress, although literature presents a dual interpretation: Lyu et al. (2022) indicate lower blink rates during acute stress (indicating hyper-focus), while increased rates may point to early fatigue onset (Zhao et al., 2024). This underscores the nuanced interpretation of blink patterns under combined stress and fatigue conditions.

Gaze spread narrowed significantly, reflecting visual tunneling a phenomenon where drivers under pressure focus more narrowly, potentially compromising peripheral awareness (Ahmadi et al., 2022). This adaptive behavior may improve task focus but reduces situational awareness.

Physiological Responses

Heart rate increased by an average of 17%, aligning with studies by Hughes et al. (2019), who report HR elevation as a reliable stress marker during demanding driving tasks. These findings support the idea that heightened cardiovascular output is a sympathetic response to increased workload.

Skin conductance rose by 31%, corroborating its role as a fast-reacting stress biomarker across age groups (Fan et al., 2023). This aligns with the finding that sympathetic arousal manifests as elevated electrodermal activity.

Heart rate variability (HRV) decreased by 19% under stress, indicating a shift toward sympathetic nervous system dominance, consistent with Gall et al. (2023). Decreased HRV is associated with impaired cognitive flexibility and emotional regulation during high cognitive load.

Physiological response timing further validated stress induction protocols. GSR responded rapidly (within seconds), while HR adjustments showed a slower trajectory, as reported by Hebbar et al. (2021)

Classification Accuracy

The LDA classifier using eye-tracking alone achieved 82.3% accuracy, with physiological data alone yielding 84.7%. While the multimodal model achieved 91.4% accuracy, this performance should be interpreted cautiously due to the modest sample size (n=30). Variations in individual stress responses may affect generalizability, and future work should validate the model with larger and more diverse driver populations. This confirms the literature trend that multimodal integration improves stress detection performance (Jung et al., 2024).

While LDA provided baseline classification, deep learning approaches (e.g., CNN, RNN) have reported accuracies exceeding 95% (Mallick et al., 2016; Yang et al., 2024). However, our focus was on interpretability and real-time feasibility. Evaluation metrics (precision, recall, F1 score, AUC) ensured comprehensive model assessment (Rothkegel et al., 2019).

Public datasets such as Driver Behavior Dataset and OpenStress Database were reviewed as potential benchmarks for future model training (Huang et al., 2024).

These results collectively support the efficacy of multimodal approaches for real-time stress detection and provide robust evidence for advancing adaptive driver monitoring systems.

The findings of this study underscore the efficacy of a multimodal framework for detecting driver stress through the combined use of eye-tracking and physiological signals. This integrated approach enhances the accuracy and robustness of driver monitoring systems (DMS), offering potential for real-time application in modern vehicles. Pupil dilation, gaze narrowing, and changes in blink rate paired with heart rate (HR), galvanic skin response (GSR), and heart rate variability (HRV) demonstrated consistent patterns under induced stress. These findings are consistent with existing literature that highlights the sensitivity of these parameters to cognitive and emotional strain (Gall et al., 2023).

Multimodal DMS offer a key advantage over unimodal systems by synthesizing visual, physiological, and behavioral cues to generate a more complete assessment of driver state. As noted by Tabassum and El-Sharkawy (2024), this integration enables greater detection accuracy for states like drowsiness or distraction. In the current study, the combined classifier achieved over 91% accuracy, outperforming unimodal systems. This affirms previous research demonstrating the additive value of multimodal fusion (Guo et al., 2022).

However, deploying multimodal DMS in real-world settings presents substantial challenges. Environmental variability, sensor calibration, and computational latency can reduce system reliability (Sim & Kim, 2024). Sensor fusion in uncontrolled environments must be precise and adaptive, particularly when sensor accuracy fluctuates due to external conditions like lighting, temperature, or user movement (Sauerbeck et al., 2023). Future systems must be optimized to ensure low-latency, high-accuracy feedback suitable for embedded automotive contexts.

Given observed inter-individual differences in physiological reactivity and gaze behavior, adaptive personalization strategies such as individualized stress thresholds calibrated from baseline recordings are recommended to enhance detection accuracy in diverse user populations. These strategies can mitigate the influence of age, driving experience, or personality traits on stress response variability, ensuring equitable model performance across demographics.

From an ethical standpoint, continuous biometric monitoring introduces concerns regarding privacy, consent, and data usage. Stocco (2021) emphasizes the importance of preventing unauthorized access and ensuring that data is only used for safety-enhancing purposes. Algorithmic fairness must also be addressed, as biased training data could lead to systematic misinterpretation for certain user groups. Accountability frameworks should be developed to determine responsibility in cases of system malfunction, particularly in semi-autonomous driving environments (Song et al., 2022).

Advancements in artificial intelligence have made adaptive DMS increasingly feasible. As demonstrated by Bayoudh et al. (2021), machine learning algorithms, especially deep learning, can dynamically interpret multimodal input and adapt to individual drivers. Ramirez & Hamaza (2023) describe systems capable of recognizing nuanced patterns of stress and issuing real-time alerts. However, the trade-off between model complexity and interpretability remains a barrier to transparent, regulatory-approved deployment.

In conclusion, the integration of eye-tracking and physiological signals represents a powerful step forward in cognitive state monitoring. While simulation-based studies provide a controlled environment to validate these systems, future work must transition to on-road validation with diverse driver populations. Ethical, technical, and individual-specific challenges must be systematically addressed for multimodal DMS to realize their full potential in advancing road safety and driver support technologies.

CONCLUSION

This study proposed and validated a synchronized multimodal stress detection framework that integrates eye-tracking and physiological signals to enhance the real-time identification of driver stress. The findings demonstrated that combining visual and physiological modalities such as pupil dilation, blink rate, gaze narrowing, heart rate, skin conductance, and HRV yields higher sensitivity and accuracy than unimodal approaches. With a classification accuracy of 91.4%, the framework provides a comprehensive representation of cognitive and emotional stress, forming a strong foundation for adaptive Driver Monitoring Systems (DMS).

Beyond technical performance, this study emphasizes the importance of personalization and ethical implementation. Individual variability in stress reactivity highlights the need for adaptive calibration and personalized thresholds, while data governance and privacy protection remain essential for real-world deployment. Future research should focus on large-scale, on-road validation using deep learning and contextual data integration to further improve generalizability and reliability. Overall, the multimodal framework contributes to advancing safer, intelligent, and ethically responsible driver monitoring technologies.

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