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Review

A Review of Artificial Intelligence and Machine Learning for Incident Detectors in Road Transport Systems

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Abstract: Road transport is the most prone to accidents, resulting in significant fatalities and injuries. It also faces a plethora of never-ending problems, such as the frequent loss of lives and valuables during an accident. Appropriate actions need to be taken to address these problems, such as the establishment of an automatic incident detection system using artificial intelligence and machine learning. This article explores the overview of artificial intelligence and machine learning in facilitating automatic incident detector systems to decrease road accidents. The study examines the critical problems and potential remedies for reducing road traffic accidents and the application of artificial intelligence and machine learning in road transportation systems. More, new, and emerging trends that reduce frequent accidents in the transportation sector are discussed extensively. Specifically, the study organized the following sub-topics: an incident detector with machine learning and artificial intelligence and road management with machine learning and artificial intelligence. Additionally, safety is the primary concern of road transport; the internet of vehicles and vehicle ad hoc networks, including the use of wireless communication technologies such as 5G wireless networks and the use of machine learning and artificial intelligence for road transportation systems planning, are elaborated. Key findings from the review indicate that route optimization, cargo volume forecasting, predictive fleet maintenance, real-time vehicle tracking, and traffic management are critical to safeguarding road transportation systems. Finally, the paper summarizes the challenges facing the application of artificial intelligence in road transport systems, highlights the research trends, identifies the unresolved questions, and highlights the essential research takeaways. The work can serve as reference material for road transport system planning and management.

Keywords: artificial intelligence; machine learning; incident detector; road transport systems; traffic management; automatic incident detection

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1. Introduction

One of the most efficient methods for predicting what will happen on the road is the implementation of an automatic incident detection (AID) system, which obtains its feed from the CCTV installed throughout road networks to monitor traffic flow and detect incidents or traffic bottlenecks. In the monitoring room, the system supports the human operator. Modern signal controllers and creative applications of video-based vehicle identification have been the main focuses of ITS implementation on arterial highways. As technology advances quickly, arterial ITS components are becoming more frequently used and less expensive [1]. Continuously scanning the highway network for issues and acting swiftly to lessen their effects are necessary for maintaining traffic flow. This procedure can become more effective and efficient because of recent developments in computational intelligence, embedded systems, and wireless communication technologies [2].

Typically, automatic or non-automatic approaches are used by traffic management systems to detect incidents. Automatic incident detection (AID) techniques are more frequently used; they use a range of sensors and procedures such as image processing. In addition, detector/sensor-based event detection algorithms and vehicle probes which evaluate traffic data to identify incidents quickly are studied [3]. It takes time to integrate new technology. The transportation industry is one area where disruption is already occurring due to artificial intelligence and other emerging technologies. In his book *Innovators Dilemma*, Harvard management professor Clayton Christensen introduced the concept of disruptive technology. Technology disruption creates new product opportunity windows. It may make a piece of technology available to low-income markets that would not otherwise have it. Disruptive technologies can affect the education and healthcare sectors [4]. In other words, understanding the process from inspiration to AI/ML technology may be conducted by looking at the route for an AMI initiative. Establishing a structure and platform for bottom-up, cross-functional intent evaluations is essential to choosing which new AI/ML technology to develop. An innovative AI/ML technology can require a disruptive approach, which frequently stresses characteristics that are complimentary to those of existing AI/ML technologies. A new AI/ML technology will frequently perform better than an old one; as a result, the existing AI/ML technology will be disrupted [5].

Analyzing traffic patterns to decrease road accidents and optimizing sailing routes to cut emissions are two examples of how artificial intelligence (AI) opens up the choices for making transportation safer, more dependable, more efficient, and cleaner [6]. This technology helps in the obtaining of pertinent information on their effects and of new measures to illustrate this procedure and validate the benefits of new technologies in transportation [7].

According to results from previous studies, incident detection algorithms can be divided into five main categories based on how they analyze data throughout their operations. They are the following: comparative algorithms, statistical algorithms, time series- and filtering-based algorithms, and traffic theory-based algorithms [8,9]. Traffic issues such as parking, speeding, and congestion are examined based on the spatiotemporal map's dispersion and the creation state of the trajectory. According to experimental findings, the proposed method significantly speeds up vehicle detection and tracking and produces high MAP, MOTA, and MOTP indicators [10]. This paper presents an overview of incident detector applications in road transportation systems, utilizing machine learning and artificial intelligence.

Artificial intelligence and machine learning play a significant role in predicting road system incidents. The study aims to address the constant cause of road accidents and the application of AI and ML to curb the cause of this growing menace.

The primary motivations of this study are listed below:

- To better understand the various applications of artificial intelligence and machine learning as related to the incident detectors in the road system.
- Despite various research concerns with incident detectors by researchers, various challenges and concerns about road transport systems still need to be investigated.
- The need to study the impacts of 5G and emerging 6G technologies on road transport systems is of the utmost importance.
- A wide range of wireless communication with the internet of vehicles (IOV) and different underlying networks, such as real-time vehicle tracking, traffic management, and other networks, needs to be investigated in order to be properly deployed for effective road management.

The significance of artificial intelligence and machine learning to evaluate the incident detector by applying it to road systems is crucial to avoid death and injuries. Therefore, conducting this study to address the issue is of the utmost importance as it will enhance the knowledge of the underlying mechanisms in the application AI and ML and will not forget the challenges that may occur. The layout of the paper is given in Figure 1.

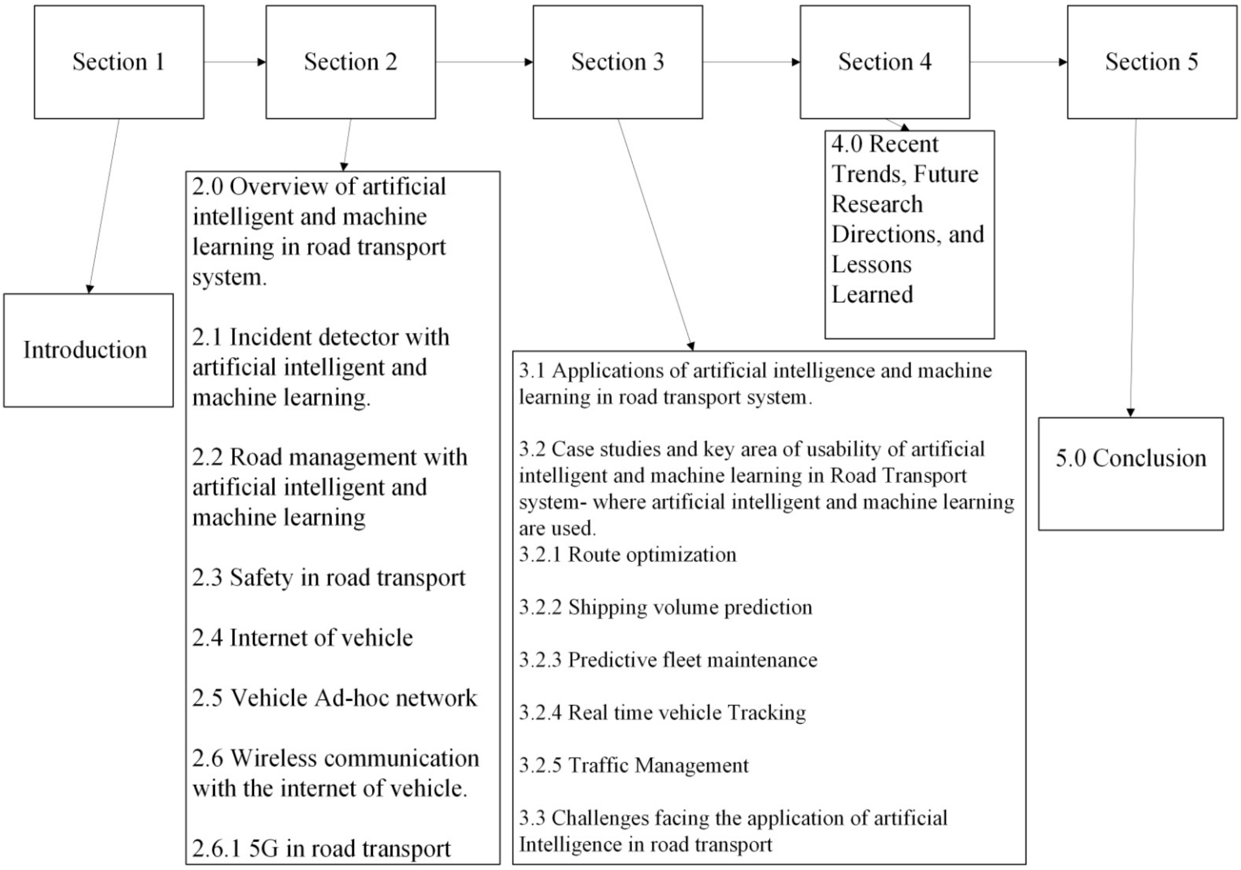

Figure 1. The layout of the review.

The contribution of this paper is as follows:

- The study contributed by extensively reviewing the literature to search for the effect of ML and AI on the incident detector in road transport systems.
- The study investigates the key areas of the usability of artificial intelligence and machine learning in road transport systems, such as the internet of vehicles, the ad hoc vehicle network, and wireless communication with the internet of vehicles, 5th generation and 6th generation.
- The study examines real-time vehicle tracking, which is vital in incident detector systems in road systems. This paper further summarizes the challenges facing the application of artificial intelligence in road transport systems.

The remaining sections of this article are structured as follows: Section 1 presents the study's introduction, Section 2 presents an overview of the artificial intelligence and machine learning in the road transport system, and Section 3 provides examples of how these technologies are used in actual road transport systems. We outline current trends, potential paths for future research, and key takeaways in Section 4. Finally, Section 5 provides the conclusion of the paper.

2. Overview of Artificial Intelligence and Machine Learning in Road Transport Systems

Artificial intelligence was effectively integrated to continuously monitor the orbital environment as deep space exploration developed; it was utterly reliant on human interaction for decisions relating to road transportation [11]. The reliability and effectiveness of artificial intelligence (AI) systems, such as the artificial neural network (ANN), for reducing or eliminating traffic volume in non-autonomous vehicles has been considered [12]. Researchers studying artificial intelligence look at effective tactics to achieve intelligent behavior. However, if a program or technique for artificial intelligence is widely utilized, it is no longer considered artificial intelligence. Examples include time sharing, graphical user interfaces, computer games, object-oriented programming, personal computers, email, hypertext, and even software agents. Symbolic programming languages (such as Lisp, Prolog, and Scheme) and symbolic math systems (such as Mathematical) are also examples [13]. It has been noted that academic research on robotics and the applications of artificial intelligence are growing daily, but the studies examine the position and importance of robotic and artificial intelligence technologies in the future [14]. Machines have long since largely replaced human labor in ways that customers can understand [15].

The goal of human computing, as promoted and demonstrated, is to turn smart surroundings and computing equipment into social companions for those using them or living in them [16]; consequently, the following means of sorting the road transport system were specifically taken into account: automobiles that have been rented; automobiles owned by friends or family; caravans and motor homes; motorcycles, scooters, and mopeds; and other vehicles (vans, lorries, trucks, etc.). Coaches and buses are publicly used, and so, they do not fall into the private road transportation used by tourists on their own. At the same time, the "other" group primarily relates to worker business travel and similar means of transport [17]. Machine learning is a science that is expanding quickly and significantly impacts daily life. A framework must be established for machine learning to be rapidly incorporated into the road transportation system [18]. Depending on the training data, machine learning techniques are determined by various training data and can be classified as supervised classification or unsupervised clustering. Unsupervised machine learning algorithms evaluate the similarity of data to determine whether or not they should be classified collectively. Using their qualities, supervised machine learning systems categorize input data and link them to the intended outputs [19,20]. The limitations of some of the associated reviews and the contributions of the current paper are highlighted in Table 1.

Table 1. Limitations of some associated reviews and contributions.

Ref.	Study Focus	Limitations	Contributions
[21]	The authors examine, compare, contrast, and assess deep learning and machine learning techniques for predicting traffic flow for autonomous vehicles and how to carry out traffic flow planning using these methods.	Who dealt with the issue that would develop when the prediction timescales widened? The current approaches are still inadequate as simulating stochastic traffic flow aspects is challenging.	This study will highlight the numerous applications for structure optimization, machine learning, and artificial intelligence. This study proves the efficacy of the journey time prediction model-specific gradient-boosting decision tree (GBDT).
[22]	The article discusses how the internet of things (IoT) is being utilized to produce SMART vehicles; it advances transportation technology and reduces the frequency of road incidents caused by microsleep that result in serious accidents.	In order to correct this and make it better, research must be integrated with IoT due to the distinctive properties of internet protocol that IoT employs, such as recognition, control, and data transfer to people and databases.	Additionally, this study uses ground truth as its classification model and may use a driver monitoring system (DMS) to determine an automobile's manufacturing capacity.
[23]	Creates accurate intrusion detection system models using artificial intelligence techniques.	The task can be expanded by considering the classifiers for multiclass classification and solely considering the crucial qualities for intrusion detection.	In F1 score and accuracy, the results show that the random forest classifier outperforms other classifiers for the parameters and dataset under consideration. The NSL-KDD dataset is used to test algorithms.

Table 1. *Cont.*

Ref.	Study Focus	Limitations	Contributions
[24]	The author comprehensively analyzes cutting-edge technology for constructing a three-tier solution classification in machine learning to study the planning and distribution based on real-time traffic density.	The ITS applications were limited. The future research is not addressed in depth.	The first tier has numerous technologies and techniques for gathering traffic statistics. The second tier concerns how accurate the machine learning algorithms are as they form. In the third tier, numerous traffic planning strategies are explored.
[25]	In this study, traffic behavior is analyzed, and any vehicles that travel differently from the flow of traffic are considered for potential accidents.	Due to roadway layout, intersections, speed restrictions, and vehicle size, there is a limited mobility pattern.	The results demonstrated that accident detection using clustering techniques is successful. Accident detection will help prevent additional collisions and assist the authorities in reopening a road segment to traffic.
[26]	The internet of vehicles (IoV) is a method for intervehicle communication used in intelligent transportation. It enhances traffic management programs and services to ensure road safety.	When building applications and services, it is important to consider cost, performance, implementation complexity, and timing. A major difficulty is the raising of QoS standards for IoV services.	The control and development of smart cities will benefit from the current study. According to the findings of this research, performance is evaluated by services and applications 34% of the time. Safety and data correctness is evaluated 13% of the time, and security is evaluated 13% of the time in the selected papers.
[27]	This article explores a shared vision among participants along the value chain regarding the use of radio location and sensing for traffic safety in the 5G ecosystem.	Experimentation and extensive measurements are required to validate the radio location and sensing used for traffic safety in the 5G ecosystem.	This study presents a comprehensive analysis of the performance requirements, enabling technologies in 5G and beyond and the critical architectural characteristics that make it possible for the sensing and location data to be collected, processed, and efficiently shared in the network. In 5G, either the network or the UE can position itself (with network assistance) (network-based). Without the help of the network, the UE can localize itself in RAT-independent positioning (such as GNSS/RTK-GNSS) (standalone).
[28]	In order to extract similar traffic patterns over time for accurate and successful short-term traffic flow prediction in massive IoT, this work provides a large data-driven study of the non-parametric model supported by 6G. The model's main foundation is time-aware LSH (Locality-Sensitive Hashing).	Because only a tiny percentage of the sampled data is used to anticipate traffic flow, the outcome is not sufficiently accurate.	These sensors will gather all the real-time traffic data, which will then be transmitted to the cloud for the processing and utilizing of the cutting-edge 6G technology to guarantee the efficiency, stability, and integrity of the massively distributed data transfer. The implementation of the 6G-enabled short-term traffic flow forecasting is a viable technique to give traffic managers strategies to detect flow breakdowns in the future, according to the combined data collected from all the sensors.

2.1. Incident Detectors with Artificial Intelligence and Machine Learning

Early in the 1970s, the first event detection algorithms were created, and the work on them is still ongoing. The suggested method employs sensors to monitor accidents. With the help of the force and impact data collected from car wrecks, the severity of the accidents is assessed using machine learning methods such as k-means clustering and support vector machine (SVM) classification under reinforcement learning [29]. Smartphones, vehicular ad hoc networks, and GSM and GPS technologies are used, and among these detection methods are mobile applications. Every vehicle must be equipped with an automatic road accident detection and information communication system [30] as they are typically not constrained by energy and space restrictions. Detecting devices with high processing power and high cost and weight, such as GPS, chemical spill detectors, video cameras, vibration sensors, sound detectors, etc., can be installed in vehicles [25]. Based on multimodal in-vehicle sensors, we recommend a machine learning framework for automatically detecting car accidents. The study uses cutting-edge feature extraction techniques and common automobile sensors to identify real-world driving collisions [31]. Artificial neural network (ANN) models are another type of detection technology. These are the most popular artificial intelligence algorithms, but they have not been as successful as their more modern support vector machine counterparts. Support vector machine (SVM) models have greater learning and prediction potential than ANN models because they may produce results more quickly and offer the modeler more options [8,32].

One way to make contracts more precise is to insist on the specific use of new technology, especially that which comes with new vehicles [33]. The system must be reactive in the first place (detecting actual abnormal congestion rather than possible abnormal congestion), not predictive, and it must only be based on recently deployed on-street equipment. The second principle states that the algorithm must be able to run by utilizing only the U06 messages from a single detector [34]. The thorough examination of each vehicle's behavior at crossings should serve as the foundation for automatic monitoring systems rather than the current practice of using global flow analysis. Each vehicle should be recognized by the systems, which should also be able to monitor how it behaves and to identify potentially harmful scenarios or the circumstances that precede them [35]. As a result, the techniques that use the relevant data from traffic flow metrics and unique algorithms to process this data to detect issues automatically are the most effective. However, new information-gathering techniques and a sufficient detector saturation of the road network are required [36].

Over the past few years, as shown in Figure 2, accident detection and alert systems have been the subject of in-depth research. A telematics model with the main module, the CCTV system, which intends to record the accident scene and provide the position information to rescue systems through GPS, has been proposed by research that adds to the field [37].

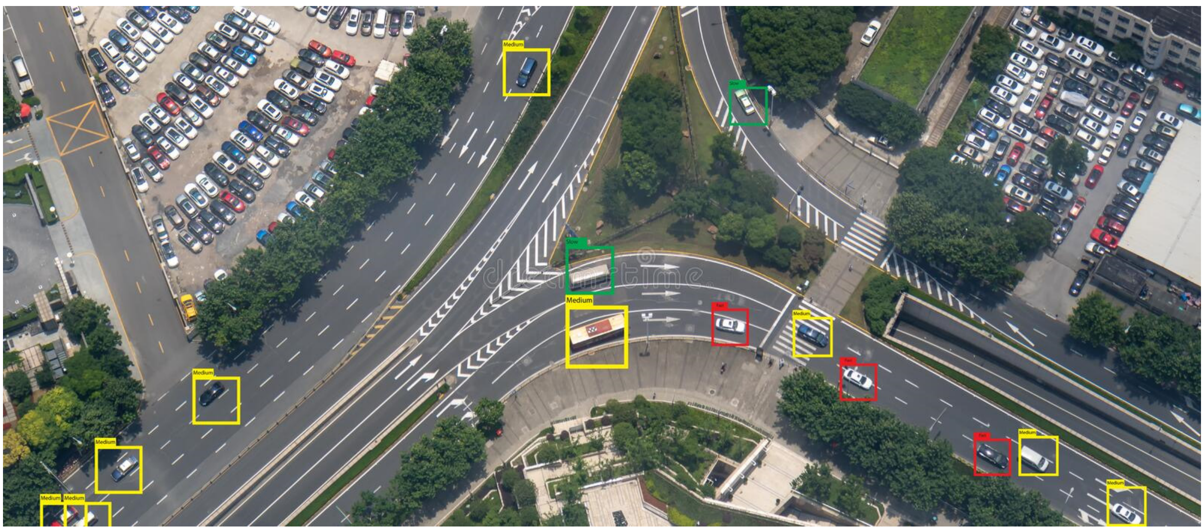

Figure 2. Artificial intelligence and machine learning for the internet of things; speed automobile object detection.

2.2. Road Management Using Artificial Intelligence/Machine Learning

The dynamic nature of vehicle networks and their underlying heterogeneous structure introduce additional requirements for networking algorithms that deal with network control and resource allocation. While network control works with the handover, routing, and offloading of network traffic, network resource allocation deals with the spectrum, transmission power, and computer resources. Traditional approaches cannot detect the underlying patterns in in-vehicle networks, but the use of ML methods in this field of vehicular networking is coupled with several enabling technologies [38]. Developing a message queue telemetry-based traffic congestion monitoring system is suggested for looking at traffic congestion trends (MQTT). The benefits of an infrastructure-based approach and the MQTT techniques are combined in the proposed system, and the adaptability to support the integration of various types of sensors for traffic flow observation in low-bandwidth and high-latency vehicular networks environments is offered [37].

A country's ability to maintain economic growth and development is greatly influenced by its transportation infrastructure. People wish to travel to more and more destinations in a shorter time due to their hectic lifestyles and limited free time [39].

Relevance analysis would be programmed into the software, showing the sample picture of road traffic management artificial intelligence and machine learning, which will be executed if the database does not contain any similar circumstances [40].

2.3. Artificial Intelligence and Machine Learning and Deep Leaning Approaches in Automated Incident Detection

Artificial intelligence is an intelligent machine that emulates or imitates how a human behaves; it encompasses learning concepts and obtains an understanding of those concepts and uses them to engage humans in dialogue. AI contains machine learning and deep learning. Machine learning is a subset of artificial intelligence; it allows data to be fed into the machine for it to learn, and in [41], it is postulated that machine learning offers a flexible network architecture and large data and path loss forecasts. Radial basis function (RBF) and support vector regression (SVR) models provide path loss estimates in the examined settings. Multiple input parameters might be processed by the SVR model without complicating the network design. Deep learning is a bigger part that represents data and is focused on the neural network; it is also a computing system that allows the system to identify objects.

There are several approaches to detecting road traffic accidents according to [42]. Multiple sub-sections (links) of the target corridor are separated by the same unit of distance. Consider comparing the journey times of a probe vehicle at two successive links. The travel time of the link is longer than that of the downstream link if there is congestion in the upstream link. The bottleneck is located using both absolute and relative disparities in the probe vehicle's connection trip timings. To detect foreground regions in the videos with a semi-stationary background, the technique of adaptive non-parametric kernel density estimation (AKDE) is identified as the baseline system. AKDE addresses both scene independence and the multi-modality of the backdrop. The advantages of AKDE are caused by the fact that individual pixels can have distinct and adaptive thresholds, and thus, a global threshold is not necessary for the pixels in a video scene. The system can consistently operate with varied video scenarios without changing settings [43].

Another detecting device is the installed automatic device, such as CCTVs that run continuously and alert action when necessary. In [44], the Haar-like algorithm and the AdaBoost algorithm are discussed. The primary function of the Haar-like algorithm is to extract details about certain object features, such as edges, contours, and intensity gradients. This may be accomplished by adjusting the size, scale, location, and other characteristics of the Haar-like temple. Integral pictures make it relatively simple to apply and compute this feature, and the AdaBoost algorithm utilizing a sliding window system allows for detection. During this procedure, a sub-window is moved over the screen to identify any item and determine whether it is a vehicle. However, this technique requires a lot of time for sliding and detection.

In order to identify the occurrence of accidents, the study in [45] compares the performance of two well-known machine learning models, support vector machine (SVM) and probabilistic neural network (PNN). As a result, using traffic condition data after the actual occurrence, several models are trained and tested for each machine learning technique in order to ensure the quickest possible detection of accidents. A Haar-like feature is comparable to a CNN (convolutional neural network) kernel. An input layer, an output layer, and several hidden layers make up a CNN. It is the machine learning neural network model that is mostly utilized for issues with picture categorization.

Furthermore, there is a new technique for ground vehicles to estimate their velocity. Using video sequences captured by a fixed-mounted camera, the challenge at hand is to automatically estimate vehicle speed. Using an optical flow technique, the motion of the vehicle is recognized and tracked over the frames [46].

2.4. Road Safety Modeling

Road safety modeling, a practical method for promoting safe mobility, enables the construction of collision prediction models (CPM) and the investigation of factors impacting crash occurrence. This modeling has historically employed statistical techniques, despite the approach's limitations (certain assumptions and the construction of the link functions in advance) being acknowledged. This development offers a chance to look into alternatives, including applying machine learning (ML) approaches [47], identifying three areas where AI controllers have the greatest potential to reduce congestion and increase safety, and considering fully or partially autonomous driving, intersection management, and road pricing for optimized traffic flow [48]. The sector′s ongoing objective is to increase transportation safety, especially road transportation, which is the most popular. Having fewer fatalities from traffic accidents benefits society [49], with all modern vehicles equipped with electronic aides to facilitate safety. Assistance can keep you on the road at a safe distance from the automobile in front of you [5].

Until recently, the main objective in improving positioning methods and architectures has been accuracy, which is connected to the estimation error for the absolute or relative position with regard to the genuine position. The position estimate related to other network components or UEs is referred to as "relative positioning" [27]. Consequently, It will not be long before AI contributes more to enhancing traffic safety. Improved CNN, computational capacity, unsupervised learning, pattern recognition, and more robust computer hardware will lead to better autonomous driving [50].

2.5. Advance Approaches for Incident Detectors of Road Traffic Accidents Using AI and ML

2.5.1. Incident Detectors through In-Vehicle Equipment

Equipment installed in vehicles is crucial for detecting incidents and preventing users from irregular use. For example, installing a speed limiter is a clear way to regulate speed and prevent traffic accidents. Speed restrictions must be in line with the intended speed of the road to be successful. Speed is a major cause of accidents. Lowering the risks put forward by drivers in their choice of speed with speed restrictions serves the primary objective of improving safety. Tachographs, or speed logging devices, are examples of in-vehicle equipment [51]. Technologies for detecting and monitoring vehicles are being developed to deliver better data on speed monitoring, traffic counting, presence detection, headway measuring, and vehicle categorization [52], and several other characteristics, including symmetry, color, edge (horizontal/vertical), shadow, etc., have been employed as crucial signals for vehicle recognition because of the rectangular shape of vehicles [53].

The equipment employed in vehicles varies in classification, and the accuracy of incident detectors differs; the findings indicate that the success rate of the length-based classification of sedans, passenger trucks/SUVs, motorcycles, buses, small commercial trucks, and big commercial trucks is poor. With an extremely low classification rate between sport utility vehicles (SUVs) and small commercial vehicles, their multi-class support vector machine (SVM) classifier has an average accuracy of 74%. However, the outcome of the classification of vehicles by make and model and subjection to video resolution has not been provided [54], and based on the algorithm's comparatively greater practical value, a kind of magnetoresistive traffic flow collecting equipment with low power consumption and compact size was created. It uses the vehicle speed detection algorithm of micro-magnetoresistive vehicle detection equipment for accuracy [55]. The vehicle equipment necessary in road safety has seen a significant evolution with the introduction of active safety systems such as the anti-lock braking system, the traction control system, the stability control system, etc. Vehicle active safety systems are those that aim to prevent collisions or lower the likelihood of having one in the automobile industry [56].

In the automobile industry, on-road vehicle detection has always been the main emphasis. The inclusion of the collision avoidance system (CAS) in current automobiles may lower the accident rate by rapidly and effectively recognizing all types of vehicles and alerting drivers to the possibility of an accident. The review of sensors and methods for tracking and detecting vehicles for the collision avoidance system (CAS), an automobile safety system, is intended to lessen the likelihood of an accident. It may gather information on on-road traffic using various sensors (such as radar, laser, and cameras) and then identify and categorize cars. When a collision is foreseen, these devices either warn the driver or respond automatically without the driver's involvement (by braking or steering or both) [57]. What may pose a challenge for this in-vehicle equipment is the managing of the maintenance of a commercial fleet; this is an active new application field for mining and utilizing vehicle on-board sensor data for vehicle problem diagnosis and failure prediction [58].

Another type of vehicle equipment is the two loop detector that makes up the dual loop detectors. It has the ability to assess vehicle speed and length depending on the set longitudinal distance between the two loop detectors; this is a fundamental advantage of dual loop detectors over single loop detectors. Specifically, the speed of the vehicle is determined by calculating the distance travelled in a certain amount of time between two longitudinally positioned magnetic sensors; different machine learning classifiers, including the decision tree (DT), support vector machine (SVM), k-nearest neighbor (kNN), and naive Bayes classifier, are used to classify vehicles using the vehicle magnetic length as the primary feature (NBC) [59]. The intrusion detection system IDS is also a vital method that is frequently used in information and communication technologies (ICT) to monitor and analyze local and/or network activities to spot attacks or other inappropriate behavior when road users and drivers try to distort and mutilate data that may cause a traffic accident. IDS reveals such violations of the stated traffic and security policy by identifying aberrant patterns whenever potentially suspicious behavior takes place (such as the transmission of unusually large amounts of data) [60].

2.5.2. Incident Detector through Image Processing at Intersections

This provides a method for incident detection that takes advantage of categorized vehicle interactions. A video-based automated incident detection at intersections (AIDI) system is built around this algorithm. Both in a driving simulator and in actual traffic, the AIDI system's effectiveness was successfully tested. Because the rate of detection depends on the particular method used, only the most efficient methods should be used. These include reports by witnesses calling rescue services on a mobile phone, information from CCTV cameras, incident detection using detection systems (generally using inductive loops or video processing techniques), incident detection using monitoring systems in vehicles (e.g., eCall), or traffic incident detection by specialized patrols supervising individual sections of the road (generally on dual carriageways) [61].

Intelligent transportation systems must effectively and reliably recognize vehicles from photos and videos. New uses for on-road vehicle identification algorithms have been made possible by the advancement of computer vision methods and the ensuing accessibility of the video image data [53].

Ref. [62], the usage of an omnidirectional (fisheye) camera for junction surveillance is explained. We offer a methodology for incident detection that includes the following three steps: (1) identify cars in the field of view of the camera (FoV); (2) monitor the cars entering and leaving the field of view; and (3) compare their trajectory with the expected path and look for any anomalies.

The "hybrid" approach uses two distinct models: (1) the rapid video-based vehicle identification System (RVIS), an image processing technique-based tool that attempts to identify the number of vehicle axles and is particularly applicable to light traffic conditions; and (2) VEVID, a semi-automatic system that is particularly applicable to heavy traffic conditions [54].

2.5.3. Incident Detector through Deep Spatio-Temporal Representation and Stacked Autoencoder

The prevention of accidents is essential to traffic safety. Numerous users experience the effects of traffic accidents, including delays, gridlock, air pollution, and other negative outcomes. Long short-term memory (LSTM) and gated recurrent units (GRUs), two cutting-edge deep learning approaches, are used in this investigation to identify traffic incidents [63]. Ref. [64], a basic one-hidden-layer neural network with unsupervised learning is described; using the back-propagation technique is a stacked denoising autoencoder (SDAE). By reducing the degree of distortion in reconstructed samples, an SDAE aims to discover latent patterns from partly damaged data by converting them into a compressed representation. To create the deep representation for the spatio-temporal video volumes STVVs from the previously unseen traffic video, a separately stacked denoising autoencoder (SDAE) trained over STVVs from the previously viewed regular traffic video is employed, one for each representation. Based on the reconstruction error and the likelihood of the deep representations, for which the outlier score is produced using the one-class SVM, the probability of an accident is calculated. The ultimate determination of whether to classify an occurrence as an accident is computed using all of these individual ratings (also known as local scores). Two procedures make up the denoising autoencoder:

Encoding: The encoder creates a hidden representation by using nonlinear mapping from the partially damaged input.

Decoding: The decoder is used to turn the hidden representation into a reconstructed representation; in addition, the three categories developed for incident detection are the modeling of patterns of traffic movement, vehicle activity analysis, and automobile interaction modeling.

Deep learning techniques often succeed brilliantly, which accounts for their exceptional effectiveness in expressing visual data. To identify accidents during this stage, we employ deep learning. We demonstrate an unsupervised deep learning system that can automatically identify distinguishing elements in security footage for accident detection [65]. Ref. [66], it is shown that the stack denoising convolutional autoencoder differs from stack denoising autoencoder in that it uses convolutional connections rather than completely linked connections between layers. In general, SDCAE's prediction impact is unquestionably superior to SDAE's. The primary reason is that the convolutional autoencoder, as opposed to the autoencoder itself, is better able to manage the spatial dependence on traffic flows.

2.5.4. Incident Detector through the Internet of Vehicles

IoT equipment has been created that can detect an accident and gather all the accident-related data, including position, pressure, gravitational force, speed, and more, and send it to the cloud. A deep learning (DL) model is utilized in the cloud to evaluate the IoT module's output and activate the rescue module when the accident is recognized [67].

If this system is to be used, it must first locate the accident and then contact emergency personnel. Sensors make it possible to identify vehicle accidents.

Implementing intelligent traffic management, intelligent dynamic information services, and intelligent vehicle control is one frequent application of the internet of things in the field of transportation systems [68]. To withstand the challenging communication environment within and/or outside the car and to provide effective and trustworthy wireless communications, the provision of vehicle-to-everything (V2X) connectivity as an alternative to more expensive radio interfaces, such as Wi-Fi, 3G/4G-TE, and DSRC/WAVE, is one way to reduce costs [69].

The internet of vehicles (IoVs) network has numerous difficulties, including collisions caused by covert terminals and interference from concurrently transmitting vehicles [70]. The idea of the internet of vehicles (loV) can be used for all forms of transportation, significantly altering how information is exchanged between them [71].

2.5.5. Incident Detector through Vehicle Ad Hoc Networks

The majority of systems designed for VANET incident detection rely on individual cars to infer the existence of an incident from reports from other vehicles [72]. To construct a network with a large coverage area, a technique called a vehicular ad hoc network (VANET) uses automobiles as wireless routers or mobile nodes. Therefore, understanding the mobility model representing the actual behavior of vehicle traffic is necessary before beginning the simulation. To properly model vehicular mobility, we must differentiate between macro- and micro-mobility descriptions [69]. VANET transforms each participating vehicle into a router or wireless node, enabling vehicles up to 300 m distant to join a vast network. Automobiles can link to other cars and connect vehicles to form a mobile internetwork when they are outside of the signal range and out of the network [73]. IoT is a key network in VANET that links all physical objects and entities to the internet and transmits data without involving humans. IoT enables connectivity in the form of objects-to-objects (vehicle-2-infrastructure) and things-to-humans (vehicle-2-human). IoT uses cutting-edge communication technologies to make devices smarter, reducing the consequences of population expansion, climate change, human mobility, and environmental changes. A potential initiative in intelligent transportation is VANET. It illustrates how MANET networks can support internal management and inter-node communication without relying on external infrastructure [74].

First, topology-based routing techniques apply network link information to determine the best route for packet forwarding. These routing protocols can also be split into hybrid, reactive, and proactive routing. In order to choose the subsequent forwarding hops, location-based routing systems communicate geographic position data with nearby nodes obtained using GPS sensors. Third, for cluster-based routing protocols, a node is chosen as the cluster head in each cluster, which manages communications inside and between clusters. Direct links connect nodes inside a cluster, and cluster heads handle communications between clusters. Fourth, VANETs typically share information via broadcast routing techniques. The fifth is the geocast routing protocol, which sends packets from a source to every node in a specific area. This routing strategy is advantageous for numerous VANET applications [75].

In order to exchange information for purposes related to safety, comfort, or entertainment, vehicles are equipped with on-board Units (OBUs), which enable them to communicate with their surroundings (including other vehicles, roadside units (RSUs), people, and sensors).VANET is a terrestrial networking paradigm [76].

2.5.6. Incident Detector through Wireless Communications with the Internet of Vehicles

In recent years, extensive research has been conducted on the effectiveness of wireless communication systems, either under the influence of small- and large-scale fading or their composite fading [77]. The freeway accident log includes local road traffic data from 15,000 loop detectors and tweets about accidents. Over 80% of the tweets tied to accidents can be correlated to nearby abnormal traffic data, according to the accident log, which can detect roughly 66% of accident-related tweets [78].

Incident detection by wire communication is crucial but some require data transfer from a vehicle to an infrastructure (V2I), while others are vehicle-to-vehicle (V2V). For three basic reasons, wireless communication for automobiles is complicated. Firstly, there are a lot of surfaces that reflect radio waves in the environment where automobiles operate, particularly in cities. Secondly, different types of communication disruption are caused by the large variety of speeds that cars drive at. Finally, adjacent transmitters and sources within cars frequently cause radio frequency (RF) interference [79].

Figure 3 demonstrates how vehicular ad hoc networks (VANETs) enable wireless communication between vehicle-to-vehicle (V2V) and vehicle-to-fixed infrastructure (V2FI) in this situation (V2I). Additionally, by connecting to the city's roadside units (RSUs) via multi-hop V2V communication, VANET routing protocols can lessen the need for fixed infrastructure [80].

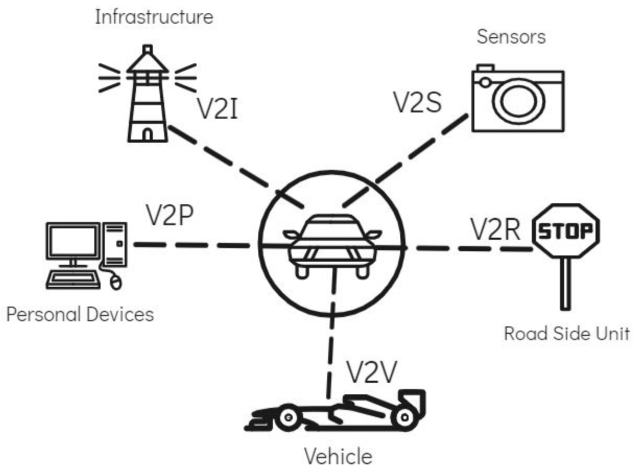

Figure 3. Epic wireless communication with the internet of vehicles.

This study created the HNMI to measure the networks of various suppliers simultaneously. We find that the lone wireless network struggles to provide the internet access demands in the high-speed mobility scenario. Heterogeneous network utilization in its entirety provides several benefits [81]. Initial networks are compressed, using network quantization by lowering the bit count for each weight parameter. Quantization utilizes low-precision data to represent the original high-precision data by converting 32-bit floating-point data into 16-bit floating-point data, 16-bit fixed-point data, 8-bit fixed-point data, etc.; this is the conventional method. Binarized neural networks, ternary weight networks, and XNOR networks are a few of the related technologies [82].

V2I vehicle-to-infrastructure communication offers a solution for longer-range vehicular networks in the detection of the incident using vehicle-to-vehicle (V2V) communication multi-hop/multicast techniques. It is most effective in close-proximity vehicular networks (such as traffic signal timing adaptation) (e.g., route guidance). According to their principal use, VANET applications can be divided into two broad categories: safety applications, such as collision and accident avoidance, and non-safety applications. Various wireless communication technologies are employed for VANET communications to create a local and integrated information system [83] and address the characteristics of wireless infrastructure-based and ad hoc networks for communication between mobile devices in automobiles. As there are so many different ports and interfaces for wired communication due to the heterogeneity of gadgets, wireless communication systems are extremely attractive for automobile communication [84].

The seamless integration and convergence of vehicular communication networks, information and transportation systems, and mobile devices and networks will face numerous technical, economic, and governmental challenges. It is crucial to create vehicle communication systems that allow drivers and other participants to share information in real time with high dependability. This enables pervasive sensing to keep track of vehicles' conditions and surroundings, develop data analytics tools to process the massive amounts of data generated by connected vehicles, and create middleware platforms for data management and sharing [85].

2.6. Detection of Road Accidents Using Wireless Technology

2.6.1. Detecting Incidents with 5G in Road Transport

To address the escalating need for urban innovation in the modern world, 5G gives city and transportation experts the chance to update their key technology infrastructure [86]. Additionally, networked autonomous driving will promote and simplify the use of 5G artificial intelligence and other information technologies. This new infrastructure system of "pedestrian-vehicle-road-cloud" collaboration will be developed more quickly [87]. For instance, with 5G you may share a vehicle's location every second along with its speed, internal temperature, condition, and the status of any cargo it has instead of just sharing it every ten seconds. For programs that rely on data-intensive streaming programs such as high definition video, 5G's enhanced bandwidth is crucial [49].

These technologies include intelligent sensors for detecting the surroundings, using artificial intelligence and big data, blockchain, and connectivity technologies such as C-V2X and 5G [88]. The 5G core network communicates with purported network functionalities through service-based interfaces. The expanded 3GPP location service architecture defines any UE, including those in a vehicle, to have the gateway mobile location center (GMLC) location-related features. The GMLC is a network element that interacts with the position of the control plane service to receive and process location data. It may initiate a control plane location service on its own or in response to a request from a location services client. The client could be inside the UE or anywhere else in the architecture [27].

What is unique about 5G? Renault's Remi Bastien highlighted the unique aspects of 5G. For the network, we could benefit from network slicing, which would allow us to have a specialized network for smartphones, automobiles, and the internet of things with 5G. This could be useful to distinguish between the various consumers [89]. Future innovation and economic growth will be possible through next-generation communication technologies, benefiting businesses, consumers, and society. The rapid development of 5G is happening in parallel with developments in the internet of things, artificial intelligence (AI), and smart platforms for novel applications such as mission-critical communications (IoT). These connections are used for a variety of services, the majority of which are non-commercial safety services, such as automatic crash notification (ACN) services such as eCall, the detection of stationary or slowly moving vehicles, and informational alerts for traffic jams, roadwork, weather warnings, and other hazardous conditions [90]. The effectiveness of urban public transportation operations can be increased by 5G. A more accurate match between supply and demand could be achieved through technology-based real-time monitoring of public vehicles and real-time management of user demand, leading to the development of nearly real-time origin-destination (OD) matrix proxies. This would increase transport operators' efficiency by preventing the operation of either empty or overloaded vehicles, enhancing the service quality for users and accident avoidance [91].

High-quality connection is essential for intelligent transportation systems because it allows the various road users to communicate and share information instantly. According to Telefónica, the 5G network can concurrently offer the entire mobility ecosystem high levels of connectivity, high bandwidth, and extremely low latencies thanks to edge computing [92], and time-sensitive information will always be sent reliably. For instance, if an autonomous vehicle's function fails, it might be remotely driven in real time. To maximize safety, efficiency, and sustainability, we anticipate the adoption of completely autonomous capabilities in certain locations at first, using long-term progress toward an utterly autonomous transport ecosystem and 5G signal coverage [93].

2.6.2. 6G in Road Transport

For 6G to achieve the aforementioned lofty goals, it will be necessary to integrate various cutting-edge technologies, such as more dependable and effective air interfaces, resource management, decision making, and processing. For example, UAVs and low-earth orbit satellites can provide V2X systems with considerably enhanced and seamless coverage, helping to improve the communication quality of the service, especially in some potential blind spots that could exist in conventional terrestrial communication systems [94]. A 6G-V2X network is predicted to feature a significant number of connected vehicles in a dense environment, a more diverse variety of applications, a complex signal analysis compared to 5G-based V2X systems, and a greater demand for dependability and computational power. Because of this, 6G-V2X networks require more processing power than is typically provided by the network [74].

Mobility is the maximum speed at which a mobile station can move while being supported by a network and receiving an adequate quality of experience (QoE) [95,96]. The deployment scenario for high-speed trains is supported by the maximum mobility allowed by 5G, which is 500 km/h. Commercial aircraft systems' top speed in 6G is 1000 km/h [97].

In meeting the further stringent key performance indicators (KPIs), which only partially satisfied 5G for vehicle communication [98], and accomplishing the challenging objectives for IoV, 6G is essential [95,99].

After that, 6G technology allows these remote sensors to communicate with the cloud platform while maintaining a reliable data stream. Finally, it is possible to integrate the large-scale traffic-sensing data to produce a useful reference for traffic management [28], where 6G will serve as a powerful enabler and catalyst for CAV's key services. The primary use of 5G is for communications (either human-to-human or machine-to-machine). Beyond communication, 6G will do more. Radio frequency (RF) has been studied as a potential tool for positioning and object sensing. Our opinion is that 6G mobile systems, also known as CCPS for short, make it easier for missions to combine communications (C), computing (C), positioning (P), and sense (S) to meet service/application needs while being deployed at a wide and affordable scale [100].

3. Incident Detector Using Big Data Analytics and Neural Networks

Both datasets with many instances and datasets with many features are referred to as "big data". Big data has recently been used in many applications (such as banking, social media, healthcare, transportation, and industry). As a result, managing this data type is now a difficult issue. This problem influences the learning time for an algorithm in the classification context, especially for the single classifier [101]. The many advancements in AI today are centered on the concept of coexisting with AI on Earth (ANN). These technologies include hardware and artificial intelligence (AI), which will affect how we live and how our working software techniques attempt to recreate the nervous system more resiliently than any system of the human brain.

By solving the issues that are easily impacted by hostile conditions, vehicles, for example, can capture more data owing to NLOS perception than they otherwise could. The systematic decision making between vehicles, the vehicles, and the roads are improved in the calculation and decision-making process, such as in the resolution of the problem of managing vehicle priority and traffic intersection optimization control [86]. The next generation vehicular service, platooning autonomous/assisted driving, remote driving support, and vehicle data services are all expected to be available, according to [102]. Every email and a phone call between users can be understood by an AI computer that can recognize speech and understand spoken language. It might also cover user privacy. In the modern world, artificial intelligence is applied in various applications. AI has numerous applications. There are uses in the military, applications in medicine, applications in space, business utilizations [103], and applications in telecommunications [104].

Roadways become more crowded and hazardous because the number of vehicles is increasing, sometimes exceeding the rate at which the population is growing. Using real-time transport location data and projected operating delays, with the amount of time it takes to load people at various stations, machine learning algorithms can be utilized to reliably estimate the time of arrival of many means of transport [105]. The skill to getting around the difficulty of processing raw data, a typical issue with many ML techniques, is a key requirement. The most common examples of this methodology are deep neural networks (DNNs), recurrent neural networks (RNNs), and convolution neural networks (CNNs), which are frequently used in speech recognition, visual object recognition, and object detection [47].

3.1. Other Approaches for Road Accident Detectors

ANNs are frequently, though not always, the foundation for various machine learning (ML) techniques, which are gaining popularity. According to May, ML is about giving machines the ability to learn independently. Additionally, parking, accident detection, and route optimization are the most often used applications [106].

The usage of machine learning and artificial intelligence in different aspects of road transportation and technology is being used to reduce incidents, develop solutions to mitigate incidents, and improve user comfort and safety in more efficient ways. The following are some ways that artificial intelligence and machine learning are applied in road transportation. Machine learning algorithms have also been applied in different engineering applications and systems designs. Machine learning and AI have been adopted in path loss modeling, healthcare management, construction industries, and signal propagation, as in [19,41,107–115].

3.1.1. Detecting Road Accidents Using Predictive Fleet Maintenance

The integrated internet of things (IoT) system is connected by an artificial intelligence engine employing a multilayer perceptron artificial neural network (MLP-ANN). It can predict car maintenance by categorizing driver behavior. By using data mining's k-means technique, the key performance indicator (KPI) of the driving behavior has been determined [116], which investigates the ways that AI could be used to analyze real-world circumstances in real-time. Recurrent neural networks (RNNs) and road condition predictions offer a data-driven environment. Deep reinforcement learning uses machine learning to implement RNN predictions and enable autonomous decision making. Real-time road condition sensing is provided using convolution neural networks [117].

Figure 4 shows the predictive fleet maintenance, the fleet vehicle, the telematic service provider, and the predictive analytical engine to the service manager.

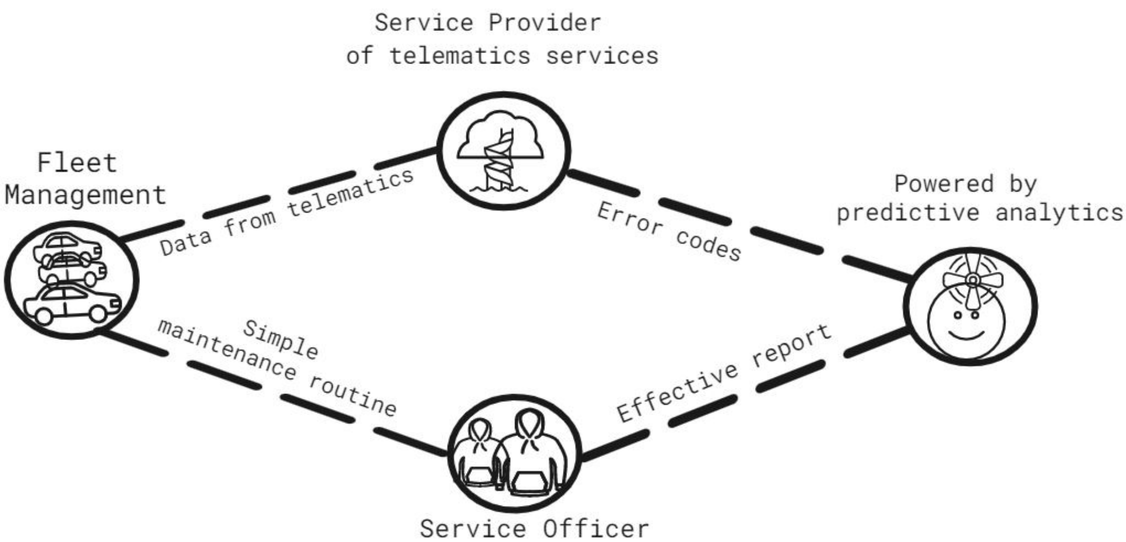

Figure 4. Predictive fleet maintenance.

Predictive vehicle maintenance using machine learning COSMO is an unsupervised, self-organized method that has been proven on a fleet of city buses using both off-board and on-board data. It automatically generates the most intriguing onboard data representations and isolates the offending car using a consensus-based method. The second strategy is a supervised classification based on previously gathered and aggregated vehicle statistics, where the usage statistics are labelled depending on the repair history [118].

3.1.2. Action Recognition for Accident Detection in Real-Time Vehicle Tracking

Within the network, dynamic changes in traffic patterns occur throughout the day and on a global scale. Therefore, signal timing parameters need to be continuously monitored depending on the performance and variability demands. Travel times must be computed regularly to do this [119]. AI technologies are being used to create automated vehicles for personal and commercial transportation usage. These vehicles rely on various sensors, including GPS, cameras, radar, actuators (things that put motion into an input signal), control systems, and software [120].

It is necessary to have a system for tracking and managing bus transportation that is both time- and money-efficient because of the expanding population and technological sophistication of the world. The growing population has caused poor real-time data analysis of transportation facilities, taxing paper-and-pen methods, inadequate bus transportation corporation facilities, and improper human resources and cost management. As a result, distant users and bus transportation services such as MSRTC require an intelligent system that offers real-time bus locations and information. Figure 5 demonstrates the transport tracking system: vehicle tracking, data storage, GPS satellite, cellular network, and a database [121].

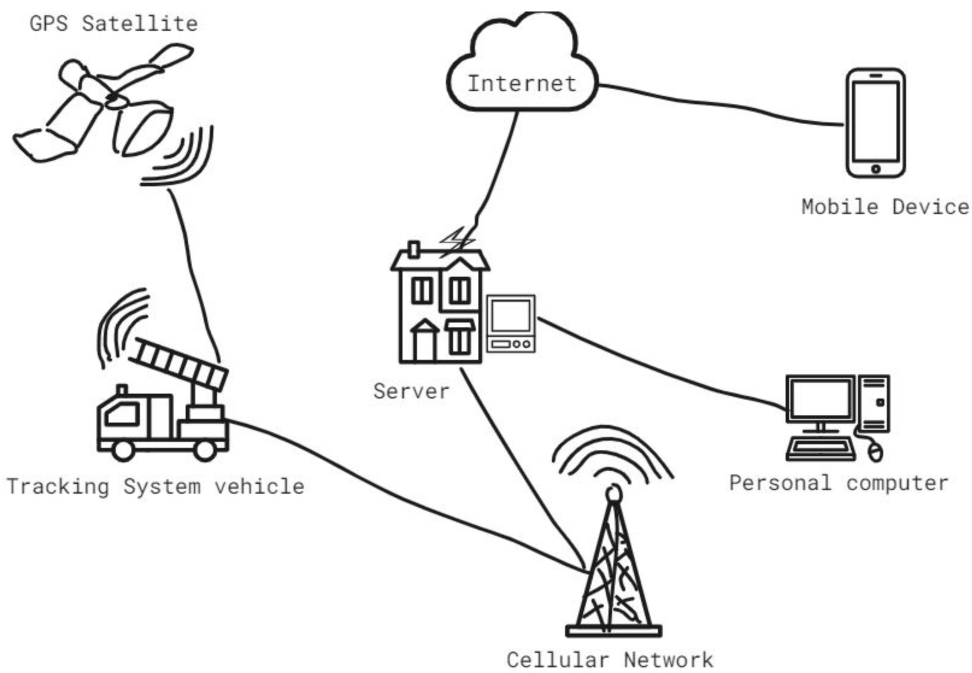

Figure 5. Real-time GPS tracker system.

3.1.3. Detecting Road Accidents Using Traffic Management

Most traffic accidents take place in metropolitan areas, where there is a larger concentration of road users who are more prone to injury and mortality in the case of an accident, as well as a more complex traffic environment. Reducing speed restrictions is a reasonably simple and economical traffic management strategy. In the literature on traffic safety, the association between vehicle speed, accident risk, and accident result seriousness is well established [51].

The goal of traffic management is to affect supply and demand in traffic in a way that improves the temporal and spatial alignment between traffic demands and the network's capacity supply. The issues with the road network are primarily related to certain bottlenecks and times (i.e., peak hours, incidents, and events). The intelligent transportation system (ITS) can provide safety, effectiveness, and sustainability for critical complications with vehicle traffic on a broad scale. ITS uses machine learning with the current traffic control system to ensure traffic flows smoothly, and it offers a real-time strategy [24].

Additional applications include real-time transportation management, ridesharing design, implementation, and management, and the scheduling of logistical systems and freight transportation planning and predicting, as well as the administering of transportation policy [122]. Others include environmental, toll-road, dependability, and safety-related questions about operating transport systems. Moreover, the utilization and the management of emerging technologies analysis, forecasting, and planning of travel require travel information systems and services technology for the transportation and environmental intelligence analysis and simulations of pedestrian and herd behavior. The planning for sustainable mobility in cities requires vehicles with service-oriented design and those in a communication infrastructure, the review and assessment of transportation technologies, and simulated and artificial transportation systems [123].

3.2. Challenges Facing the Detection of Road Accident Using AI/ML

The difficulties in applying AI and ML for incident detection on the road are ILD installation, upkeep, replacement, and some recurring upkeep. The accuracy is bad, especially when it comes to crucial road infrastructure. The sample size restriction makes accurate measurements of the speed and travel duration difficult [73]. With the IoV's development tendency, large-scale sensors and vehicles frequently connect to the internet, which may cause a network capacity issue [37]. With the help of this study, it is possible to analyze the driving characteristics of drivers, the days with the highest accident rates, and the roadways with the worst accident rates. The distribution by season and vehicle type was shown on the heat maps, which added more complex variables to the research. Even with a three-year time limit, the prediction model produced good results. A longer time frame and more variables included in the predictive model's eligibility could help to improve accuracy [124]. It summarizes the state of the art, the challenges, and the opportunities for researchers in the linked domains of context sensing, human affect sensing, and social signaling analysis. According to some, the most promising method for obtaining precise context sensing in realistic surroundings is to develop multimodal, multi-aspect context sensing. The W5+ (who, where, what, when, why, and how) approach provides context sensing [16].

Interference and collisions by concealed nodes present a significant obstacle to efficient data sharing between vehicles. Vehicles are unaware of other vehicles that are simultaneously broadcasting due to the ad hoc nature of vehicular communications for safety applications, which can lead to crashes. When there is a high vehicle density and a high data traffic load, this is a severe concern of the network [70], which causes accidents; another issue that needs to be addressed is liability. For the various levels of automation, a distinct line defining the scope of liability must be established to determine the cause of the accident. As a result, legislation, traffic laws, and insurance regulations may need to be changed. The existing restrictions are based on the idea that a human driver is aboard while the vehicle is driven. However, automation technology is supposed to completely or partially replace the driver, shifting the responsibility [120].

Another challenge is the utilization of AI-based transport systems in low-income and unstable nations, which is extremely difficult because of the lack of readiness for use of their infrastructures and the inability to provide maintenance and repairs. This barrier includes a shortage of dependable power sources and frail communication networks. Countries that invest less of their GDP in technology research and physical infrastructure may find it more difficult to take advantage of AI [6].

4. Recent Trends, Research Directions, and Lessons Learned

Artificial intelligence and neural networks are widely used in every aspect of transportation. All systems that handle the movement of goods by road contain their applications [123]. It is anticipated that future smart cities will include ITS as a crucial component of urban design as they will improve energy efficiency while enhancing road and traffic safety and transit efficiency [125].

The findings unmistakably demonstrate that when vehicle speed and class descriptions were considered the ANN model could accurately predict vehicle traffic flow. Data loggers are electronic devices used in road transportation networks to gather data or information that has been gathered over time by moving cars on highways and at crossings. This data can be examined or preserved for later use, using sensors to capture the data [12]. Future logistics requirements will change due to new technology and societal advancements, which could also have a disruptive impact on markets and dramatically expand the bounds of current services [126]. The high mortality toll is partly due to inadequate infrastructure, including bad roads and vehicles without current safety equipment, but human error also contributes significantly. More than 90% of traffic collisions in the EU are caused by human error, including speeding, distracted driving, and intoxicated driving [6].

Future vehicle networks will have to upgrade from the existing two-dimensional handover and resource allocation situations to three-dimensional ones with the potential incorporation of UAVs, further increasing the task complexity. The best option right now for its explanatory power is NN-based DL. However, because of the deep network topology, NN training frequently consumes a sizable amount of computational resources [38]. In order to help traffic planners reduce congestion, numerous attempts have been made to pinpoint the date, place, and severity of an occurrence. Their endeavors cover a wide range, from manual reporting to automatic algorithms to neural networks. Human-written manual reports may take longer to detect incidents and be less economical, whereas experts in public transportation and AI professionals are developing innovative ideas that might help the sector address its expanding problems. To achieve high accuracy, incident-responsive algorithms and prediction systems are crucial for public transit networks' safety and security [127].

Today's world needs ubiquitous AI, notably in road transportation, where its use is essential to prevent accidents and increase user safety. The majority of automobile accidents are related to human mistakes. Keeping an eye out for ways to improve safety by developing autonomous incident detectors using ML and AI applications is crucial. The ability to improve road transportation through AI and ML is vital. However, we must investigate automatic incident detectors as numerous studies have focused on various aspects of road transportation and its use with AI and ML. However, AI will unavoidably change the public transportation industry and understanding how AI might affect the sector is essential. Public transportation stakeholders should proactively consider AI's opportunities in order to enhance their offerings and create the mobility of the future [128]. As human error (such as speeding, distracted driving, and drunk driving) causes more than 90% of accidents on EU roads, where more than 25,000 people died in 2017, AI-based systems deployed in autonomous transportation could dramatically increase road safety [120].

Previous research focused on autonomous vehicles connected with smart vehicle communication systems. A smart crossroad management system based on the internet of things is further explained. A wireless network type known as an ad hoc network does not rely on the established infrastructure. A wireless network type known as an ad hoc network does not rely on established infrastructure. This wi-fi or ad hoc network serves as a conduit for data transmission. This also sends accident locations. A camera fixed to the vehicle's back and rear sides take pictures of the objects it strikes, for the investigation of hit-and-run incidents [29].

Vehicle data is supplied via the cloud to a data-mining engine that predicts engine stress using MLP-ANN algorithms and uses k-means clustering analysis to create a driver

KPI score [116]. This work's follow-up research aims to more thoroughly analyze traffic monitoring video data and to offer helpful traffic travel advisory services [10]. With a software system, the circumstances of an accident can be determined by identifying overlapping images in real-time video streaming [129]. To create various condition-specific datasets for model testing, we advise a more thorough comparison of these two, employing field data for model calibration, simulation, DTW, and SVM. In order to estimate accident and emergency response, artificial intelligence and machine learning models with different algorithms are still necessary and should be discussed.

5. Conclusions

This study presented a review of the automatic incident detector in road transport systems, and the role of artificial intelligence and machine learning in road management systems. From the review, it is logical to state that by using multiple data sources, such as fixed detectors (gathering point data) and probing vehicles (collecting spatial data), the input data accuracy and comprehensiveness could be improved, thereby enhancing the performance of an event detection system applied to roads. Additionally, the analysis of the incident detector usage, leveraging artificial intelligence and machine learning, revealed that the camera calibration yields the vehicle speed employed in the tracking algorithm and event detection. Furthermore, the camera calibration would generate calculation mistakes if the internal and exterior camera parameters were not precisely acquired. Finally, a detailed application of machine learning and artificial intelligence in incident detection systems is highlighted, and the most recent literature, trends, and potential issues that may arise when the technology is gainfully applied are discussed extensively. Future studies would focus on conducting more in-depth analyses on these issues to address road incident occurrences.

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Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
IOV	Internet of Vehicles
UAV	Unmanned aerial vehicle
DL	Deep learning
NN	Neural network
ITS	Intelligent transportation system
VRP	Vehicle routing problem
V2I	Vehicle to an infrastructure
V2V	Vehicle to vehicle
VANET	Vehicular Ad Hoc Network

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