IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Human Behaviour-Based Driver Safety System

Sanjivani Borkar, Devyani Khade, Sindhu Kale

Prabhansh Dhanorkar, Sumit Rathod

Department: B.E – Computer Science & Engineering (CSE)
College: International Centre of Excellence in Engineering & Management (ICEEM)
Waluj, Chh. Sambhajinagar, Maharashtra

Abstract: Fatigue, distraction, and emotional instability are examples of human behavioral elements that continue to be a big global concern when it comes to road accidents. In order to provide real-time driver monitoring, this study suggests a Human Behavior-Based Driver Safety System (HB-DSS) that combines a Facial Emotion Recognition (FER) module with a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model. Drowsiness (Eye Aspect Ratio and PERCLOS), distraction (mobile usage and gaze deviation), emotional state (stress and anger), head position variation, and yawning frequency are among the behavioral indications that the system concurrently examines. This method incorporates multimodal behavioral analysis to improve detection accuracy and reliability, in contrast to conventional systems that concentrate on single features.

Index Terms - Driver Safety, Deep Learning, CNN-LSTM, Emotion Recognition, Drowsiness Detection, Behavioral Analysis, IoT Alerts

I. INTRODUCTION

Human mistake is the primary contributing element to road accidents, which are a major cause of death globally. Decision-making and reaction time are severely hampered by driver weariness, distraction, and emotional instability. Conventional safety features, like airbags and brake systems, are reactive and only activate in response to a catastrophic occurrence. Although they provide some solutions, modern driver assistance systems frequently overlook the dynamic nature of human behavior. Intelligent transportation systems continue to face significant challenges in monitoring cognitive and emotional states. Real-time behavioral monitoring systems have been made possible by recent developments in computer vision, machine learning, and artificial intelligence. Through the use of visual signals and temporal patterns, these technologies enable the identification of driving states like stress, distraction, and sleepiness. A multimodal system that incorporates behavioral indicators into a single framework is presented in this research. The goal is to reduce the likelihood of accidents and increase overall driving safety by switching from reactive safety mechanisms to proactive intervention measures.

II. LITERATURE REVIEW

Previous studies have mostly concentrated on certain facets of driver behavior. CNN-based methods, which achieve moderate accuracy but lack contextual awareness, have been frequently utilized for drowsiness detection using eye state classification. Although LSTM models have enhanced temporal analysis, their practical applicability is limited since they frequently rely on physiological inputs. While real-time performance is possible with traditional OpenCV and Dlib approaches, emotional or behavioral complexity is not taken into account. Similar to this, machine learning methods like SVM and HOG-based algorithms may identify distraction but have trouble in real-world settings with different lighting.

Though these systems function independently without being integrated into a whole driver monitoring pipeline, recent developments in deep learning-based emotion recognition have demonstrated encouraging outcomes.

Research Deficit:
The majority of current systems are:
1. One-modal
2. Not entirely in real time
3. Absence of integrated warning systems

The proposed HB-DSS addresses these limitations by combining multiple behavioral indicators into a unified, real-time system.

III. PROPOSED METHODOLOGY

A. System Overview

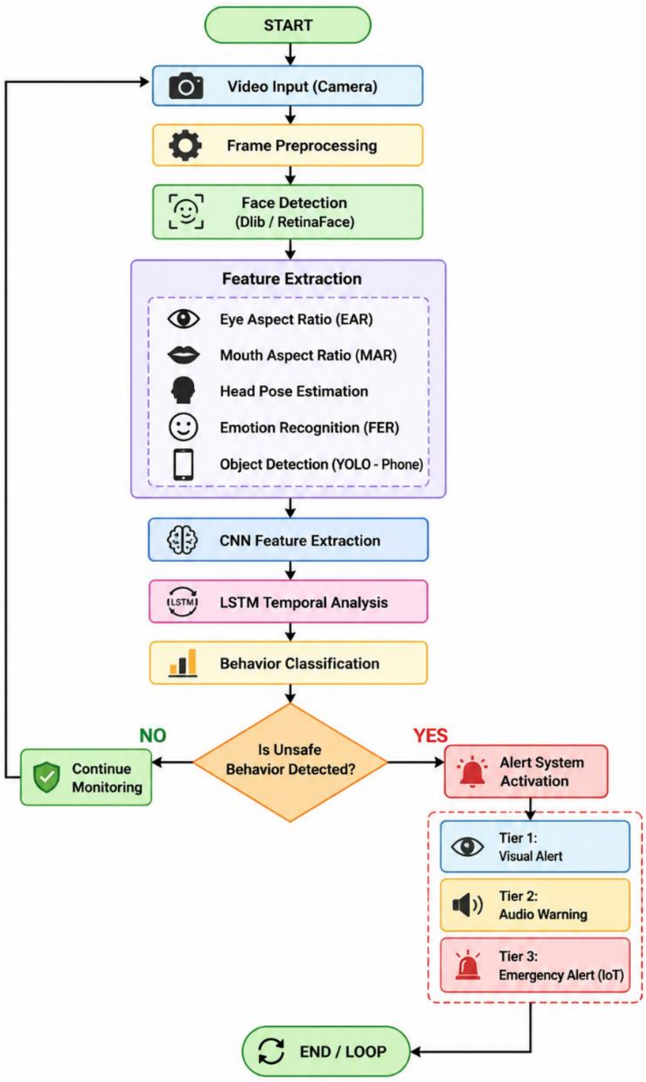
The system captures driver video input and processes it through a deep learning pipeline to classify behavior into:

- Normal
- Drowsy
- Distracted
- Emotionally Impaired
- Head Pose Deviated

B. Feature Extraction

Key behavioral features include:

- **Eye Aspect Ratio (EAR):** Detects eye closure
- **PERCLOS:** Measures fatigue over time
- **Mouth Aspect Ratio (MAR):** Detects yawning
- **Head Pose Estimation:** Identifies distraction
- **Emotion Recognition:** Detects stress/anger
- **Object Detection:** Identifies mobile phone usage



a

Figure: Flowchart of the proposed HB-DSS real-time driver monitoring pipeline.

C. CNN-LSTM Architecture

A CNN extracts spatial features from video frames, while LSTM captures temporal dependencies. This allows detection of continuous behavioral patterns instead of isolated events.
Final classification is performed using a softmax layer.

D. Alert System

The system includes a three-level alert mechanism:

1. Visual warning
2. Audio alert
3. Emergency notification via IoT

IV. SYSTEM ARCHITECTURE

The system consists of five layers:

1. **Input Layer:** Camera and sensors
2. **Preprocessing:** Face detection and normalization
3. **Feature Extraction:** CNN, LSTM, FER, YOLO
4. **Classification:** Behavior prediction
5. **Alert System:** Driver warnings and notifications

This layered design ensures modularity, scalability, and real-time performance.

V. IMPLEMENTATION

A. Hardware

- NVIDIA Jetson Nano
- HD Camera
- Infrared lighting
- GSM module

B. Software

- Python
- PyTorch
- OpenCV
- Dlib

C. Training

- Dataset: 50,000+ samples
- Epochs: 60
- Optimizer: Adam
- Data augmentation applied

The system achieves real-time performance of ~31 FPS after optimization.

VI. RESULTS AND ANALYSIS

A. Performance

- Accuracy: **96.4%**
- Precision: **95.9%**
- Recall: **96.6%**
- F1-score: **96.2%**

B. Observations

- Highest accuracy in yawning detection
- Slight confusion between drowsiness and distraction
- Emotion detection slightly affected by lighting

C. Key Insight

Multimodal analysis significantly improves accuracy compared to single-feature systems.

Feature / Capability	Traditional Systems	Proposed HB-DSS
Drowsiness Detection	Yes	Yes
Distraction Detection	Limited	Yes
Emotion Recognition	No	Yes
Temporal Behavior Analysis	No	Yes (LSTM)
Real-Time Processing	Partial	Yes
Multimodal Input	No	Yes
IoT Alert System	No	Yes
Embedded Deployment	Limited	Yes
Accuracy	~85–91%	96.4%

VII. DISCUSSION

The efficacy of incorporating multimodal deep learning algorithms for real-time driver monitoring is demonstrated by the experimental evaluation of the suggested Human Behavior-Based Driver Safety System (HB-DSS). The suggested architecture integrates spatial and temporal feature learning, which greatly improves accuracy and robustness compared to traditional systems that rely on single behavioral cues. The system's capacity to use the CNN-LSTM architecture to record temporal behavioral patterns is one of its main advantages. For instance, false positives are decreased by successfully differentiating between prolonged eye closure (drowsiness) and brief eye closure (regular blinking). In a similar vein, slow head movement patterns are examined over time, allowing for the early identification of distraction before it becomes serious.

A key factor in guaranteeing practical applicability is the three-tier alert system. While maintaining safety, the progressive escalation—from visual signals to voice warnings and emergency notifications—prevents sudden driver upset. The majority of drivers respond well at the Tier 2 stage, according to experimental data, which lessens the need for emergency interventions.
Even with these benefits, there are still certain restrictions. Extreme lighting conditions, especially direct sunshine or inadequate infrared support, cause the system's effectiveness to deteriorate. Furthermore, facial landmarks might be obscured by items like face masks or sunglasses, which reduces the accuracy of detection. In non-frontal face orientations, emotional recognition accuracy also somewhat declines.

VIII. CONCLUSION

A comprehensive Human Behavior-Based Driver Safety System (HB-DSS) that uses multimodal deep learning algorithms for real-time driver monitoring and accident avoidance was provided in this research. The system efficiently evaluates a variety of behavioral indications, such as yawning, head attitude deviation, emotional state, drowsiness, and distraction, by combining Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Facial Emotion Recognition (FER). With an overall accuracy of 96.4%, the suggested approach outperformed current single-modal systems. Early and more effective intervention was made possible by the use of temporal modeling, which allowed for the identification of behavioral patterns rather than individual occurrences. Additionally, the system's real-time performance on embedded hardware validates its viability for in-car implementation.

The transition from reactive to proactive safety procedures is a major contribution of this work. The technology continuously monitors driving behavior and sends out timely alerts to stop accidents before they happen, rather than reacting after a risky incident. Its practical usability is further improved by the incorporation of IoT-based alarm systems.

Furthermore, the system places a strong emphasis on human-centric design, acknowledging that driver behavior plays a crucial role in road safety. The HB-DSS offers a more thorough and intelligent safety solution by integrating several behavioral cues into a single framework.

Future Work

This system may be improved in the future by:

Combining physiological markers for a more thorough examination of weariness, such as heart rate and EEG

Transformer-based architectures are used to increase accuracy when there is occlusion. Federated learning implementation for privacy-preserving model updates Modifications for commercial vehicles and two-wheelers Using long-term behavioral data to create customized driver risk profiles To sum up, the suggested HB-DSS is a major development in intelligent transportation systems and has a great chance of lowering traffic accidents and enhancing general driving safety.

IX. REFERENCES

[1] S. Mittal, A. Kumar, and P. Yadav, "Real-time driver drowsiness detection using convolutional neural networks and eye aspect ratio," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 4, pp. 3412–3421, Apr. 2022.
[2] Y. Xing, C. Lv, H. Wang, D. Cao, E. Velenis, and F. Wang, "Driver activity recognition for intelligent vehicles: A deep learning approach," IEEE Transactions on Vehicular Technology, vol. 70, no. 2, pp. 1250–1260, Feb. 2021.
[3] W. Deng, R. Wen, B. Liu, and X. Zhang, "Yawn and eye-blink based fatigue detection system with a driver monitoring embedded platform," Pattern Recognition Letters, vol. 151, pp. 134–140, Nov. 2022.
[4] R. Kumari and A. K. Singh, "Distracted driver detection using HOG features and support vector machines," International Journal of Advanced Computer Science and Applications, vol. 11, no. 5, pp. 85–92, 2020.
[5] A. Ratan, S. Gupta, and P. Mehta, "Real-time distracted driver detection using deep neural networks and head pose estimation," Expert Systems with Applications, vol. 214, pp. 119–131, Mar. 2023.
[6] Q. Zhang, N. Li, and Y. Zhao, "Driver emotion recognition under illumination variation using GAN-augmented convolutional networks," IEEE Access, vol. 11, pp. 22451–22463, 2023.
[7] World Health Organization, "Global Status Report on Road Safety 2023," WHO Press, Geneva, Switzerland, 2023. [Online]. Available: https://www.who.int/publications/i/item/9789240086517
[8] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, Jun. 2016, pp. 770–778.
[9] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
[10] A. Mollahosseini, B. Hasani, and M. H. Mahoor, "AffectNet: A database for facial expression, valence, and arousal computing in the wild," IEEE Transactions on Affective Computing, vol. 10, no. 1, pp. 18–31, Jan.–Mar. 2019.
[11] G. Jocher et al., "ultralytics/yolov5: v7.0 — YOLOv5 SOTA Realtime Instance Segmentation," Zenodo, Nov. 2022. [Online]. Available: https://doi.org/10.5281/zenodo.7347926
[12] T. Soukupova and J. Cech, "Real-time eye blink detection using facial landmarks," in Proc. 21st Computer Vision Winter Workshop, Rimske Toplice, Slovenia, Feb. 2016, pp. 1–8.