

Article

A survey on intelligent transportation systems for accident detection and risk prediction using AI

Vivek Sharma*

MITS Deemed University, Gwalior, MP, India

* Corresponding Author: viveksmits@gmail.com**ABSTRACT**

The complexity of today's transportation networks has made road safety, accident detection, and risk management increasingly challenging. Intelligent Transportation Systems (ITS) offer a technological base to enhance transportation safety by incorporating sensors, communications, data processing, and intelligent decision-making. This review discusses the application of Artificial Intelligence (AI) for accident detection and risk prediction in ITS by examining information sources, methodologies, accident investigation, and associated challenges. It examines the use of machine learning, deep learning, computer vision, spatiotemporal modeling, and multimodal AI for accident detection, risk prediction, severity analysis, and active safety management. This review of studies suggests that collecting traffic, vehicle, road, environmental, geographical, historical, and driver-related information can improve understanding of collisions and support timely safety decisions. The review also highlights the importance of explainable and reliable AI that provides transparency, dependability, and accountability. However, the obstacles include data heterogeneity, model generalization, dynamic conditions, scalability, quick implementation, privacy considerations, security requirements, and compatible information systems. In conclusion, incorporating AI in ITS may have the power to shift road-safety management from reactive measures to data-driven approaches.

Keywords: *Intelligent Transportation Systems (ITS), Spatiotemporal analysis, Accident detection, Machine learning, Accident risk prediction, Road safety*

Received: 25 July 2026

Received in revised form: 10 September 2026

Accepted: 26 September 2026

DOI: 10.55670/fpll.fer.1.1.4

1. INTRODUCTION

The surge in urbanization, vehicle ownership, and transportation demand has introduced considerable complexity into modern transportation systems and raised serious issues of congestion, mobility, efficiency, and road safety. To meet these challenges, Intelligent Transportation Systems (ITS) have emerged as a fusion of information, communication, sensing, and computing technologies applied to transportation and transit systems [1]. The growing integration of ITS in smart cities has made it an important element in applications such as road traffic management, traveler information services, public transportation management, connected vehicles, and automated driving [2]. These systems are expected to improve road and traffic safety, transportation efficiency, energy efficiency, and environmental sustainability [3]. Modern ITS are comprised of vehicles, roadside

infrastructure, communication networks, traffic management centers, and cloud- or edge-based computing platforms. Vehicles are becoming more cyber-physical systems and less mechanical. Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X) communications can enable cooperative awareness, collision avoidance, dynamic traffic management, and automated mobility services [4]. Meanwhile, connected vehicles, roadside sensors, GPS, cameras, and IoT devices generate vast amounts of heterogeneous transportation data. While this connectivity offers great potential for intelligent transportation, it also comes with challenges such as scalability, data management, communication reliability, security, and real-time decision-making [5]. Security issues can include malicious message injection, communication disruption, sensor data alteration, and attacks on vehicle or infrastructure systems; appropriate

authentication, anomaly detection, and resilient architectures are needed. Road traffic collisions are a serious public safety and transportation issue worldwide because they result in lost lives, injuries, property damage, economic loss, and loss of mobility. In India, estimated fatalities from traffic accidents in 2017 were 25,859, and estimated injuries were 100,000 [6]. Worldwide, an estimated 1.17 million deaths and 10 million injuries or disabilities occur annually from motor vehicle crashes. After a few fluctuations in reported motor vehicle incidents, the number of incidents reported in India rose from 95,906 in 2014 to 98,970 in 2015 and further to 105,374 in 2016. Several factors can affect the occurrence of an accident, such as human factors, vehicle factors, road factors, traffic factors, environmental factors, and weather conditions. Human factors are well known as a significant factor in road accidents, with around 75% of the accidents reported in the study being attributed to human factors on toll roads [7].

AI is an effective solution for analyzing the complex, heterogeneous data generated by ITS. ML and DL methods can assist with real-time traffic monitoring, accident detection, risk prediction, traffic-flow analysis, and traffic safety assessment by learning patterns from traffic, vehicle, environmental, geographic, and historical accident data [8]. Accident detection identifies incidents or unusual events as they occur, while risk prediction estimates the likelihood of occurrence or the potential severity under certain circumstances [9,10]. Thus, AI-powered ITS can shift from reactive accident response to proactive, data-driven safety management. When reviewing approaches to accident detection and risk prediction using AI-ITS, consider data sources, AI techniques, preprocessing, evaluation metrics, applications, obstacles, and future research objectives [11].

1.1 Structure of the paper

The remainder of this paper is organized as follows: Section 2 discusses ITS and data sources for accident analysis. Section 3 presents AI techniques. Section 4 discusses challenges. Section 5 reviews existing literature, while Section VI presents the conclusion and future work.

2. INTELLIGENT TRANSPORTATION SYSTEMS AND DATA SOURCES FOR ACCIDENT ANALYSIS

Intelligent Transportation Systems (ITS) integrate sensing, communication, computing, and artificial intelligence to enhance the safety, efficiency, and reliability of road transportation. ITS continuously collects and exchanges information through vehicles, roadside infrastructure, traffic sensors, communication networks, cameras, and connected devices [12]. This transportation data can be analyzed to understand traffic conditions, recognize abnormal events, detect accidents, and predict accident risks. These features support real-time monitoring, proactive safety management, and intelligent decision-making in today's transportation landscape. Figure 1 shows an ITS that links vehicles, cellular networks, roadside infrastructure, traffic signals, and personal ITS stations via 5G communication and traffic management centers for coordinated, connected, and intelligent transportation operations, as well as real-time, efficient road safety [13].

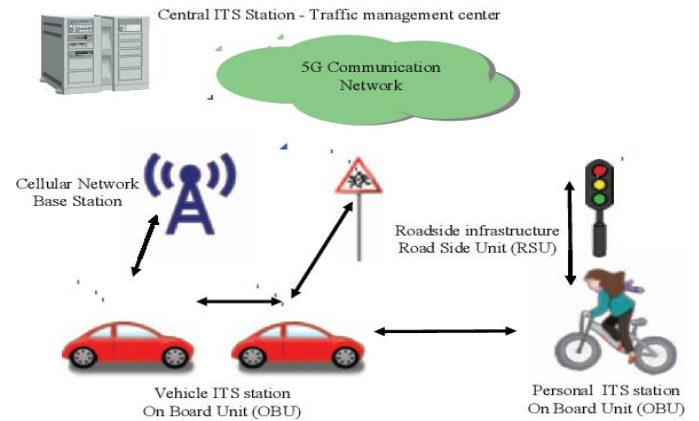


Figure 1. Intelligent transportation systems

2.1 Architecture of intelligent transportation systems

ITS Architecture offers a structured framework to integrate transportation sensing, communication, data management, and intelligent services [14]. It outlines a structured approach to delivering information from physical traffic monitoring to advanced transportation applications, enabling coordinated monitoring, information sharing, and intelligent decision-making. As shown in Figure 2, the ITS architecture consists of four interdependent layers.

Application layer: Provides transportation services such as traffic information, transportation services, traffic guidance, and traffic accident prevention through traffic centers, information centers, dispatching centers, data-sharing centers, and other industries.

Database layer: Collects, stores, manages, and exchanges transportation data received from different sources. It provides the required data resources for processing and supporting ITS applications.

Network transmission layer: Enables the communication and transmission of transportation information between different system components through mobile networks, satellite networks, the Internet, and private networks.

Perception layer: Performs real-time sensing and data acquisition using cameras, speed detectors, signal lamps, vehicle detectors, and GPS. The collected information forms the basic data for subsequent transmission, storage, analysis, and transportation services.

2.2 Accident detection in intelligent transportation systems

Rapid, accurate accident detection is vital to improving traffic safety, reducing emergency response time, and minimizing traffic disruption. Modern intelligent transportation environments use information from cameras, traffic sensors, connected vehicles, GPS, and communication networks to identify abnormal traffic events. AI and ML models can analyze these data sources to detect accidents faster and more accurately.

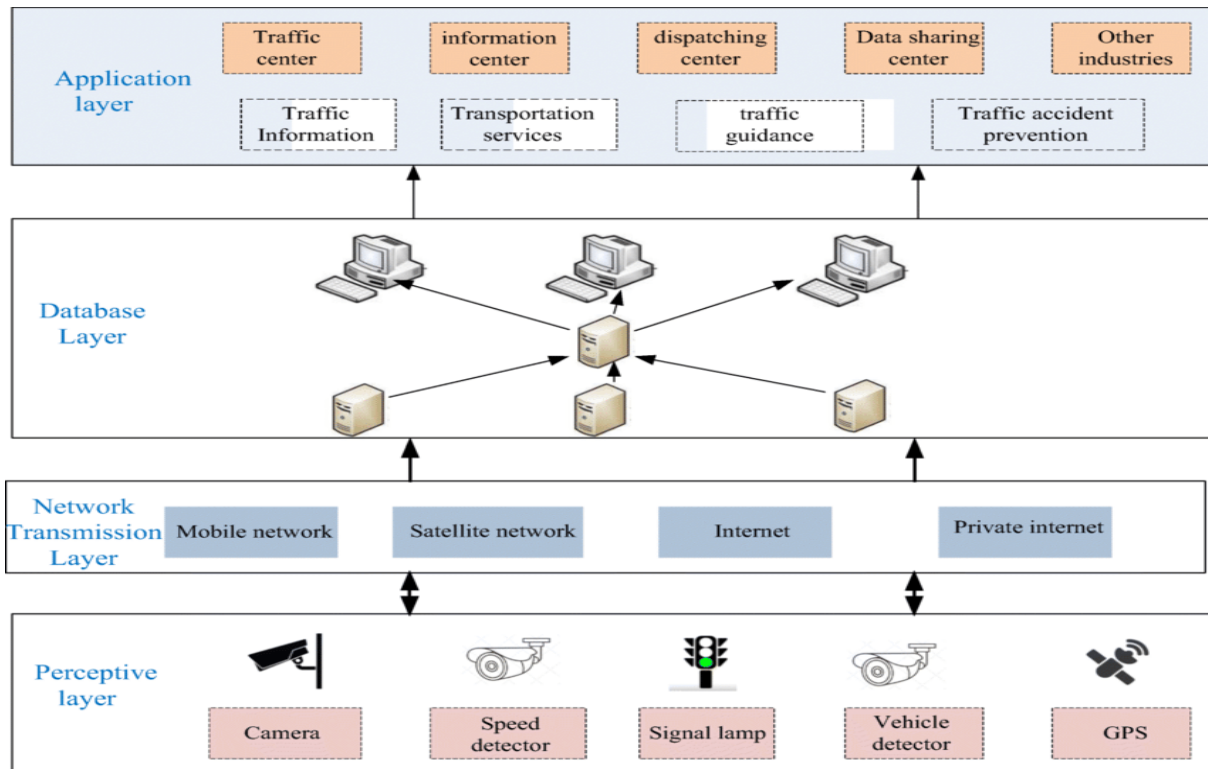


Figure 2. The intelligent transportation system architecture

These systems can provide timely warnings, assist first responders, help traffic control agencies manage affected areas, and minimize the likelihood of secondary accidents [15]. As a result, automatic accident detection is a significant component of intelligent and safe transport networks.

2.3 Accident risk prediction and severity assessment

Estimating accident risk and potential severity is crucial for effective road safety management, and it can help identify dangerous situations before or during an accident. AI and ML techniques can reveal factors such as traffic jams, car speed, weather, road conditions, and others. AI and ML algorithms can estimate accident probability and severity by examining traffic flow, vehicle speed, weather, road conditions, time, location, and historical accident trends [16]. Risk prediction typically relies on categorization or likelihood calculation, and severity assessment divides accidents into outcomes such as minor injury, major injury, or fatality [17]. These approaches can help with early-warning systems, intervention targeting, emergency planning, and effective use of safety resources, including the following:

Risk estimation: An assessment of the probability that an accident will occur under certain traffic and environmental circumstances.

Severity prediction: Prediction of the possible severity of an accident, based on contextual and historical circumstances.

Spatio-temporal analysis: Patterns of previous accidents to identify high-risk regions and periods.

Multifactor analysis: Integrate weather, traffic, road, vehicle, and driver-relevant variables.

Proactive safety management: Enables proactive safety measures and warnings, and improved emergency response.

2.4 Data sources for accident detection and risk prediction

Transportation data should be diverse, complete, and time- and space-harmonized to properly identify incidents and foresee hazards. Modern ITS can combine traffic, vehicle, road, environmental, geographic, and historical accident data, helping capture the complex factors involved in road incidents [18]. Transportation systems can generate a tremendous amount of real-time and historical data with the growing deployment of connected vehicles, IoT devices, surveillance cameras, and roadside sensors. These heterogeneous data sources allow for AI-driven techniques to detect abnormal traffic conditions, estimate the likelihood of an accident occurring, pinpoint high-risk areas, and determine the potential for severe accidents to occur, including:

Traffic sensor data: Traffic volume, speed, density, occupancy, and flow collected through loop detectors, radar, and roadside sensors.

CCTV and video data: Video streams provide information for detecting collisions, stopped vehicles, congestion, and abnormal driving events.

GPS and vehicle data: The danger is estimated in real time using the vehicle trajectory, acceleration, speed, braking, and position information.

Weather data: Rainfall, temperature, visibility, humidity, wind speed, and road-surface conditions can describe environmental risk variables.

Road and infrastructure data: Roadway context includes items such as road shape, junctions, lane design, speed restrictions, lighting, signals, and surface conditions.

Historical accident data: Model training and pattern analysis are based on accident timing, location, kind of collision, severity, casualties, and contributory variables.

Connected vehicle and IoT data: V2V, V2I, and IoT-connected devices give near real-time information for proactive accident detection.

Geospatial and map data: Road networks, coordinates, land use, and points of interest support spatial risk analysis.

Crowdsourced and social media data: User reports and online traffic information can supplement conventional sensing infrastructure.

2.5 Risk factors influencing accident detection and prediction

Human, operational, environmental, and technological factors affect accident detection and prediction in Intelligent Transportation Systems (ITS). The following factors are crucial: nighttime operation, inattentive passengers, high-stress environments, inadequate training, no surveillance systems, anonymous drivers and passengers, and racial and gender bias. These factors can affect the reliability of AI-based risk detection and prediction systems, as well as the likelihood of accidents. Figure 3 shows the variables linked to accident identification and prediction. It shows that accident risk results from multiple interconnected factors involving human behavior, operational conditions, surveillance infrastructure, and potential biases. Developing trustworthy, precise, and equitable AI-enabled ITS for real-time accident detection and risk prediction requires careful consideration of these aspects and their interactions [19].



Figure 3. Identified risk factors

3. AI TECHNIQUES FOR ACCIDENT DETECTION AND RISK PREDICTION

AI technology provides an all-encompassing solution in intelligent transportation systems for automatic accident detection and risk prediction. ML and DL models perform accident classification, rating, and severity estimation, while computer vision enables real-time vehicle detection, abnormal traffic-situation detection, and collision detection. Spatiotemporal methods identify temporal and spatial trends in incident risk, while multimodal and/or hybrid methods integrate multiple transportation and incident data to predict incidents more effectively. Explainable and trustworthy AI further improves the interpretability, reliability, transparency, and safety of AI systems in transportation applications.

3.1 Machine learning and deep learning approaches

The ability to infer complex relationships in complex transportation data sets is required for effective accident analysis using computational techniques. DT, RF, SVM, KNN, NBs, LR, Gradient Boosting, and XGBoost are among the most popular ML methods for classification, risk assessment, and predicting accident severity. The DL methods, such as CNNs, RNNs, LSTM, GRU, CNN-LSTM, hybrid models, and Transformers, enable automatic feature extraction and modeling of the spatio-temporal relationships. Together, they help detect accidents reliably, predict accidents, and predict accident severity in structured, sequential, and visual transportation data.

3.2 Computer vision for accident detection

Visual analysis of abnormal road events has become an essential component of intelligent transportation systems and is an important element for rapid event detection. Computer vision analyzes images and video streams from surveillance cameras and other sensing platforms to provide insights into vehicle and pedestrian activity, traffic, and collision-related events [20]. They can automatically monitor the road environment and deliver real-time information for accident detection and traffic safety management [21].

Vehicle and pedestrian detection: Detects and tracks vehicles and pedestrians in a traffic scene to track their position, movement, and interaction.

Traffic-event recognition: Identifies abnormal traffic events including sudden stopping, lane changing, congestion, moving in the wrong direction, and other unusual driving behaviors.

Collision detection: Identifies possible vehicle-to-vehicle or vehicle-to-object collisions by analyzing vehicle motion patterns, spatial relationships, and sudden shifts in vehicle paths.

Video-based accident detection: Analyzes video and automatically detects accidents and sends alerts to traffic and emergency response systems in time.

3.3 Spatiotemporal accident risk prediction

The risk of an accident is affected by spatial and temporal variations in traffic, road, and environmental conditions, as well as variations in mobility. The spatiotemporal prediction methods use accident history, road network characteristics, traffic volume, vehicle

movement characteristics, weather elements, and temporal patterns to identify high-risk accident locations and times [22]. CNN–LSTM and other hybrid networks can learn local spatial features and temporal dependencies, which helps model the recurrent and dynamic features of accidents. These facilitate proactive risk assessment, early warning, and targeted road-safety interventions, particularly in complex urban transportation environments.

Temporal traffic patterns: Examines the fluctuating traffic levels, speeds, congestion, and number of accidents at various times of day – during peak and off-peak hours.

Spatial risk analysis: Classifies roadway segments, intersections, and geographic areas as high-risk based on the spatial distribution and concentration of accidents over time.

Traffic-flow prediction: Forecast future traffic conditions based on historical traffic data and real-time data in order to identify conditions that could pose an accident hazard.

Weather and road-condition integration: This allows for the incorporation of rainfall, visibility, temperature, road-surface conditions, lighting, and other environmental and infrastructure-related factors to enhance spatiotemporal risk assessment.

3.4 Multimodal and hybrid AI approaches

A major trend for improving the reliability of accident detection and risk prediction is combining heterogeneous transportation data. Sensor–vision fusion combines data from cameras, LiDAR, radar, and other sensors to provide complementary information about the environment and traffic, especially when single sensing modalities are occluded or perform poorly [23]. Vehicle–infrastructure data fusion integrates vehicle trajectories, onboard sensors, roadside units, traffic signals, and communication networks to provide a more complete picture of road conditions. Recent reviews of over 50 studies on LiDAR–camera fusion show that complementary sensing in intelligent vehicles is increasingly used to improve perception. ML and DL hybrid models, which integrate traditional models and neural architectures, can also improve results by leveraging structured features as well as complex spatial or temporal patterns. Multisource data integration also combines accident data, traffic-flow data, GPS trajectories, weather, road characteristics, video, and connected-vehicle data—providing for more comprehensive accident-risk models. Recent systematic studies show that multi-source data integration is an important direction for improving the accuracy and timeliness of traffic accident prediction, but data heterogeneity, synchronization, and sharing remain challenging issues [24].

3.5 Explainable and trustworthy AI for ITS

In intelligent transport systems, where AI forecasts directly influence actions that affect road safety, the AI must be dependable. Explainable and reliable models provide insights into how input parameters affect model outputs and the amount of confidence in model predictions [25]. These features allow safe, transparent, and responsible usage of AI-ITS. Model interpretability helps explain how traffic, weather, road, vehicle, and time influence AI model choices, making forecasts easier to understand.

Explainable accident-risk prediction: Provide accessible reasons for the predicted risk levels and determine what factors enhance the probability of an accident. Reliability and uncertainty evaluation quantify confidence in the forecast and help identify when the model output may be less dependable due to missing data, noise, or data changes. Safety and transparency support human monitoring and accountability for AI-based decisions, making them easier to track and reducing the risk associated with opaque prediction models.

4. CHALLENGES OF AI-BASED ITS

AI-based Intelligent Transportation Systems (ITS) face many challenges, including multiple data sources, dynamic transportation settings, system deployment, security and privacy issues, and interoperability. Addressing these challenges is essential for reliable and scalable development of AI systems that can detect accidents and predict risk.

4.1 Accident detection and risk prediction

Accident detection and risk prediction are two different aspects of an AI transportation safety system [26]. Accident detection identifies what is happening or has happened to a vehicle or driver, while risk prediction forecasts what may happen in the future based on historical, temporal, spatial, environmental, and traffic-related data. As a result, detection focuses on quick identification and action, while prediction enables proactive risk assessments and preventative action [27,28]. Detection is often linked to short-term or immediate decision-making, while risk prediction can account for short- and long-term accident patterns. Moreover, occurrence prediction addresses whether an accident happens, while severity prediction addresses the potential consequences or level of severity of a predicted or identified accident.

(1) Transportation data integration: Transportation data integration is challenging because ITS generates diverse, continuously changing information from multiple sources that differ in format, timing, location, quality, and communication standards [29].

- **Heterogeneous data formats:** Transportation systems generate structured, semi-structured, and unstructured data that require compatible processing methods.
- **Temporal synchronization:** Data collected at different time intervals must be synchronized to accurately represent evolving traffic and accident conditions.
- **Spatial alignment:** Information from vehicles, sensors, cameras, and geographic systems must be correctly mapped to common locations and road segments.
- **Inconsistent collection procedures:** Differences in sensing technologies, sampling rates, and data-collection methods can reduce consistency across datasets.
- **Limited interoperability:** Smooth information sharing across various ITS systems and devices might be difficult due to incompatible communication protocols, formats, and data standards.
- **Dynamic real-time availability:** Continuous variations in data availability, gearbox delays, missed

observations, and transient sensor failures may impair rapid and accurate accident investigation.

(2) Model generalization: AI models built for accident analysis may behave differently when applied to transportation systems with differing infrastructure, traffic characteristics, and data distributions. Differences in training and deployment settings may limit transferability and reduce prediction reliability for unforeseen events [30].

- **Urban–rural variations:** Model applicability across urban and rural locations might be affected by different traffic volumes, road layouts, vehicle compositions, and driving conditions.
- **Geographic infrastructure differences:** Road geometry, junctions, lane configurations, traffic signals, and infrastructure quality variations might affect model projections.
- **Regional traffic behavior:** Driving patterns, speed characteristics, congestion levels, and road user behavior may fluctuate dramatically across geographical locations.
- **Changing transportation patterns:** Data distributions might vary over time due to seasonal fluctuations, population expansion, the introduction of new mobility services, and changes in traffic demand.
- **Limited cross-dataset transferability:** Models trained on one dataset may not provide consistent results when used on datasets from various sources, geographies, or collection processes.
- **Unseen environments:** New road conditions, uncommon traffic situations, and accident patterns not seen before may decrease the dependability of the model and require adaptation and/or retraining.

(3) Robustness in dynamic and uncertain environments

Current transport settings are highly dynamic; road, traffic, ambient, and sensor conditions continually change over time. These variations may introduce uncertainty that affects the accuracy and trust of AI-powered accident detection and risk prediction systems [31]. Effective and dependable transportation safety systems must account for weather and road conditions, abnormal traffic events, sensor failures, insufficient or noisy information, traffic-flow variations, and uncertainty in accident occurrence.

(4) Deployment, scalability, privacy, and security challenges in ITS

AI-enabled ITS systems must also be implemented, maintained, and secured across varied transportation environments. Several considerations arise when deploying at scale, including compatibility with existing infrastructure, processing power, connectivity demands, data security, cybersecurity threats, and the ethics of automated safety decision-making.

- **Infrastructure integration:** AI solutions must be designed to work seamlessly with current traffic control systems, roadside equipment, cars, and legacy transportation infrastructure [32].
- **Scalable deployment:** Extending AI applications to massive transportation networks would need systems that can manage an increasing number of cars, sensors, and constant data streams.
- **Computational and resource limitations:** Processing power, memory, storage, and energy are

constrained for continuous AI running on roadside and car platforms.

- **Model maintenance and updating:** Regular model updates, monitoring, and maintenance are required to accommodate changing traffic patterns, infrastructure, and data distributions.
- **Communication dependency:** Reliability is needed for communicating information between vehicles, infrastructure, edge devices, and centralized systems, and network failures may interfere with AI services.
- **Privacy and data protection:** The continuous collection of trajectories, positions, and behavioral characteristics of vehicles presents problems about unauthorized access, monitoring, and exploitation of transportation data.
- **Cybersecurity and ethical risks:** Connected ITS may be vulnerable to tampered data and cyberattacks, and automated safety judgments need responsible treatment of personal data, fairness, responsibility, and monitoring by humans.

4.2 Standardization and interoperability issues

Proper implementation of AI-based ITS requires common standards and effective communication among the various components involved in transportation [33]. Unfortunately, a lack of standardized data, differences in accident types and definitions, incompatible transportation modalities, limited interoperability between vehicles and infrastructure, the absence of standardized AI deployment frameworks, and issues with legacy systems may prevent data exchange and operational coordination.

5. LITERATURE REVIEW

The literature review examines AI-driven methodologies for accident identification and danger forecasting in smart transport systems, with particular emphasis on data integration, driver supervision, real-time detection, and intelligent decision support. Road traffic accidents are a global public safety and economic problem. The emergence of Smart Transportation Systems has generated huge volumes of spatio-temporal data from Traffic Sensors, Weather Reports, and Road Networks for accident prediction. However, the complexity of traffic environments, the variety of data sources, and the non-linear interactions among Traffic Flow, Weather Conditions, Road Geometry, and Time-Dependent Patterns make predicting road traffic accident risk very challenging. This project aims to develop an Intelligent Road Traffic Accident Risk Prediction Framework based on ML to integrate multimodal spatio-temporal data. The framework incorporates Traffic, Environmental, Temporal, and Spatial Features to improve accident-risk prediction and detect risky Road Segments and Time Periods [34].

Microsleep-related incidents pose a serious road safety risk, especially in commercial transport, where long-haul driving and fatigue increase the likelihood of driver impairment. Current tiredness monitoring systems include face recognition, blink-rate measurement, and seat-pressure sensors, but cannot intervene in real time or inform other vehicles. The paper proposes an IoT-based microsleep detection and intervention system that integrates steering wheel grip pressure sensors, biometric monitoring, AI-driven prediction models, and adaptive

braking mechanisms. The system includes internal driver alarms, external vehicle signaling, and automatic brake assistance to reduce the chance of an accident. The project adopts a Design Science Research (DSR) approach for conceptual design and system architecture, with future validation through simulated driving conditions and survey-based evaluations. The proposed method addresses the lack of external vehicle alerts, real-time intervention, and IoT-based smart steering control in current microsleep detection systems [35].

An innovative AI-based approach to real-time accident detection by seamless integration of driver health indicators and vehicle dynamics. Unlike existing models that analyze these factors in isolation, this system integrates physiological data, such as heart rate variability and fatigue indices, with vehicular parameters, such as speed, steering angle, and braking intensity, to provide a comprehensive analysis of unsafe driving behaviors. The system uses powerful ML algorithms to interpret data in real time, with a predicted accuracy of 94.7% and a response latency of 0.48 seconds. The model was trained on a large dataset of more than 50,000 data points, covering diverse driving situations and circumstances, which supported the model's reliability and robustness. The experimental findings show the system's capacity to detect high-risk behaviors such as tiredness and aggressive driving with a 97.5% detection rate, surpassing previous methods [36].

B. S, et al. [37] presented a Driver Decision Support System (DDSS) for anticipating and handling unusual driving behavior in ITS. The system uses a driving behavior prediction method to classify drivers as normal or abnormal and detect anomalous driving patterns to advise nearby vehicles to change lanes or alter speed to prevent accidents. The prediction algorithm uses K-Means clustering to group drivers into behavior categories and is compared with SVM, DT, KNN, LR, and NB.

Integrating the DDSS into ITS infrastructure supports accident prevention by enabling timely interventions and reducing accident risks through driver behavior monitoring and analysis. Autonomous transportation and smart city systems rely on accident detection and traffic analysis to reduce accident occurrence and impact and improve traffic management. Using statistics from the NHTSA Crash Report Sampling System, this article examines traffic accidents across several US areas. It proposes a framework that uses traffic surveillance cameras and action recognition systems to detect and respond to traffic accidents automatically. Integrating the framework with emergency services and ML algorithms can improve accident response, reduce human errors, and enhance traffic management and accident severity [38].

S. Olugbade et al. [39] report that the number of accidents that occur in road transport is quite high, and the figures for fatalities, injuries, loss of life, and loss of valuables are also quite high. This article explains the AI and ML aspects of building an automatic incident detection system to reduce road accidents. The study analyzes key issues, potential solutions, and emerging trends for minimizing road traffic accidents using AI and ML in road transportation systems. It covers ML- and AI-based incident detection, road management, Internet of Vehicles, vehicular ad hoc networks, 5G wireless networks, and AI and ML applications in the planning and safety of road transportation systems. Based on the evaluated papers, a research gap has emerged: current techniques mostly focus on specific elements such as traffic conditions, driver behavior, fatigue, health measures, or accident detection. A comprehensive real-time framework that incorporates environmental, vehicle, driver-related, and multimodal spatio-temporal data has received little attention.

Table 1. Summary of the study on intelligent transportation systems for accident detection and risk prediction using AI

Reference	Research Focus	Approach	Key Findings	Challenges and limitations	Future Directions
[34]	Road accident risk prediction	ML-based integration of traffic, environmental, temporal, and spatial data	Identifies high-risk road segments and time periods	Complex multimodal data and nonlinear relationships	Develop robust real-time and scalable prediction frameworks
[35]	Microsleep and fatigue-related accidents	IoT sensors, biometric monitoring, AI prediction, and adaptive braking	Enables driver alerts, external warnings, and braking assistance	Mainly conceptual; limited real-world validation	Validate through real-world and simulated driving experiments
[36]	Real-time accident and unsafe-driving detection	Physiological and vehicle-dynamics data with ML	Achieved 94.7% prediction accuracy and 97.5% risk-behavior detection	Requires diverse sensor data and reliable real-time processing	Improve generalization and deployment in real vehicles
[37]	Abnormal driving behavior prediction	K-Means with SVM, DT, KNN, LR, and NB	Supports early identification of abnormal driving and preventive actions	Focused mainly on driver behavior; limited multimodal integration	Integrate traffic, environmental, and vehicle data
[38]	Accident detection and traffic analysis	Surveillance cameras, action recognition, NHTSA crash data, and ML	Supports automated accident detection and emergency response	Dependence on surveillance infrastructure and regional datasets	Develop real-time, broader-scale detection systems
[39]	AI/ML-based automatic incident detection	Review of AI, ML, IoV, VANETs, and 5G applications	Highlights AI/ML potential for road safety and incident management	Broad review with limited empirical validation	Develop integrated AI-enabled real-time safety systems

Furthermore, many proposed systems lack extensive real-world validation, scalability, and reliable early-risk prediction, highlighting the need for robust, generalizable AI-based accident prediction and prevention frameworks. Table 1 summarizes the reviewed studies, approaches, findings, limitations, and future research directions.

6. CONCLUSION

The increasing complexity, connectivity, and data-rich nature of transportation systems have made this an important issue in road safety. Intelligent Transportation Systems (ITS) provide an inherent foundation for answering these questions through their sensing, communication, computation, and intelligent decision-making capabilities. With the study of different transportation data, Artificial Intelligence (AI) has the ability to recognize and anticipate complex patterns of accidents, according to this survey. This might greatly aid in the detection of accidents and the prediction of risks. The use of multimodal techniques, spatiotemporal modeling, computer vision, DL, and ML allows for proactive safety management, real-time detection, and risk calculation and severity evaluation. Moreover, the research stresses the importance of consolidating traffic, vehicle, road, ecological, geographic, historical, and driver data. However, obstacles remain, including data heterogeneity, model generalization, dynamic environments, real-time deployment, scalability, privacy and security, and compatibility. Ultimately, AI-based ITS offers a chance to transform conventional approaches to road safety from real-time reaction to proactive accident prevention. Future work should focus on robust multimodal AI frameworks that integrate real-time traffic, vehicle, environmental, road, and driver data. Research should also focus on cross-region generalization, real-world validation, explainable AI, uncertainty estimates, edge computing, privacy preservation, cybersecurity, and scalable deployment to provide accurate accident prediction and prevention.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The author declares no potential conflict of interest.

REFERENCES

- [1] T. Yuan, W. Da Rocha Neto, C. E. Rothenberg, K. Obraczka, C. Barakat, and T. Turletti, "Machine learning for next-generation intelligent transportation systems: A survey," *Trans. Emerg. Telecommun. Technol.*, vol. 33, no. 4, pp. 1–35, November, Apr. 2022, doi: 10.1002/ett.4427.
- [2] M. Elassy, M. Al-Hattab, M. Takruri, and S. Badawi, "Intelligent transportation systems for sustainable smart cities," *Transp. Eng.*, vol. 16, p. 100252, Jun. 2024, doi: 10.1016/j.treng.2024.100252.
- [3] K. M. Hussain and S. C. Pallaprolu, "Improving Passenger Safety with Machine Learning Techniques on 2022 Incident Data," in 2025 International Conference on Sensors and Related Networks (SENNET) Special Focus on Digital Healthcare (64220), Vellore, India: IEEE, 2025, pp. 1–6, July. doi: 10.1109/SENNET64220.2025.11136102.
- [4] S. Aluko, "Security Challenges and Risk Analysis in Intelligent Transportation Systems," Feb. 27, 2026. doi: 10.36227/techrxiv.177223070.03782885/v1.
- [5] Y. Pei, Y. Wen, and S. Pan, "Road Traffic Accident Risk Prediction and Key Factor Identification Framework Based on Explainable Deep Learning," in IEEE Access, 2024, pp. 120597–120611. doi: 10.1109/ACCESS.2024.3451522.
- [6] D. G. Takale, S. D. Gunjal, V. N. Khan, A. Raj, and S. N. Gujar, "Road Accident Prediction Model Using Data Mining Techniques," *NeuroQuantology*, vol. 20, no. 16, pp. 2904–2101, November, 2022, doi: 10.48047/NQ.2022.20.16.NQ880299.
- [7] H. K. Yadav, "Design and Implement Machine Learning Based Predictive Analytics for Road Safety and Accident Prevention," in 2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India: IEEE, 2026, pp. 1–6, March. doi: 10.1109/IATMSI68868.2026.11465965.
- [8] J. P. Bharadiya, "Artificial Intelligence in Transportation Systems A Critical Review," *Am. J. Comput. Eng.*, vol. 6, no. 1, pp. 34–45, Jun. 2023, doi: 10.47672/ajce.1487.
- [9] D. Gangwani and P. Gangwani, "Applications of Machine Learning and Artificial Intelligence in Intelligent Transportation System: A Review," in Applications of Artificial Intelligence and Machine Learning, A. Choudhary, A. P. Agrawal, R. Logeswaran, and B. Unhelkar, Eds., Singapore: Springer Singapore, 2021, pp. 203–216.
- [10] A. M. Mostafa et al., "AI-based prediction of traffic crash severity for improving road safety and transportation efficiency," *Sci. Rep.*, vol. 15, no. 1, p. 27468, 2025, doi: 10.1038/s41598-025-10970-7.
- [11] R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee, "Applications of Artificial Intelligence in Transport: An Overview," *Sustainability*, vol. 11, no. 1, p. 189, Jan. 2019, doi: 10.3390/su11010189.
- [12] N. Niture and I. Abdellatif, "A systematic review of factors, data sources, and prediction techniques for earlier prediction of traffic collision using AI and machine Learning," in Multimedia Tools and Applications, 2025, pp. 19009–19037. doi: 10.1007/s11042-024-19599-6.
- [13] J. Casademont, A. Calveras, D. Quiñones, M. Navarro, J. Arribas, and M. Catalan-Cid, "Cooperative-Intelligent Transport Systems for Vulnerable Road Users Safety," in 2019 7th International Conference on Future Internet of Things and Cloud (FiCloud), IEEE, Aug. 2019, pp. 141–146. doi: 10.1109/FiCloud.2019.00027.
- [14] G. Santo, L. Santos, R. L. C. Costa, and C. Rabadão, "Intelligent Transportation Systems Security and Privacy," in Information Security and Privacy in Smart Devices: Tools, Methods, and Applications,

- 2023, pp. 122–141. doi: 10.4018/978-1-6684-5991-1.ch005.
- [15] S. Sreevathsa, “Strategies for Reducing Alert Fatigue and Improving Signal Quality in Enterprise Monitoring Architectures,” *Int. J. Adv. Eng. Manag. Sci.*, vol. 12, no. 3, pp. 444–451, 2026, doi: 10.22161/ijaems.123.42.
- [16] M. F. I. Buian, R. A. Arde, M. M. Billah, A. Debnath, I. Md, and Siddique, “Advanced analytics for predicting traffic collision severity assessment,” *World J. Adv. Res. Rev.*, vol. 21, no. 2, pp. 2007–2018, Feb. 2024, doi: 10.30574/wjarr.2024.21.2.0704.
- [17] X. Shi, Y. D. Wong, M. Z. F. Li, and C. Chai, “Key risk indicators for accident assessment conditioned on pre-crash vehicle trajectory,” *Accid. Anal. Prev.*, vol. 117, pp. 346–356, Aug. 2018, doi: 10.1016/j.aap.2018.05.007.
- [18] B. Tyagi, A. Agrawal, H. Jajaniya, and G. Bhardwaj, “Smart Traffic Management and Accident Detection System: A Review,” *DMPedia Lect. Notes Comput. Sci. Eng.*, vol. 1, no. Impact, pp. 335–345, Mar. 2026, doi: 10.65890/dmp-incse.IMPACT26.138.
- [19] S. Jaydarifard, T. Yigitcanlar, and A. Paz, “Risk factors and safety strategies for mitigating violations, harassment and assault in taxi and ride-hailing services,” *Transp. Rev.*, vol. 45, no. 5, pp. 776–800, Sep. 2025, doi: 10.1080/01441647.2025.2512251.
- [20] E. Naranjo, J. D. Erazo Rodríguez, I. Sinaluisa, and N. Ulloa, “Artificial Intelligence and Computer Vision for Intelligent Traffic Light Systems: A Systematic Review,” *Automation*, vol. 7, no. 4, 2026, doi: 10.3390/automation7040113.
- [21] S. Darla, K. P. U. K. A. P. B. R, and V. D, “Automated Vehicle Collision Detection: Multi-Model Computer Vision Framework,” in 2026 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), IEEE, Jan. 2026, pp. 1–9. doi: 10.1109/IITCEE67948.2026.11394603.
- [22] S. Guo et al., “Sparse Traffic Accident Risk Forecasting With Spatial-Temporal Knowledge Graphs,” *IEEE Trans. Knowl. Data Eng.*, vol. 38, no. 9, pp. 6152–6165, 2026, doi: 10.1109/TKDE.2026.3706345.
- [23] F. Adeola and E. Dave, “Hybrid Deep Learning Architecture For Predicting Neurological Disorders And Road Accident Severity,” Apr. 10, 2026. doi: 10.22541/au.177585097.72176336/v1.
- [24] N. Barua and M. Hitosugi, “A Multi-Modal AI System for Detecting Pedestrians Lying on the Road: Simulation-Based Safety and Injury Risk Analysis,” *Vehicles*, vol. 8, no. 6, p. 136, 2026, doi: 10.3390/vehicles8060136.
- [25] O. I. Aboulola, E. A. Alabdulqader, A. A. AlArfaj, S. Alsubai, and T.-H. Kim, “An Automated Approach for Predicting Road Traffic Accident Severity Using Transformer Learning and Explainable AI Technique,” *IEEE Access*, vol. 12, pp. 61062–61072, 2024, doi: 10.1109/ACCESS.2024.3380895.
- [26] D. Santos, J. Saias, P. Quaresma, and V. B. Nogueira, “Machine Learning Approaches to Traffic Accident Analysis and Hotspot Prediction,” *Computers*, vol. 10, no. 12, 2021, doi: 10.3390/computers10120157.
- [27] Z. Jin and B. Noh, “From Prediction to Prevention: Leveraging Deep Learning in Traffic Accident Prediction Systems,” *Electronics*, vol. 12, no. 20, 2023, doi: 10.3390/electronics12204335.
- [28] S. Moosavi, M. H. Samavatian, S. Parthasarathy, R. Teodorescu, and R. Ramnath, “Accident Risk Prediction based on Heterogeneous Sparse Data: New Dataset and Insights,” in *Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, in SIGSPATIAL '19. New York, NY, USA: Association for Computing Machinery, 2019, pp. 33–42. doi: 10.1145/3347146.3359078.
- [29] N. Fiorentini, D. Pellegrini, and M. Losa, “Overfitting Prevention in Accident Prediction Models: Bayesian Regularization of Artificial Neural Networks,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2677, no. 2, pp. 1455–1470, Feb. 2023, doi: 10.1177/03611981221111367.
- [30] S. Adomako, I. K. V. Amponsah, D. K. Mensah, and J. Damsere-Derry, “Road Accident Case Modeling in Ghana: A Perspective of Negative Binomial–Based Generalized Linear Models,” *J. Probab. Stat.*, vol. 2025, no. 1, p. 10, Jan. 2025, doi: 10.1155/jpas/3900755.
- [31] M. Graf, D. Steinhauser, O. Vaculín, and T. Brandmeier, “Impact of Adverse Weather on Road Safety: A Survey of Test Methods for Enhancing Safety of Automated Vehicles and Sensor Robustness in Challenging Environmental Conditions,” in *IEEE Access*, 2025, pp. 179817–179838. doi: 10.1109/ACCESS.2025.3622501.
- [32] A. Pembuain, S. Priyanto, and L. Suparma, “The Effect of Road Infrastructure on Traffic Accidents,” in *Proceedings of the 11th Asia Pacific Transportation and the Environment Conference (APTE 2018)*, Paris, France: Atlantis Press, 2019. doi: 10.2991/apte-18.2019.27.
- [33] F. Alanazi and M. Alenezi, “Interoperability for intelligent traffic management systems in smart cities,” *Int. J. Electr. Comput. Eng.*, vol. 14, no. 2, pp. 1864–1874, April, 2024, doi: 10.11591/ijece.v14i2.pp1864-1874.
- [34] A. Srivastava, R. Kalim, K. K. Singh, S. Srivastava, A. Choudhary, and V. S. Sharma, “Intelligent Road Accident Risk Prediction Using Multi-Modal Spatio-Temporal Data and Machine Learning,” in 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST), Ghaziabad, India: IEEE, 2026, pp. 1–6, June. doi: 10.1109/EVST69093.2026.11660585.
- [35] A. Subbiah, N. 'Ain Amirrudin, N. I. A. Katim, R. Hamidun, T. P. Subramaniam, and A. Mahfoud, “Mitigating Microsleep-Related Accidents in Commercial Transport: An IoT-Based Detection and Instant Alert System for Enhancing Driver Safety and Road Security,” in 2025 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), Kuala Lumpur, Malaysia: IEEE, 2025, pp. 7–12, June. doi: 10.1109/I2CACIS65476.2025.11101236.
- [36] A. P, S. B, V. K. I, and A. K, “AI-Powered Real-Time Accident Detection Through Integration of Driver Health and Vehicle Dynamics,” in 2025 2nd International Conference on Trends in Engineering Systems and Technologies (ICTEST), Ernakulam, India: IEEE, 2025, pp. 1–6, April. doi: 10.1109/ICTEST64710.2025.11042307.

- [37] B. S, J. A. D, P. N. Renjith, and K. Ramesh, "DDSS: Driver decision support system based on the driver behaviour prediction to avoid accidents in intelligent transport system," *Int. J. Cogn. Comput. Eng.*, vol. 5, pp. 1–13, 2024, doi: 10.1016/j.ijcce.2023.12.001.
- [38] V. Adewopo, N. Elsayed, Z. ElSayed, M. Ozer, V. Wangia-Anderson, and A. Abdelgawad, "AI on the Road: A Comprehensive Analysis of Traffic Accidents and Autonomous Accident Detection System in Smart Cities," in *2023 IEEE 35th International Conference on Tools with Artificial Intelligence (ICTAI)*, IEEE, Nov. 2023, pp. 501–506. doi: 10.1109/ICTAI59109.2023.00080.
- [39] S. Olugbade, S. Ojo, A. L. Imoize, J. Isabona, and M. O. Alaba, "A Review of Artificial Intelligence and Machine Learning for Incident Detectors in Road Transport Systems," *Math. Comput. Appl.*, vol. 27, no. 5, p. 77, September, 2022, doi: 10.3390/mca27050077.



This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).