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Driver Behavior Assessment Using Machine Learning in ADAS and ITS

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***Abstract*—Unsafe driving behaviors such as fatigue, aggressive acceleration, and distraction contribute to 94% of traffic accidents and significantly impact fuel efficiency and emissions. Current ITS and ADAS technologies are largely reactive, lacking predictive capabilities for real-time risk prevention. This study presents a machine learning-based approach to proactively assess driver behavior using Random Forest, XGBoost, and Neural Networks. Data is collected from telematics systems, GPS tracking, on-board diagnostics, and driver monitoring sensors across public transport fleets. The methodology involves feature engineering, model training, cross-validation, and real-world scenario testing. The proposed system aims to enhance road safety, reduce fuel consumption, and lower emissions by integrating predictive analytics into existing ITS and ADAS infrastructure. The research adheres to ethical standards, ensuring data privacy and fairness, and offers actionable insights for transport authorities, policymakers, and fleet managers seeking intelligent and sustainable mobility solutions. The findings offer practical insights for transport operators, policymakers, and safety advocates toward achieving sustainable and intelligent mobility solutions.**

Keywords—Driver Behavior, Machine Learning, ADAS, ITS, Telematics Data, Predictive Modeling, Road Safety, XGBoost, Neural Networks, Fuel Efficiency.

I. Introduction

The evolution of Intelligent Transportation Systems (ITS) and Advanced Driver Assistance Systems (ADAS) has significantly shaped modern transportation by improving monitoring and control mechanisms. However, persistent challenges in road safety, fuel efficiency, and environmental sustainability remain, particularly due to unsafe driver behaviors such as fatigue, distraction, and speeding. These behaviors are responsible for an estimated 94% of road accidents, leading to about 1.3 million deaths annually (WHO, 2021; NHTSA, 2020). Furthermore, aggressive driving can increase fuel consumption and emissions by up to 40% and 30%, respectively (IEA, 2021).

While existing ADAS and ITS technologies offer real-time alerts, they are largely reactive, triggering interventions after risky behavior has already occurred. This study proposes a proactive solution using machine learning (ML) to predict unsafe driving behaviors before they manifest. By leveraging algorithms such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Neural Networks, the system can detect patterns of risk in real time.

The aim of this study is to provide a predictive analytics model integrated with telematics and sensor data, enhancing road safety, operational efficiency, and reducing environmental impact. This is particularly valuable for public transport fleets, where vehicles operate under diverse and challenging urban conditions. The model supports informed decision-making for fleet operators, regulators, and policymakers while maintaining ethical data usage and fairness.

The study focuses on evaluating a predictive ML model that can anticipate risky driving behavior and integrate it into real-time ITS and ADAS applications. The core objectives are:

Analyze driver behavior patterns using real-time vehicle telematics data.

Evaluate and compare ML techniques (Random Forest, XGBoost, Neural Networks) for behavior prediction.

Optimize model accuracy through feature selection, hyperparameter tuning, and ensemble learning.

Validate ML models using real-world driving scenarios.

This study focuses on public transport fleet drivers operating in urban environments. Data sources will include telematics data, GPS tracking, vehicle sensors, and driver biometrics. The study will specifically target:

Prediction of unsafe driving events (e.g., harsh braking, speeding, distracted driving).

Impact of driving behavior on fuel efficiency and emissions.

Integration of ML-based insights into existing ADAS technologies.

The research addresses primary questions:

Which algorithm performs best accuracy in predicting unsafe driving within ITS/ADAS settings

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I. *Proposed Research Approach and Methodology*

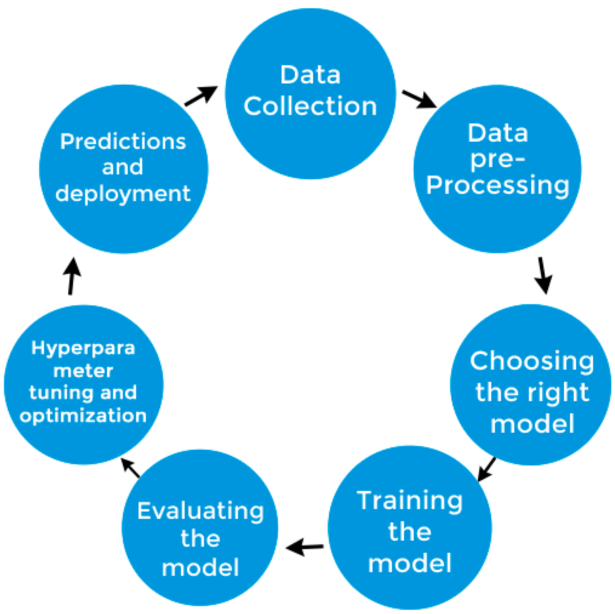

Figure 1: Methodology Overview

The study adopts a multi-phase methodology to ensure a robust evaluation of driver behavior using machine learning. The process begins with comprehensive data collection from telematics, OBD, and driver monitoring systems, targeting public transport drivers in urban UAE settings. Data are preprocessed through feature engineering to extract relevant indicators of unsafe driving behavior. Multiple ML models—Random Forest, XGBoost, CNN-LSTM, and GNN—are trained and validated. Model performance will be assessed using metrics such as accuracy, F1-score, and ROC-AUC through k-fold cross-validation and real-world driving scenario tests to ensure generalizability and fairness.

Table 1: Research Approach and Methodology Flow

Section	Description
Research Ethics	-Ensures compliance with GDPR and data privacy laws, anonymization of driver data, and mitigation of bias in ML models for fairness.
The Methodology	-Multi-phase approach integrating data collection, feature engineering, ML model development, and real-world validation.
Data Sources & Collection	- Sources: On-board diagnostics (OBD) data, GPS tracking systems, CAN bus signals, and Camera-based driver monitoring systems. - Collection: IoT sensors, vehicle diagnostics, and real-world driving datasets.
Analytical Approach	- Feature Engineering: Identifies key behavioral indicators (speed, braking, fatigue, lane changes). - ML Models: Random Forest, XGBoost, CNN-LSTM, Graph Neural Networks (GNNs). - Evaluation: Accuracy, F1-score, ROC-AUC, real-world validation.
Required Technology	- Software: Python (Scikit-learn, TensorFlow, PyTorch), MATLAB. - Hardware: Cloud-based computing, edge AI for real-time processing.

II. LITERATURE REVIEW

Prior studies have demonstrated the potential of machine learning (ML) to predict and understand driver behavior. Khan et al. (2021) utilized artificial neural networks (ANNs) on a dataset of 94,000 instances with 54 features, achieving a high correlation (0.9962) between predicted and actual driver actions. However, they noted instability in early training, which limits real-time adaptability. Niu et al. (2021) applied traditional classifiers such as GBDT, AdaBoost, and Random Trees to detect unsafe truck driver behaviors. Model accuracy ranged from 0.64 to 0.95, and F1 scores varied from 0.52 to 0.72, highlighting challenges in predicting rare, context-specific behaviors. Their study also underscored the value of using correlation and odds ratios to interpret risk.

Abdelrahman et al. (2020) developed a Random Forest-based risk profiling model using the SHRP2 dataset, achieving 90% accuracy and an F1-score of 0.945. Their framework supported continuous learning via cloud-based updates. In vision-based systems, Qu et al. (2024) used a hybrid CNN-BiLSTM model to detect distracted driving, achieving 91.7% accuracy but struggling with full-body posture recognition. This reveals the need for multimodal systems integrating visual and sensor data.

Table 2: Summary of the Literature Review

Author/Year	Purpose/Objectives	Methodology, Findings, Discussion
Khan et al. (2021)	Develop an ANN-based driver behavior model to predict intelligent	Used Dynamic Nonlinear Autoregressive ANN validated through time-series backpropagation, multilayer perceptron (MLP), random subspace, linear regression, and

	driving patterns.	decision tree. Dataset: 94,380 instances, 54 attributes (MATLAB & Weka). MLP had the highest accuracy: 0.9962 correlation coefficient, 30.39 MAE, 69.44 RMSE. Findings showed ANN models effectively capture behavioral changes in ADAS and ITS. However, early-phase fluctuations limit real-time adaptation.
Niu et al. (2021)	Investigate unsafe truck driver behavior using classification models.	Surveyed 2,000 truck drivers and classified behavior based on six first-level input dimensions and 51 second-level indicators. Compared GBDT, AdaBoost, RT, and CART models. Accuracy varied by behavior type: Classification accuracy (0.64–0.95), F1-scores (0.52–0.72). Findings showed difficulty in predicting behaviors due to different formation mechanisms. Recommended a hybrid ML approach integrating context-aware data.
Elassad et al. (2020)	Review ML applications in Driving Behavior (DB) and propose a conceptual framework (Driver-Vehicle-Environment System).	Systematic Literature Review (SLR) of 82 studies (2009–2019). Identified 8 widely used ML models for DB. ML outperformed traditional models in prediction accuracy. Challenges: Lack of standard evaluation frameworks and model generalizability. Unlike Khan et al. (2021) and Niu et al. (2021), emphasized holistic behavioral modeling.
Abdelrahman et al. (2020)	Propose a machine learning-based driver profiling framework for risk assessment in fleet management and insurance telematics.	Used SHRP2 dataset (9,000 crash events, 20,000 baseline events). Compared Random Forest (90% accuracy, F1-score 0.945), Deep Neural Networks (88.8%), and Extreme Learning Machines (86.2%). Findings: ML-based risk assessment is scalable, supports IoIV, and improves insurance risk evaluation.
Ontañón et al. (2020)	Improve long-term driving behavior prediction through indirect prediction.	Evaluated Baseline averaging, Linear Regression, M5P regression trees, and MLP neural networks. Linear regression had the lowest MSE (0.03 for steering, 6.79 for throttle, 1.26 for braking). However, long-term prediction errors compounded, limiting supervised learning models. Proposed context-based reasoning and indirect prediction to improve reliability.
Qu et al. (2024)	Computer vision and ML are used to classify driver behavior via distracted driver monitoring.	Applied CNN-BiLSTM models to detect distracted driver postures. Evaluated 10 deep learning models on AUC's Distracted Driver Dataset. Best model: CNN-BiLSTM (91.7% accuracy, 93.1% F1-score). Despite high accuracy, noted CNNs struggle to analyze full-body postures. Recommended enhancing feature engineering for ADAS.
Azadani & Boukerche (2021)	Apply ITS-oriented approach to driving behavior analysis (DBA).	Integrated in-vehicle networks, sensors, and communication technologies to improve traffic safety, fuel efficiency, and driver risk profiling. Unlike Qu et al. (2024), which relied on computer vision-based CNN models, ITS methods provided sensor-driven, multimodal risk assessment.
Chandra et al. (2021)	Apply graph-theoretic ML to predict driver behavior in AV navigation.	Used StylePredict (GCN & MLP models) on real-world traffic datasets (U.S., India, China, Singapore). Findings: AVs adapted lane-changing behavior dynamically—in conservative traffic, AVs overtook confidently; in aggressive traffic, fewer lane changes reduced risk. AV speeds: 29 m/s (aggressive) vs. 19.7 m/s (conservative). Unlike traditional AV models, graph-based reinforcement learning enables social awareness and efficient navigation.

III. Research Gaps

Despite progress in machine learning (ML) for driver behavior analysis, key gaps remain. Current models lack generalizability across varied environments and suffer from bias, reducing predictive accuracy (Khan et al., 2021; Niu et al., 2021). Hybrid approaches using ML, computer vision, and sensor fusion show potential (Qu et al., 2024), but struggle with real-time adaptability (Chandra et al., 2021). The absence of standardized evaluation frameworks limits cross-study comparisons (Elassad et al., 2020), and data privacy concerns restrict large-scale deployment.

ML models can predict risky behavior and improve ADAS, but often ignore long-term reliability and fluctuating driving conditions (Ontañón et al., 2020). CNNs excel in classification but lack full-body posture detection for distraction analysis (Qu et al., 2024). Sensor-based methods require integration with real-time risk assessment (Azadani & Boukerche, 2021).

Future research should focus on hybrid ML models that integrate heterogeneous data sources, such as biometrics and environmental variables (Imani et al., 2025), and expand to public transport systems and sustainability impacts (Moujahid et al., 2018; EPA, 2024).

IV. Conclusion

This study proposes a predictive driver behavior modeling using machine learning to enhance safety, efficiency, and environmental sustainability through integration with ITS and ADAS.

This research contributes in several meaningful ways:

A robust ML-driven predictive model that supports real-time risk mitigation.

A comparative model evaluation across RF, XGBoost, Neural Networks, and GNNs.

A rich dataset and feature set tailored to the needs of urban public transport fleets.

An ethical and practical implementation strategy ensuring adaptability and acceptance.

The solution benefits fleet operators (through improved efficiency and safety), policymakers (via data-driven interventions), and insurance providers (via more accurate risk profiling). The project also supports sustainability by reducing fuel usage and emissions through better driving practices.

This work directly addresses the core research objective of evaluating predictive ML models for risky driving behavior using real-time sensor data. The findings provide a foundation for future pilot implementations in UAE's public transportation sector. Subsequent research could explore integrating these models into live ITS dashboards, enhancing real-time traffic interventions and policy planning.

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