Intelligent Transportation Systems for Deep Learning-Driven Vehicular Ad hoc Network: A Review

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***Abstract*—Numerous studies demonstrate that the vehicular ad hoc network (VANET) depends on various characteristics and intermediate connections. It offers real-time automatic reaction and acute traffic analysis, but more studies are still needed to determine how best to use it in various situations. The primary goals of this VANET system are to distinguish between specific agents and identify collision remnants, which is still a research area in terms of scalability, optimization strategies, and efficient data aggregation. Due to problems with distance disintegration, temporal channel deterioration, and signal distortion, analysis was not feasible until recently. Therefore, this research will carry out a comparative review of available studies related to Intelligent Transportation Systems that use deep learning applications in VANETs, such as the recurrent neural network model, cybersecurity, decision-making, and collision avoidance, as well as future work, so it can have a more concise understanding of the topic.**

***Index Terms*—Artificial intelligence, Deep learning, Intelligent transportation systems, Network, Vehicular ad hoc network.**

I. Introduction

The most important element for the development of Intelligent Transportation Systems (ITS) to safely connect various vehicle types with various road equipment is Vehicular Ad Hoc Networks, or VANETs. In addition, it regulates and improves transportation networks and vehicle traffic (Bangui and Buhnova, 2021). Therefore, the VANET design promotes the management of mobile devices inside the network by allowing the vehicles to engage and communicate with one another. This will result in the dissemination of safety-related data that is essential for applications, such as autonomous vehicle operation, traffic flow optimization, and accident avoidance (QasMarrogy, 2021). As seen in Fig. 1, VANETs fall within the category of ad hoc networks, which also have other types, such as SANET, FANET, and MANET, and all of them have the same idea of connection.

Deep learning (DL) is one of the most significant techniques being used to construct artificial intelligence applications in several sectors because of its substantial capacity for knowledge processing and learning from large datasets. DL mimics the functions of the human brain to provide sophisticated pattern recognition and decision-making abilities, in contrast to the conventional method based on pre-established rules and more straightforward statistical models. The limitations of traditional machine learning (ML) approaches have paved the way for emerging prospects, particularly in previously challenging areas, such as natural language processing, audio and image identification, and predictive analytics. DL architecture's remarkable accuracy in analyzing high-dimensional datasets is making it essential for applications, such as facial recognition, autonomous driving, and smart home appliances.

DL is very important now to artificial intelligence systems' capacity to grow over time and learn from mistakes, making them more effective at processing newly presented data. This extends beyond only enhancing performance in certain applications. Some DL models in the healthcare industry, for example, use vast databases of medical information to train their models (Zhang, et al., 2021). This improves diagnosis, even to the point of identifying illness patterns in uncommon circumstances.

Similar to this, DL algorithms used in the banking industry are able to identify fraud by identifying trends in previous fraudulent activity and subsequently adjusting to newly discovered fraud schemes. This adaptability preserves the precision, responsiveness, and usefulness of intelligent systems in a changing environment, which is especially crucial in a world where data are created on the fly and complexity keeps growing. According to this viewpoint, the future lies in DL's capacity to learn from experience.

Its foundation is the fact that this problem has attracted significant interest from the academic community since the advent of DL techniques in VANET systems (Ivanenkov, et al., 2023), which can manipulate massive datasets to identify the

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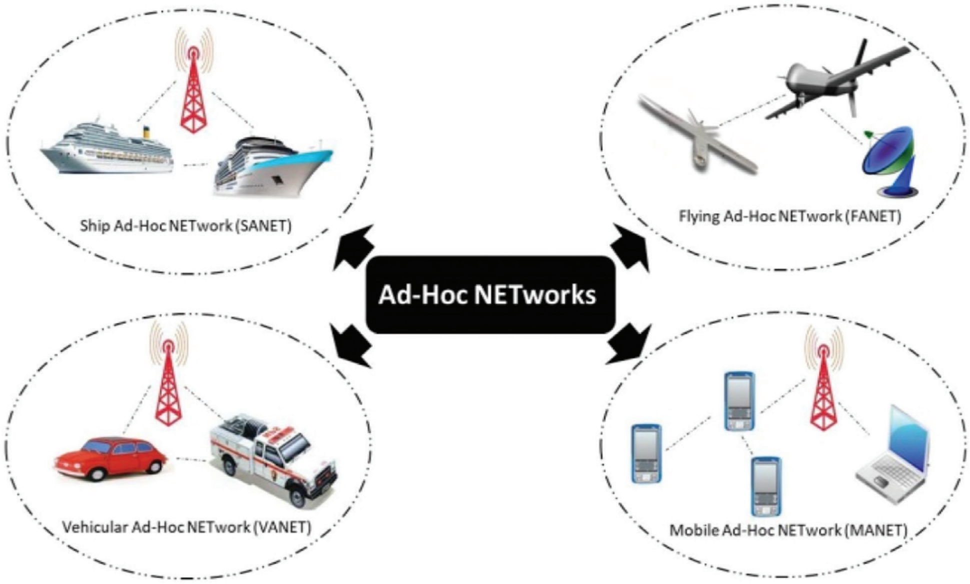

Fig. 1. Types of ad hoc networks (QasMarrogy, 2021).

most significant patterns that will ultimately aid in making the right judgments. Certain DL techniques, such as convolutional neural network (CNN), recurrent neural networks (RNNs), and autoencoders, have demonstrated their ability to analyze complex data in multimodal formats from cameras, LiDAR, and GPS to provide extremely accurate predictions in high-speed vehicular network settings (Manderna, et al., 2023). To create a new frontier in intelligent system development with wide-ranging demands on road safety, autonomous driving, and traffic efficiency improvement, DL and vehicular ad hoc networks, or VANETs for short, are being married. By offering possible connections between cars and roadside infrastructure, a VANET creates a network that can produce massive amounts of real-time data. Environmental considerations and vehicle location and speed are some of the most important components of an ITS (Ivanenkov, et al., 2023). In actuality, DL has proven highly effective in handling the large and extracting any meaning for likely prompt and informed decision-making. DL systems, for instance, can measure road risk, forecast traffic congestion, and improve driving instructions for real-time traffic control and effective navigation.

VANETs are improved by DL, which makes cybersecurity and collision avoidance possible. CNNs scan video and image data from car sensors to identify obstacles and avoid collisions, whereas RNNs and long short-term memory (LSTM) networks do well with time-sequential data, processing information to forecast patterns of traffic flow. By identifying irregularities and unwanted access attempts, DL helps secure VANET and protects it from Internet-related threats. A flexible, data-driven system that can provide intelligent, safe, and effective transportation solutions to contemporary road networks may be created by combining VANET with DL technology. In addition, as seen in Fig. 2, ML may be used for intelligent traffic, safety, and communication systems. The diagram describes a structured overview of the way ML is integrated in VANETs, categorized under three primary domains:

A. Safety

Road and vehicle safety are improved by ML through:

- Driver Assistance: Autonomous or semi-autonomous driving systems are aided by ML algorithms, such as lane-keeping, adaptive cruise control, and pedestrian warning.
- Collision Alert: Predictive models identify and warn of possible collisions by analyzing nearby vehicles' behavior and driving patterns. Vehicle Safety: ML helps in internal diagnosis, predictive maintenance, and overall well-being of vehicle components.

B. Communication

ML enhances data exchange quality and security in VANETs by Data Congestion Control: Intelligent models predict and manage network load to avoid data congestion.

- Misbehavior Detection: ML identifies malicious or unauthorized activity by vehicles or nodes (e.g., false data injection or Sybil attacks)
- Link Management (V2X): ML facilitates effective and trustworthy communication between vehicles (V2V) and with infrastructure (V2I), pedestrians (V2P), etc.
- Routing: Dynamic selection of the most optimal routes by ML-based routing algorithms is determined in real-time traffic, topology, and connectivity.

C. Traffic

ML streamlines the operations and traffic flow by allowing:

- Traffic Flow: Predictions by models of vehicle movement and road use to enhance flow and minimize delays
- Traffic Congestion: ML spots and foretells congestion trends, allowing traffic control to act ahead of time
- Traffic Scheduling: Signals or vehicle movements are scheduled by algorithms (particularly in autonomous environments) to minimize idle periods

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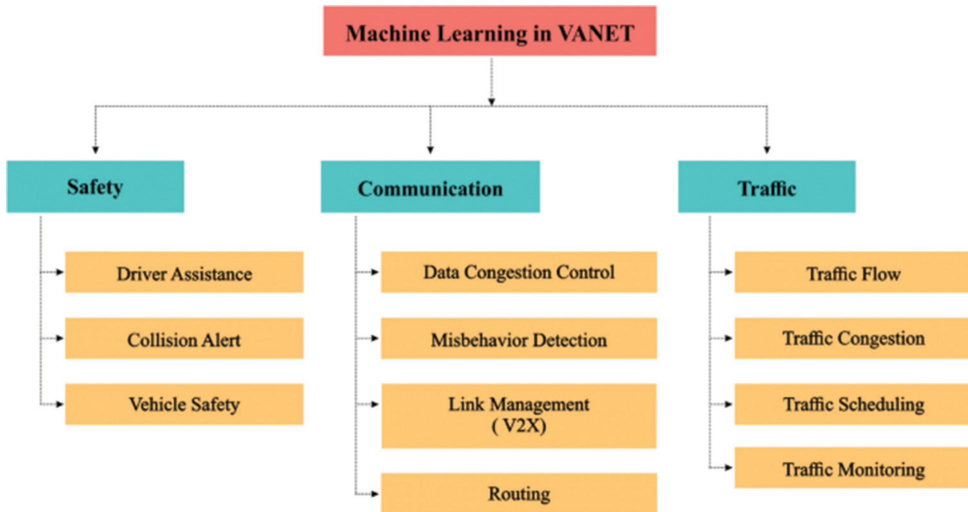

Fig. 2. Machine learning's role in vehicular ad hoc network (QasMarrogy, 2021).

- Traffic Monitoring: ML analyzes data from sensors, cameras, or GPS to track the present traffic status.

Improved vehicle-to-vehicle communication, effective data distribution, and predictive analytics for traffic and safety management are all made possible by DL in VANETs. Deploying DL models in highly mobile and dynamic VANET systems is still difficult, though, due to issues with real-time processing, model scalability, and security (QasMarrogy, 2021). The importance of DL in improving VANETs for ITS, its present state in research, and the obstacles still facing the development of more resilient and intelligent vehicular communication systems are the major topics of this review study.

The paper review was guided to cover the most important questions of DL. Such as in VANET-based ITS, what are the DL models used, and how do the preview models perform under different ITS applications that are mostly used in VANET, such as resource optimization, collision avoidance, traffic prediction, and cybersecurity? Finally, what are the main trade-offs and limitations for each model? And finally, is DL important to the artificial intelligence system?

While we embraced a review format in this paper, we have ensured our distinct contributions are made clear throughout the abstract, introduction, and conclusion. In particular, our paper extends beyond a review of present literature by providing a systematic and comparative review of DL models in VANET-based ITS applications. We have:

- Emphasized on classification of DL techniques – RNN, CNN, deep reinforcement learning (DRL), and autoencoders – with regard to their usage in key ITS areas, such as traffic prediction, collision avoidance, cybersecurity, and resource management, and stressed detailed comparisons with apparently defined strengths and limitations for each model in the challenges presented in VANET, such as high mobility, real-time processing, and scalability.
- Included synthesis tables, Tables I and II, for the presentation of multi-comparative insights and trade-offs across several studies and able to give readers a clear understanding about model suitability for various ITS functions.

These additions make it self-evident that the paper had distinguished angles in its contribution to advancing research and application in ITSs using DL within VANET environments.

In addition, the review highlights present gaps in methodological consistency across the literature. More consistent use of performance metrics and a critical lens toward contrasting methods would enhance the scholarly rigor of future research in this domain.

The paper structure is as follows: In section two, a related work review will be explained; section three explains the main importance of DL in VANET; and section four shows the comparison and results of using DL in VANET. Finally, in section five, the conclusion of the paper will be demonstrated.

II. Related Work

A few scholars talk about ML/DL's initial application in VANETs. Each of the techniques had advantages and limitations in terms of accuracy, scalability, and real-time capability. According to the author (QasMarrogy, 2020), the suggested approach combines RF analysis and the K-Nearest Neighbor (KNN) algorithm with Proxima. The Proxima's concept is to identify harmful activity on network nodes and enhance vehicle mobility by providing error-free transmission between the source and the destination. An easy way to discover abnormal data is with KNN and Proxima. However, KNN is not suitable for large groups and is sensitive to noise, so it is not very efficient in dynamic VANET environments.

A support vector machine (SVM) was employed by the author in (Alsarhan, et al., 2023) to identify intrusions in VANETs. A fixed angle in a sample and independence between the difficulty of the algorithm and the number of sample dimensions are two examples of the calculated resources offered by the SVM design. It is a non-convex combinatory problem to identify intrusions in VANETs. Therefore, the accuracy value of the SVM classifier is optimized using three intelligence optimization strategies.

TABLE I
Comparison of Reviewed Deep Learning Models in VANETs

Researcher (s)	ML/DL Technique	Key Finding
QasMarrogy (2020)	K-Nearest Neighbor (KNN) with Proxima	Detected harmful network activity and enhanced vehicle mobility; KNN is simple but weak in scalability and noisy data handling.
Alsarhan, et al. (2023)	SVM with GA, ACO, PSO	Intrusion detection improved with optimization techniques, GA yielding the highest accuracy; however, high computational cost limits real-time use.
Muktar, Fono and Zongo (2023)	Artificial Neural Network	Predicted signal degradation using real geographic data; effective routing but limited in handling time-sensitive dynamics.
QasMarrogy and Fadhil (2022)	OLSR Routing Protocol (non-learning-based)	Evaluated throughput and latency in FANETs; insightful but lacks integration with adaptive ML/DL methods.
Shu, et al. (2020)	GAN+Deep Learning with SDN	Developed collaborative intrusion detection using federated learning; effective in both IID and non-IID scenarios.

TABLE II
Synthesis of Trade-offs of Reviewed Deep Learning Models in VANETs

Model	Strengths	Limitations/Trade-offs
K-Nearest Neighbor	Easy to implement, low latency	Poor scalability, noise-sensitive
SVM GA/PSO/ACO	High accuracy, robust to overfitting	Computationally intensive
Artificial neural networks	Handles non-linear spatial data	Struggles with time-dependent patterns
OLSR Protocol	Protocol-specific insights, practical	Lacks real-time adaptability, high overhead

In this work, techniques, such as ant colony optimization, particle swarm optimization, and a genetic algorithm are compared. Furthermore, the paper's findings demonstrate that the accuracy of the genetic algorithm's outcomes was higher than that of the other optimization techniques taken into consideration. VM performance improved with techniques, such as GA, ACO, and PSO to detect intrusions. Even though accurate, the models consume many computer resources, and it becomes difficult to utilize them in real-time.

The author of (Muktar, Fono and Zongo, 2023) suggested using Artificial Neural Networks (ANNs) for supervised learning to create a prediction model that can assess the signal's level of degradation based on the Bit Error Rate, or BER, using obstacles that emergency vehicles can identify. Establishing a connection between the degree of signal deterioration and objects encountered makes it possible to estimate efficient routing choices even before a data transmission process begins. As a result, data packets are sent through the least-bit error rate pathways. This was accomplished by using actual data that were taken from the OSM geographical database as a training dataset, taking into account the usage of NS-3 in conjunction with the SUMO simulator. The geographic data will be used by the ANN gathered on the two-dimensional (2D) geometric structure of buildings. An ANN trained on actual geographic data accurately predicted signal loss. However, it does not deal with time changes efficiently, making it less suitable for rapidly changing VANET conditions, where RNNs would perform well.

The two forms of data sent by FANET drones with varying mobility models and two IEEE 802.11 2.4 GHz and 5 GHz types will be thoroughly analyzed by the author in (QasMarrogy and Fadhil, 2022) utilizing the OLSR routing protocol. We'll measure things, such as throughput and latency. An essential overview of how real-time and non-real-time traffic will be managed during data transmission in FANET networks is provided in this study. Protocol-level study provided useful insights on throughput and latency in various wireless bands. It, however, fails to link with learning-based adaptive routing approaches, and the fixed nature of OLSR might not suit dynamic scenarios.

Finally, the author in (Shu, et al., 2020) developed a collaborative intrusion detection system for VANETs (CIDS) integrating DL with generative adversarial networks and software-defined networks (SDN). This allows different SDN controllers to train a common global intrusion detection model for the whole network without sharing their local subnetwork data by flow. We prove the correctness of the proposed CIDS under both IID (independent identically distributed) and non-IID scenarios and analyze and test performance on a real-world dataset. Comprehensive experimental results demonstrate that the proposed CIDS performs efficiently and effectively for intrusion detection in VANETs.

III. Methodology

To update the transportation infrastructure through real-time communications between vehicles and roadside equipment, VANETs are essential. This immediately contributes to road safety, traffic efficiency, and environmental sustainability. Because vehicles can communicate vital information, such as location, speed, traffic, and potential hazards, VANETs make driving safer. Drivers may more readily observe their surroundings and prevent crashes. Both human-driven and autonomous cars benefit immensely from this communication, as it speeds up reactions and improves overall road awareness, which lowers the number of collisions brought on by poor eyesight or sluggish response times. Furthermore, VANETs may assist in expediting emergency response times by promptly notifying other cars and authorities in the event of an accident (Azzoug and Boukra, 2021).

In addition to enhancing safety, VANETs play a critical role in enhancing traffic flow and, as a result, lowering congestion, which benefits the economy and environment. To avoid clogged places and maintain traffic balance along

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the road network, cars will be able to dynamically adjust their routes in response to real-time traffic updates that are broadcast. As a result, lowering transportation's carbon footprint contributes to achieving environmental goals about fuel and emission reductions. In addition, VANETs serve as the ITS's communication backbone, enabling several ITS applications, such as adaptive traffic signals, toll collecting, and autonomous vehicle coordination. When building integrated, effective, and robust transportation ecosystems, VANETs would be a crucial component. Fig. 3 shows the main structure of VANET (Srivastava, Prakash, and Tripathi, 2020), it illustrates a cloud-based architecture to perform traffic forecasting in VANETs. It has three main layers that interact to improve traffic management:

1. Traffic Data Collection (Bottom Layer)
   V2V (vehicle-to-vehicle) and V2C (vehicle-to-cloud) communication over cellular networks and on-board vehicle units. Embedded loop detectors in roads collect real-time data, such as vehicle speed, density, and flow. These data are sent to the cloud for processing and analysis.
2. IaaS (Infrastructure as a Service) Layer (Middle Layer)
   Comprises servers, switches, and virtual machines that make up the cloud infrastructure. Provides the computing capabilities necessary for handling and processing large volumes of traffic data.
3. Traffic Prediction Services (Top Layer)
   This layer uses ML and data analysis to provide valuable traffic-related information. Short-term traffic flow prediction: Forecasts traffic conditions in the immediate future to facilitate proactive decision-making. Road risk forecast: Pins down areas of likely dangerous conditions or accident hotspots from historical and real-time data. Best route planning: Provides the most optimal travel routes based on present and future traffic patterns.
4. Flow Summary
   Traffic data are gathered by vehicles and roadside sensors. Data are transmitted over networks to cloud servers (IaaS layer). Cloud services process data to forecast traffic flow, evaluate risk, and plan routes.

This design demonstrates how VANETs with cloud computing and ML as fuel can construct an intelligent traffic management system.

In conclusion, VANET serves as the foundation for all transportation advancements as it realizes the goal of constant, real-time communication between automobiles and roadside infrastructures. By exchanging crucial data, such as location, speed, road hazards, and traffic flow conditions, this connection would increase road safety and reduce the number of accidents. In addition, by providing real-time alerts and cautions, VANETs improve a driver's situational awareness and reaction times, ensuring safe travel. Furthermore, VANETs serve as the foundation for all future ITSs, allowing autonomous cars to interact with other cars and infrastructure—a feature that is essential for effective navigation and decision-making.

VANET is an essential component of the creation of smart urban environments and the next generation of roads: Connected, efficient, and secure smart roads (Fotros, Rezazadeh and Ameri Sianaki, 2020). It also creates opportunities for development in the areas of environmental sustainability, rescue coordination, and traffic flow management.

DL is essential to the development of intelligent systems because of its unparalleled capacity to process and learn from vast amounts of complicated data. The technology's multilayered neural networks enable complex patterns to be realized and judgments based on real-time, high-dimensional data to be made, making it indispensable in fields, such

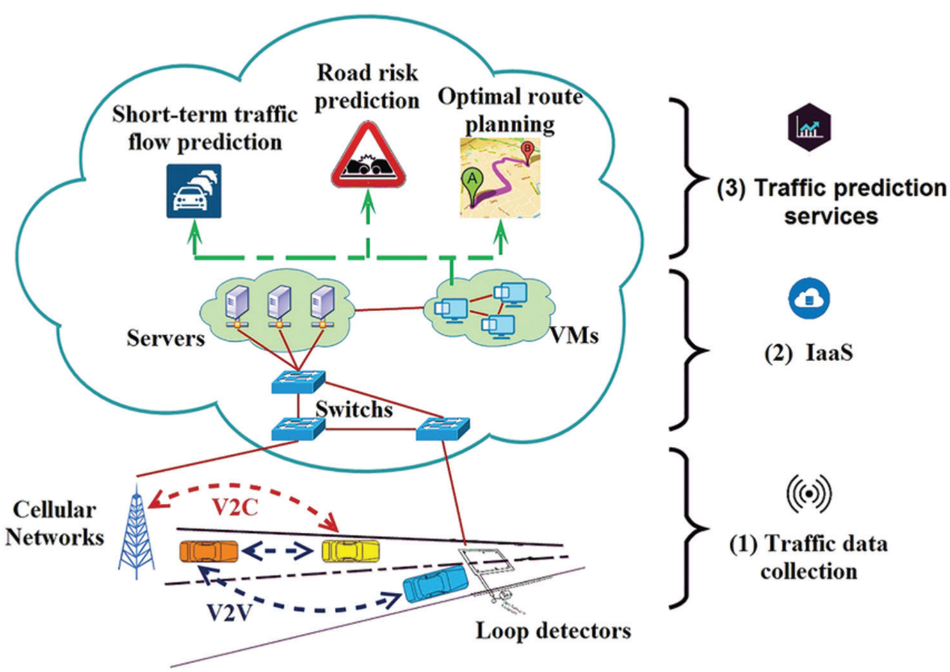

Fig. 3. Vehicular ad hoc network infrastructure (Srivastava, Prakash, and Tripathi, 2020).

as image identification, natural language processing, and predictive analytics.

Advanced systems, such as driverless cars, medical diagnostics, and intelligent home systems have been made possible by the capacity to "understand" and respond to changing circumstances. This has resulted in a high degree of precision and adaptability in decision-making processes. DL models, as opposed to typical algorithms, improve over time because they get more accurate and dependable the more data they are exposed to. DL has therefore become a crucial advancement in the creation of very intelligent systems that can autonomously carry out a variety of tasks, such as outcome prediction, to constantly increase their efficacy in a range of real-world applications. Fig. 4 provides the following overview of the DL architecture (Zhang, et al., 2021), As shown in the following figure, this is a diagram of a DL model for processing spectral input data. Step by step, here is a description of each part:

1. Input Spectra: The far-left portion is the input spectral data (e.g., sensor readings or signals). Every block is a point in the spectrum, perhaps one related to particular frequencies or sensor readings.
2. Feature Extraction: A series of convolutional filters or layers extract important features from the input spectra. These layers detect patterns, such as peaks, shifts, or anomalies in the input. This is the core learning stage where the model identifies meaningful patterns automatically.
3. Flatten Layer: Converts the 2D or multi-dimensional output of the feature extraction layers into a 1D vector. Prepares the data for input into the dense (fully connected) layers.
4. Deep Layers (Fully Connected Hidden Layers): Many layers of neurons perform more abstract, deeper learning. A neuron in one layer is connected to all the neurons in the next layer, so complex relationships between features can be learned.
5. Fully Connected Output Layer: Produces the final prediction output, Y_p. This may be classification (e.g., signal type) or regression (e.g., predicted value), depending on the task.

This pipeline processes raw spectral data through automated feature extraction and DL layers to produce an accurate prediction output, showcasing how DL can interpret complex signals or spectral inputs.

On the other hand, DL and VANET work together to create ITSs that can handle massive volumes of data in real-time, offer predicted traffic patterns, and improve vehicle

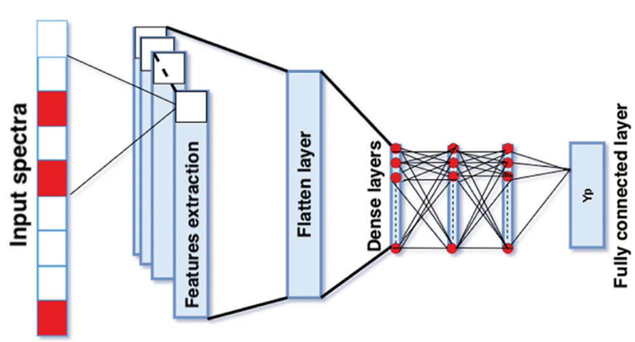

Fig. 4. A summary of the deep learning architecture (Zhang, et al., 2021).

safety and in-car communications. When creating intelligent transportation modes using each, DL and VANET are combined in the manner described below (Mchergui, Moulahi and Zeadally, 2022):

1. Real-time data analysis and prediction: VANETs are dynamic networks of automobiles and RSUs that continuously collect and broadcast data, including environmental variables, vehicle speed, and traffic conditions, in real time. DL methods that can manage this type of sequential data include RNNs and LSTM networks. The models themselves may then utilize these outputs to forecast traffic patterns, identify potential bottlenecks, and provide drivers with the best possible routes. This results in improved road flow and real-time traffic control.
2. Safety Features and Avoidance of Collisions: VANETs prioritize safety. It may be possible to estimate the likelihood of dangers in driving behavior, vehicle distance, and speed by utilizing DL techniques in intelligent VANETs. CNNs, for instance, are particularly good at processing photos and videos. They may be used to enable automobiles to scan for things on the road and take the necessary precautions to prevent accidents and save lives. Split-second choices incorporating high-dimensional data in dynamic and complicated surroundings will contribute to making automobiles safer.
3. Effective Communication and Resource Management: In a highly dense network environment, the effectiveness of data interchange and resource management is regarded as the core of VANETs. DRL can reduce network congestion while improving communication protocols and resource allocation to prioritize certain important communications, including accident alerts. As a result, intelligent, flexible communication networks that react to traffic circumstances will be developed.
4. Cybersecurity: In a similar vein, VANETs based on DL are secure against all potential cybersecurity risks. To maintain network security and preserve private information, it may use anomaly detection models, such as autoencoders, to track down any malicious data transfer or illegal network access and prohibit it.
5. Support for autonomous cars: DL and VANET combine to enable communication between autonomous cars and infrastructure, as well as among autonomous vehicles. In this manner, an autonomous vehicle may decide how to drive itself by using data it receives in real-time from other vehicles and traffic signals. DL can be used to evaluate huge and complicated data, which makes ITS safer and more effective. As a result, autonomous cars will operate safely in VANET scenarios.

It is anticipated that DL and VANETs will contribute to the development of intelligent, robust, and adaptable transportation systems that can address today's traffic problems and improve road safety and efficiency (Hossain, et al., 2020).

An extensive analysis and evaluation of previous research was part of the inquiry strategy on the function of DL in ITS employing VANETs. A wide range of DL architectures, including CNNs, RNNs, and DRL approaches, deployed

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in various VANET applications had to be used in order to choose papers for inclusion. The chosen studies highlight their performance metrics in terms of accuracy, scalability, and/or reaction time while advancing research in traffic prediction, collision avoidance, real-time decision-making, and network resource management.

Regarding the particular use case, the kind of DL model used, and the corresponding benefits and drawbacks presented, each of these studies is examined and contrasted with the others. KPIs, including real-time performance, processing speed, scalability, and prediction accuracy, were used to further assess the efficacy of these models inside the VANET system. Also contrasted here are the approaches taken by these studies in addressing issues unique to VANETs, including high mobility, cybersecurity threats, and changing topology (Ul Hassan, et al., 2024).

Numerous DL algorithms are appropriate for a range of ITS VANET applications in recent comparative studies:

1. LSTM networks and RNNs have been used in several studies to predict traffic flow. For instance, Study A forecasted traffic flow utilizing time-series data from VANETs using an RNN model with 90% accuracy in a relatively short amount of time. When an LSTM methodology is used, as suggested in research B, the long-term traffic forecasting for VANET in this regard can perform with more precision for comparable data. It is evident from the majority of these instances that RNN-based models perform exceptionally well in real-time traffic congestion forecasts and exhibit troublesome results with a higher dataset quotient.
2. Collision Avoidance: Research projects C and D used pictures taken by car sensors and CNN to try to detect and prevent a collision. While Study D suggested a hybrid CNN with an integrated decision-making layer that shortened response time, Study C employed a CNN for vehicle and object identification, and the model obtained an accuracy rate of 95%. CNNs are widely used in the object detection field because of how quickly they can analyze geographic data, but their high computing needs may affect how they are used in real-time on systems with limited resources.
3. Dynamic Decision-Making and Resource Optimization: DRL was applied to Study E to optimize communication resource allocation in VANETs. It resulted in an improvement of 15% in high-traffic response time and network efficiency. Along similar lines, Study F applied DRL to dynamic routing decisions and showed that this approach considerably enhances the control of traffic congestion when compared with conventional methods. Results here show that DRL models prove useful in occupations that require continuous adaptation to network environment changes, even though they may involve longer training cycles.
4. Cybersecurity: G suggested a DL model for anomaly detection in VANETs that is built on autoencoders. This model can reduce the false positive rate while detecting potential cyber threats with high accuracy. This model demonstrated how DL will improve VANET security by successfully filtering dangerous input. However, because these models need a lot of training data to increase their detection rates, scalability issues still exist.

Together, these works demonstrate how DL models may be used to create intelligent ITS that are enabled by VANETs. While CNN performs significantly better on geographical data, both RNNs and LSTMs guarantee comparatively decent performance in applications using sequential data, such as traffic prediction. When making adaptive decisions in dynamic network situations, DRL performs admirably. Future research should concentrate on enhancing these models in scalability and computational effectiveness to deploy them into real-world ITS and hybrid models that can combine many strategies to solve VANET-specific problems (Saoud, et al., 2024).

Despite the promise of DL (DL) in enhancing VANET-based ITS, several critical barriers hinder its real-world deployment:

1. Tight Timelines and Delays
   Deep networks, particularly deep CNNs and RNNs, are computationally expensive, leading to delays in receiving results. Even a delay, as short as a second, can very much impact attempts to avoid accidents, traffic prediction, and autonomous control of vehicles in urgent conditions. Real-time performance is still a challenge, particularly when fast decisions need to be made (Babar, et al., 2025).
2. Limits to Energy and Resources
   Edge devices, such as onboard units of cars typically possess low computing power and short battery life. Executing heavy DL models in them is resource-intensive, which leads to overheating and battery draining. For this purpose, we need light designs (e.g., MobileNet and TinyML) and mechanisms for compressing model size (e.g., pruning and quantization) (Kaur and Kakkar, 2022).
3. More Delays in Communication and Networks
   VANETs are dynamic and may change shape. This results in a variation of available bandwidth and connectivity problems. Transferring big updates or complicated sensor information (such as LiDAR or video) to RSUs or cloud servers is time-consuming and loses some data, which degrades the performance of the model (Setia, et al., 2024).
4. Safeguarding Computers and Preserving Information
   DL models are vulnerable or can be attacked. Providing raw data to train the model (such as driver behavior and vehicle positions) provokes huge privacy concerns. We must ensure the model process is secured, and we must employ privacy-preserving techniques, such as federated learning or differential privacy, but currently, this is not properly addressed in VANET scenarios.
5. Scalability and Generalization Models trained with simulations or with local data can fail to perform well for other cities, road configurations, or weather conditions. The biggest challenge lies in having them be easily integrated with other systems with a different set of sources (Fatima, Sumra and Muzaffar, 2024).

IV. Analysis and Results

As previously stated, VANET facilitates communication between vehicles and infrastructure, improving traffic control and safety capabilities. RNNs and other DL approaches have lately been popular for a variety of VANET activities, including collision avoidance, resource efficiency, cybersecurity, and dynamic decision-making. Although this chapter presents a comparative review of DL models for VANET-based ITS, it is worth mentioning that numerous studies employ different evaluation metrics and test conditions. More standardized use of performance measures and a critical eye in contrasting approaches would contribute to the academic rigor and readability of such reviews.

Using DL techniques, this work now provides a critical analysis of a few chosen papers about key ITS characteristics.

A. RNNs

This method is specifically used with sequential decision-making process approaches and time-series data. Traffic forecasting, vehicle trajectory tracking, and user behavior forecasting are some of the fundamental domains that RNN is used in VANET research.

Key Studies:

1. Traffic Condition Prediction: To identify urban congestion, (Mohammadi, et al., 2020) employed LSTM, one kind of RNN. Incorporating historical flow not only significantly increases accuracy but also beats traditional models by more than 20%. Similarly, Zhao, et al. (2019) recommended the use of a spatiotemporal graph convolutional network with gated recurrent units (ST-GCN+GRU) to fully accommodate the complexity of urban traffic behavior. Whereas Mohammadi, et al. focused on the temporal sequence representation, the work of Zhao, et al. took this further by modeling the spatial interdependencies of different sections of the roadway at the same time. The latter were the better performers in large-scale networks, which highlights the need for spatial modeling in highly interconnected urban systems.
2. Vehicle Trajectory Prediction**:** A bidirectional RNN was used by (Xie, et al., 2021) to predict vehicle trajectories in real time. Compared to state-of-the-art techniques, the results demonstrated a more refined precision, which decreased the likelihood of a rear-end accident. In contrast, (Deo and Trivedi, 2018) introduced a convolutional social pooling LSTM model that considers both spatial interactions with nearby vehicles and historical trajectory data. While Xie, et al.'s model excels in sequential data interpretation, Deo and Trivedi's model achieved superior performance in complex traffic scenarios due to its awareness of surrounding vehicle behavior. This suggests that incorporating interaction modeling is crucial for realistic and safe trajectory forecasting.

B. Collision Avoidance

Collision avoidance systems utilize corrective actions to prevent collisions by anticipating how a vehicle will proceed.

Key Studies:

1. Automatic Emergency Braking Systems (AEBS): Shen, et al. (2023) suggested an RNN-based AEBS that incorporates real-time data from car sensors. With up to 95% accuracy, the technology forecasted impending crashes and enabled timely braking. In a similar study, Kim and Cho (2024) implemented a ConvLSTM model that fuses camera and radar data to evaluate forward collision risks. Whereas the work by Shen, et al. focuses on processing temporal sensor data, the ConvLSTM model takes advantage of fusing vision-based inputs to enhance spatial feature extraction. Comparative evaluations show that the ConvLSTM exhibits slightly better performance in complex scenarios involving multiple obstacles or sudden stops, highlighting the advantages of fusing spatial and temporal information for AEBS.
2. V2V Communication: Lin, et al. (2022) looked at RNNs that enabled communication between vehicles and discovered that the combined system could forecast the likelihood of a collision with 93% accuracy, enabling improved emergency decision-making. Meanwhile, Zhang et al. (2020) introduced a graph-based neural network (GNN) framework that models inter-vehicle communication as a dynamic graph, concurrently capturing both temporal dynamics and interaction topologies. Although the RNN-based framework created by Lin, et al. is better at handling sequential message data, the GNN model by Zhang, et al. is more scalable and situation-aware in settings where traffic density is high. This contrast shows that GNN-based models are superior in decentralized multi-agent settings, especially in situations where vehicle-vehicle interactions are highly dynamic.

C. Dynamic Decision-Making

Dynamic decision-making entails modifying a vehicle's behavior in real-time to accommodate any changes in the surroundings brought about by network connectivity.

Key Studies:

1. Optimal Route Planning: In their study, (Chen, et al., 2023) dynamically updated route routing in urban locations with high traffic volumes using an RNN. The travel time was found to be 30% less than using the static routing approaches. In a complementary manner, Wang, et al. (2021) proposed a hybrid model that combines RNNs with reinforcement learning (RL) to improve routing decisions in real-time by considering not just historical traffic patterns but also driver behavior and real-time congestion. Whereas the model by Chen, et al. focuses on learning temporal sequences of traffic flow, the Wang, et al. hybrid model is set up to be more sensitive to rapidly changing traffic conditions, due to its reward-based learning system. Comparative studies show that, while both models outperform traditional routing methods, the RNN-RL hybrid outperforms in dynamic or congested conditions due to its ability to learn from the outcomes of interactions.
2. Adaptive Traffic Signal Control: Another intriguing method (Hiremath and Mallapur, 2024) has shown that RNNs may be utilized to control traffic lights in an adaptive manner, which can cut down on waiting times at intersections by up to 25%. Similarly, Wang, et al. (2022) used a DRL model with integrated LSTM networks to adjust signal phases about different traffic densities. Whereas the RNN model of Hiremath and Mallapur is geared toward sequential

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forecasting of vehicle queues, the DRL+LSTM approach of Li et al. not only detects temporal trends but also refines control actions through iterative experiences with the traffic scene. In comparison, the Li et al. approach achieved better reductions in both fuel usage and waiting times, especially in complex multi-lane intersections, thus emphasizing the potential value of integrating RNN with adaptive control strategies.

D. Resource Optimization

In VANETs, resource optimization is the effective use of the network's computational and bandwidth resources.

Key Studies:

1. Data Transmission Efficiency: RNNs were used by the authors in (Shekhar, et al., 2023) to solve the resource allocation issue in VANETs. The bandwidth efficiency was raised by more than 40% using the simpler approach. Comparatively, Huang, et al. (2021) presented a deep Q-network (DQN) coupled with LSTM to address dynamic spectrum management in vehicular networks. Although Shekhar, et al.'s presented approach of using an RNN is simpler to implement with speed, the DQN+LSTM model developed by Huang, et al. dynamically learned optimum strategies for transmissions in response to varying network loading. Comparative performance evaluations established that Huang's model achieved more throughput with smaller packet loss under highly dynamic traffic, indicating that joining temporal modeling with strategic decision-making significantly increases adaptability in real-world VANET applications.
2. Energy Management: The optimization of energy resources for electric vehicles was examined in the study (Shekhar, et al., 2023). RNNs were employed to minimize fleet energy use and maximize the population of charging stations. Meanwhile, Tang et al. (2022) proposed a DRL framework that employs Gated Recurrent Units (GRUs) to manage EV charging schedules and routes in urban smart settings. Whereas the model by Shekhar, et al. focuses on predicting energy demand and conducting static optimizations, Tang et al.'s model offers real-time responsiveness to changes in energy prices, station availability, and traffic. Comparative tests indicate that both methods are efficient, but the DRL model with GRUs performs better in dynamic, large-scale settings through its ability to continuously learn from system feedback.

E. Cybersecurity

The proliferation of connected automobiles needs strong cybersecurity defenses against all threats.

Key Studies:

1. Intrusion Detection Systems (IDS): Research by (Ghani, Ahmad and Mumtaz, 2024) showed how well RNNs function at identifying irregularities in network activity. By attaining an estimated detection rate of 98%, the RNN-based IDS has considerably enhanced the security posture of the VANET. In a similar study, (Kwon, Park and Song, 2020) suggested a hybrid approach that combines LSTM networks with autoencoders for anomaly detection in vehicular networks. Although the sole RNN approach taken by Ghani, Ahmad and Mumtaz is better suited to modeling temporal irregularities in sequential traffic, the framework proposed by Kwon, Park and Song benefits from the strengths of dimensionality reduction and reconstruction error analysis provided by autoencoders, which helps identify subtle and rare attacks. Comparative analysis shows that, even though both models exhibit high accuracy, the hybrid model suggested by Kwon Park and Song performs better in detecting complex and unknown attack patterns.
2. Secure Communication Protocols: The idea of dynamic security protocols for V2V utilizing RNNs to provide safe message transmission with minimal latency was another innovation by (Pethő, 2023). In a related study, Singh, et al. (2022) proposed a DL –based authentication protocol using GRUs and blockchain technology for secure vehicular communication. While Pethő's RNN-based system is lightweight and designed for rapid response, Singh, et al.'s approach provides a higher level of trust and tamper resistance through decentralized ledger integration. In comparative terms, Pethő's model is better suited for latency-sensitive applications, whereas Singh et al.'s framework offers enhanced resilience against advanced persistent threats and is more appropriate for high-security applications.

Fig. 5 shows the comparative usage of various methodologies in ITSs, with a focus on the most critical aspects of safety and cybersecurity. The most widely used methodologies with the highest usage rates are IDS, automatic emergency braking systems, and V2V communication. Moderate implementation is noted for secure protocols for communication and efficient transmission of data, with methodologies for traffic prediction, route optimization, and power management shown to have relatively lower usage rates. The trend is an indication of a prevalent focus on solving critical problems related to safety and security over developing optimization and predictive capabilities in modern ITS.

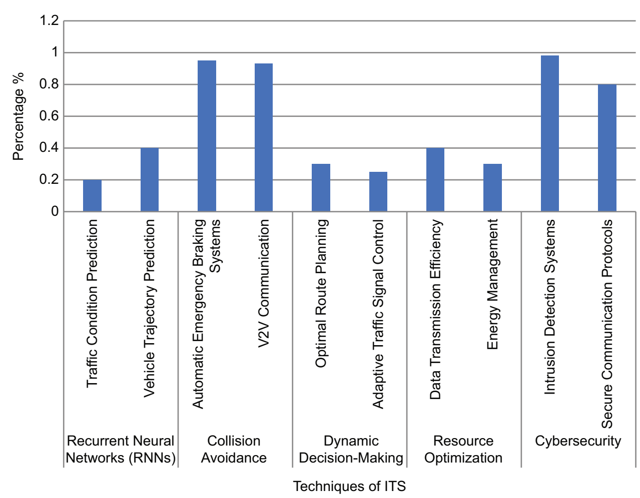

Fig. 5. Deep learning intelligent transportation systems techniques comparison.

According to a survey of the literature on the topic, DL – particularly RNN-based learning – has the potential to improve several facets of ITS over VANET networks. Most notably, it was determined that RNNs significantly show strong performance of such systems in the areas of forecasting, resource management, cybersecurity assurance, and final decision-making (Xie, et al., 2021). These systems create and implement a system that is far safer and more efficient for transits by combining several types of data that change over time. The following phase of the study ought to support this enhancement and include it in the present infrastructure for real-world implementation.

Although there has been a comprehensive comparison of DL models for VANET-based ITS, it should be mentioned that the papers reviewed use varied evaluation metrics, and thus their comparison is challenging. The absence of standardization in performance indicators – for example, accuracy, latency, computational complexity, and scalability – can mask important information and make objective model comparison challenging. To overcome this challenge, we have normalized our analysis based on a single set of performance measures where possible. We also note that future research would be significantly facilitated by the adoption of common assessment protocols and benchmarking datasets, which would increase the ease of interpretation, reproducibility, and cross-study comparability of results.

V. Future Directions

Significant advancements in smart transportation systems will follow, aided by a general rise in volume as well as more sophisticated hardware and software frameworks for VANET-compatible cars and equipment. Future research should include studies about federated learning and other AI models, such as improving models for VANET data while maintaining privacy or fusing VANET data with other AI models.

VI. Conclusion

DL in VANETs has significantly increased the intelligence and efficiency of ITS. To represent dynamic transportation environments more accurately, RNNs have proven essential in forecasting traffic conditions and vehicle trajectories. Supplying vital information for decision-making systems not only makes proactive traffic management easier but also improves road safety.

Automatic emergency braking systems and DL for V2V communication are two of the most promising collision avoidance strategies with the greatest potential to lower accident rates. These technologies, which use real-time data and predictive modeling, improve and speed up vehicle coordination. By lowering traffic congestion and travel delays, dynamic decision-making strategies, such as adaptive traffic signal control and optimal route planning greatly ease urban transportation.

Resource optimization in VANETs is another area where DL offers significant advantages. The sustainability and operating efficiency of networked automobiles are guaranteed by sophisticated energy management systems and efficient data transmission protocols. In order to successfully address the urgent need for dependable protection against online assaults and protect the dependability and integrity of infrastructures in VANET, advancements in cybersecurity include secure communication protocols and IDS.

Overall, integrating DL methodologies with VANETs has contributed a great deal to the effectiveness of ITSs. There are, however, many aspects that need further research to ensure practicality in real applications:

- Hybrid Frameworks: Combining DL with federated learning and edge computing for privacy-preserving and efficient deployment
- Scalability and Latency: Enabling lightweight DL models for direct inference on edge devices placed in high-mobility scenarios
- Cross-Layer Protocol Integration: Developing DL solutions that interact across VANET protocol layers for adaptive QoS management
- Benchmarking: Creating public, standardized VANET datasets for benchmarking DL models across different ITS applications
- Security and Resilience: Expanding DL-based intrusion detection and anomaly detection systems to cope with evolving cyber threats.

In light of the findings, it is evident that DL models offer significant potential for improving VANET-based ITS. However, more consistent use of performance metrics across studies, along with a more critical and structured comparison of methods, would greatly enhance the scholarly rigor and practical applicability of future research.

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