Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

A Comprehensive Review of Vehicular Ad Hoc Network-Based Accident Identification Systems

V. Nanda Kumar, J. Benadict Raja

1 Assistant Professor, Department of CSE, PSNA College of Engineering and Technology, Dindigul

2 Associate Professor, Department of CSE, PSNA College of Engineering and Technology, Dindigul

Abstract:- In current years, there has been a rapid increase in the amount of automobiles on the road as well as an expansion in the ways in which they are utilised. This can be due to people's growing demand for and need for vehicles. The number of road accidents has increased as a result of this issue. Road accidents endanger human life and put contemporary society's dedication to public safety at jeopardy. Thus, a clear solution to this problem must be presented. Traffic accident prediction and prevention are essential steps for the security of motor vehicles. Vehicle Ad-hoc Networks (VANETs), which provide in-vehicle immediate connectivity and sensing, have emerged as a feasible solution for improving road safety. Recent research have put forward the idea of VANET-based traffic accident prediction systems, which use the information gathered from VANETs to calculate the chance of accidents in a certain location. A summary of the most advanced VANET-based traffic accident recognition systems is given in this review study. For VANET, both early detection and transmission lag have been problems. The present problem and challenges with accident identification in VANET technology are also covered in this paper. Our analysis demonstrates the potential for VANET-based traffic accident identification systems to dramatically increase traffic safety, but additional study is required to solve the difficulties associated with real-world implementation, such as confidentiality of information, adaptability, and dependability.

Keywords*: Vehicular Ad-hoc Networks (VANET),vehicular safety, accident identification, real-time communication.*

1. Introduction

Road accidents are the most unwelcome and unexpected event that may happen to a road user, even though they occur often. Unfortunately, we are seeing an increase in traffic accidents in India, particularly serious ones in recent years. Due to the high cost of deaths and injuries, it has a significant influence on both society and the economy of our nation [1].Plenty of traffic data has lately been obtained as a result of the increase in the number of vehicles on the road and the rapid development of self-driving vehicles. Many academics are interested in developing data-driven approaches to uncover hidden beneficial information in the vast traffic data, which might not only assist individuals pick more efficient transport options but also advance pertinent departments to operate cities more effectively.In contrast, there hasn't been much progress in finding satisfactory solutions to the forecast of road accidents, which may prevent significant harm to human lives and property [2-3].Every year, 1.35 million people are killed in vehicle crashes, according to the World Health Organization (WHO)’s 2018 worldwide status report on road safety. Estimating the likelihood that a traffic accident will occur in a certain area in advance is crucial for reducing the damage brought on by traffic accidents. An accurate evaluation of the likelihood that traffic accidents will occur would advise drivers to choose a safer route or assist urban traffic control agencies in making choices and preparing for emergencies [4].From 2009 to 2018, the number of fatalities due to traffic accidents varied throughout Asian nations. Figure 1 compares the number of fatalities in 14 Asian nations, including “Afghanistan, Bangladesh, China, India, Iran, Japan, Kazakhstan, Kyrgyzstan, Malaysia, Pakistan, Philippines, Sri Lanka, Turkey, and Vietnam", using information from WHO reports on global road safety that was released in 2009, 2013, 2015, and 2018.

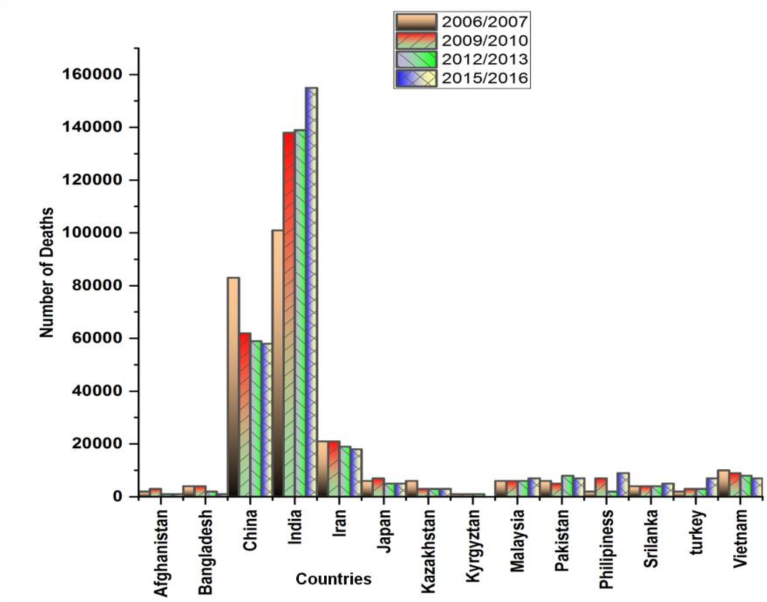

Figure 1: Asian nations' road accident death rates

A significant worldwide public health issue is road safety. Road traffic accident reduction may be significantly aided by accurate traffic collision prediction. Existing Machine Learning (ML)methods, however, often concentrate on forecasting crashes involving cars in isolation, failing to take into account possible connections between various accident sites within road networks [5].The applications of VANETs are wireless communication networks that enable vehicles to communicate with one another and with roadside infrastructure. For military-based applications, it offers clever and effective solutions. Increased traffic accidents caused by enhanced dynamic mobility and a lack of congestion management are the main research problems in VANETs [6]. Numerous Internet-based and mobile social networks have been discussed in the literature as potential solutions for smart mobility in smart cities. Inconsistencies with network overlaps are another disadvantage of VANETs. With the aid of a routing board, a unique reliable routing protocol is created. Road accident prediction in VANETs involves using the network to collect real-time data about traffic conditions, vehicle movements, and other relevant factors that can contribute to accidents [7].

2. Vehicular Ad-hoc Networks (VANETs)

Roadside services like navigation, safety, and others are offered through VANETs. Because VANETs are a fundamental component of the Intelligent Transportation System, they are sometimes referred to as Intelligent Transportation Networks. A system called VANET can recognize a vehicle at a certain network location and treat it as a node. There has been a lot of study and significant advancement on VANET during the last several decades. Figure 2 shows the structure of VANET. The goals of several of these initiatives include increasing network security, enhancing traffic safety, lowering pollution levels, and improving road safety. Network, road infrastructure, and vehicle-to-vehicle communication are the three elements that may be used to construct a VANET network. Vehicles serve as nodes in the VANET and are connected through wireless technology [8].

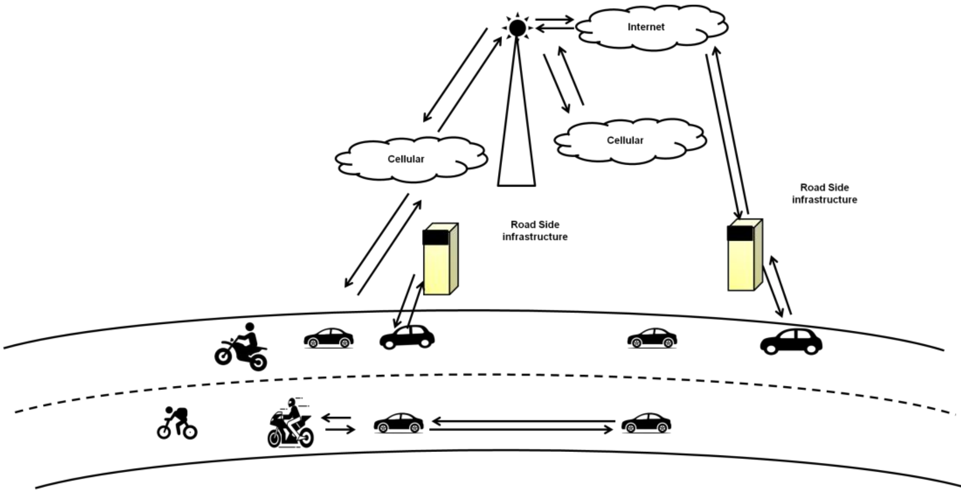

Figure 2: VANET structure

The two major communication channels in VANETs are “Vehicle to Infrastructure (V2I) and Vehicle to Vehicle (V2V)”. During the V2V connection, two cars exchange traffic updates and alerts. The location, travel direction, braking, speed, and instability loss would all be included in this data. In V2I communication, cars may talk to base stations, traffic lights, and other roadside infrastructure [9]. Intelligent transport systems link data storage through V2I sensors and provide real-time user guidance. These two VANET methods for interaction might considerably enhance transportation.

Activities on VANET can be split into two distinct groups: security programs and non-security programs.Programsof VANETs that are focused on safety include situation awareness features like adaptive cruise control, blind spot warning, and warnings for automated brake light and traffic signal violations. Human life preservation takes priority in these applications. By disseminating information about impediments and risks, these apps reduce the probability of traffic accidents. According to some prior studies, if the motorist gets a warning a few seconds before the impact, more than half of accidents may be preventedIn an accident, the second fraction is equally crucial. As a result, VANET's security applications are severely constrained [10]. Applications that are not safety-oriented mostly include those that enhance driving comfort, provide entertainment, and provide context. Compared to applications that are safety-oriented, these applications have fewer stringent requirements and limitations. Where other traditional wireless choices are not accessible, passengers in a car may benefit from the ability to connect to the internet. Many businesses may utilize VANET for advertising purposes. These programs have a role in VANET as well, including file sharing, gaming, and web surfing [11].

3. Advantages and difficulties of accident detection

Road accidents may be caused by a variety of circumstances, some of which are (somewhat) predictable, such as rush hour or road construction, as well as other unanticipated factors like accidents, the weather, people's actions, and other unusual or remarkable happenings that influence the usage of the roads. The most common road occurrences include traffic congestion, road accidents, and other dangerous issue that might exist without any previous knowledge of the drivers. As a consequence, after the root cause has been removed or fixed, it will take longer to fix the issue the more severe it is. Normal road capacity is constrained during an event, and there are often lines and delays, just as when there is a traffic jam. Delays are mostly caused by incidents, which also have significant effects on safety, traffic, pollution, and travel expenses. Previous studies have indicated that accidents are one of the key reasons why transport networks experience delays and higher unnecessary expenses [12].

A) Information on incidents that is unimportant

Drivers could only be provided with important information. Information that is superfluous or independent should be filtered away. This involves disseminating factual information. The management of traffic is often significantly impacted by irrelevant data sent by the detector node or by ringed cars. The identical information was occasionally relayed to every node within the automobile, setting off false alerts [13]. This causes traffic to shift lanes and causes extra traffic to build up along the road, which confuses the Intelligent Transport Systems (ITS) system. As a result, a crucial part of the ITS's ability to recognize VANET-based occurrences is the information to be given to cars.

B) Information that cannot be accessed in real-time

Real-time traffic statistics must be accessible. Alternatively put, high-speed drivers must have access to the relevant traffic information. Information broadcast by a sensor node or a vehicle node often reaches other nodes beyond its scheduled time. When an emergency warning is needed to stop tragic accidents, it often gets communicated too late and results in an undesirable mishap [14]. As a result, real-time data access is essential for VANET-based ITS. The strengths and weaknesses of the strategies used in incident detection are shown in Table

Table 1: Baseline simulation settings

Technique	Characteristics	Strength	Limitation
Technology	Based on vehicles.	Include cell phones	measures of journey time
Wireless location	The majority of people use mobile phones.	Some vehicle owners	Produce reliable speed and
Automatic vehicle location	Use Global Positioning System (GPS) data to determine its location.	There aren't many necessary long-term infrastructure elements.	Sample size limitations.
Identification	Non-intrusive	With information gathering	Road architecture
Inductive loop detectors	Intrusive, comprising a wire coil.	Information on the volume and occupancy of traffic.	ILD installation, upkeep, and replacement.
Video detection system	Non-intrusive software for processing images from cameras.	Multiple cameras may be controlled by a single device.	Some periodic maintenance.
Automatic vehicle	Non-intrusive	Provide effective vehicles	Include important
Microwave radar sensors	Non-intrusive	Precisely monitor rate	Poor accuracy

The superior method of traffic monitoring is incident detection and management. An incident may be found using several traffic surveillance models. “Inductive loop detectors, video detection systems, microwave radar sensors, automated vehicle identification, automatic vehicle location, and wireless location” technologies are some of the incident detection methods now in use [15].

4. Predictions of Road Accidents

Machine Learning (ML) techniques are widely used in the area of predicting road accidents due to their outstanding prediction abilities, flexibility in implementation and coding, and ability to comprehend multi-dimensional data. The goal of the study in the field of predicting road accidents is to determine the probability of an accident happening based on a certain set of events or causes, estimate the severity of road accidents, or do a post-mortem investigation [16].One of the most common approaches used to forecasting road traffic is accident analysis, as seen in Figure 3.

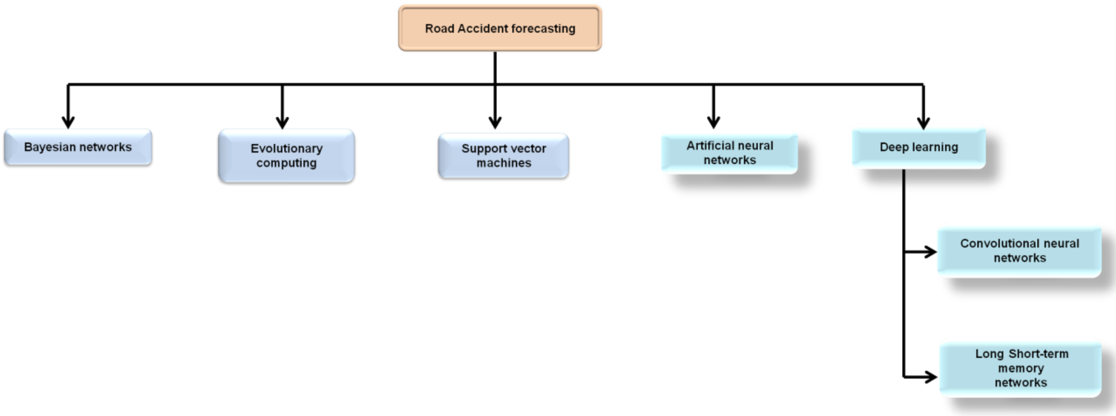

Figure 3: Typical algorithms and techniques for predicting traffic accidents

- **Bayesian Networks (BN)**

The application of several random factors, as well as how they interact, which are shown as probability distributions, allows for the modeling of events using Bayesian Networks (BN). The factors are used as an illustration for the quantitative understanding of the system via the conditions of the Directed Acyclic Graph (DAG) as vertices in a representation. As arcs connect the nodes, the relationships of conditional independence and dependency between the factors are shown [17]. The prediction of accident-causing factors and the development of accident severity models both employ BN.

- **Evolutionary computing and Genetic Algorithms (GAs)**

Since GAs prefer to converge on the optimal answer rather than falling the initial data collection often has to be transformed into specific ideal values altered or normalised in order to be used as an entry to the method. Every gene might be thought of as a specific value of a factor in the population, which is a particular set of genes. GAs depicts a chromosome as the solution to an issue. An ideal solution may be attained by carrying out a repeated evolution that begins with a randomly selected population. To create an emerging class, an operator's mutations, and crosses are applied to different genes [18]. The procedure is continued until the stop conditions, this may be the value of the fitness measure or the number of repetitions that have been completed, were satisfied.Using decision trees and GAs, the extent of injuries sustained in vehicular crashes on both urban and rural routes may be predicted using a prediction model. To create the model, a multi-objective GA was used to a collection of training data to draw up a list of categories and criteria that could be used to forecast the severity of the traffic incidents.

- **Support Vector Machines (SVMs)**

Support vector machines may be used to solve issues including separable or nonseparable problems, linear categorization jobs, and nonlinear classification tasks. Using a kernel function, an SVM converts the input space data points into a high-dimensional feature space, or hyperplane, that represents the optimal margin within the sets.The framework used to anticipate crashes on the road used SVMs to determine whether a driver was leaving or staying in their lane, and a Hidden Markov Model (HMM) to distinguish between patterns associated with accidents and non-accidents [19]. The model's accuracy was 0.8730, which the authors claim is a promisingly outstanding result on forecasts made by the model.

- **Artificial Neural Networks (ANNs)**

ANNsare Forward-Feeding Neural Networks (FFNN) putting a layer or layers among the input and output stages. In conclusion, the objective of the NN training course is to choose the weight coefficient numbers that will result in the desired output. The amounts of weighting parameters, which link every neuron in every layer communicates with every neuron in the next layers, determine how well the network functions [20]. The input layer receives training or testing vectors, which are then processed by the hidden layers and output layer. An MLP learns by data is accepted in the input layer, after which weight coefficients that were initially random quantities are delivered. These values are subsequently communicated progressively to the next levels by being input into neurons of the next layer.

To forecast traffic accidents, anticipate accident severity, and predict accident circumstances, artificial neural networks are deployed. The following procedures must be taken to model an appropriate ANN that will address the foregoing issues: There are various steps in the process, determining the amount of levels and cells that will be used to integrate the model, selecting the kind of ANN and its requirements, such as the activating function, that are most appropriate for the issue, describing efficiency and accurateness measurements, and choosing the type of ANN architecture[21].

- **Deep Learning (DL)**

"Convolutional neural networks (CNN), recurrent neural networks (RNN)", and combinations of both are examples of DL designs for complicated classification problems, classification of text, imaging, computer vision, and voice recognition that leverage high-dimensional data to uncover hidden connections and structures. The architecture of a CNN is correlated to that of an ANN, but they differ in three ways: (a) the neuronal connection patterns in nearby layers; (b) the introduction of a specialized layer known as a pooling layer reduces the variables scale in the model, and (c) only the final layer is fully connected. RNN, on the other hand, is a kind of neural network design that makes use of hidden layers to enable information propagation across layers [22].The method for detecting the danger of road crashes included encoding the accident data matrix into a grey picture that reflected the weights of the characteristics of the accident and then using the grey images as input for a CNN to predict the severity of the event.

5. Related works

The related works consists of vehicle accident detection that are detected by various existing technologies, which is shown in table 2.

Table 2: Vehicle accident detection by various existing technologies

Author & year	Dataset	Technique used	Performance metrics	Limitations
Pathik et al. (2022)	The database contains 500 images, 250 of which belong to each of the two classes (accident and non-accident)	Internet of Things (IoT) and Artificial Intelligence system (AI)	Performance in comparison to ResNet with a test accuracy of 98% after training and assessment.	The suggested approach does not take security into account.
Zhou et al. (2022)	There are various publicly accessible video databases for the identification of traffic and abnormalities	Spatio–temporal feature encoding with a multilayer neural network.	The accuracy (98%), and detection time (0.201s).	The process has many complexities.

Uma and Eswari (2022)	They tested datasets from 20 different drivers for our suggested system. There is a database that stores the variables Date of Travel, Time of Travel, Time of Drowsy, Alcohol, and Gas	Internet of Things and machine learning	The detection accuracy is high (95%) AND f1-Score (93%).	Less parameters is used in the dataset.
Li et al. (2022)	The information utilised in this research was gathered from a public website that provides traffic flow statistics	Generative adversarial network (GAN)	The suggested approach enhances real-time capabilities and detection precision (97%).	The sample parameters do not take into account external influences like the weather.
Pawarand Attar (2022)	This database was compiled from the network of CCTV cameras located in various public spaces around the Indian city of Hyderabad that record the scenes of traffic accidents	Deep learning	They were able to identify traffic accidents at the frame level with an area under curve of 84.70% and an F1-score accuracy of 78.58%.	This method are prone to overfitting, when the training dataset is small or noisy.
Chandand Karthikeyan (2022)	The dataset includes several levels of driving behaviour, such as normal, fatigued, hostile, disturbed, and intoxication	Convolution Neural Networks (CNN) and emotion analysis	An accuracy score of 93% is produced in identifying both the driver's behaviour and emotions using empirical evaluation and comparing comments.	CNNs are very challenging to interpret.
Kumar et al. (2022)	Simulations were performed using the VIVID, VEDAI, UC Merced Land Use, and Self datasets, it consists of road vehicle images.	YOLO-V3 (You Only Look Once)	The findings imply that the suggested method has a higher detection percentage, which on the Self dataset is about 96.16%.	It has few error rate
Josephinshermilaet al. (2023)	The microcontroller-monitored vehicle parameters from the cloud database are utilised.	Automotive Smart Black-Box based Monitoring system	The accuracy improvements made by the suggested method are 22.70%, 29.3103%, 18.103%, and 11.206%.	The computation time is very high

6. Impact of weather conditions on the road

Driving security and effectiveness may be significantly impacted by weather circumstances on the road. Here are a few instances: Rain may make the road slick and limit vision. Additionally, it may leave standing water on the ground, which raises the possibility of hydroplaning. In wet weather, drivers must slow down and keep a secure separation from other cars. The road may become slick and lose traction as a result of snow and ice. Accident risk may rise as a result, particularly if motorists are used to operating a vehicle under such circumstances. Drivers should slow down, use chains or winter tyres, and give themselves more stopping time. Fog may impair vision, making it challenging to notice other cars and other roadside hazards. In foggy situations, drivers have to slow down and make use of their spotlights and fog lights [23]. **Strong winds** can make it difficult to control the vehicle, especially if it is a large vehicle like a truck or an RV. Drivers should reduce their speed and maintain a firm grip on the steering wheel in windy conditions.**Extreme temperatures** can affect the condition of the road, especially if there are frequent freeze-thaw cycles. This can lead to potholes and cracks in the road, which can be hazardous to vehicles. Drivers should watch out for such hazards and avoid them if possible. Figure 4 depict the five categories that were merged to make the study easier to understand: slushy road surface, highly slushy road surface, poor visibility, ice rain, and slippery road surface [24].

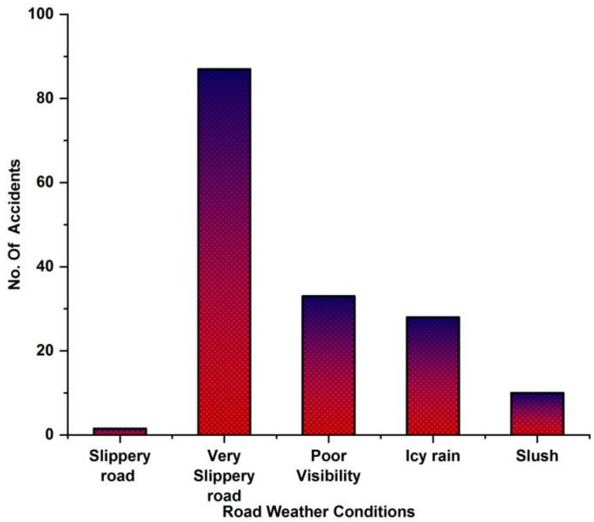

Figure 4: Distribution of accidents according to weather

Slippery road conditions had the greatest risk of occurring (7%) for the weather conditions on the roads. Palm chance was less than 1% for the other types of road weather conditions. Every kind of road weather elevated the chance of accidents by more than 50%. The relative accident risk was more than four times greater for slushy roads and more than two times higher for slippery and very slippery roads.Drivers should always be aware of the weather conditions and adjust their driving accordingly [25]. They should drive cautiously and defensively to ensure their safety and the safety of others on the road.

7. Accident-related to traffic

Around the globe, a variety of research projects have been carried out to try to solve incidents that are connected to traffic. The literature has already examined the kinds, reasons for, and impact of traffic collisions as well as the time between them. Additionally, throughout time, we have seen a remarkable change in the approaches used to create traffic security initiatives. Additionally, a lot of studies have been done to identify the likely reasons why accidents happen, how different drivers drive depending on their gender, and how pedestrians behave at crosswalks [26].Numerous earlier studies that provide a thorough examination of injury-severity estimates and results have also addressed accident severity and a variety of variables that contribute to the severity of the driver's injuries.

According to these researches, the severity of driver injuries is highly influenced by age, gender, and alcohol intake. The impact of the driver's accidents is also affected by the relationship between the driver and the other passengers of the vehicle, and it has been reported that both the age and gender of the passenger(s) matter. In addition to discussing the ramifications of such instability on the various modeling approaches used for accident data, the work has tackled the topic of the computed model variables' temporal inconsistency in data on highway accidents. Traffic accidents' kinds and their causes have also been discussed [27].

8. Distribution of accidents for different types of vehicles

Road accidents can happen to any type of vehicle, but the distribution of accidents can vary depending on the type of vehicle involved. Here is a general overview of the road accident distribution for different types of vehicles:Cars are the most common type of vehicle on the road and therefore, are involved in the most accidents. The most common types of car accidents are rear-ending collisions, side-impact collisions, and single-vehicle accidents such as rollovers.Because of their smaller dimensions and absence of rider safety, motorcycles are more likely to be involved in collisions than vehicles. Motorcycle crashes with other vehicles, accidents with stationary objects, and single-vehicle incidents such sliding or losing direction are the most frequent forms of accidents [28]. Trucks are less common than automobiles to be engaged in collisions, but when they are, they frequently cause more serious injuries because of their size and weight. Rollovers, side-impact crashes, and rear-end collisions are the three most typical forms of truck crashes. Although buses are often regarded as safe transportation, accidents may nevertheless happen. Accidents with other automobiles, collisions with stationary objects, and rollovers are the three most frequent forms of bus crashes. The absence of rider safety makes bicycles more prone to accidents than automobiles and motorbikes, and these collisions may be quite serious. Collisions with other automobiles, accidents with stationary objects, and single-vehicle incidents such losing control or striking a pothole are the most frequent forms of bicycle accidents. All drivers should, in general, be aware of the dangers posed by the kind of vehicle they are operating and use care to prevent collisions. This includes obeying traffic laws, maintaining a safe following distance, and being aware of other vehicles on the road.Figure 6 depict the accident distribution in Khulna Metropolitan City for various vehicle categories. It was discovered that 43% of the vehicles involved were buses and 28% were trucks [29].

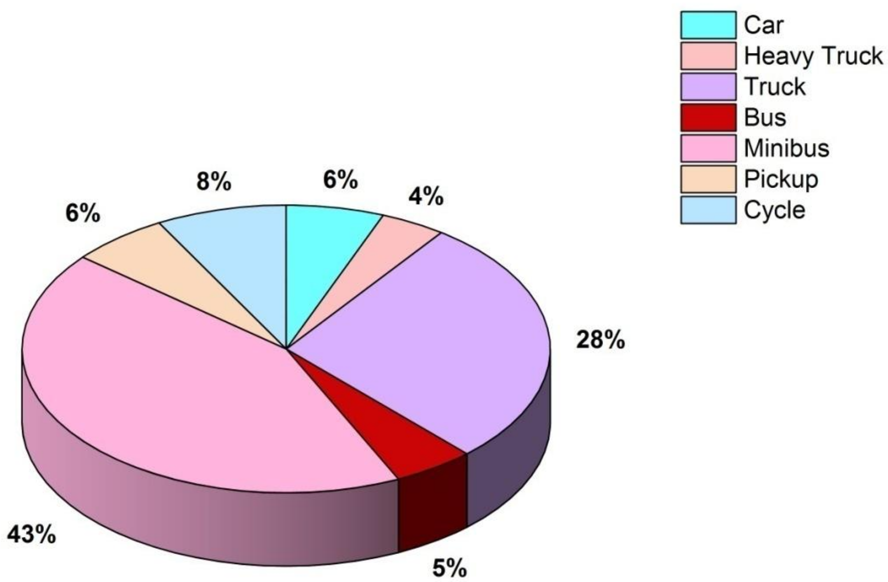

Figure 5: Distribution of accidents for various kinds of vehicles

The majority of study efforts on family vehicle ownership choices have focused on the selection of new cars, as mentioned in the opening part of this article. The market for used automobiles is expanding, however, much like the marketplace for new cars. According to their statistics, there are three times as many transactions in the used automobile market in the US as there are in the new car industry. Additionally, the price dispersion for used cars is around five times greater than the price dispersion for new cars. This blatantly implies that used vehicle markets are crucial to expanding the number of automobiles that are accessible to families and, therefore, to fleet renewal. Used automobile sales are two or three times as common in other nations as new car sales [30].

9. Conclusion

This review article offers a thorough analysis of the methods used now to identify incidents. Based on traffic monitoring and incident detection, current strategies have been researched. The research provided a comparative analysis of the advantages and disadvantages of several traffic incident detection techniques,the Impact of weather conditions on the road, distribution for different types of vehicles, and accident-related traffic. To find uses for incident detection and management, proprietary incident detection methods have also been investigated. The review study included a thorough rundown of all the field-related research that has been done.However, the literature has offered a comprehensive review of relevant work in areas including traffic statistics, incident detection strategies, distribution of VANET data, and safety of VANETs. The research analyzed all of the accident detection methods currently in use and provided a comparative analysis of their strengths and weaknesses.

Refrences

[1] Ajayi, A., Oyedele, L., Davila Delgado, J.M., Akanbi, L., Bilal, M., Akinade, O. and Olawale, O., 2019. Big data platform for health and safety accident prediction. World Journal of Science, Technology and Sustainable Development, 16(1), pp.2-21.

[2] Alani, S., Zakaria, Z. and Hamdi, M.M., 2019. A study review on the mobile ad-hoc network: Characteristics, applications, challenges, and routing protocols classification. International Journal of Advanced Science and Technology, 28(1), pp.394-405.

[3] An, C., Wu, C., Yoshinaga, T., Chen, X., and Ji, Y., 2018. A context-aware edge-based VANET communication scheme for ITS. sensors, 18(7), p.2022.

[4] Arias, N.B., Hashemi, S., Andersen, P.B., Træholt, C. and Romero, R., 2019. Distribution system services provided by electric vehicles: Recent status, challenges, and prospects. IEEE Transactions on Intelligent Transportation Systems, 20(12), pp.4277-4296.

[5] Ayhan, B.U. and Tokdemir, O.B., 2020. Accident analysis for construction safety using latent class clustering and artificial neural networks. Journal of Construction Engineering and Management, 146(3), p.04019114.

[6] Chand, H.V. and Karthikeyan, J., 2022. CNN Based Driver Drowsiness Detection System Using Emotion Analysis. Intelligent Automation & Soft Computing, 31(2).

[7] Chang, W.J., Chen, L.B. and Su, K.Y., 2019. DeepCrash: a deep learning-based Internet of Vehicles system for head-on and single-vehicle accident detection with emergency notification. IEEE Access, 7, pp.148163-148175.

[8] Chaudhary, U., Patel, A., Patel, A. and Soni, M., 2021. Survey paper on automatic vehicle accident detection and rescue system. In Data Science and Intelligent Applications: Proceedings of ICDSIA 2020 (pp. 319-324). Springer Singapore.

[9] Dibaei, M., Zheng, X., Jiang, K., Abbas, R., Liu, S., Zhang, Y., Xiang, Y. and Yu, S., 2020. Attacks and defenses on intelligent connected vehicles: A survey. Digital Communications and Networks, 6(4), pp.399-421.

[10] Febres, J.D., García-Herrero, S., Herrera, S., Gutiérrez, J.M., López-García, J.R. and Mariscal, M.A., 2020. Influence of seat-belt use on the severity of injury in traffic accidents. European transport research review, 12(1), pp.1-12.

[11] Godse, S.P., Mahalle, P.N. and Pathan, M.S., 2019. The priority-based message-forwarding scheme in VANET with intelligent navigation. In Applied Machine Learning for Smart Data Analysis (pp. 169-182). CRC Press.

[12] Hammad, H.M., Ashraf, M., Abbas, F., Bakhat, H.F., Qaisrani, S.A., Mubeen, M., Fahad, S. and Awais, M., 2019. Environmental factors affecting the frequency of road traffic accidents: a case study of sub-urban area of Pakistan. Environmental Science and Pollution Research, 26, pp.11674-11685.

[13] Josephinshermila, P., Malarvizhi, K., Pran, S.G. and Veerasamy, B., 2023. Accident detection using Automotive Smart Black-Box based Monitoring system. Measurement: Sensors, 27, p.100721.

[14] Kuang, L., Yan, H., Zhu, Y., Tu, S. and Fan, X., 2019. Predicting the duration of traffic accidents based on cost-sensitive Bayesian network and weighted K-nearest neighbor. Journal of Intelligent Transportation Systems, 23(2), pp.161-174.

[15] Kumar, S., Jain, A., Rani, S., Alshazly, H., Idris, S.A. and Bourouis, S., 2022. Deep Neural Network Based Vehicle Detection and Classification of Aerial Images. Intelligent Automation & Soft Computing, 34(1).

[16] Kundu, S., Al Banna, M.H. and Sayeed, A., 2020. Road traffic accidents in Bangladesh: A top public health issue? Population Medicine, 2(May).

[17] Labib, M.F., Rifat, A.S., Hossain, M.M., Das, A.K. and Nawrine, F., 2019, June. Road accident analysis and prediction of accident severity by using machine learning in Bangladesh. In 2019 7th international conference on smart computing & Communications (ICSCC) (pp. 1-5). IEEE.

[18] Li, L., Lin, Y., Du, B., Yang, F. and Ran, B., 2022. Real-time traffic incident detection based on a hybrid deep learning model. Transportmetrica A: transport science, 18(1), pp.78-98.

[19] Liu, J., Bai, F., Weng, H., Li, S., Cui, X. and Zhang, Y., 2020. A routing algorithm based on real-time information traffic in the sparse environment for VANETs. Sensors, 20(24), p.7018.

[20] Magnussen, A.F., Le, N., Hu, L. and Wong, W.E., 2020. A survey of the inadequacies in traffic sign recognition systems for autonomous vehicles. International Journal of Performability Engineering, 16(10), p.1588.

[21] Mari Kirthima, A., Verma, R., Hegde, C.R. and Shanbhag, A.S., 2019. Intelligent accident prevention in VANETs. Int. J. Recent Technol. Eng., 8(2), pp.2401-2405.

[22] Mohammed, A.A., Ambak, K., Mosa, A.M. and Syamsunur, D., 2019. A review of traffic accidents and related practices worldwide. The Open Transportation Journal, 13(1).

[23] Ospina-Mateus, H., Quintana Jiménez, L.A., Lopez-Valdes, F.J., Berrio Garcia, S., Barrero, L.H. and Sana, S.S., 2021. Extraction of decision rules using genetic algorithms and simulated annealing for prediction of severity of traffic accidents by motorcyclists. Journal of ambient intelligence and humanized computing, 12(11), pp.10051-10072.

[24] Pathik, N., Gupta, R.K., Sahu, Y., Sharma, A., Masud, M. and Baz, M., 2022. AI enabled accident detection and alert system using IoT and deep learning for smart cities. Sustainability, 14(13), p.7701.

[25] Pawar, K. and Attar, V., 2022. Deep learning based detection and localization of road accidents from traffic surveillance videos. ICT Express, 8(3), pp.379-387.

[26] Rashid, S.A., Audah, L., Hamdi, M.M. and Alani, S., 2020. Prediction-based efficient multi-hop clustering approach with adaptive relay node selection for VANET. J. Commun., 15(4), pp.332-344.

[27] Retallack, A.E. and Ostendorf, B., 2019. Current understanding of the effects of congestion on traffic a ccidents. International journal of environmental research and public health, 16(18), p.3400.

[28] Shaaban, K., Gaweesh, S. and Ahmed, M.M., 2020. Investigating in-vehicle distracting activities and crash risks for young drivers using structural equation modeling. PLoS one, 15(7), p.e0235325.

[29] Shen, J., Liu, D., Chen, X., Li, J., Kumar, N., and Vijayakumar, P., 2019. Secure real-time traffic data aggregation with batch verification for the vehicular cloud in VANETs. IEEE Transactions on Vehicular Technology, 69(1), pp.807-817.

[30] Shendekar, S., Thorat, S. and Rojatkar, D., 2021, June. Traffic Accident Prediction Techniques in Vehicular Ad-hoc Network: A Survey. In 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 652-656). IEEE.

[31] Toan, T.D. and Truong, V.H., 2021. Support vector machine for short-term traffic flow prediction and improvement of its model training using the nearest neighbor approach. Transportation research record, 2675(4), pp.362-373.

[32] Uma, S. and Eswari, R., 2022. Accident prevention and safety assistance using IOT and machine learning. Journal of Reliable Intelligent Environments, 8(2), pp.79-103.

[33] Yeole, M., Jain, R.K. and Menon, R., 2022. Prediction of Road Accident Using Artificial Neural Network. International Journal of Engineering Trends and Technology, 70(3), pp.151-161.

[34] Yu, L., Du, B., Hu, X., Sun, L., Han, L. and Lv, W., 2021. Deep spatio-temporal graph convolutional network for traffic accident prediction. Neurocomputing, 423, pp.135-147.

[35] Zhao, H., Cheng, H., Mao, T. and He, C., 2019, May. Research on traffic accident prediction model based on convolutional neural networks in VANET. In 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 79-84). IEEE.

[36] Zheng, M., Li, T., Zhu, R., Chen, J., Ma, Z., Tang, M., Cui, Z. and Wang, Z., 2019. Traffic accident's severity prediction: A deep-learning approach-based CNN network. IEEE Access, 7, pp.39897-39910.

[37] Zhou, Z., Dong, X., Li, Z., Yu, K., Ding, C. and Yang, Y., 2022. Spatio-temporal feature encoding for traffic accident detection in VANET environment. IEEE Transactions on Intelligent Transportation Systems, 23(10), pp.19772-19781.

[38] Zhou, Z., Dong, X., Li, Z., Yu, K., Ding, C. and Yang, Y., 2022. Spatio-temporal feature encoding for traffic accident detection in VANET environment. IEEE Transactions on Intelligent Transportation Systems, 23(10), pp.19772-19781.