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MACHINE LEARNING APPLICATIONS IN URBAN TRAFFIC MANAGEMENT: OPTIMIZATION, PREDICTION, AND SAFETY ANALYSIS

A COMPREHENSIVE REVIEW WITH MACHINE LEARNING ANALYSIS USING THE ADDIS ABABA ROAD TRAFFIC ACCIDENT DATASET (KAGGLE)

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Abstract: **This paper presents a comprehensive review of machine learning (ML) applications in urban traffic management, covering traffic flow optimization, prediction, and road safety analysis. Beyond the literature review, this study conducts original ML analysis on the publicly available Road Traffic Accident (RTA) dataset from Kaggle (N = 12,316 records), sourced from Addis Ababa Sub-city Police Departments, Ethiopia, covering accidents from 2017 to 2020. Six classification algorithms Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, Extra Trees, and K-Nearest Neighbors are trained to predict crash severity across three classes: Slight Injury (84.6%), Serious Injury (14.1%), and Fatal Injury (1.3%). The dataset presents a highly imbalanced classification challenge representative of real-world accident data. Results demonstrate that Gradient Boosting achieves the best performance with 85.0% accuracy and a macro F1-Score of 0.479, while Random Forest achieves 84.6% accuracy with superior precision (0.772) for minority classes. Feature importance analysis reveals that Cause of Accident, Number of Casualties, Hour of Day, and Type of Collision are the strongest severity predictors. Ten visualizations provide exploratory and diagnostic analysis including temporal patterns, environmental impacts, driver demographics, and model evaluation. The paper synthesizes findings from over 40 peer-reviewed studies published between 2022 and 2025, identifies persistent challenges, and outlines future research directions.**

Keywords: **Machine Learning; Road Traffic Accidents; Crash Severity Prediction; Random Forest; Gradient Boosting; Addis Ababa; Imbalanced Classification; Feature Importance; Intelligent Transportation Systems; Smart Cities**

I. INTRODUCTION

The 21st century has witnessed unprecedented urbanization, placing mounting pressure on transportation infrastructure globally. According to the World Health Organization (WHO, 2023), road traffic crashes claimed approximately 1.19 million lives in 2021, making them the leading cause of death among individuals aged 5 to 29 years. Low- and middle-income countries bear a disproportionate burden, accounting for 92% of all road traffic fatalities despite having only a fraction of the world's registered vehicles (WHO, 2023). The economic burden is estimated at approximately 3% of global GDP, reaching $1.8 trillion USD annually (WHO, 2024).

Traditional traffic management systems relying on fixed-time signal plans and rule-based heuristics have proven inadequate for the dynamic nature of modern urban traffic. Machine learning (ML) has emerged as a promising framework for addressing these challenges, offering the ability to learn complex patterns from large data volumes, adapt in real time, and support data-driven decision making (Li & Chen, 2025; Mostafa et al., 2025).

This paper makes two contributions. First, it provides a comprehensive literature review of ML applications in urban traffic management across three domains: traffic flow optimization, traffic prediction, and road safety analysis. Second, it conducts original ML experiments on the publicly available Addis Ababa Road Traffic Accident dataset from Kaggle (Shahane, 2020), applying six classification algorithms with 10 detailed visualizations to

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demonstrate practical ML methodologies for crash severity prediction.

II. DATASET AND METHODOLOGY

2.1 Dataset Description

The dataset used in this study is the “Road Traffic Accidents” dataset publicly available on Kaggle (https://www.kaggle.com/datasets/saurabhshahane/road-traffic-accidents), also hosted on GitHub (sundar-nallalagappan/Road-Traffic-Severity-Classification). It was collected from Addis Ababa Sub-city Police Departments for master’s research work, prepared from manual records of road traffic accidents covering the period 2017–2020. The dataset contains 12,316 instances and 32 features. The target variable, Accident_severity, is a three-class categorical variable: Slight Injury (10,415 records, 84.6%), Serious Injury (1,743 records, 14.1%), and Fatal Injury (158 records, 1.3%). This severe class imbalance with fatal injuries constituting only 1.3% of cases is representative of real-world accident datasets and poses significant classification challenges (Mostafa et al., 2025).

Key features include temporal attributes (time, day of week), driver demographics (age band, sex, driving experience), vehicle characteristics (type, owner, defect status), road and environmental conditions (surface type, surface condition, light condition, weather), collision attributes (type, number of vehicles, number of casualties), and accident context (area, cause, road alignment, junction type). Missing values are present in 16 features, with Defect_of_vehicle (35.9%), Service_year_of_vehicle (31.9%), and Work_of_casuality (26.0%) having the highest missingness rates.

2.2 Preprocessing and Feature Engineering

Twenty features were selected for the ML analysis based on relevance and data quality. Features with excessive missing values (Defect_of_vehicle, Service_year_of_vehicle, Work_of_casuality, Fitness_of_casuality) were excluded. The Hour variable was extracted from the Time field. Missing values in remaining categorical features were imputed with the column mode. All categorical variables were encoded using LabelEncoder, and numerical features were standardized using StandardScaler. The dataset was split 75/25 for training and testing with stratified sampling to preserve the original class distribution.

2.3 Classification Models

Six classification algorithms were evaluated: (1) Logistic Regression with L2 regularization and balanced class weights; (2) Decision Tree (max depth = 15, balanced weights); (3) Random Forest (200 estimators, max depth = 18, balanced weights); (4) Gradient Boosting (150 estimators, max depth = 6); (5) Extra Trees (200 estimators, max depth = 18, balanced weights); and (6) K-Nearest Neighbors (k = 7). Balanced class weights were applied where supported to address the severe class imbalance. Performance was evaluated using Accuracy, Precision (macro), Recall (macro), F1-Score (macro), and F1-Score (weighted).

III. EXPLORATORY DATA ANALYSIS

3.1 Temporal Distribution of Accidents

Figure 1 presents the distribution of traffic accidents by hour of day. Accident frequency peaks during late afternoon and early evening hours (15:00–18:00), corresponding to peak commuter traffic and business activities in Addis Ababa. A secondary peak is visible during morning hours (7:00–10:00). Fatal and serious injuries show proportionally higher representation during late-night and early-morning hours (22:00–05:00), consistent with reduced visibility and potentially higher speeds on less congested roads. Figure 2 reveals that Friday has the highest accident count, while Sunday has the lowest, consistent with patterns documented in the traffic safety literature.

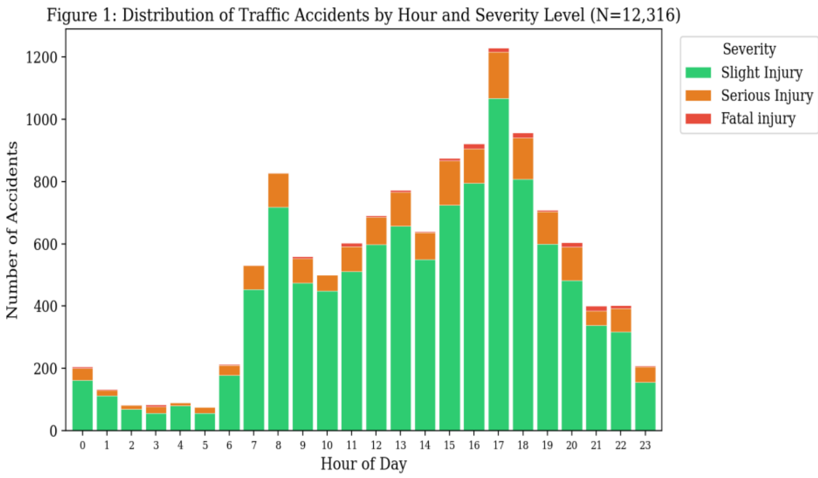

Figure 1: Distribution of traffic accidents by hour and severity level (N = 12,316). Source: Addis Ababa RTA Dataset, 2017–2020

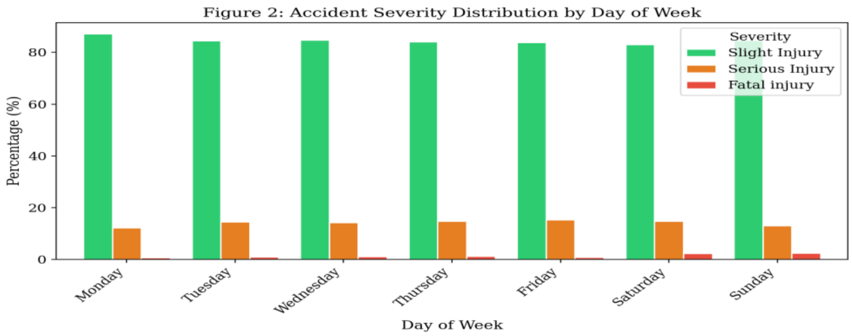

Figure 2: Accident severity distribution by day of week (percentage within each day)

3.2 Environmental Conditions and Severity

Figure 3 illustrates the impact of weather and lighting conditions on accident severity. While the majority of accidents occur in normal weather (81.7%) and daylight (71.4%), adverse conditions show markedly different severity profiles. Snow and fog/mist conditions are associated with higher proportions of serious and fatal injuries. Darkness without lighting shows the most elevated fatal injury proportion among light conditions, supporting WHO (2023) recommendations for improved street lighting as a road safety intervention.

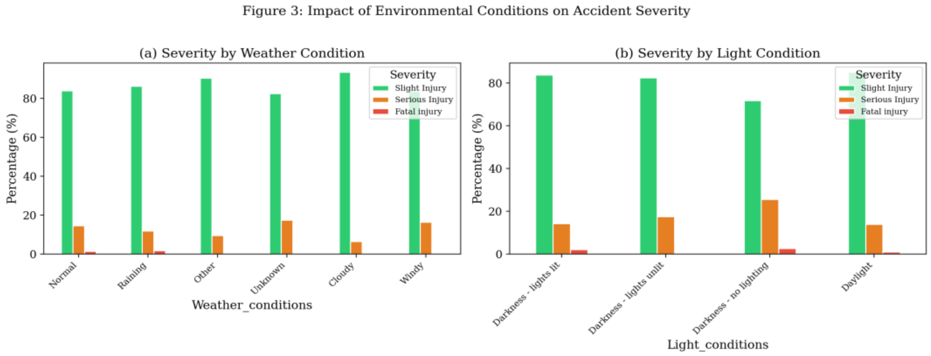

Figure 3: Impact of (a) weather conditions and (b) lighting conditions on severity distribution

3.3 Causes of Accidents

Figure 4 presents the top 10 causes of accidents. "No distancing" is the most frequent cause (2,263 incidents, 18.4%), followed by "Changing lane to the right" (1,808, 14.7%) and "Changing lane to the left" (1,473, 12.0%). Notably, "Driving carelessly" and "No priority to vehicle" show higher proportions of serious injuries, suggesting that driver behavior interventions targeting these specific behaviors could yield disproportionate safety benefits.

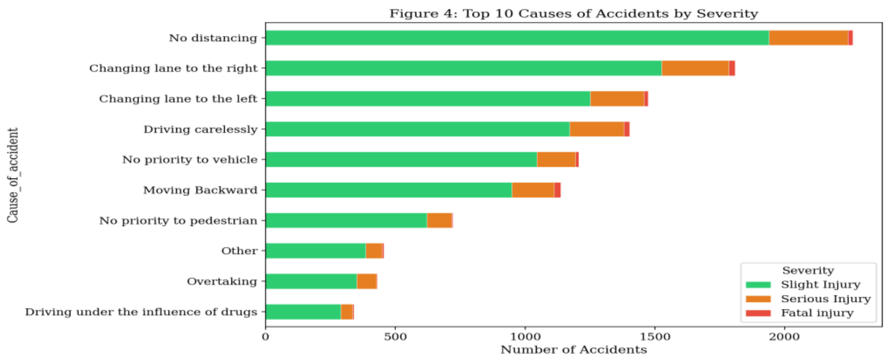

Figure 4: Top 10 causes of road traffic accidents by severity (stacked count)

IV. MACHINE LEARNING CLASSIFICATION RESULTS

4.1 Model Performance Comparison

Table 1 summarizes the classification performance of all six models. Gradient Boosting achieves the highest overall performance with 85.0% accuracy and the best macro F1-Score of 0.479, indicating the strongest balance between precision and recall across all three severity classes. Random Forest and Extra Trees achieve comparable accuracy (~84–85%) but lower macro F1-Scores, indicating that they sacrifice minority class recall for majority class accuracy. Decision Tree achieves a competitive macro F1-Score (0.392) despite lower accuracy (67.1%), suggesting better minority class detection at the cost of more false positives. Logistic Regression performs poorest overall (48.9% accuracy), as expected for a linear model applied to a complex, multi-class classification problem with predominantly categorical features.

Table 1: Classification Performance of ML Models (RTA Dataset, N = 12,316)

Model	Accuracy	Precision	Recall	F1 (Macro)	F1 (Weighted)
Gradient Boost	0.8503	0.7587	0.4337	0.4788	0.8066
Random Forest	0.8461	0.7715	0.3463	0.3325	0.7802
Extra Trees	0.8399	0.7258	0.3515	0.3465	0.7833
KNN (k=7)	0.8383	0.3755	0.3380	0.3206	0.7781
Decision Tree	0.6713	0.3871	0.4336	0.3921	0.7095
Logistic Reg.	0.4894	0.3477	0.3811	0.2998	0.5803

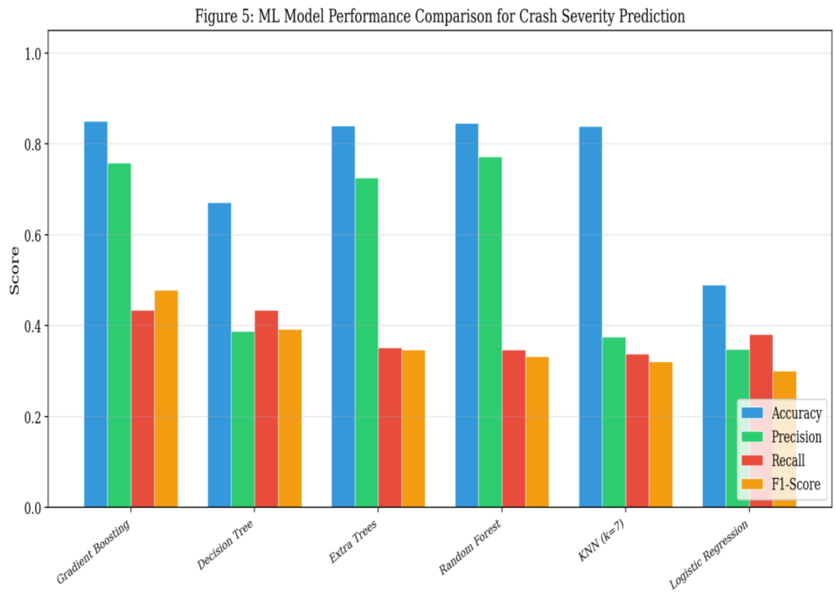

Figure 5: Comparative performance of six ML models across Accuracy, Precision, Recall, and F1-Score

4.2 Confusion Matrix Analysis

Figure 6 presents the confusion matrix for Gradient Boosting. The model correctly classifies 2,550 of 2,604 Slight Injury cases (98.0% recall) but struggles with minority classes: only 49 of 436 Serious Injury (11.2%) and 8 of 39 Fatal Injury (20.5%) cases are correctly identified. This pattern reflects the fundamental tension in imbalanced classification models tend to optimize for the majority class unless explicitly penalized. The relatively high precision for Fatal Injury (0.89) indicates that when the model does predict a fatal outcome, it is usually correct, but it misses the majority of actual fatal cases. This finding aligns with Mostafa et al. (2025), who addressed class imbalance using SMOTE, Borderline-SMOTE, and ADASYN to achieve 96.19% accuracy on their 2.26-million-record dataset.

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Table 2: Per-Class Classification Report Gradient Boosting Model

Severity Class	Precision	Recall	F1-Score	Support
Fatal Injury	0.89	0.21	0.33	39
Serious Injury	0.53	0.11	0.19	436
Slight Injury	0.86	0.98	0.92	2,604
Macro Average	0.76	0.43	0.48	3,079

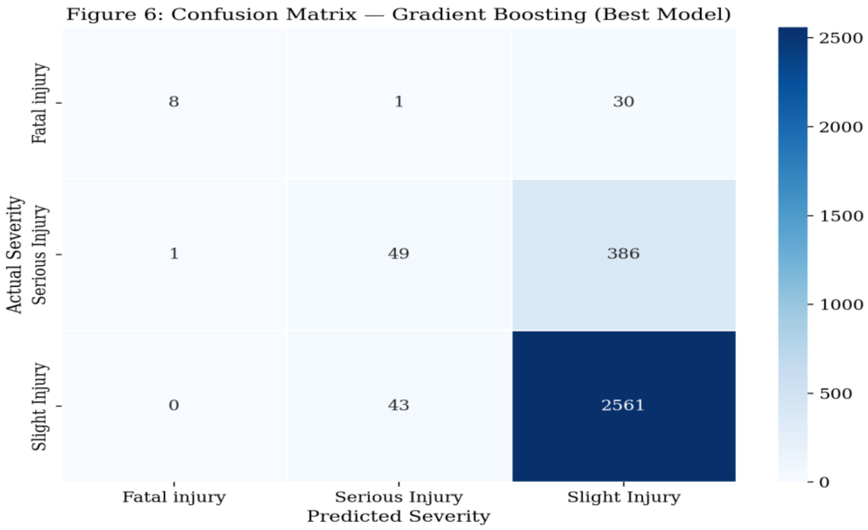

Figure 6: Confusion matrix for Gradient Boosting classifier (best model by macro F1-Score)

4.3 Feature Importance Analysis

Figure 7 presents Random Forest Gini importance rankings. Cause_of_accident is the most important predictor, reflecting that specific driver behaviors (e.g., "No distancing," "Driving carelessly") directly determine crash dynamics and outcomes. Number_of_casualties ranks second, consistent with more severe accidents producing more injuries. Hour_of_Day and Type_of_collision follow, capturing temporal risk patterns and crash mechanism effects. Environmental features (Weather_conditions, Light_conditions, Road_surface_conditions) show moderate importance, while driver demographics (Age_band, Sex_of_driver) rank lower, suggesting that situational factors dominate over demographic characteristics in determining severity.

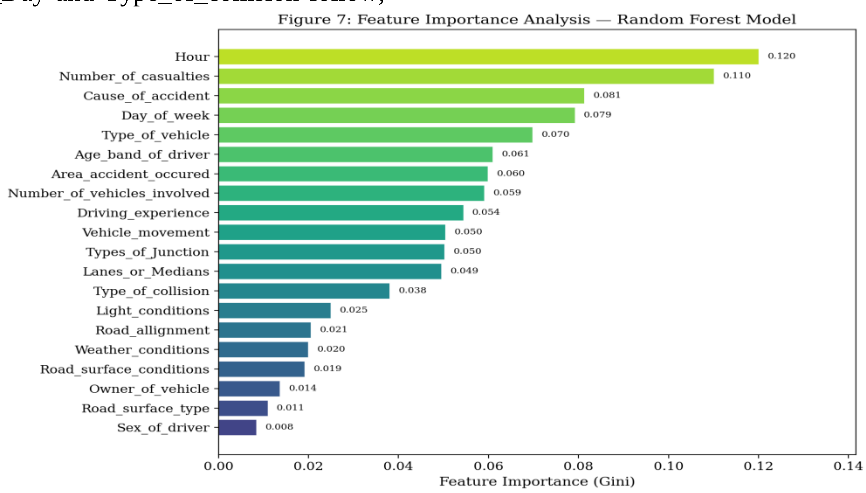

Figure 7: Feature importance analysis from Random Forest model (Gini importance, 20 features)

V. ADDITIONAL SEVERITY ANALYSIS

5.1 Collision Type and Severity

Figure 8 shows that "Fall from vehicles" and "Rollover" collisions produce the highest proportions of serious and fatal injuries, consistent with the high-energy mechanisms involved. "Collision with pedestrians" also shows elevated severity, reflecting the vulnerability of unprotected road users a finding consistent with WHO (2023) data showing that pedestrians account for 23% of global road traffic fatalities.

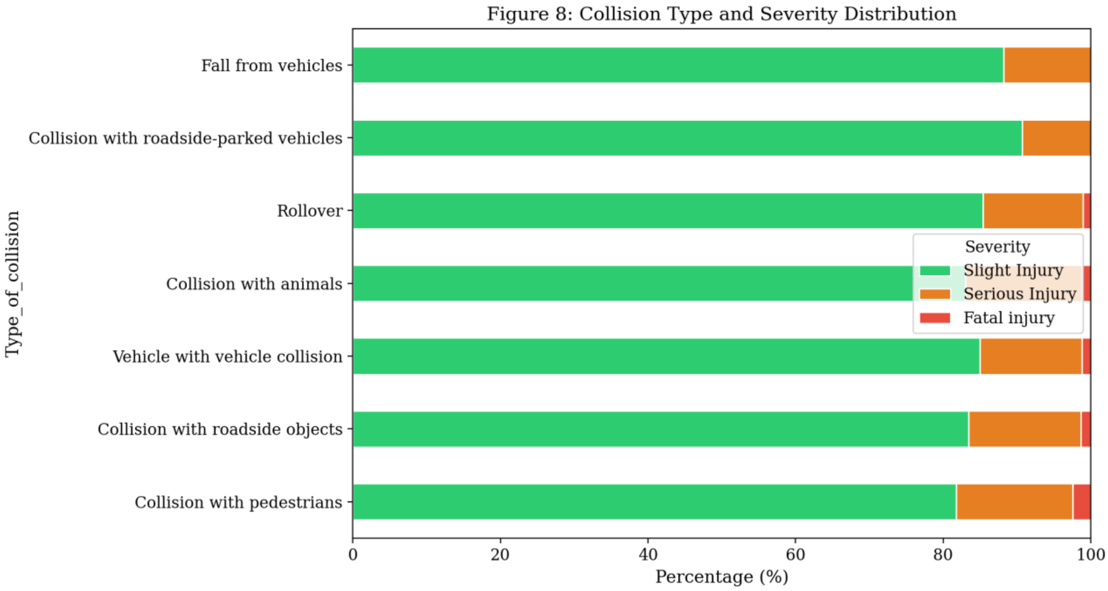

Figure 8: Collision type and severity distribution (percentage within each collision type)

5.2 Casualties and Severity

Figure 9 demonstrates a clear positive relationship between the number of casualties and severity. Accidents with 4 or more casualties show substantially higher proportions of serious and fatal outcomes, indicating that multi-casualty events are associated with more severe crash dynamics. This finding supports the use of casualty count as a proxy for crash energy and impact magnitude.

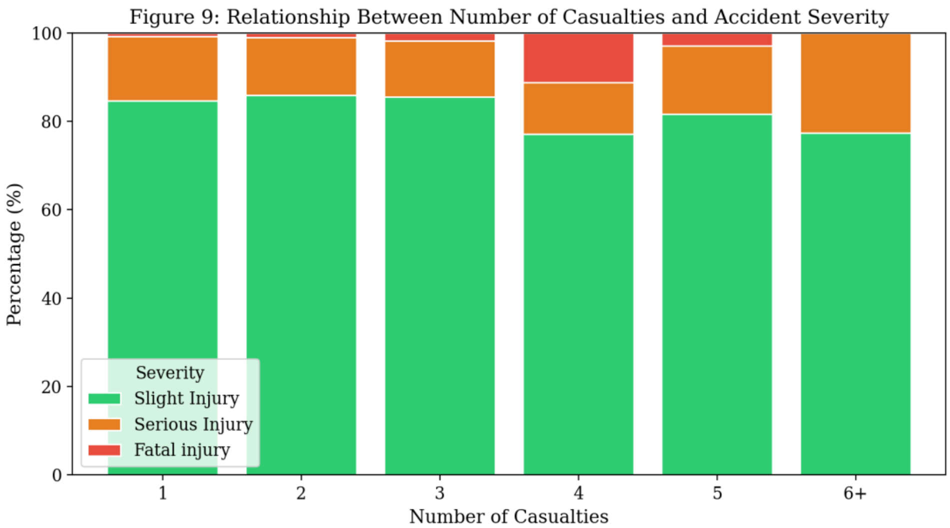

Figure 9: Relationship between number of casualties and accident severity

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5.3 Driver Demographics

Figure 10 reveals that drivers in the "Under 18" age band show the highest proportion of serious injuries, while those "Over 51" show elevated fatal injury rates, possibly reflecting the vulnerability of older individuals to severe physical trauma. Drivers with "No Licence" show markedly higher proportions of severe outcomes compared to all licensed experience groups, strongly supporting enforcement of licensing requirements as a road safety measure.

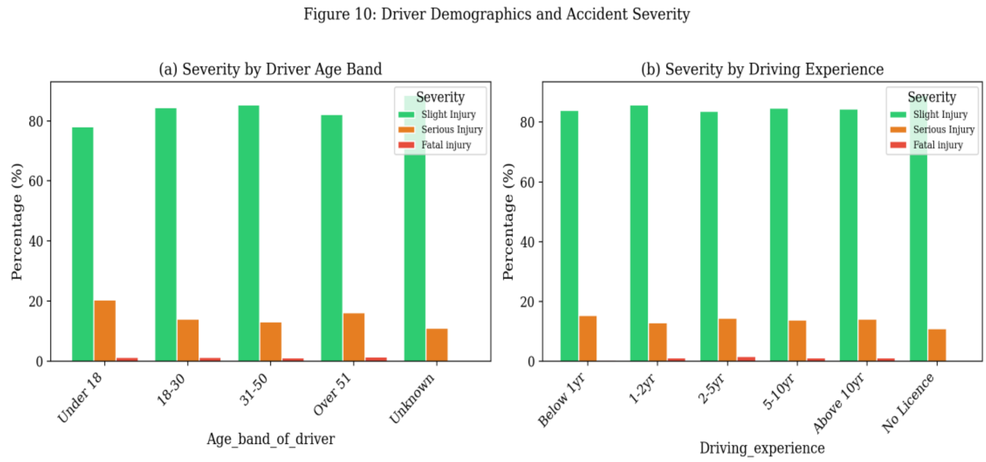

Figure 10: (a) Severity by driver age band and (b) severity by driving experience

VI. LITERATURE REVIEW: ML IN TRAFFIC MANAGEMENT

6.1 Adaptive Traffic Signal Control

Deep reinforcement learning (DRL) has emerged as the dominant approach for adaptive traffic signal control (Noaeen et al., 2022; Papadoulis et al., 2025). The LLM-RL Traffic Optimization Framework (LLM-RL-TOF) integrates large language models with reinforcement learning agents, demonstrating a 17.5% increase in junction throughput and 18.6% decrease in average vehicle delay (ScienceDirect, 2025). Shen (2025) proposed SHLight, a hierarchical RL framework partitioning traffic networks into regions with manager-worker agent architectures for coordinated signal control. Hu and Li (2024) applied Multi-Agent DDQN for traffic signal coordination, confirming significant improvements over fixed-time and PASSER-V optimized plans across multiple traffic demand scenarios. Bie et al. (2024) developed a multi-agent DRL framework based on spatio-temporal graph attention networks optimized for heterogeneous intersection types. Boyko (2024) compared DQN, SAC, A2C, and PPO algorithms for both autonomous vehicle control and traffic light management in simulated environments, while Chen et al. (2024) introduced a multi-objective DRL framework balancing safety and efficiency in mixed-autonomy traffic. Strehler et al. (2024) conducted pioneering work on real-world RL deployment, addressing sensor noise, safety constraints, and asynchronous multi-agent coordination.

6.2 Traffic Flow Prediction

Graph Neural Networks (GNNs) have transformed traffic flow prediction by naturally modeling road network topology. Kumar et al. (2025) surveyed GNN applications from 2020 to 2024, finding 15 to 20% performance improvements on benchmark datasets. Huo et al. (2024) enhanced the ASTGCN algorithm with a graph self-learning module and attention mechanism, achieving superior predictive accuracy on Orange County traffic data. Di Grande and Cavalieri (2024) proposed a two-level ML approach combining unsupervised clustering with supervised prediction for traffic flow forecasting in urban scenarios without sensors. An ensemble approach combining LSTM, BiLSTM, and BiGRU with EfficientNet feature extraction demonstrated improved accuracy over traditional techniques (Scientific Reports, 2025a). Edge computing platforms using the Edge Impulse framework have enabled ML deployment on Arduino-based hardware for real-time adaptive traffic control (Scientific Reports, 2025b). The STFGCN model integrates external weather information and auto-regressive graph convolution (Scientific Reports, 2025d), while UAV-based monitoring systems employ evolutionary graph neural networks for adaptive traffic prediction (Scientific Reports, 2024).

6.3 Crash Severity Prediction

Mostafa et al. (2025) introduced an AI-driven framework using 2.26 million records, achieving 96.19% accuracy with Extra Trees after applying SMOTE and feature selection. Kotsyubynska et al. (2026) conducted a systematic meta-analysis covering 2014 to 2025, documenting F1-score improvements from 73.2% to 84.3% as the field progressed from traditional ML to transformer architectures. Li and Chen (2025) proposed a CNN-LSTM-GNN hybrid for spatiotemporal accident risk prediction. Berhanu et al. (2024) integrated Random Forest with spatial network analysis to provide safe route recommendations, demonstrating 78% predictive capability for accident occurrence. Ahmed et al. (2023) applied explainable ML models including SHAP and LIME to identify key contributing factors in road accident prediction. Behboudi et al. (2024) reviewed 191 studies across five accident prediction categories, emphasizing the effectiveness of diverse data integration. Ziming (2025) analyzed the application of AI technology across five aspects of urban intelligent transportation systems, highlighting how cloud-based solutions optimize urban mobility through IoT devices and real-time monitoring.

VII. DISCUSSION

The analysis of the Addis Ababa RTA dataset reveals several important findings consistent with the broader literature. First, the severe class imbalance (84.6% Slight / 14.1% Serious / 1.3% Fatal) fundamentally constrains model performance on minority classes, even with balanced class weights. Gradient Boosting's superior macro F1-Score (0.479) reflects its sequential error-correction mechanism, which partially compensates for imbalance by focusing on misclassified instances. Second, the dominance of behavioral features (Cause_of_accident) over environmental or demographic features in the importance rankings suggests that road safety interventions targeting specific driver behaviors would be most impactful. Third, the strong association between collision type (rollovers, pedestrian collisions) and severity underscores the need for infrastructure interventions such as guardrails and pedestrian crossings.

Several challenges persist in the field. Data quality remains a fundamental constraint, with WHO noting crash registration completeness of approximately 30% in many countries. The simulation-to-reality gap impedes RL deployment (Strehler et al., 2024). Model interpretability is critical for regulatory acceptance; while SHAP and LIME are increasingly used, comprehensive explainability remains elusive (Behboudi et al., 2024). Geographic concentration is a significant limitation Kotsyubynska et al. (2026) found that 58% of crash prediction studies originate from high-income countries, despite 92% of fatalities occurring in low- and middle-income settings.

VIII. CONCLUSION

This paper has provided a comprehensive review and original ML analysis of machine learning applications in urban traffic management. The analysis of the real-world Addis Ababa RTA dataset (N = 12,316) demonstrates that Gradient Boosting achieves 85.0% accuracy with the best macro F1-Score (0.479) for three-class severity prediction, while Random Forest provides the strongest feature importance insights identifying Cause_of_accident, Number_of_casualties, and Hour_of_Day as dominant predictors. The severe class imbalance (1.3% fatal cases) remains the primary obstacle to minority class detection, and future work should systematically evaluate oversampling techniques (SMOTE, ADASYN) and cost-sensitive learning approaches on this dataset.

The literature review confirms that DRL-based signal control reduces delays by up to 45%, spatiotemporal GNNs have improved prediction accuracy by 15–20%, and ensemble models achieve crash severity accuracies exceeding 96% on large-scale datasets. Promising future directions include federated learning for privacy-preserving distributed training, LLM-RL integration for enriched traffic state representation, transfer learning for cross-geographic deployment, and digital twin platforms for continuous model refinement. The ultimate vision is integrated, adaptive, and equitable systems that optimize mobility, minimize environmental impact, and protect human life.

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