Journal of Soft Computing and Computer Applications

Volume 1 | Issue 1 Article 1004

2024

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Recommended Citation

Atheem, Hussein K. Abdul; Ali, Israa T.; and Al Alawy, Faiz A. (2024) "A Comprehensive Analysis of Deep Learning and Swarm Intelligence Techniques to Enhance Vehicular Ad-hoc NETwork Performance," *Journal of Soft Computing and Computer Applications*: Vol. 1: Iss. 1, Article 1004.
DOI: https://doi.org/10.70403/3008-1084.1004

JOURNAL OF SOFT COMPUTING AND COMPUTER APPLICATIONS 2024;1:1004

REVIEW

A Comprehensive Analysis of Deep Learning and Swarm Intelligence Techniques to Enhance Vehicular Ad-hoc NETwork Performance

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ABSTRACT

The primary elements of Intelligent Transportation Systems (ITSs) have become Vehicular Ad-hoc NETworks (VANETs), allowing communication between the infrastructure environment and vehicles. The large amount of data gathered by connected vehicles has simplified how Deep Learning (DL) techniques are applied in VANETs. DL is a subfield of artificial intelligence that provides improved learning algorithms able to analyzing and process complex and heterogeneous data. This study explains the power of DL in VANETs, considering applications like decision-making, vehicle localization, anomaly detection, traffic prediction and intelligent routing, various types of DL, including Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) are mentioned for their efficiency in VANET applications. The DL algorithms in VANETs have garnered attention from academia and industry, leading to the development of architectures and algorithms tailored for VANETs. The challenges and advantages of DL in VANETs are expected as future research directions in this field. Moreover, this study explains the operations of Swarm Intelligence (SI) techniques, such as Ant Colony Optimization (ACO), Stochastic Diffusion Search (SDS), Particle Swarm Optimization (PSO), and Artificial Swarm Intelligence (ASI) in VANETs. The techniques of SI offer solutions for improving problems and can be utilized to diagnose and manage routing protocols and traffic congestion malicious nodes in VANETs. This study offers a detailed diagnose of how SI and DL help improve the efficiency and performance of VANETs. This improvement facilitates the development more safer and active transportation systems with intelligent capabilities.

Keywords: Convolutional neural networks, Swarm intelligence, Deep learning, Recurrent neural networks, Vehicular ad-hoc networks

Received 9 March 2024; accepted 12 May 2024.
Available online 27 June 2024

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https://doi.org/10.70403/3008-1084.1004

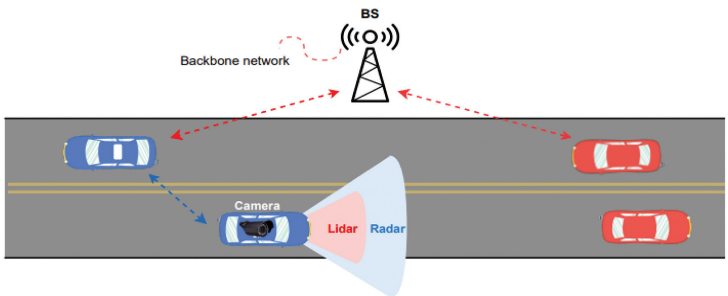

Fig. 1. An illustration of vehicular networks [5].

1. Introduction

Vehicular Ad-hoc NETworks (VANETs) are pivotal to enhancing the Intelligent Transportation Systems (ITSs). VANETs authorize cars to contact among themselves and with many infrastructure components, for instance, traffic signals and road sensors, to promote road safety, driving experience and traffic adequacy, as shown in Fig. 1. The enormous information amount that is created via these cars and the deployment of connected cars have blazed the way for the DL algorithms in VANETs [1].

DL represents the major subfield of Artificial Intelligence (AI), it works on transformations across multiple fields by proposing algorithms of sophisticated learning capable of extracting and acquiring complex representations and patterns from enormous data sets. This robustness makes DL especially appropriate for VANETs, where massive data are created from roadside infrastructure, cars and other resources [2].

In VANETs, the suitability of DL relies on the accuracy in analyzing and processing complex and heterogeneous information to derive important insights. VANETs can explore challenging duties via leveraging Deep Neural Networks (DNN), which involve intelligent routing, decision-making, anomaly detection, vehicle localization, and traffic prediction.

DL techniques like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) have shown elegant performance in many VANET applications. For example, features of RNNs are dealing with temporal and sequential data, subsequently making them appropriate for services like the prediction of traffic flow and driving behavior analysis. CNNs can pull high-level features from visual data, such as pictures taken via in-vehicle cameras or roadside cameras, allowing services, such as classification of traffic signs, vehicle detection objects and recognition.

The utilization of DL in VANETs has obtained sturdy attention from industry and academia. Investigators have offered many DL architectures and algorithms appropriated for VANETs, concentrating on upgrading the adequacy and performance of diverse VANET applications. Automotive manufacturers, technology companies and transportation agencies have determined the DL potential in VANETs and are exploiting it in research and development [3, 4].

The contribution of this study explains the power of DL in VANETs and investigates its applications in various circumstances, including autonomous driving, safety enhancement and traffic management. Also, this study presents insights into future research in this field and the features and challenges of DL in VANETs.

This study is organized as follows: Section 2 presents VANETs and their communication via 5G and 6G networks. Section 3 presents the background of VANETs and AI. Section 4 explains the DL techniques in VANETs, while Section 5 presents the challenges and opportunities in VANETs using DL and SI techniques. Finally, Section 6 describes the conclusion.

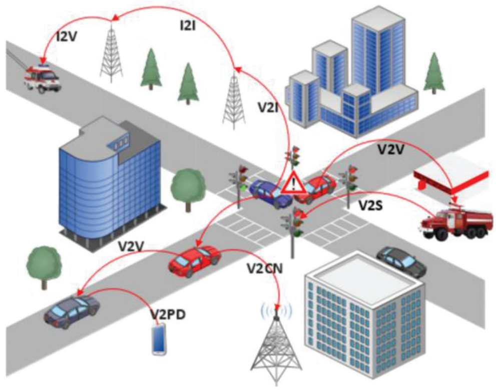

Fig. 2. Communications in VANET [6].

2. Vehicular Ad-hoc NETworks and their communications via 5G and 6G network

VANETs are formed by advancing and integrating wireless communication technologies, automotive construction technologies and ITSs. VANETs can be classified as a distinct subset of Mobile Ad-hoc NETworks (MANETs) that possess unique characteristics and requirements, with vehicular nodes playing a crucial role. VANETs consist of stationary entities (roadside units) and mobile entities (vehicles) collaborating to swap essential information regarding the state of roads and other vehicles [6]. Fig. 2 illustrates six types of communication in VANETs:

- Vehicle-to-Vehicle (V2V): - Communication between vehicles.
- Vehicle-to-Sensor (V2S): - Communication between vehicles and sensors.
- Vehicle-to-Infrastructure (V2I): - Communication between vehicles and Infrastructure.
- Intra-Infrastructure (I2I): - Infrastructures Communication.
- Vehicle-to-Cellular Network infrastructure (V2CN): - Communication between vehicle and Cellular Network infrastructure.
- Vehicle-to-Personal Device (V2PD): - Communication between vehicles and Personal Devices

VANETs utilize short-distance wireless communication to facilitate data exchange between vehicles and roadside infrastructure. This data serves various functions, including:

- Supporting ITSs: VANETs play a vital role in implementing ITSs applications, encompassing features such as intelligent traffic lights and automated parking systems.
- Improving Traffic Efficiency: By enabling V2V communication, VANETs allow for coordinated movements among vehicles, ultimately aiding in reduced traffic congestion.
- Enhancing Traffic Safety: VANETs enable the dissemination of crucial information to vehicles, notifying them about potential dangers like accidents or ongoing road construction.

5G and 6G networks represent upcoming advancements in cellular networks, providing several benefits compared to their predecessors:

- Enhanced Capacity: Both 5G and 6G networks offer substantially greater bandwidth than earlier generations of cellular networks. This expanded capacity enables the support of various novel applications, including VANETs.

- Decrease Delay: The 5G and 6G networks latency is seriously reduced compared to generations of previous cellular. This reduction delay is especially valuable for applications that rely on real-time communication, like VANETs.
- High Accuracy: The 5G and 6G networks characteristic is the enhanced accuracy compared to the generations of earlier cellular. This enhancement to accuracy is serious for applications that need performance with high levels, like VANETs.

These characteristics can develop transportation via rising, safety and efficiency. There are several ways in which VANETs and (5G or 6G) networks can be successfully combined:

- ITSs: VANETs can employ the capability of 5G or 6G networks to back several ITS applications, including systems for automated parking and lights of smart traffic. These applications can advance the adequacy of transportation systems, like using VANETs to rule smart traffic lights, which leads to enhanced traffic flow.
- Improving Traffic Adequacy: Consolidating 5G or 6G networks with VANETs supports coordinating vehicle movement, and decreases and improves traffic flow and congestion. For instance, VANETs can minimizing traffic delays by coordinating car movements.
- Promoting Traffic Safety: VANETs can swap essential information about hazards such as road maintenance or accidents using 5G or 6G networks. Cars can utilize this data to take action to prevent accidents. Such as changing lanes or adjusting speed to avoid a collision.

3. Vehicular Ad-hoc NETworks and Artificial Intelligence: Background

VANETs have been a key field of study for about a decade. Rapid progress in computing technologies has extremely eased the integration of AI techniques in diverse domains such as transportation medicine, healthcare, engineering and manufacturing [7]. The major target of vehicular networks is to develop the safety and adequacy of transportation systems by enabling the swap of information among roadside infrastructure, cars, and pedestrians. Fig. 3 provides an AI tools classification for techniques like Swarm Intelligence (SI) and DL. AI methods are widely used in practical situations because of their exceptional problem-solving ability. The impressive growth of AI techniques can be attributed to

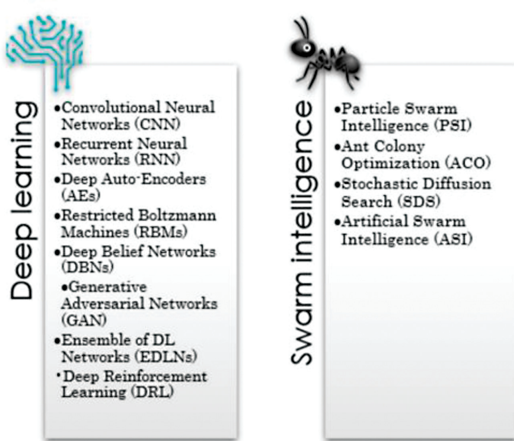

Fig. 3. Swarm techniques and deep learning taxonomy [9].

Table 1. DL techniques and their role with VANET.

DL techniques	Properties	Role with VANET
CNN	Highly efficient, simplified, and scalable.	– Evaluating multimedia data obtained from vehicle control cameras or roadside units. – Anticipating accidents using video analysis. – Managing 5G/6G resources. – Security depends on blockchain.
RNN	Optimal results are achieved when working with sequential and discrete information.	– Enabling the exchange of information across collaborative fog, cloud computing platforms, and edge. – Enhancing mobility prediction. – Performing efficient handovers. – Detecting obstacles. – Decreasing latency.
Generative Adversarial Network (GAN)	A fixed quantity of iterations is employed to generate samples.	– Predicting vehicle trajectory. – Enhancing the efficiency of infotainment applications by boosting the rate at which data are delivered and minimizing the delay in transmission.
Deep Belief Network (DBNs)	Attributes represented through an iterative process.	– Ensuring the security of 6G VANETs. – Predicting driver emotions prediction. – Preventing 51% of blockchain attacks. – Predicting traveling time.

the development of computationally efficient algorithms and the abundance of extensive datasets. DL and machine learning have undergone significant advancements in the past few years, transitioning from experimental research to practical implementation in critical applications [8]. The next sub-section provides a concise overview of some prominent AI techniques and explores their potential applications in key areas of VANETs.

3.1. Deep Learning in Vehicular Ad-hoc NETworks

DL is a subset of AI and a branch of machine learning that focuses on extracting knowledge automatically from vast amounts of data. The effectiveness of DL has led to its widespread adoption in various practical applications. The keys of DL techniques have been outlined, highlighting their benefits and exploring their potential applications in the context of VANET, as illustrated in Table 1. A summary of prominent and significant DL techniques is also presented.

3.1.1. Convolutional Neural Network

CNNs are renowned for their ability to scale effectively and their low complexity [10]. As an AI technique, they demonstrate high efficiency, making them particularly useful for analyzing multimedia data, such as predicting accidents and congestion in videos, with the help of computer vision CNN-based systems. They prove valuable in tasks like identifying pedestrians, detecting potential hazards, and recognizing traffic signs through captured images. Moreover, CNNs can successfully control the allocation of 5G or 6G resources by hiring network slicing methods and executing blockchain technology security solutions to guarantee the legitimacy of the vehicular nodes [11]. Fig. 4 describes CNN and GAN mechanisms [9].

3.1.2. Recurrent Neural Networks

RNNs are suited to dealing with sequential data, especially generating and learning signals. They handle discrete and sequential data and are highly useful for collaborative

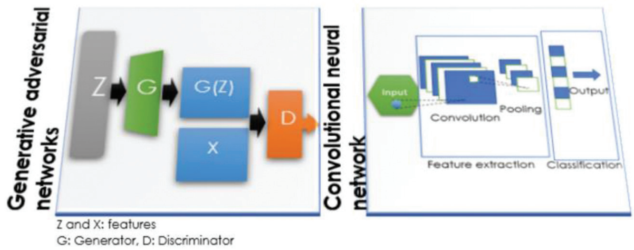

Fig. 4. Tools of deep learning: Explaining CNNs and GANs [9].

computing across cloud environments, fog, and edge. RNNs can be applied to assess the likelihood of a vehicle entering a specific region soon based on its current trajectory, predict mobility patterns, and benefit from insights obtained from analyzing input data by forecasting the future quality of received signal sequences, also RNNs prove valuable in detecting optimal handover timings. Also, RNNs can help reserve resources by extracting resource availability patterns from frequency band utilization data. In addition, RNN-based methods can be used to analyze captured road images and detect obstacles on the road [12].

3.1.3. Deep Belief Network

DBN is a powerful tool for enhancing the security of 6G VANET because of its iterative depiction of attributes. It is also characterized by its depth, which points to the presence of multiple hidden layers. In VANETs, DBN is considered more secure and plays a critical role in 6G VANETs. It can also be used to estimate travel time and predict driver emotions.

The process includes gathering traffic information from real road scenarios and decomposing it into different intrinsic elements within the input space. Each data segment is then trained using a DBN, and the resulting predictions are combined to form the ensemble model output.

In addition, DBN is valuable in mitigating blockchain attacks in vehicular communications. It considers factors such as the number of trustworthy and malicious nodes within the vehicular network, message delivery time among vehicles, and the computational time required for blockchain puzzle-solving [13].

3.1.4. Generative Adversarial Network

GANs are an AI technique used to generate accurate replicas of images or other forms of data. They utilize a fixed quantity of iterations to produce samples. GANs enhance the efficiency of infotainment applications and reduce communication latency. By optimizing resource allocation to align with the requirements of each vehicular application, they can improve trajectory prediction by making rough approximations of semantic spaces constructed by projecting contextual information into a semantic space using a DL model. GANs can catch semantics such as merging and turning by simulating and regulating the trajectory of each vehicle and the anticipated distribution of vehicles.

3.2. Swarm Intelligence in Vehicular Ad-hoc NETworks

SI points to the combined behavior of independent and decentralized systems. In the vehicle context, SI involves a group of vehicles communicating with each other and their environment. Unlike traditional centralized control systems, these vehicles adhere to fundamental principles such as following road structures, adhering to speed limits, and obeying traffic signals. SI draws inspiration from various natural phenomena, such as birds flocking, bacterial growth, the behavior of ant colonies, the schooling of fish, and microbial cognition [9].

3.2.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a global optimization technique that can be applied to solve problems involving single-point or multi-dimensional surface solutions. This technique ensures that each particle chooses the best position it has previously encountered or moves towards a new position by adjusting its speed if the new position is more favorable [14]. Several probable solutions are mapped in the solution space using an initial speed as input [15, 16]. The particles navigates through this space based on fitness parameters, gradually advancing towards regions with improved fitness characteristics over time.

3.2.2. Ant Colony Optimization

Ant Colony Optimization (ACO) aims to find nearly optimal solutions for different graph optimization problems. The ACO ants try to navigate the shortest possible route, as described in reference [17].

3.2.3. Stochastic Diffusion Search

Stochastic Diffusion Search **(**SDS) was initially presented as a mapping algorithm that operates on a population level. It utilizes direct interaction patterns to assess the validity of various paths, including the collaborative movement observed in social insects [18, 19].

3.2.4. Artificial Swarm Intelligence

Artificial Swarm Intelligence (ASI) is a form of SI that brings together interconnected individuals into a real-time system. It draws inspiration from natural swarms and is governed by AI algorithms. By utilizing real-time networks and AI algorithms, ASI fosters a collective intelligence known as a "hive mind" among human participants, enabling teams to achieve solutions that surpass what individuals could accomplish on their own [20, 21].

Unlike other problem optimization approaches, most SI techniques do not rely on specific hypotheses. Instead, they combine exploring various paths with utilizing natural intelligence to uncover high-quality solutions.

SI is also known for its simplicity and ease of implementation compared to other AI methods. It finds applications in optimizing routing, determining the shortest path, clustering algorithms, and Geocast routing [22, 23], addressing challenges like traffic congestion and detecting malicious nodes. Table 2 provides an overview of the main characteristics of various SI techniques and their potential applications in VANET domains.

Table 2. SL techniques with VANET.

SI technique	Properties	Role with VANET
PSI	No hypotheses are necessary to optimize the problem.	Enhancing routing Protocols (Geocast, clustering, shortest path).
SDS	It is possible to uncover solutions of exceptional quality- by integrating the process of discovering paths with the utilization of human intelligence.	Facilitating traffic jams.
ACO	To optimize, there is no need for gradient information, meaning it can be done without relying on gradients or being gradient-free.	Identifying nodes that are acting with malicious intent.
ASI	Easy and simple to implement.	Assisting in mitigating the risk of routing attacks.

4. Practical applications of Vehicular Ad-hoc NETworks-Deep Learning and Vehicular Ad-hoc NETworks-SI techniques

VANETs have several practical applications where DL and SI techniques can be effectively employed. Here are some examples:

Table 3. VANET Applications for DL and SI Techniques.

VANET Apps	Benefit	Descriptions
Intrusion Detection Based on DL in VANET	This work proposes a DL-based intrusion detection system for VANET to detect malicious activities and attacks.	[24] The proposed model utilizes a combination of LSTM and CNN networks to analyze the behavior patterns of vehicles and identify potential security threats.
Vehicle Localization in VANET-Based DL	This study focuses on accurate vehicle localization in VANET using DL techniques.	[25] Proposed a model that exploits DNN to evaluate the accurate location of cars based on measurements of received signal strength.
Traffic Sign Recognition Based on DL in VANET	This research presents traffic sign recognition based on a DL approach in VANET.	[26] The proposed model employs an integration of CNNs and RNNs to classify and detect traffic signs from captured pictures.
Energy Management in Electric Vehicles within VANET-Based DL	This research focuses on optimizing energy management in Electric Vehicles (EVs) within VANET using DL techniques.	[27] The presented model acquires knowledge to make energy-influential decisions for EV charging and discharging depending on battery and traffic conditions.
Vehicle-to-Vehicle Communication in VANET-Based DL	This paper concentrates on improving V2V communication in VANET using DL techniques.	[28] The proposed model hires DNNs to detect and decode signals and improve interference mitigation in V2V communication, a guide to enhanced communication activity and reliability.
An ACO Approach for Traffic Signal Control in VANETs	This article explores a method for traffic signal control in VANETs using ACO.	[29] Proposed an enhancement to traffic signal timing and duration using an ACO algorithm based on the data gathered from cars in the network. The characteristic of this design is to reduce congestion and enhance traffic flow by dynamically modifying the traffic timing of signals in response to traffic conditions.
PSO-based Handover Decision Algorithm in VANETs	This paper proposed an algorithm for handover decisions for VANETs depending on PSO.	[30] A PSO is employed to enhance the process of handover decision when a car moves between diverse Base Stations (BSs) or Access Points (APs) in the network. Components such as channel quality network congestion and signal strength enhance the handover decision. The presented algorithm aims to improve the performance and connectivity of vehicles in VANETs during handover scenarios
Vehicle Detection and Tracking based on DL in VANET	This paper presents a DL model for vehicle tracking and detection in VANET	[31] Proposed a model that employs the algorithms of object detection like CNNs or You Only Look Once (YOLO) to explore and track vehicles from video or sensor data, subsequently, helping applications like traffic analysis and collision avoidance.

5. Challenges and opportunities in Vehicular Ad-hoc NETworks using Deep Learning and Swarm Intelligence techniques

DL has a huge impact on VANETs as shown above. Numerous research challenges and opportunities remain. The most notable of these challenges and article directions are as follows:

1. Durability and Security: In VANETs, the durability and security of DL models is an enormous challenge. Both adversarial strikes and data intoxication can affect the efficiency and accuracy of these models. Investigators should focus on enhancing the durability of DL architecture and techniques that can pact with such strikes and pledge the originality and integrity of the information gathered from cars [32–34].
2. Confidentiality Preservation: DL algorithms need an enormous information amount for training, which can boost confidentiality problems regarding VANETs. Investigators should concentrate on developing techniques that allow cars to share information while protecting the individual driver's confidentiality, such as federated learning, secure multi-party computation and differential privacy [35–37].
3. Multi-Modal Data Fusion: VANETs generate diverse data from several sensors, including radar, LiDAR and cameras. Investigators should focus on improving the DL models that can exploit and merge multi-modal data for functions like a prediction of the behavior, object detection and scene understanding. Multi-modal fusion mechanisms such as graph neural networks and attention mechanisms can be explained in this context [38–40].

SI techniques are used in VANETs for proposing research opportunities to address different challenges. These research challenges and directions are the most notable as follows:

1. Swarm-based Traffic Control: In VANETs, SI algorithms such as ACO or PSO, can be used for control of dynamic traffic. Studies should focus on enhancing swarm-based algorithms to reduce congestion and improve traffic efficiency via enhancing the coordination of traffic flow, lane assignment timing, and traffic signals [41–43].
2. Swarm-based Network and Routing Management: SI algorithms can be utilized to improve efficiency and algorithms of self-adaptive routing for VANETs. Studies should focus on swarm-based routing protocols that consider components such as vehicle mobility patterns, network congestion and link quality, allowing robust and scalable communication within VANETs [44–46].
3. Intelligent Routing: SI techniques can enhance routing protocols and VANETs by considering, network connectivity, real-time traffic conditions and vehicle density [47–49].

Integrating SL and DL techniques into VANETs can develop several network features, including localization, routing, data fusion and traffic control, guiding to more active and intelligent vehicular communication systems [50].

6. Conclusion

This study explains the DL techniques application and SI techniques in VANETs that can improve the adequacy and performance of ITSs. It highlights the impact of DL in VANETs for services such as vehicle localization, decision-making, anomaly detection, intelligent routing, and traffic prediction. Diverse DL technique models, including RNNs and CNNs, are discussed for their ability in VANET applications. The DL techniques utilized in VANETs have earned attention from academia and industry, guiding to the development of architectures and algorithms appropriated for VANETs. Moreover, this study explains the SI techniques' role such as ACO, PSO, ASI, and SDS and proposes solutions to improve the detection of malicious nodes and routing protocols and traffic congestion management. The study includes the advantages and challenges of DL and SI in VANETs and proposes future research directions. Merging DL and SI in VANETs promises to build more safer, efficient and intelligent transportation systems.

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