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Survey of Artificial Intelligence Approaches for Traffic Accident Analysis, Prediction, And Prevention

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ABSTRACT: Road traffic accidents are a major public safety concern, causing substantial fatalities, injuries, and economic losses every year. The increasing availability of traffic data and advances in Artificial Intelligence (AI) have accelerated the development of intelligent techniques for traffic accident analysis, prediction, and prevention. This paper presents a comprehensive survey of AI-based approaches for traffic accident analysis, covering traditional statistical methods, Machine Learning (ML), Deep Learning (DL), computer vision, and Intelligent Transportation Systems (ITS). The survey discusses the role of AI in accident risk prediction, smart traffic monitoring, and intelligent transportation infrastructure, along with conventional accident prevention strategies. Furthermore, recent literature is systematically reviewed to compare commonly used algorithms, application domains, advantages, and existing limitations. The paper also examines key enabling technologies, including IoT, connected vehicles, GPS, wireless communication, and traffic surveillance systems, that support real-time accident prevention. Finally, current research challenges and emerging trends are discussed to provide insights into future intelligent traffic accident prevention systems. This survey provides a structured overview of current research and highlights emerging directions for developing more accurate, explainable, and scalable AI-driven traffic accident prevention systems.

KEYWORDS: Traffic Accident Prevention, Internet of Things (IoT), Vehicle-to-Everything (V2X), Computer Vision, Artificial Intelligence (AI), Machine Learning (ML).

1. Introduction

Traffic is the flow of cars and people on the road networks. One of the primary concerns of public safety has always been the prevalence of traffic accidents. The yearly death toll from road accidents exceeds 1.25 million, according to data from the World Health Organization (WHO). The leading cause of death at the moment is traffic accidents. This highlights the critical need to address the issue of road accidents as a societal priority. The goal of accident prediction is to decrease the likelihood of traffic accidents by understanding their trend of development, evaluating the practicality and impact of safety measures for traffic, and making informed decisions. Timely and accurate traffic accident prediction in local regions is the aim [1]. Thus, one important area of traffic safety is learning how to identify risk factors in road networks and developing strategies to mitigate them. The traffic police can better prepare for crises by conducting preemptive investigations into the possible dangers of pertinent roadways or intersections made possible by precise prevention and control. Travelers' safety would be prioritized, and the road network's smooth, efficient functioning would be ensured, in such a scenario.

The main goal of accident data analysis is to solve significant road safety problems by identifying key factors impacting the occurrence of road traffic accidents (RTAs) [2]. The validity of the measured and gathered data, together with the suitability of the selected analytical procedures, are critical to the success of accident prevention initiatives. Selecting the right data analysis methods is important for figuring out what causes accidents in certain study areas or zones and for correctly predicting the number of accidents that happen each day or figuring out how safe those areas are for different sections of road users. In the age of big data, AI has emerged as the most significant subfield in computer science [3]. AI has come a long way since its inception 50 years ago, with notable advancements in areas such as data mining, computer vision, expert systems, robotics, natural language processing, and ML [4]. For AI, ML is head and shoulders above the others. Additional branches of AI encompass game theory, artificial neural network systems, DL, and probabilistic models. Many other fields make use of these classes. Research in this field has recently surpassed all others in transportation engineering, particularly in the areas of analysis, prediction, and prevention of traffic accidents.

A. Structure of the paper

This paper is structured as follows for the rest of it. Analysing traffic accidents and their underlying principles is covered in Section II. Section III delves into the function of AI within ITS, specifically addressing its use in traffic accident avoidance systems. Section IV presents a comprehensive review of recent literature and the identification of key research gaps. Finally, Section V concludes the paper and outlines future research directions.

2. Overview of Traffic Accident Analysis

The term "traffic accident" refers to an unforeseen occurrence that causes harm to people or their property without their knowledge or consent. Vehicles crash with each other, with people or animals, or with any other impediment, causing this to happen. As an illustration: The primary focus of the accident investigation is the police report [5]. Accident reconstruction is employed to re-create the chain of events that led up to the accident and its consequences. Forensic science that seeks to identify the elements that contributed to an accident is known as reconstruction. Traffic accidents happen when a car hits something else. The presence of humans, animals (both passing and staying), or stationary obstacles (such as trees or utility poles) are the main causes of these accidents. Multiple vehicle pile-ups, rear-end collisions, side-impact crashes, rollovers, head-on collisions, and incidents involving a single vehicle are among the most prevalent types of traffic accidents [6].

A. Rear-end collision

A rear-end collision happens when one vehicle collides with the back of the vehicle ahead of it. In most cases, a rear-end accident occurs when one vehicle suddenly slows down or suddenly speeds up. Passengers in the car that takes the brunt of an accident are more likely to suffer injuries than those in the vehicle that causes the accident.

B. Side-impact collision

Side impact crashes happen when the front or back of another car hits the side of a car [7]. Vehicle damage and injuries are worse in side impact incidents. The reliability of car safety systems like airbags and crumple zones, as well as the vehicle's build and materials, determine the severity of potential injuries and property damage. On the other hand, when two cars collide, it's called a sideswipe crash. In most cases, the only harm that happens when a sideswipe contact occurs is superficial.

C. Multiple vehicle pile-up

On roads and motorways, accidents involving several automobiles are known as multiple vehicle pile-ups. This is one of the deadliest traffic incidents when several cars are hit from different directions, causing extensive damage and loss of life. In a pile-up disaster, cars can even spin out of control, posing a much greater threat to the lives of everyone within. Those who make the hasty decision to flee their cars are still vulnerable to collisions with oncoming traffic. Accidents involving many vehicles are often difficult to pin down.

D. Single car accident

There are several different types of automobile accidents, but one of them is a single-car collision. The driver is either too sleepy to maintain control of the car or the brakes don't work, leading to an accident.

E. Head-on collisions

Accidents involving vehicles traveling at high speeds, particularly head-on accidents, are regarded as particularly deadlys.

F. Rollover a vehicle

The most common cause of a rollover is a sudden and quick turn at high speed, which causes the vehicle to topple over onto its side or roof. The elevated height of SUVs makes them more likely to topple over in the event of a rollover accident.

G. AI in Intelligent Transportation Systems

Adaptive and data-driven management of transportation network behaviour is achieved through the use of Intelligent Transportation Systems (ITS), which integrate communication technologies, cyber-physical systems, sensor infrastructure, and AI. The bulk of the existing research on Intelligent Transportation Systems' use of AI focuses on theoretical frameworks, performance improvements resulting from simulations, or discrete prediction tasks, despite the fact that this field has been studying AI for almost a decade [8]. The economy suffers from the real and perceived losses caused by road accidents. The real costs include things like:

- Insurance premiums, vehicle damage (replacement and repair costs), medical care, lost productivity, and organization expenses.
- The physical and social environments are both affected by road accidents. The family usually ends up footing the bill for medical expenses after an accident, or worse, the family may become bankrupt if someone in the family passes away.

H. Traffic Accident Prevention System

There are a lot of people hurt or killed and a lot of money lost every year due to road traffic accidents; this is one of the biggest problems with public safety on a worldwide scale. Major contributing factors include distracted driving, speeding, driver fatigue, adverse weather, and traffic congestion. Recent advances in AI, DL, computer vision, and connected vehicle technologies have enabled intelligent traffic accident prevention systems that identify potential hazards and prevent collisions before they occur[9]. These systems gather data in real-time from several sources, including cameras, Internet of Things sensors, GPS, radar, LiDAR, and vehicle telemetry. [10]. AI and DL models, such as YOLO, CNN[11], LSTM, and Transformer networks, analyze traffic conditions, detect road users, predict collision risks, and generate timely warnings for drivers and traffic authorities. Furthermore, integration with ITS and Vehicle-to-Everything (V2X) communication enhances situational awareness and supports proactive road safety.

I. Traditional Traffic Accident Prevention Methods

Traditional traffic accident prevention methods primarily rely on traffic regulations, road infrastructure, and human intervention to reduce accident risks. These approaches focus on improving road safety through standardized traffic control measures and vehicle safety mechanisms[12]. Although they have contributed significantly to reducing accidents, they are generally reactive and depend on driver compliance rather than proactive risk prediction. The major traditional accident prevention measures include:

- **Traffic Control Devices**: Traffic signals, road signs, lane markings, pedestrian crossings, and speed limit boards regulate vehicle movement and improve traffic discipline.
- **Road Infrastructure Improvements**: Speed breakers, guardrails, rumble strips, street lighting, and regular road maintenance enhance driving safety and reduce hazardous road conditions[13].
- **Law Enforcement**: Traffic police, speed cameras, and drunk-driving inspections help ensure compliance with traffic regulations and discourage risky driving behaviors.
- **Vehicle Safety Features**: ABS, ESC, airbags, seat belts, and traction control systems reduce the likelihood and severity of collisions.
- **Driver Education and Awareness**: Responsible driving is promoted through public awareness campaigns, driver training programs, and road safety campaigns.

Despite their effectiveness, these methods have several limitations. They cannot continuously monitor dynamic traffic environments, accurately predict potential collisions, or provide real-time alerts based on changing road conditions. These constraints have prompted the creation of AI-driven traffic accident avoidance systems that can proactively evaluate risks and make smart decisions [14].

J. AI-Based Traffic Accident Analysis and Risk Prediction

There are a number of areas where AI can significantly improve road accident prediction. AI has the ability to forecast many pieces of information pertaining to road accidents, including past accident records, current road conditions, weather, and traffic. Accident risk variables, trends, and patterns can be uncovered using AI. The factors that impact the frequency of road accidents can be better understood with the use of AI-generated forecasts. Using AI, can create models that can foretell when accidents happen on the road. Predicting the likelihood of an accident in a specific region or at a specific time requires models to take into account a number of parameters, including location, time of day, weather, and road conditions. In order to focus preventative efforts on areas most at risk, this forecast is useful [15].

Traffic congestion poses significant challenges in urban areas, impacting efficiency, safety, and the environment. The IoT, AI, and data analytics are some of the cutting-edge tools used by smart traffic management systems (STMS) to track and improve traffic flow in real-time. Using sensors and AI algorithms, STMS is able to adaptively operate traffic lights, which helps to reduce congestion and improve efficiency [16]. They also integrate with smart infrastructure to enable features like connected vehicles for enhanced safety.

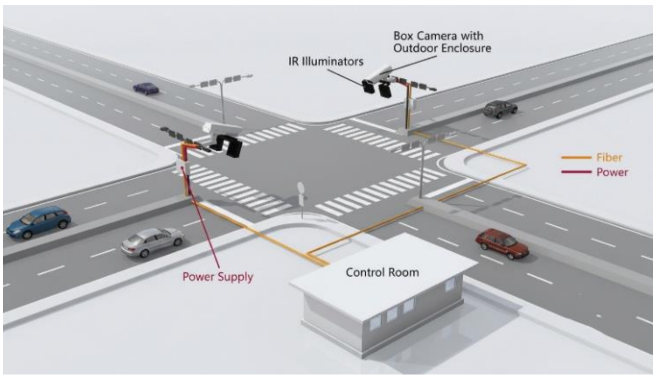

Fig. 1. Architecture of an Intelligent Traffic Intersection Monitoring System

Despite benefits such as reduced commute times and emissions, deploying STMS requires addressing privacy, security, and infrastructure concerns. Fig. 1 presents a smart traffic monitoring system in which cameras with IR illuminators are installed at an intersection and connected to a central control room through fibre-optic communication. The system enables real-time traffic surveillance, vehicle monitoring, and efficient traffic management.

K. Intelligent Transportation Infrastructure

The Intelligent Transport System (ITS) improves transportation in many ways by using cutting-edge ICT for things like traffic control, vehicle operation, and public transportation. By combining real-time data with sensor networks and smart algorithms, ITS aims to reduce travel times, increase safety, and lessen the impact on the environment [17].The future of mobility is heavily dependent on ITS, given the ever-increasing need for efficient transportation and the continuous acceleration of urbanization. The goal of establishing smarter, more linked, and ecologically friendly transportation ecosystems is being pursued by governments, businesses, and researchers throughout the world through the use of ITS technology. Here are a few examples of ITS technologies:

1) Global positioning System(GPS)

GPS receivers built into vehicles' on-board units receive signals from multiple satellites and send them to the vehicle's location. This necessitates direct line-of-sight to satellites, which might hinder GPS functioning in urban canyon situations. Ten meters is generally the upper limit for location [18]. Many satellite-based navigation and route-guidance systems rely on global positioning systems (GPS). Some countries' transport systems are being financed by tracking the miles driven by trucks and cars using OBUs fitted with GPS devices that are based on satellites. This is happening in countries like Germany and Holland.

2) Wireless networks

Wireless networks allow for quick communications between cars and the roadside, much as the technology typically utilized for wireless Internet access; however, its range is limited to a few hundred meters at most [19]. The good news is that each succeeding car or roadside node may increase this range to relay information on to the following one. South Korea's transport network is progressively using WiBro, a wireless communications infrastructure based on WiMAX technology, to relay traffic and public transit information.

3) Mobile Telephony

Applications of ITS can make use of conventional 3G or 4G mobile phone networks to transport data [20]. The widespread availability of mobile networks in urban areas and along main thoroughfares is one of their many benefits. Network providers may have to foot the bill for extra network capacity if mobile networks are installed in automobiles [21]. The potential slowness of mobile telephony makes it unsuitable for use in some safety-critical ITS systems.

4) Radio Wave or Infrared Beacons

The Japanese VICS system, which stands for Vehicle Information Communications System, transmits traffic updates in real time using radio wave beacons on motorways and infrared beacons on major routes. The 5.8GHz DSRC wireless technology is utilized by VICS. Arterial roads, which are medium-capacity roadways slightly below highways in terms of service quality, typically employ traffic lights, which is a crucial difference. Massive amounts of traffic are transported between different parts of cities via arterial highways.

L. Traditional Methods for Traffic Accident Analysis

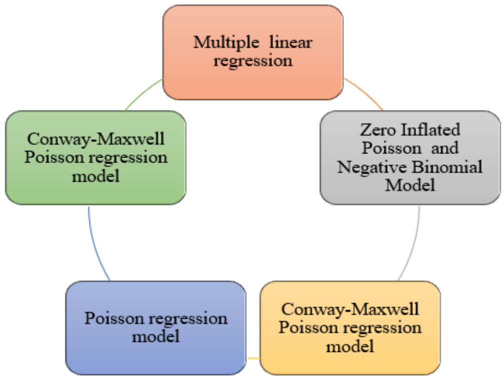

Fig. 2. Methods of Traffic Accident Analysis

The mainstay of conventional traffic accident analysis is the use of statistical models to investigate the correlation between crash frequency and variables including traffic flow, road design, and ambient elements. These methods provide valuable insights into accident frequency and risk patterns and have served as the foundation for road safety research. The commonly used traditional approaches are described and shown below in Figure 2:

1) Multiple Linear Regression Models

Multiple linear regression modeling techniques have been used to model the relationship between an outcome variable, in this case, crash rate or crash frequency, and two or more explanatory variables by fitting a linear equation assuming normally distributed errors . Today it is not widely used because accident data frequently violates linear regression analysis assumptions such as normal error structure and constant error variance.

2) Zero Inflated Poisson and Negative Binomial Model

A typical occurrence in crash data is zero-inflated data, which is characterized by an abnormally high number of zero observations. This happens when negative binomial or Poisson regression models are applied. The purpose of building zero-inflated models was to accommodate data that had more zeros than what a standard Poisson or negative binomial/Poisson gamma model would anticipate [22]. A two-state crash system has been developed using the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) modeling approaches; one state is the zero crash state, which is essentially safe for the observation period, and the other is the non-zero crash state.

3) Poisson Regression Model

Poisson regression model is more suited than multiple linear regression models, since crashes are unavoidable, discrete and more probably random events. A limitation of Poisson models is that, for road accidents, the mean must match the variance. Nevertheless, it is common for road collision data to have a variance higher than the mean, suggesting that the data are distributed.

4) Conway-Maxwell Poisson Regression Model

A generalisation of the Poisson distribution, the Conway-Maxwell Poisson regression takes into account crash data that is either under-or over-dispersed, or a mix of the two, according to a variable known as the dispersion parameter. Because neither the Poisson nor the Negative Binomial models can account for the underdispersion in accident data, this becomes crucial. Potentially detrimental effects of a short sample size and a low sample mean on the Conway Maxwell-Poisson regression. Because of this, it hasn't been used much in car safety research.

3. Literature Review

Recent studies have highlighted the growing use of AI, ML, and DL for traffic accident analysis, prediction, and prevention. These approaches have improved prediction accuracy and supported intelligent transportation systems.

Affou et al., (2026), explore the many statistical models used for accident prediction, including those that rely on ML and DL approaches. In this study, look at a number of forecasting methods and their strengths and weaknesses, comparing and contrasting them analytically. also look at where this field could go from here, including into hybrid models and RL. The strengths of DL models in feature representation and non-linear spatiotemporal correlation extraction make them well-suited to complicated forecasting issues, according to this review's findings. [23].

Verma and Agarwal, (2026), focus on accident prediction, accident severity prediction, ML algorithms, IoT integration and DL models. The study highlights the various approaches used by researchers to develop predictive models for road accidents and discusses the advantages and limitations of different ML and DL methods. The findings indicate that these methods have the potential to accurately predict road accidents, providing insights into the contributing factors and allowing for targeted interventions [24].

Niture and Abdellatif, (2025), examine the grave repercussions of these accidents, which include decreased production, loss of life, and other socio-economic aspects that necessitate timely action. Accurate, location-specific traffic collision forecasts are essential, but there is currently no agreement on datasets and prediction methods. This paper aims to contribute significantly to the discourse on long-term preventative strategies for traffic collisions by carefully analyzing relevant factors and data sources and using state-of-the-art ML and DL methods to create accurate, location-adapted predictions [25].

Behboudi et al., (2024), examine 191 analyses of accident data over the past five years, with an emphasis on risk, frequency, severity, and duration prediction. So far as aware, this research is the first of its kind to offer such an all-encompassing assessment of the current state of the art in accident analysis and prediction. Improving prediction accuracy and handling the complexity of traffic data are both emphasized by the assessment as successful outcomes of combining varied data sources and sophisticated ML approaches [26].

Adewopo et al., (2023), suggest a system that can automatically react to traffic accidents by monitoring the road using cameras and using action recognition software. An effective method for reacting to traffic accidents while minimizing human error may be achieved by integrating the suggested framework with emergency services. This allowed for the utilization of traffic cameras in conjunction with ML algorithms. Better traffic management and fewer severe traffic accidents are possible outcomes of smart city accident detection systems and other forms of advanced AI [27].

Shaygan et al., (2022), make an effort to present an exhaustive review of traffic forecast approaches. Recent successes and promising future directions in traffic prediction have prompted them to zero in on AI-based traffic prediction methods, particularly multivariate traffic time series modeling, and the new avenues of inquiry into these approaches. First, they lay out the many kinds of data and sources utilized in the literature and explain each one. The next section provides a brief overview of the most important data preparation techniques used for traffic prediction, followed by a classification of these techniques [28].

Table I compares recent review studies on AI approaches for traffic accident analysis and prediction. It highlights that advanced ML and DL models improve prediction performance, while challenges such as limited explainability, real-time implementation, and standardized datasets continue to drive future research.

TABLE I. COMPARATIVE REVIEW OF ARTIFICIAL INTELLIGENCE APPROACHES FOR TRAFFIC ACCIDENT ANALYSIS

Authors	Focus Area	Techniques	Advantages	Key Findings	Challenges & Limitations
Affou et al., (2026)	Review of traffic accident prediction using statistical, ML, DL, hybrid, and RL models	Statistical models, SVM, RF, XGBoost, CNN, LSTM, Hybrid Models, Reinforcement Learning	Comprehensive comparison of traditional and AI-based approaches; identifies future research directions; highlights superiority of DL models	DL models effectively capture complex nonlinear spatiotemporal relationships and generally outperform traditional models.	Limited focus on Explainable AI (XAI), real-time implementation, heterogeneous data fusion, and cross-region model generalization.
R. Verma and M. M. Agarwal (2026)	Systematic review of ML/DL techniques for road accident prediction	Machine Learning, Deep Learning, IoT-based systems	Covers a wide range of ML and DL algorithms; discusses IoT integration for intelligent transportation systems	ML and DL techniques improve accident prediction accuracy and support proactive road safety management.	Lack of benchmark datasets and standardized evaluation metrics. Limited discussion of model interpretability, uncertainty estimation, and transfer learning.
Niture and Abdellatif, (2025)	Literature review of traffic collision prediction and contributing factors	ML, DL, Feature Engineering	Provides comprehensive analysis of collision factors, datasets, and prediction methods; emphasizes location-specific prediction	Identifies the importance of integrating multiple influencing factors for accurate accident prediction.	No consensus on datasets or prediction techniques. Limited multimodal data integration and poor model transferability across different regions.
Behboudi et al., (2024)	Comprehensive review of ML techniques for accident analysis and prediction	Random Forest, XGBoost, LightGBM, ANN, CNN, LSTM, Ensemble Learning	Reviews 191 recent studies; summarizes accident risk, severity, duration, and frequency prediction methods	Integration of multiple data sources with advanced ML techniques significantly improves prediction performance.	Limited exploration of Graph Neural Networks (GNNs), Transformers, Explainable AI, federated learning, and real-time Intelligent Transportation Systems (ITS).
Adewopo et al., (2023)	AI-based traffic accident detection using surveillance cameras	Computer Vision, CNN, Action Recognition	Enables automatic accident detection and rapid emergency response;	AI-powered surveillance systems can improve traffic management and	Focuses mainly on accident detection instead of accident prediction and prevention. Limited validation under

			reduces human intervention	reduce accident response time.	adverse weather, nighttime conditions, and large-scale deployment scenarios.
M. Shaygan et al., (2022)	Survey of AI-based traffic prediction methods	AI, ML, DL, Time Series Models	Comprehensive categorization of datasets, preprocessing methods, prediction models, and applications	AI-based traffic prediction methods demonstrate high potential for intelligent traffic management and forecasting.	Primarily focuses on traffic flow prediction rather than accident prediction. Limited discussion of explainable AI, accident prevention, causal inference, and multimodal sensor fusion.

Research Gaps: Despite significant progress in AI-based traffic accident prediction, several research gaps remain, as summarized in Table 1. Most existing studies primarily focus on reviewing ML and DL algorithms rather than developing integrated real-time accident prevention frameworks. Limited attention has been given to combining heterogeneous data sources, such as vehicle sensors, traffic cameras, weather conditions, and IoT devices, for comprehensive risk assessment. Additionally, issues related to model explainability, standardized benchmark datasets, real-time deployment, and scalability across diverse traffic environments remain insufficiently addressed. These limitations highlight the need for explainable, adaptive, and intelligent traffic accident prevention systems capable of providing accurate risk prediction and timely preventive interventions.

4. Conclusion and Future Work

Traffic accidents continue to pose a major challenge to road safety, emphasizing the need for intelligent and proactive prevention strategies. The study discussed the role of ML, DL, computer vision, ITS, IoT, and connected vehicle technologies in improving accident prediction, detection, and prevention. A comparative analysis of recent literature demonstrated that AI-driven methods provide higher prediction accuracy and better adaptability than conventional approaches by effectively learning complex spatial and temporal traffic patterns. Furthermore, the integration of computer vision, IoT, and intelligent transportation systems has enhanced real-time monitoring and emergency response capabilities. Despite considerable progress, challenges such as limited explainability, the absence of standardized datasets, real-time deployment constraints, and poor model generalization remain unresolved. Future research should emphasize explainable AI, multimodal data fusion, edge AI, V2X communication, and privacy-preserving techniques such as federated learning to develop intelligent, reliable, and scalable traffic accident prevention systems.

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