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Advancements in Machine Learning and Data Mining Techniques for Collision Prediction and Hazard Detection in Internet of Vehicles

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ABSTRACT

The Internet of Vehicles (IoV) has transfigured transportation with connected vehicles, smart infrastructure, and self-driving cars. Road collisions and accidents are still a problem for road safety. This review of the literature discusses the prediction of IoV accidents and collisions as well as the detection of hazards using data mining, deep learning, and machine learning techniques. It describes the most recent developments to these methods and how they enhanced IoV safety. The article starts off by going over data collection, data quality, and the ever-changing nature of IoV traffic scenarios. What follows is a detailed breakdown of the ML, DL, and DM methods used in IoV safety applications. Convolutional neural networks, artificial neural networks, recurrent neural networks, support vector machines, and decision trees. As examples of real-world applications and case studies, intelligent accident prediction models, driver attention forecasting, traffic congestion forecasting, spatiotemporal analysis in autonomous vehicles, scene-graph embedding, and V2P collision risk alerts are discussed. The goal of this review is to give readers a comprehensive overview of the cutting-edge methods enhancing IoV accident prediction, collision avoidance, and hazard detection.

Keywords: Internet of Vehicles (IoV), Collision Prediction, ML, Datamining, DL.

1. Introduction

This comprehensive systematic literature survey focuses on collision prediction and hazard detection in the Internet of Vehicles (IoV). The prevalence of connected vehicles and challenging traffic conditions highlight how crucial it is to have trustworthy safety systems. In order to address this issue, the survey examines state-of-the-art data mining, machine learning, and deep learning methods used for IoV collision prediction and hazard detection.

The survey shows how the field has changed. Data mining, machine learning, and deep learning algorithms are investigated to enhance collision prediction and hazard detection systems. We learn about the operation of IoV safety technology from the analysis of the benefits and drawbacks of these techniques.

The objective is to provide a comprehensive overview of IoV collision prediction and hazard detection techniques for researchers. The survey also identifies patterns, gaps, and potential research areas.

The Internet of Vehicles (IoV) has emerged as a crucial area for enhancing the effectiveness, safety, and environmental impact of transportation in the era of Intelligent Transportation Systems (ITS)[1]. The IoV is made up of a network of infrastructure and vehicles that are all interconnected. This enables communication and data sharing between users. In the Internet of Things (IoT), models for accident, collision prediction, and hazard detection are required to guarantee the safety of passengers, vehicles, and pedestrians[2]. As solutions to these issues, machine learning (ML), deep learning (DL), and data mining (DM) have grown in importance in IoV research. Large-scale data analysis, pattern discovery, and the forecasting of mishaps, collisions, and other hazards are all very effective uses of these techniques[3]. ML, DL, and DM techniques for IoV accident prediction, collision avoidance, and hazard detection have recently undergone improvements, which are examined in this review. Additionally, it suggests potential research directions for the future.

1.1 Background

The Internet of Vehicles (IoV) is an advanced integration of the Internet of Things (IoT) into the automotive domain, facilitating seamless communication between vehicles, infrastructure, and other devices. By leveraging advanced technologies like V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), and V2X (Vehicle-to-Everything) communication, IoV aims to enhance driving safety, optimize traffic management, and provide enriched in-vehicle entertainment and services. This

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interconnected ecosystem not only promises a future of autonomous vehicles interacting intelligently with their surroundings but also paves the way for more efficient, environmentally friendly, and user-centered transportation solutions.

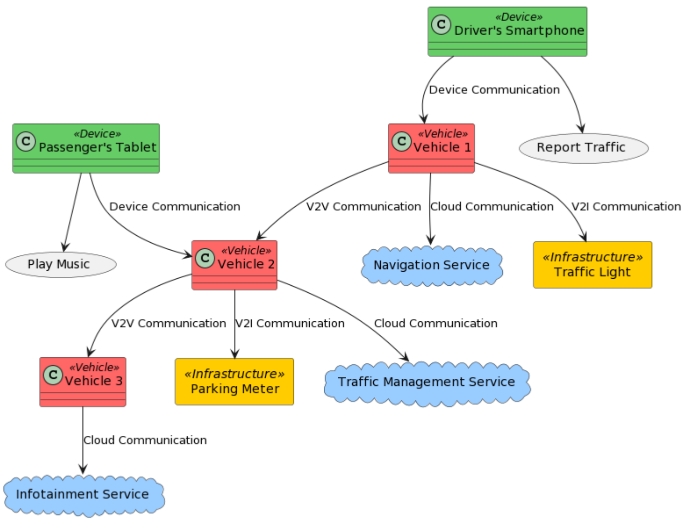

Figure 1: Operational flow diagram of the IoV.

The diagram in figure 1 visualizes a connected vehicular ecosystem. It features three vehicles, each equipped with Internet of Vehicles (IoV) capabilities. These vehicles can communicate with each other through Vehicle-to-Vehicle (V2V) communication, as showcased by the direct links between them. Additionally, they interact with roadside infrastructure, such as a traffic light and a parking meter, using Vehicle-to-Infrastructure (V2I) communication. The vehicles also connect to cloud-based services, including a navigation service, a traffic management service, and an infotainment service. This cloud communication underlines the vehicles' abilities to tap into broader networked resources. Furthermore, personal devices, represented by a driver's smartphone and a passenger's tablet, play a pivotal role in this ecosystem. These devices communicate directly with the vehicles, and they are also linked to specific use cases like reporting traffic or playing music. The styling of the diagram segments these entities into color-coded categories, making it visually intuitive to differentiate between vehicles, infrastructure, cloud services, and devices.

The application of ML, DL, and DM techniques to accident, collision prediction, and hazard detection in IoV is becoming increasingly popular because of the availability for a lot of data from various sources, including traffic sensors, surveillance cameras, and vehicle-to-vehicle communication systems[2]. ML techniques are used to learn patterns from data as well as build models that can be used for prediction and classification tasks. DL techniques, on the other hand, are a subset of ML that can learn multiple levels of representation from the data, making them particularly useful for tasks that involve complex, high-dimensional data. Finally, DM techniques are used to extract valuable insights from large datasets by identifying patterns, trends, and relationships[1, 2].

2. Review strategy

A review strategy is a methodical way to find and combine relevant literature on a given subject. A review strategy's main objective is to offer a thorough summary of the current state of knowledge. The research process entails defining research topics, locating relevant literature from databases using specific search terms, screening literature through title and abstract review to include only relevant studies, evaluating full-text content of selected studies, extracting data from them, and finally synthesizing findings in a structured manner to present an organized overview of developments in machine learning and data mining techniques for hazard prediction and collision detection in the context of the Internet of Vehicles.

2.1 Research Questions

1. What are the most effective data mining techniques for predicting various parameters of road accidents, such as causes, time, and locations, and how do these techniques compare with one another?
2. How can ML, DL, and DM techniques be effectively integrated into the design of ADAS ("Advanced Driver-Assistance Systems") to enhance traffic safety as well as avoid collisions?
3. How well does ("vehicle-to-vehicle") V2V opportunist connectivity function in real-world scenarios to identify hazardous places on roads utilising machine learning algorithms and mobile sensors on commercial vehicles? How can this strategy help to more accurately pinpoint risky areas for all automobiles in a neighborhood?
4. What are the implications of using machine learning techniques to predict crashes, and how can real-time data be integrated to improve the accuracy of current crash prediction models?
5. How effective are deep learning models in predicting traffic accidents, and how do they compare to traditional machine learning methods?
6. Can deep learning models using social media and open data effectively predict traffic accidents, and how do they perform compared to models that do not use these sources of data?

2.2 Search Strategy

To locate research articles on a given subject, a search strategy may employ a variety of techniques:

1. Find and use the key terms associated with the subject in databases or search engines. By combining keywords, boolean operators (AND, OR, NOT) can improve search results. To enlarge your search, include synonyms, abbreviations, and acronyms.
2. Databases Locate pertinent academic databases such as Web of Science, IEEE Xplore, Scopus, Google Scholar, and PubMed. These databases provide research articles from journals, conferences, and book chapters.
3. Use filters, such as publication date, language, document type, and source, to hone your search results. By excluding

irrelevant articles, this aids in concentrating on pertinent articles.

2.3 Search Statistics

Table 1: Distribution of Articles According to Keywords.

S.No	Number of Articles	Keywords	ratio of articles
1	11	collision avoidance	32%
2	12	machine learning	35%
3	19	Internet of Vehicles	56%
4	10	deep learning	29%
5	12	data mining	35%
6	10	road safety	29%
7	19	accident prediction	56%
8	8	Driving Assessment	24%

Out of the 34 articles chosen, each was selected based on relevant keywords. The frequency of the keywords and the corresponding article count were analyzed. Table 1 illustrates the proportion of articles associated with each keyword.

Table 2: Distribution of Articles by Publisher.

S.No	Publisher	Ratio of articles
1	Elsevier	26%
2	Springer	3%
3	IEEE	26%
4	Conference	6%
5	Other Journals	38%

Additionally, articles were filtered according to their publication type (journal, conference, book chapter, and other contents), resulting in the removal of 6 articles. Table 2 presents the distribution of the selected articles based on their type. The remaining 34 articles were then assessed by publisher, with no articles being discarded during this process. Table 2 also provides a detailed breakdown of the articles by publisher.

Table 3: Fraction of articles by year of publication.

Article Count	Publish Year
3	2019
15	2020
7	2021
9	2022

In the final stage, articles were filtered based on their year of publication, resulting in the removal of two articles. The remaining 34 articles were further assessed using qualitative synthesis factors, leading to the exclusion of two more articles. Table 3displays the distribution of the articles by their year of publication.

3. Review of Literature

ML, DL, and DM techniques have revolutionized the way accidents, collisions, and hazards are detected and predicted in the IoV. These techniques have provided a new dimension to the field of vehicle safety by enabling vehicles to make intelligent decisions based on real-time data, patterns, and trends.

This literature review aims to provide a comprehensive overview of the advancements made in ML, DL, and DM Techniques for collision prediction, accident, and hazard detection in the IoV. The review includes a critical analysis of the latest research studies, publications, and patents in the field Tables 4, 5, and 6.

3.1 Datamining based Models

In real-time traffic scenarios, the data mining-based models are intended to foresee potential collisions and identify hazards. These models collect and examine a wide variety of data, including information on traffic patterns, weather, road conditions, and vehicle behavior. The system can predict collision probabilities and spot potential hazards by extracting patterns and correlations from these datasets using sophisticated data mining algorithms. The vehicles and hazard management systems receive these predictions and alerts, allowing drivers and authorities to make proactive decisions. This method makes it possible to reduce the likelihood of collisions and improve the accuracy of hazard detection, making transportation networks safer and more effective.

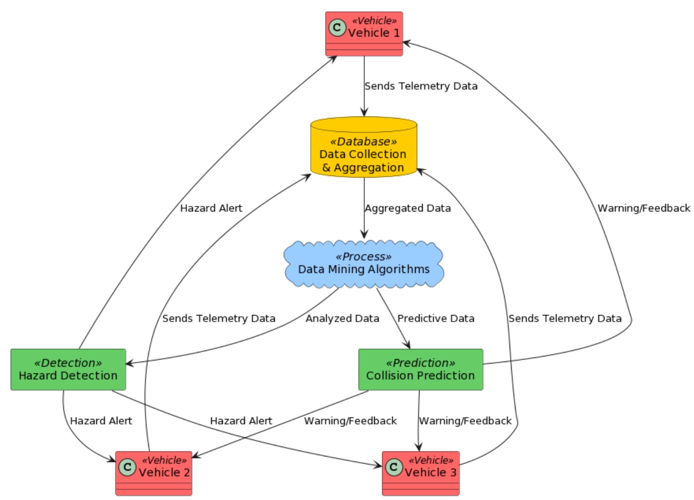

Figure 2: The Model of Data Mining based Collision and Hazard Detection system for IoV.

The diagram in figure 2 illustrates a "Data Mining based Collision Prediction and Hazard Detection in the Internet of Vehicles (IoV)" system. Vehicles equipped with IoV capabilities continuously transmit telemetry data, such as speed, direction, and environmental conditions, to a centralized Data Collection & Aggregation system. This aggregated data then serves as fodder for sophisticated Data Mining Algorithms, which analyze patterns and extract valuable insights from the vast data pool. Leveraging these insights, the system can predict potential collisions, represented by the Collision Prediction component, and detect potential hazards, like slippery roads or obstacles, indicated by the Hazard Detection component. In a crucial safety measure, vehicles in the system are fed with real-time feedback based on these predictions and detections. This allows them to take immediate preventive actions, such as adjusting speed or changing routes, thus enhancing overall safety within the IoV ecosystem.

Collision Prediction and Hazard Detection in the Internet of Vehicles (IoV) can be considered as a supervised learning problem where historical data about vehicular movements, environmental conditions, and previous collisions are used to predict future collisions or hazards. A generalized mathematical representation can be modeled as:

Given:

- V is a set of vehicles. $V = \{v1, v2, ..., vn\}$.
- X is an input feature matrix. Each row xi represents a vehicle's state at time t, including attributes like speed, position, and acceleration.
- Y is an output vector. Each element yi indicates the occurrence (1 for true, 0 for false) of a collision or hazard for the vehicle vi at time t.

The primary goal of the data mining model is to identify or approximate a function f such that: $f(X)$ is approximately equal to Y.

This function f maps the input X to the output Y, and the aim is to have f be as accurate as possible in predicting Y from X.

When it comes to hazard detection, the same structure can be applied. However, in this scenario, the output vector Y would represent specific types of hazards rather than collisions.

To account for the temporal nature of the data, especially in an IoV context, the state of a vehicle vi at time t might be influenced by its state at previous time points, requiring models that can handle sequential data.

Moreover, with the specific focus on IoV, Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure $(V2I)$ data can be added as additional features in X, enabling the model to use real-time communication data for its predictions.

Cosic et al.[4] propose an ADAS algorithm using video frames to calculate the Time to Potential Collision (TTC) from an oncoming vehicle's camera-installed external mirror. The algorithm tracks and detects vehicles, providing TTC data based on distance and speed. With high accuracy and real-world testing, this methodology aids safer lane changes. However, the algorithm's effectiveness may be influenced by adverse weather conditions or occlusions.

Hussain et al.[5] compare data mining techniques using Weka and Orange on a dataset of 150 road accidents. Their study achieves 85.33% accuracy with Multi-layer Perceptron, emphasizing algorithm efficiency in predicting accident characteristics. Nonetheless, the generalizability of the model to diverse traffic environments and varying data quality might be a challenge.

Davis et al.[6] introduce NH-TTC, utilizing implicit differentiation and sub-gradient descent for collision avoidance in quick, autonomous robots. This flexible method optimizes complex cost functions for collision-free navigation, demonstrating effectiveness in real and virtual robot scenarios. Yet, real-world implementation might encounter computational challenges due to the complexity of the optimization process.

Li et al.[7] analyze rear-end accident changes over time using vehicle trajectory data from NGSIM databases. They introduce TTCD to measure changing TTCs and identify dangerous scenarios, providing insights for preventive measures. However, this approach might not consider all contextual factors that could impact rear-end accidents.

Yuan et al.[8] present an adaptive framework for Front-Vehicle Collision Warning (FCW) in ADAS, using single-eye distance assessment and vehicle recognition. Their approach improves recognition accuracy and offers personalized FCW based on driver behavior. Yet, the framework's effectiveness might vary with different vehicle and road conditions.

Zhang et al.[9] devise an algorithm for safety crash mitigation considering driver and environmental parameters, using a Mazda algorithm modification and kinematic analysis for effective warning level selection. Nevertheless, the algorithm's performance could be influenced by the accuracy of the input data, and it might not account for unpredictable scenarios.

Li et al.[10] examine vehicle crash features in Shenzhen, China, using Bayesian network analysis to understand relationships in motor vehicle-involved collisions, offering insights for ADAS and traffic control strategies. However, the analysis might not fully capture the complexity of human behavior and external factors in accidents.

Li et al.[11] propose a collision avoidance system for autonomous cars, using probabilistic scenario evaluation and risk assessment to cater to diverse driving preferences, ensuring dependable crash avoidance. The system's effectiveness might depend on accurate risk assessment and driver preference predictions.

Zhao et al.[12] explore driver risk models by merging online IoV data and offline behavior data, revealing the significance of combining different data sources for enhanced risk evaluations. However, data privacy concerns and challenges in integrating and processing diverse data streams could limit the practical implementation.

Yang et al.[13] suggest a transfer learning-based model for vehicle collision prediction, using operational data from vehicle interiors and highlighting its superiority over existing models. However, the model's performance might be sensitive to variations in the input data quality and may not cover all possible collision scenarios.

Suat-Rojas et al.[14] propose a low-cost road accident identification technique using social network mining and Twitter data, showing its potential impact on supplementing traditional detection methods. Yet, the accuracy of this method could be influenced by the reliability of social media data and the potential for misinformation.

Morimoto et al.[15] offer an analytical framework for road safety, evaluating traffic safety policies across nations and emphasizing collaboration and stakeholder involvement for enhancing road traffic safety. However, implementing this framework on a global scale might face challenges due to variations in regulations, infrastructure, and societal norms.

Table 4: Summary of the Contemporary Articles on Datamining based Models.

Author	Contribution	Methodology	Limitations
Osi, L., et al. [4]	ADAS algorithm for oncoming vehicle identification	Vehicle tracking, video frame processing	Limited to TTC estimation from behind, camera frames
Hussain, S., et al. [5]	Data mining for road accident prediction	Data mining tools, classification algorithms	Limited to specific dataset, no non-data mining comp.
Davis, B., et al. [6]	NH-TTC technique for collision avoidance in autonomous robots	Implicit differentiation, robot testing	Limited to autonomous robots, applicability unknown
Li, Y., et al. [7]	Analysis of rear-end accident conditions	Transition categorization, TTCD indicator	Limited to specific rear-end accidents, dataset
Yuan, Y., et al. [8]	Adaptive FCW framework for front vehicle distance estimation	Camera calibration, adaptive FCW strategy	Limited to forward collision warning, dataset
Zhang, Y., et al. [9]	Algorithm for safety crash mitigation	Safety time model, kinematics analysis	Limited to specific driver-environment factors
Li et al. [10]	Examination of crash features in Shenzhen, China	Collision statistics, Bayesian analysis	Limited to crash features in Shenzhen, China
Li et al. [11]	Decision-making system for autonomous collision avoidance	Scenario evaluation, collision avoidance	Limited to autonomous cars, scenario testing
Zhao, X., et al. [12]	UBI and enhanced driver risk categorization models	Driving behavior analysis, data mining	Limited to UBI models, specific dataset
Yang, L., et al. [13]	Transfer learning model for vehicle collision prediction	Feature analysis, IoV dataset	Limited to predicting vehicle collisions
Suat-Rojas, N., et al. [14]	Low-cost technique for road accident identification	Social network mining, vectorial repr.	Limited to Spanish Twitter data, casual language
Morimoto, A., et al. [15]	Analytical framework for international road traffic safety	Literature review, policy comparison	Limited to analytical framework, collaboration

3.2 Machine Learning based Models

The machine learning-based models are made to reduce accidents and improve road safety in a moving vehicle environment. Based on real-time data gathered from vehicles and roadside sensors, this system uses sophisticated machine learning algorithms to predict potential collisions and identify hazardous situations. The system can forecast collision risks and spot potential road hazards by looking at variables like vehicle speed, trajectory, proximity to other vehicles, and environmental conditions. The system's machine learning models have been trained on large datasets to identify patterns and anomalies, allowing them to make precise and timely predictions.

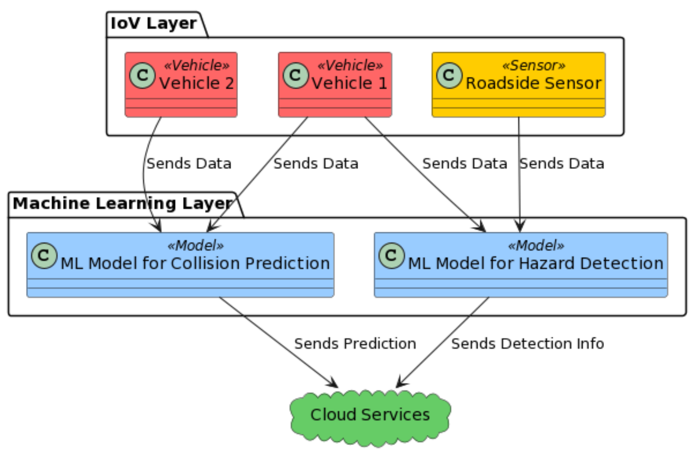

Figure 3: Architecture of ML based Collision and Hazard Detection system for IoV.

The diagram in figure 3 illustrates the Internet of Vehicles (IoV) Collision Prediction and Hazard Detection system. It consists of two main layers: the IoV Layer and the Machine Learning Layer. In the IoV Layer, two vehicles (Vehicle 1 and Vehicle 2) and a roadside sensor (Roadside Sensor) interact. Vehicles exchange data with machine learning models (ML Model for Collision Prediction and ML Model for Hazard Detection) in the Machine Learning Layer. These models use advanced algorithms to predict collisions and detect hazards based on the input data received from vehicles and sensors. The predictions and detection information are then sent to Cloud Services for further analysis and decision-making. The diagram's color-coded elements enhance the visual understanding, with vehicles depicted in red, sensors in yellow, machine learning models in light blue, and cloud services in green. This architecture enables real-time collision prediction and hazard detection in the dynamic context of the Internet of Vehicles, contributing to enhanced road safety.

A general mathematical model for Collision Prediction and Hazard Detection in the context of the Internet of Vehicles (IoV) can be framed as follows:

- X : Feature matrix. Each row in X represents a vehicle or observation, and each column represents a different feature such as speed, distance to the next vehicle, brake status, etc.
- y : Output vector. Each entry is either 0 (safe condition) or 1 (collision/hazard event).
- $theta$: A vector representing the weights for each feature.
- b : A scalar representing the bias term.

Model:

Using logistic regression as an example, we model the probability of a collision/hazard event given the features as:

$$P(y=1|X;theta)=1/(1+\exp(-z)) Where, z = X * theta + b|$$

Here, "exp" denotes the exponential function.

Objective:

The objective of training is to adjust theta such that the model's predictions closely match the true events. This is done by minimizing a loss function. For our logistic regression example, we use the cross-entropy loss:

$$L(theta)=-(1/m)*SUM[i=1 to m](y[i]*\log(y_{hat}[i])+(1-y[i])*\log(1-y_{hat}[i]))$$

Where:

- $y_{hat}[i]$ is the predicted probability of collision/hazard for the i^{th} observation.
- m is the total number of observations.
- "log" is the natural logarithm.

Features:

Features play a vital role in determining the model's effectiveness. For IoV collision prediction, features might include:

- Relative speed to nearby vehicles.
- Distance to nearby vehicles and infrastructures.
- Road conditions like $wet, dry, or\ icy$.
- Data from traffic signals or other infrastructure.
- Sensor readings, such as from LIDAR, radar, or cameras.
- Historical data about the road and typical traffic patterns.

The models might be more complex than logistic regression, especially when leveraging the vast data from IoV. They might use deep learning or other advanced techniques, but the general principle remains extracting patterns from features to predict potential hazards.

Abdelrahman et al.[16] propose a novel ML-based approach for estimating accident risk in commercial trucking. The algorithm's accuracy is evaluated using the "accuracy" metric, highlighting its superiority over other methods. While this approach shows promise in enhancing transportation safety, further research is needed to validate its practical effectiveness.

Guo et al.[17] develop a forward-collision warning system using TTC as a proxy for collision likelihood. They model TTC distribution using sub-Gaussian mixture models and employ time-series machine models for prediction. The study suggests a method to enhance pre-collision systems, but the limited sample size calls for more extensive validation.

Brahim et al.[18] propose a low-cost solution for driver behavior profiling using mobile sensors. Various ML algorithms are investigated, aiming for accurate time series classification. The framework holds potential for fleet management, but the need for real-world data and concerns about data simulation are acknowledged.

Lee et al.[19] assess driving behaviors using a dynamic riding simulator and develop a model for collision avoidance. They quantify driving behaviors based on lateral control, head motion, and mental state. While the dynamic simulator approach is innovative, the limited sample size necessitates further research for broader applicability.

C. C. Chang et al.[20] suggest a collision avoidance architecture based on vehicle dynamics and YOLOv4 for object detection. The study presents a viable approach for collision avoidance in IoV, though broader contexts require additional investigation.

Moses and Parvathi[21] propose a machine learning-based model for traffic flow prediction. Their process on the US traffic dataset demonstrates the application of ML in practical settings.

Lyu et al.[22] enhance collision alerts in V2V communication using a new model. Their study contributes to vehicle safety by optimizing cut-in collision warnings, yet further research is essential to generalize results.

Watanabe et al.[23] identify dangerous road spots using ML on mobile sensing and V2V networking. Their approach employs ML techniques and the Viterbi algorithm. The proposed V2V cooperative structure has potential for enhanced road safety.

Silva et al.[24] investigate crash prediction methods using machine learning and evaluate their effectiveness. Neural networks stand out as promising, but limitations like data quality and real-time data are discussed.

AbouElassad et al.[25] analyze driving behavior through the DVE system and evaluate it with ML models. Their research validates the efficacy of ML methods for assessing driving behavior.

Petraki et al.[26] examine driving habits using cellphone sensors and GIS data. Traffic features significantly influence aggressive driving occurrences. The study contributes insights into aggressive driving patterns and their association with road parameters.

Peng et al.[27] propose a two-stage method for emergency situations, identifying driving risk features and creating a risk index. The approach enhances collision avoidance systems, but more validation across diverse scenarios is required. The study offers potential for improved collision avoidance efficiency.

Table 5: Summary of the Contemporary Articles on Machine Learning based Models.

Author	Contribution	Methodology	Limitations
Abdelrahman, A. E. [16]	ML-based risk estimation for accidents	ML algorithms, accuracy measurement	Practical application validation needed
Guo, L. [17]	Forward-collision warning for ADAS	Sub-GMMs, time-series models	Limited trial, context validation required
Brahim, S. B. [18]	Low-cost driver profiling	ML algorithm investigation	Simulation limitations, data validation
Lee, J. [19]	Assessing driving behaviors	Utilization of sensor data	Small trial, context validation needed
C. C. Chang [20]	Collision avoidance using dynamics	Real-time object detection	Single camera setup, broader validation
Moses and Parvathi [21]	ML-based traffic flow prediction	ML process, stages breakdown	Limited to US data, no new methodology
Lyu et al. [22]	Improved collision alerts	Novel model, simulation validation	Specific scenario, broader context needed
Watanabe et al. [23]	Identifying dangerous roadplaces	Sensory data, ML application	Real-world validation, generalization
Silva et al. [24]	Various ML methods for collision	Prediction overview, evaluation	Data precision, lack of real-time data
AbouElassad et al. [25]	Framework for analyzing behavior	Conceptual framework, ML usage	Behavior focus, framework refinement
Petraki et al. [26]	Analyzing driving habits	Sensor data, spatial representation	Location limitation, context validation
Peng, L. et al. [27]	Driving risk assessment	Risk determination, explanation	Single dataset, broader validation needed

3.3 Deep Learning Models

Advanced neural network models are used by the Deep Learning-based models to improve traffic safety. This system uses deep learning algorithms to identify hazardous situations in real-time and predict potential collisions. The deep learning models can learn complex patterns, relationships, and contextual cues by processing data streams from vehicles and sensors. This enables precise predictions. By giving drivers immediate alerts and preventing accidents, this predictive capability lowers the possibility of collisions and mitigates potential risks. The system's capacity for continuous improvement through data accumulation and ability to adjust to shifting traffic conditions both contribute to its efficiency. Overall, these Deep Learning-based systems are a cutting-edge approach with enormous potential for improving traffic safety and refining the IoV environment.

The diagram in figure 4 portrays a system architecture for collision prediction and hazard detection within the Internet of Vehicles (IoV). It is structured around a central "Cloud Servers" component, which interacts with the IoV environment comprising elements like "Vehicle Sensor Data", "Inter-Vehicle Communication", and "Roadside Infrastructure Communication". Within the cloud, there are designated packages for deep learning models, specifically the "Collision Prediction Model" and the "Hazard Detection Model". Additionally, there are databases for "Training Data" and "Model Storage". The interaction pathways indicate data uploading from vehicle sensors to the cloud, inter-vehicle data transmission, and synchronization with traffic systems. The deep learning models use this data to make predictions and detect hazards, leveraging neural networks and convolutional neural networks as highlighted by notes adjacent to each model.

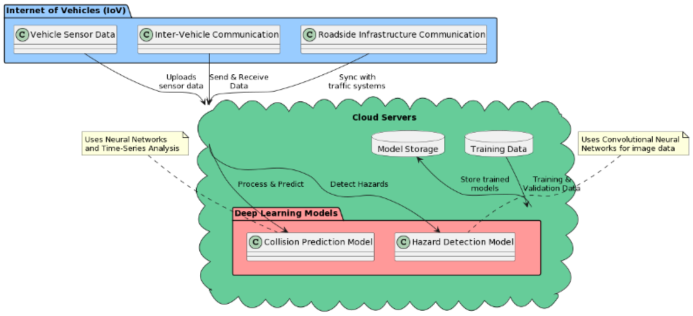

Figure 4: The Architecture of Deep Learning based Collision and Hazard Detection system for IoV.

The deep learning model would typically be trained using past IoV data, sensor readings, and known outcomes (like collisions or hazards) to predict or classify future events. In real-world implementations, additional architectural nuances and layers might be included based on the specific requirements and data nature.

1. **Input Layer**:
   - Let x be a vector representing input features, such as vehicle speed, direction, proximity to other vehicles, and sensor data like LIDAR or RADAR outputs.
2. **Hidden Layers**:
   - Assume there are L hidden layers in the deep neural network.
   - For each layer l, it has a weight matrix represented as W^l and a bias vector as b^l.
   - The activation function is denoted by f, which could be functions like $\mathrm{Re}LU$, sigmoid, or $\tanh$.
   - The output for each layer, h^l, can be computed as: $h^l = f\left(W^l * h^{(l-1)} + b^l\right)$
   - Note that h^0 is equivalent to the input x.
3. **Output Layer**:
   - The final layer produces an output vector y, which could be probabilities or scores for different events like the likelihood of a collision or level of hazard.
   - If the model is doing regression (like predicting time until a collision), y could be a scalar or a set of continuous values.
   - For classification tasks (determining if a collision will occur or not), y would be a set of discrete values.
4. **Loss Function**:
   - Denote $J(W,b)$ as the function representing the difference between predicted outputs and actual labels. Depending on the task, this could be Mean Squared Error for regression or Cross Entropy for classification.
5. **Optimization**:
   - The main objective is to find the best set of parameters W and b that minimize the loss function J. Typically, methods like Gradient Descent are used to achieve this.
   - For a given layer l, the weight and bias updates can be represented as: $W^{(l,new)} = W^l - alpha * gradient\ of\ J(W,b)$ with respect to $Wb^{(l,new)} = b^l - alpha * gradient\ of\ J(W,b)$ with respect to b
   - Here, alpha represents the learning rate.

Lin and Li[28] propose a hierarchical ML-based technique to forecast traffic flow after accidents using crowdsourcing data. ML methods like RF, SVM, and NN are employed to classify traffic situations based on congestion delay levels. The study demonstrates the potential of crowdsourced data for real-time traffic incident analysis, though further validation is necessary for practical implementation.

Yu et al.[29] introduce DSTGCN for predicting road accidents, using a multi-layered model for spatial, temporal, and embedding learning. DSTGCN outperforms conventional and state-of-the-art methods, addressing the complex causation of accidents.

Ranjan et al.[30] suggest using traffic congestion maps for quick city-wide traffic data. Their neural network design with CNN, LSTM, and TCNN enhances congestion prediction efficiency and offers potential for road network improvement.

Wang et al.[31] propose RCPM using deep learning to predict rear-end collisions. Despite class imbalance, their approach demonstrates superiority over other algorithms, emphasizing deep learning's potential in predicting rear-end crashes.

ZHAO et al.[32] present a DL-based collision risk prediction approach using CNN on edge servers. The method outperforms statistical and conventional ML algorithms, offering potential to enhance traffic safety in vehicle communication networks.

Jianwu Fang et al.[33] introduce SCAFNet for predicting driver attention in accident scenarios. Their fusion network model with GCN outperforms previous approaches, offering potential to enhance driving systems' security and reliability.

Kothai et al.[34] propose the BLSTME and CNN model for traffic congestion prediction in VANETs. The hybrid model's stability and performance surpass state-of-the-art algorithms, showcasing its potential for efficient congestion anticipation.

Malawade et al.[35] present SG2VEC for autonomous car collision prediction, utilizing GNN and LSTM layers. The method outperforms prior techniques and excels in both synthetic and real-world collision datasets, with implications for safer autonomous driving.

Gutierrez-Osorio et al.[36] suggest an ensemble DL model for traffic collision prediction using public sources and social media. The model's promising results offer insights into the potential of social media data for accident analysis.

Pan et al.[37] develop a LoRa-based V2P communication system for early collision warning. The proposed V2P approach demonstrates effective collision risk alert strategy, contributing to pedestrian safety.

These studies collectively contribute to the advancement of traffic safety through innovative ML-based techniques. However, validation in diverse scenarios and further practical implementation are necessary to fully assess their potential impact on real-world accident prediction and prevention.

Table 6: Summary of the Articles Reviewed towards Deep Learning Models.

Author	Contribution	Methodology	Limitations
Lin and Li [28]	Hierarchical traffic prediction	ML (RF, SVM, NN), data analysis	Location-specific, generalization
Yu et al. [29]	Spatio-temporal mishap prediction	Graph CNN, real-world data	Validation, broader contexts
Ranjan et al. [30]	Snapshot-based traffic data	CNN, LSTM, TCNN, web service	Dependency, real-world validation
Wang et al. [31]	Rear-end collision forecasting	Deep learning, evolutionary prep	Validation, algorithm comparison
ZHAO et al. [32]	DL-based collision risk prediction	Edge CNN setup, algorithm complex	Validation, limitations exploration
Jianwu Fang et al. [33]	Driver attention prediction	SCAFNet, GCN, dataset comparison	Validation, limitations exploration
Kothai, G., et al. [34]	VANET congestion forecast	Hybrid model, Tensorflow, simulation	Validation, scalability challenges
Malawade et al. [35]	Autonomous car collision forecast	Scenegraph embeddings, GNN, LSTM	Validation, real-world scenarios
Gutierrez-Osorio et al. [36]	Ensemble DL for collision	Ensemble DL, social media data	Validation, social media limitations
Pan et al. [37]	LoRa-based V2P collision warning	LoRa-based system, LSTM ANN	Implementation, real-world contexts

4. Observations

Numerous studies in the literature review addressed the use of DM approaches to forecast different aspects of traffic accidents, including their causes, locations, and times. For instance, Hussain et al.[5] used the data mining tools Orange and Weka to assess several data mining strategies on a dataset of 150 cases of traffic accidents. They discovered that J48, with 78.66% accuracy, BayesNet, with 80.66% accuracy, and the Multi-layer Perceptron classifier, with 85.33% accuracy, all performed better than other classifiers. In addition, the data set was clustered and the number of dimensions was reduced using the data mining tool "Orange" and the Self-Organizing Maps and K-means clustering as well as dimensionality reduction methods. The clustering was reasonably good, according to the Silhouette score of 0.7.

Several publications in the literature review addressed the integration of ML, DL, and DM approaches into the design of ADAS to enhance road safety and reduce accidents with respect to Research Question 2. For instance, Cosic et al.'s[4] algorithm with ADAS uses video frames from an outside rear-view mirror camera to estimate the time to potential collision (TTC) for a vehicle coming from behind. The programme uses vehicle detection and tracking to determine the approaching vehicle's distance and speed and provide data about the TTC. For quick, anticipatory collision avoidance for autonomous robots with arbitrary equations of motion, Davis et al.[6] introduced the NH-TTC approach. The cost distributions are non-convex and non-smooth as a result of designing across the anticipated future locations of nearby barriers, and thus need to be optimised. Subgradient descent and implicit differentiation are both used in the approach to accomplish this. These publications demonstrate the possibility for including these methods in ADAS to raise traffic safety and reduce collisions.

Regarding Research Question 3, recent advancements have been made for recognising hazardous places on highways by combining mobile sensing on heavy-duty vehicles with V2V opportunistic networking. They use ML algorithms to generate preliminary assessments of the state of the road based on the vehicle's sensor data. The final choice is made by applying their Viterbi method, which uses a (HMM) to simulate the distance connection between the state of the road and the successive outputs of the localised hazardous spot detector. The proposed V2V cooperative architecture has the ability to increase the accuracy of hazardous area detection by each vehicle in a community.

The most recent contributions looked at alternate strategies for applying machine learning to anticipate accidents in relation to Research Question 4. They give a broad review of accident prediction models and the measures that measure their effectiveness. As ML approaches can handle complicated data and identify nonlinear interactions between variables, its use in collision prediction systems seems promising. The most popular machine learning (ML) approach for predicting collisions is NN, however decision trees and support vector machines have also been employed. The absence of real-time data and the requirement for more precise accident data are two drawbacks of the present crash prediction algorithms that are highlighted in the research.

Based on the review, it can be concluded with reference to Research Question 5 that DL models have the potential to enhance traffic accident prediction, particularly in forecasting rear-end crashes. The evaluation does not, however, directly contrast deep learning models with conventional machine learning techniques.

Regarding Research Question 6, the analysis showed that DL models that make use of social media and open data may accurately forecast traffic accidents. These models outperform conventional machine learning techniques, historical techniques, and cutting-edge techniques in terms of accuracy and performance. Deep learning models that use social media and open data sources might thus be thought of as a potential method for foretelling traffic accidents. The evaluation does not, however, provide a direct comparison between models that rely on open data sources and social media and those that do not.

5. Review Findings and Future Research Scope

Based on the review of the articles provided, there are several implications and future research directions that can be identified.

5.1 Implications:

1. Deep learning models show promising results in predicting traffic accidents and improving road safety.

2. The use of social media and open data can improve the performance of DL algorithms in predicting traffic accidents.

3. Hybrid models that combine multiple deep learning architectures can achieve better performance in predicting traffic accidents.

4. Potentially preventing traffic congestion and enhancing the effectiveness as well as the capacity of the roadway network, the proposed models are capable of implementing the aforementioned improvements.

5.2 Future Research Directions:

In the realm of Collision Prediction and Hazard Detection in the Internet of Vehicles (IoV), there are promising dimensions for future research. Reinforcement Learning holds potential for training vehicles to autonomously navigate traffic by learning effective collision avoidance strategies through real-time interactions with their environment. Concurrently, embracing Interpretable Artificial Intelligence can elevate IoV safety by developing hazard prediction models that not only make accurate forecasts but also provide transparent explanations for their decisions, fostering user trust. Furthermore, the integration of Ensemble Deep Learning techniques can enhance hazard detection by combining diverse neural network architectures, thereby fortifying predictions, minimizing false positives, and elevating overall prediction accuracy. These avenues collectively offer avenues for advancing IoV safety and collision prediction.

There are promising directions for further study in the area of predicting collisions and identifying hazards in the Internet of Vehicles (IoV). The use of nature-inspired algorithms, such as the Frog Leaping Algorithm (FLA), which imitates frogs' leaping behavior to optimize collision prediction model parameters, is one promising strategy[38]. Harmony Search is a different method for optimizing the parameters of hazard prediction algorithms that is inspired by musical harmony[39]. These algorithms could help these systems be more accurate by determining the best settings. Additionally, improving deep learning techniques, in particular Convolutional Neural Networks (CNNs), has the potential to improve hazard detection from images[40]. We show that attention mechanisms and residual connections can be used to improve CNN architectures' detection of potential road hazards. To further categorize similar driving patterns or road scenarios, an Adaptive Evolutionary Clustering Algorithm known as STAR could be used[41, 42]. This clustering could help with hazard prediction and prevention by providing insights into collision patterns within various scenarios.

Conclusion

In conclusion, this review highlights the potential of DL models in predicting traffic accidents and congestion, as well as the use of social media and open data as sources of information. The reviewed articles present various DL models, such as CNN, LSTM, and GNN that outperform traditional ML methods in predicting traffic accidents and congestion. These models incorporate multiple sources of data, such as traffic data, meteorological data, and Point-of-Interest distributions, to provide more accurate predictions. Additionally, the use of social media and open data has been shown to improve the performance of these models. Future research directions may focus on developing more efficient and scalable deep learning models, validating the performance of these models in real-world scenarios, and exploring the ethical implications of using social media and open data. Overall, deep learning models offer a promising approach to improving road safety and reducing traffic congestion.

The outlined research possibilities offer strong justifications for further exploration in Collision Prediction and Hazard Detection within the Internet of Vehicles (IoV). Reinforcement Learning can revolutionize collision avoidance strategies by enabling vehicles to learn and adapt to real-time traffic situations, bolstering safety. Interpretable Artificial Intelligence adds an essential layer of transparency, ensuring users understand and trust hazard predictions, which is crucial for widespread adoption. Ensemble Deep Learning's potential to combine diverse neural networks holds promise for heightened accuracy in hazard detection, reducing false alarms. The integration of nature-inspired algorithms like the Frog Leaping Algorithm and Harmony Search can optimize predictive models effectively, while advancements in Convolutional Neural Networks with attention mechanisms and adaptive clustering through the STAR algorithm can enhance road hazard identification. These directions collectively address critical challenges in IoV safety and offer tangible pathways for significant advancements.

Conflict of interests

None

Author Contribution

Manchala Ajay Kumar, has made substantial contributions as a research scholar in the field of Electronics and Communication Engineering at Mohan Babu University. He has conducted an extensive literature review, focusing on the Internet of Vehicles (IoV), accident prediction, and hazard detection. Ajay has analyzed various machine learning, deep learning, and data mining techniques, providing critical insights into their applications for enhancing IoV safety. He has played a pivotal role in discussing real-world applications and case studies, delving into intelligent accident prediction models, driver attention forecasting, and other relevant IoV safety applications. His dedication to the research is evident, as he has provided his contact information and ORCID ID, showcasing his readiness for scholarly collaboration and his commitment to the academic integrity of the work.

Professor Vijaya Kishore.V has provided expert guidance and mentorship throughout the research and writing process of the article, leveraging his extensive experience in Electronics and Communication Engineering. He has played a crucial role in assessing the methodologies for data collection, ensuring the quality of the data, and offering valuable insights into the dynamic nature of IoV traffic scenarios. His academic expertise has been instrumental in articulating the various machine learning, deep learning, and data mining methods discussed in the article. He has also ensured that the real-world applications and case studies presented are accurate and reflect the current state of the field. By providing his contact information and ORCID ID, he has lent credibility to the article and opened avenues for future communication and validation of the work.

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