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# A Comprehensive Review on Machine Learning Techniques for Reckless Driving Detection

**Shilpy Sharma[1] • Mridula Singh[1] • Rashmi Sharma[2]**

[1]*Department of Computer Science and Engineering, Quantum University, Roorkee*
[2]*Department of Computer Science and Engineering, AKGEC Ghaziabad*

*Corresponding Author's Email Id: shilpy.cse@quantumeducation.in

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**Abstract:** With increased concerns over road safety and the incidence of reckless driving events, there is a greater demand for smart systems that identify and mitigate harmful driving behaviours. This study provides a detailed overview of machine learning approaches used in the field of reckless driving identification. The primary goal is to investigate the different approaches, algorithms, and models used for identifying patterns suggestive of potentially dangerous driving behaviour. The study comprises a detailed review of current research, showing significant advances in machine learning applications for reckless driving identification. A taxonomy of the various methodologies is offered, with classifications based on feature extraction, model topologies, and data sources. The review examines the constraints and limits of each approach, offering insights into potential areas for improvement and future research possibilities.

**Keywords:** Data Systems • Autonomous Cars • Distraction Detection • Driver Distraction • Driver Monitoring • Driving Distraction • Intelligent Transportation.

## Introduction:

Existing monitoring systems may be divided into two categories: sleepiness detection systems and distraction detection systems. However, the distinction between them is not evident because cognitive distraction might be connected to the driver's alertness in some circumstances (e.g., daydreaming). They both have an effect on the driver's physiological condition by decreasing awareness and consequently increasing reaction time. Electronics for driver assistance are found in abundance in modern automobiles (multimedia displays, navigation, temperature control, parking radar, etc.). Additionally, third-party entertainment gadgets like music players, PDAs, cell phones, etc. are diverting an increasing amount of the driver's attention, which is leading to an increase in traffic incidents and even accidents. 1.35 million fatalities attributed to traffic accidents were reported in 2018, according to the World Health Organization (WHO). Each year, traffic accidents damage almost 50 million people worldwide. As a result, in recent years, human safety while driving has become a major socioeconomic problem on a global scale. When a driver's attention wanders while they are driving, that is, when they are thinking about something other than the task of driving, it is known as a cognitive distraction. Distractions brought on by inattention, tiredness, or exhaustion include visual distractions. It most frequently refers to situations where drivers are using multimedia devices, such as navigation or entertainment systems and cell phones, which "salient visual information away from the road causing involuntary off-road eye glances and momentary rotation of the head. Olfactory distraction happens when an offensive or overpowering smell from the roadside disturbs the motorist. Gustatory distraction typically occurs if the motorist coughs as a result of the food's bitter or spicy flavor. It should be mentioned that gustatory distractions (a type of physical distraction) frequently occur after meals. Drivers may get cognitively, visually, or mechanically distracted as a result of these circumstances.

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**Literature Review:**

Driver distraction is detected by collecting photos using a camera mounted in front of the driver or within the automobile. The recorded photos are submitted for categorization in order to detect driving behaviours. Drivers are distracted in a variety of ways, as previously stated. Eating and drinking while driving, conversing with fellow passengers, using in-vehicle electronic gadgets ,watching roadside digital billboards/advertising/logo signs and using a mobile phone to contact or text are all popular distractions. Developing a system that can monitor distractions is an effective strategy to combat distracted driving. These strategies alter the in-vehicle information-system functionality based on the driver's condition. Correctly detecting the driver's status is critical in these systems. Some paper reviews in the form of their methodology, analysis, result and findings are mentioned in below table.

**Table 1: Some paper reviews in the form of their methodology, analysis, result and findings are mentioned in below table.**

| SN | AUTHOR | METHODS USED | FINDINGS AND RESULT ANALYSIS | FUTURE SCOPE |
|---|---|---|---|---|
| 1 | Qibtiah, Raja Mariatul, Zalhan Mohd Zin, and Mohd Fadzil Abu Hassan.(2023) | Classification of eye regions using HAAR and stacked CNN features.<br>Facial detection for identifying features and testing anomalies. | Accuracy over 80% at 456 iterations with minimal loss.<br>Detection of open and closed eyes with high classification accuracy.<br>Utilized CNN model with HAAR features for distraction detection. | Intelligent model with LSTM neural network for driving behavior estimation.<br>Sensor fusion layer for GPS and inertial sensor data synchronization. |
| 2 | Aliohani,Abeer .(2023) | Genetic algorithms with CNN models for driver behaviour classification.<br>DL models like VGG19, ResNet50, DenseNet121 for feature extraction.<br>KNN, random forest, SVM, extreme boost as classifiers. | Proposed model achieves 99.80% accuracy for driver distraction detection.DenseNet is the best feature extractor for driver distraction classification.KNN and SVM show best results for classification. | Evaluate newer convolutional layers as feature extractors for classification accuracy.<br>Assess MLP Mixer performance for driver distraction classification on new datasets |
| 3 | Wang,jing and Zhongchang Wu.(2023) | Multi-scale convolution for feature extraction.<br>Domain adaptation network to improve model adaptability.<br>Dropout in fully connected layer for generalization ability enhancement. | MSDAN outperformed other CNN models in driver distraction detection experiments.<br>MSDAN showed significant improvement in accuracy and generalization in experiments. | Construct larger dataset for improved generalisation performance in distracted driving.<br>Explore driver distraction detection models on videos for spatiotemporal features. |
| 4 | Aboah, Armstrong,et al.(2023) | Deep learning models like CNN, RNN, Transformers for feature extraction.<br>Proposed framework with Data, Segmentation, Classification, Postprocessing modules.<br>Rule-based algorithms, DL methods for activity recognition in driving videos. | DeepSegmenter ranked 8th with 0.5426 activity overlap score.<br>Proposed system effectively segments and classifies anomalies in driving videos. | Enhancing anomaly detection accuracy in real-time driving scenarios.<br>Integrating DeepSegmenter with Advanced Driver Assistance Systems for deployment. |
| 5 | Jayantha, gummula, and p. Velayutham. (2023) | Vehicle-based, behavioral-based, and physiological-based methods for drowsiness detection.<br>Adaptive thresholding technique developed for real-time drowsiness detection | Achieved 95.58% sensitivity and 100% specificity in SVM classification.<br>FLDA and SVM outperformed Bayesian classifier in the study. | Implement driver alert system based on drowsiness detection for real-time intervention.<br>Enhance system accuracy by integrating additional facial features for analysis. |
| 6 | Jahan, Israt, et al (2023) | Deep learning with CNN for drowsiness detection.<br>landmark coordination, image extraction, training algorithm, | 4D model achieved 97.53% accuracy,outperforming VGG16 and VGG19.4D model showed better precision and | Enhance drowsiness detection with heart rate monitoring for validation.<br>Implement head position |

| SN | AUTHOR | METHODS USED | FINDINGS AND RESULT ANALYSIS | FUTURE SCOPE |
|---|---|---|---|---|
| | | model extraction. | recall values than pre-trained models. | tracking to improve drowsiness detection robustness. |
| 7 | Rahman, Mohammed Shaiqur, et al. (2023) | Synthetic data collection with three in-vehicle cameras. Manual annotation of videos for each participant from three cameras. | Videos synchronized based on beep sound for gaze zone analysis. Annotation files for each participant with activity start and end times. Dash cam specifications and data acquisition requirements detailed. | Benchmarking ML models for driver behavior detection and classification. Enhancing driver-assist systems for improved road safety. |
| 8 | Parvez M, Muzammil, et al (2023) | Non-contact face detection using deep learning. Image processing for drowsiness | MTCNN outperformed Dlib in facial recognition with larger images. Caffe model from OpenCV in DNN module excelled in sleepiness detection. | Enhance detection with infrared camera for low-light situations. |
| 9 | Bajaj, Jaspreet Singh, et al (2023) | Hybrid model combining behavioral and physiological measures for drowsiness detection. MTCNN for facial feature recognition. Hardware components for implementation. | Proposed hybrid model detects driver drowsiness with 91% efficacy.GSR values indicate drowsy state, reducing camera limitations.Model uses AI-based MTCNN for facial features and GSR sensor.Behavioral and physiological measures combined for drowsiness detection. | Overcoming model limitations by analyzing larger datasets for validation. Enhancing accuracy by incorporating additional physiological and behavioral measures. |
| 10 | Rahman, M. Ashifur, Subasish Das, and Xiaoduan Sun. (2023) | Correspondence regression analysis for crash patterns identification Monte Carlo simulation for model identification and confidence intervals computation | Identified drowsy driving crash patterns based on injury levels. Attributes associated with fatal and severe injury crashes were determined. | Develop pattern-based drowsy driving operational definitions for prevention strategies. Enhance identification and minimization of underreported drowsy driving crashes |
| 11 | Akrout, Belhassen, and Sana Fakhfakh. (2023) | MediaPipe Face Mesh for face landmarks and eye tracking. MobileNetV3 for iris detection and feature extraction. LSTM network for driver fatigue detection based on extracted features. | Proposed model achieves 98.4% accuracy in driver fatigue detection. Multilevel fatigue detection system alerts drivers before falling asleep. Utilizes MediaPipe Face Mesh for face and eye localization success. | Consider changing light conditions for system enhancement. Detect severe distraction states and driver yawning for system improvement. |
| 12 | Bahmani, Zahra (2022) | Moving average filter, feature extraction, physiological signal range validation Connectivity analysis, functional and effective connectivity methods, facial expression signals Granger causality calculation, dimension reduction, confusion matrix analysis | Detected driver distraction using facial expressions and perinasal perspiration. Extracted 225 features from facial expressions for distraction detection | Enhancing driver safety through continuous distraction detection using facial expressions. Potential applications in real-time driver monitoring systems for improved safety. |
| 13 | Oppelt, Maximilian P., et al.(2022) | Driving simulator with physiological signals, face videos, eye tracker data. Induced cognitive load with n-back test and k-drive test. Statistical evaluation, | Statistical evaluation for subjective and performance measurements. Changes in physiological signals during cognitive load. Behavioral measurements | Enhance model training with subjective ratings and task-specific information Improve classification tasks for cognitive load levels with machine learning |

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|---|---|---|---|---|
| | | machine learning tasks for cognitive load classification. | based on facial videos for cognitive load prediction. | |
| 14 | Xue, Qingwan, et al. (2023) | SVM model with parameter optimization. Random forest model with grid search for parameterization. | SVM model outperformed random forest model in all aspects. Genetic algorithm provided the best parameter optimization effect. Lateral indicators had better identification effect than longitudinal indicators. | Study cognitive distraction in natural driving conditions for real-world applicability. Investigate cognitive distraction effects on eye movements and heart physiology. |
| 15 | Xintao Yan Zhengxia Zou Shuo Feng ,Haojie Zhu , Haowei Sun & Henry X. Liu (2023) | NeuralNDE framework for learning multi-agent behavior from trajectory data. Conflict critic model and safety mapping network for refining event generation. Behavior modeling network with frequency encoding and prediction heads. | NeuralNDE achieves realistic safety-critical and normal driving statistics in simulations. The model reproduces real-world driving environments with statistical realism | Consider AV influences on surrounding vehicles for future research. Enhance AV behavior modeling for improved safety-critical conditions. Calibrate acceptance probability for accurate crash rate and type distribution. |

**Methodology:**

The methodology used in this study is based on a qualitative review. A comprehensive review of recent research articles (2020–2023) on machine learning methods for detecting risky and inattentive driving was carried out. Studies using computer vision, deep learning (e.g., CNN, LSTM), physiological sensors, and hybrid AI models were the main emphasis of the selection. Comparing approaches in terms of feature extraction, classification accuracy, model robustness, and possibility for real-time implementation was the main goal. This comparison method aids in discovering patterns, advantages, weaknesses, and areas in the field that require more research.

**Results and Discussion:**

Together, the evaluated research highlight how artificial intelligence is increasingly being incorporated into traffic safety systems. Convolutional neural networks (CNNs), support vector machines (SVMs), and hybrid deep learning architectures are among the machine learning techniques that have shown great accuracy in identifying tiredness and distraction; some models have even surpassed 95% accuracy in this regard.

Even though these findings are encouraging, the majority of experiments are carried out in controlled or simulated settings. This limits these models' scalability and generalizability under actual driving circumstances. Another important realization is that performance comparison and model replication are hampered by the scarcity of benchmark datasets.

The significance of integrating behavioural and physiological data, including head posture, gaze, face landmarks, and GSR, for improved detection accuracy is a major topic of discussion. Real-time responsiveness and the integration of multimodal data sources continue to be important areas for future study. Therefore, rather than suggesting a novel algorithm, this paper offers a comprehensive overview of existing methods, points out important drawbacks, and offers solutions for enhancing the implementation of AI-based driver monitoring systems in the actual world.

**Performance Analysis of AI Systems for Driver Behavior Detection**

This chart visualizes the performance metrics (e.g., accuracy, overlap score) of 15 different AI-based systems for driver distraction and drowsiness detection, based on recent research publications from 2023. The models use a range of techniques including CNN, LSTM,

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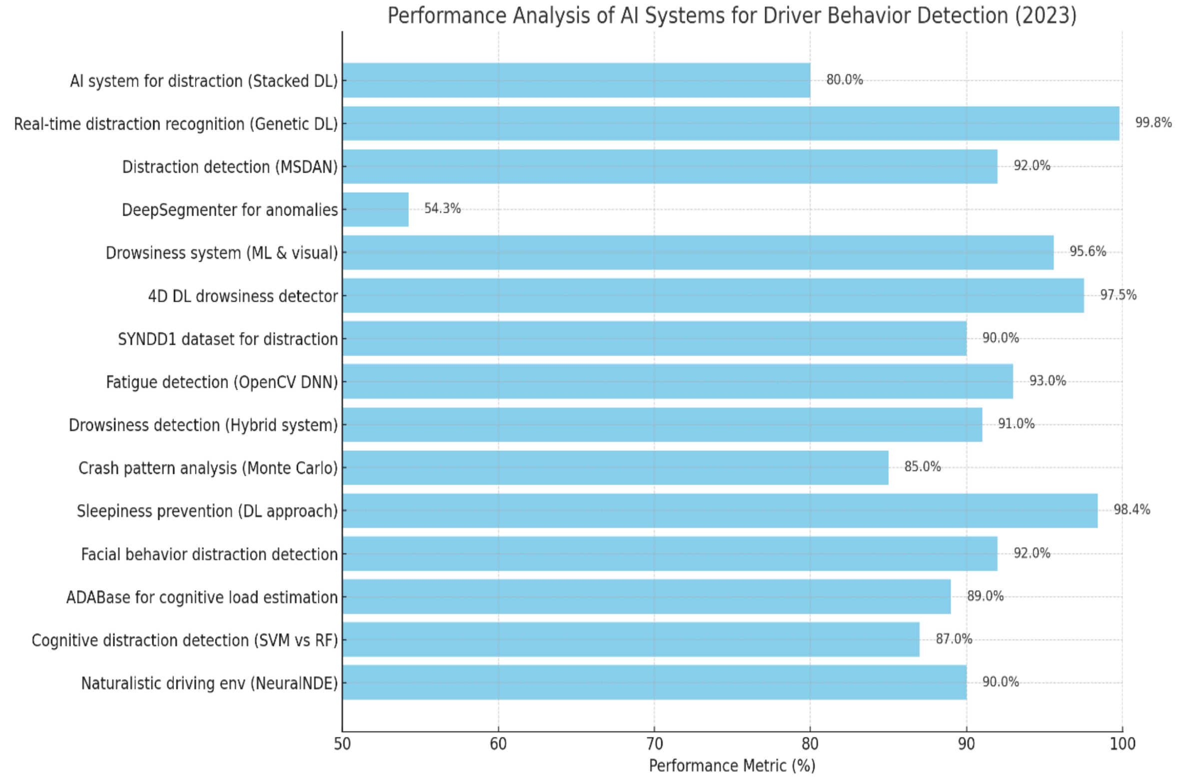
MediaPipe, genetic algorithms, and synthetic data.




**Research Gap and scope of future work:**

Road safety remains a critical concern, and the emergence of machine learning has opened up new options for solving the challenges posed by risky driving behaviours. This extensive review looks at the landscape of machine learning approaches used to detect reckless driving. While investigating existing approaches, models, and data sources, a clear research need arises. Despite significant advances, there is a need for more standardised assessment measures and datasets to enable meaningful comparisons across various methodologies.

The current research gap centres on the lack of a unified framework for evaluating the effectiveness of machine learning models in reckless driving detection. Diverse datasets, varying feature extraction techniques, and distinct evaluation criteria hinder a comprehensive understanding of the strengths and limitations of different approaches. Standardization in these aspects would not only enhance the reproducibility of results but also foster a more systematic advancement of the field.

Establishing standardised evaluation techniques, including benchmark datasets and performance criteria, should be the main goal of any future studies. Researchers can compare their suggested efforts with those of others on a near-standard dataset if additional relevant datasets with specified qualities become publicly accessible. Prior research has demonstrated that augmenting machine learning methods with spatial and temporal data enhances the comprehension of the driver's movements. As a result, driver distractions can be precisely identified. To provide deep architectures more data, data augmentation is required. With additional processing power, the accuracy may be increased by building networks from scratch, like capsnet3D, using the Kinetics dataset and fine-tuning them using data on driver manual distraction.

Eye tracking-based driver distraction detection algorithms aim to identify visual distraction. All algorithms can be fitted into a common framework: determine whether or not the driver is looking at the road, convert this information into a continuous estimate of (visual) distraction, and then use some rule, often a threshold, to determine whether the estimated level of distraction should be considered distracted or attentive. The fundamental shortcoming of these techniques is that they do not account for the present traffic scenario. This might be accomplished by enabling the driving-relevant field to alter dynamically over time. Future study is required to (a) establish the ideal driving field for various traffic conditions and traffic environments, and (b) create technologies to measure the present traffic situation and traffic environment.

Future studies are required to (a) examine the physiology of eye movements while driving, (b) create more accurate remote eye tracking technology so that these quick and small eye movements can be measured, and (c) create algorithms that reliably and accurately identify various eye movements such as fixations, saccades, and smooth pursuit from the continuous data stream.

**Conclusion:**

This paper provides a thorough analysis of the most recent methods employed in this area, highlighting the expanding significance of machine learning in identifying careless driving and driver attention. The study examines a number of models, demonstrating their efficacy in detecting risky driving practices, such as deep learning, neural networks, and sensor-based techniques. This study offers a thorough grasp of how technology might improve road safety by examining various approaches, advantages, and disadvantages.

This research is captivating since it compares various machine learning techniques in an organized manner and highlights the necessity of uniform evaluation frameworks. One important conclusion is that although existing models work well in controlled settings, they still require work to be more applicable in the actual world. Incorporating real-time monitoring, improving detection accuracy, and making sure these systems can adjust to a variety of driving situations should be the main goals of future developments.

This paper's ultimate goal is to close the knowledge gap between research and real-world application, directing future advancements in intelligent driver support systems. Machine learning has the ability to not only identify but also stop reckless driving with sustained innovation and cooperation, improving road safety for all.

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