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Survey on Artificial Intelligence (AI) techniques for Vehicular Ad-hoc Networks (VANETs)

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A B S T R A C T

Advances in communications, smart transportation systems, and computer systems have recently opened up vast possibilities of intelligent solutions for traffic safety, convenience, and effectiveness. Artificial Intelligence (AI) is currently being used in various application domains because of its strong potential to help enhance conventional data-driven methods. In the area of Vehicular Ad hoc NETworks (VANETs) data is frequently collected from various sources. This data is used for various purposes which include routing, broadening the awareness of the driver, predicting mobility to avoid hazardous situations, thereby improving passenger comfort, safety, and quality of road experience. We present a comprehensive review of AI techniques that are currently being explored by various research efforts in the area of VANETs. We discuss the strengths and weaknesses of these proposed AI-based proposed approaches for the VANET environment. Finally, we identify future VANET research opportunities that can leverage the full potential of AI.

1. Vehicular ad-hoc NETWork (VANET)

Vehicular ad hoc Networks are the result of developments and convergence of wireless communication technologies, intelligent transport systems, and automotive construction technologies. They are considered to be a specific sub-category of Mobile Ad hoc NETworks (MANETs) with vehicular nodes having specific characteristics and requirements. A VANET is a set of mobile (vehicles) and fixed (roadside units) entities working together to exchange important information about road conditions and other vehicles [2].

Fig. 1 presents several areas of VANET communications which include:

- Vehicle to Vehicle (V2V) communication.
- Vehicle-to-Infrastructure (V2I) communication.
- Intra-Infrastructure communication (I2I).
- Vehicle-to-Sensor communication (V2S).
- Vehicle-to-Personal Device communication (V2PD).
- Vehicle-to-Cellular Network infrastructure communication (V2CN).

The emergence of 5G mobile networks has brought about several innovative features which can be applied to Vehicle to Everything communications (V2X). Indeed, the latest releases (Rel-16 and Rel-17) of the 3rd Generation Partnership Project (3GPP) introduced the New Radio V2X (NR-V2X) standard that incorporates SideLink (SL) communication [3]. This new concept enables direct radio communication between two user equipments (vehicles, personal devices, and so on) without communicating with the road side unit in the data traffic transfer. This advancement can improve VANET communication to meet extended services' requirements of commercial and infotainment services in addition to safety applications. Several other improvements are being explored by the 3GPP many of which focus on increasing the reliability of the communication, achieving wider coverage, reducing latency, and also saving power particularly for battery-based equipments.

Over the last decade many VANET services (e.g., infotainment applications, driver assistance, and video on demand) have emerged. Indeed, in addition to safety applications (e.g., accident avoidance, warning message dissemination), vehicles are now equipped with hardware and software that can support various entertainment and comfort applications [4]. However, the emergence of these services opens up additional challenges not only in terms of security and privacy but particularly in terms of performance and Quality of Service (QoS).

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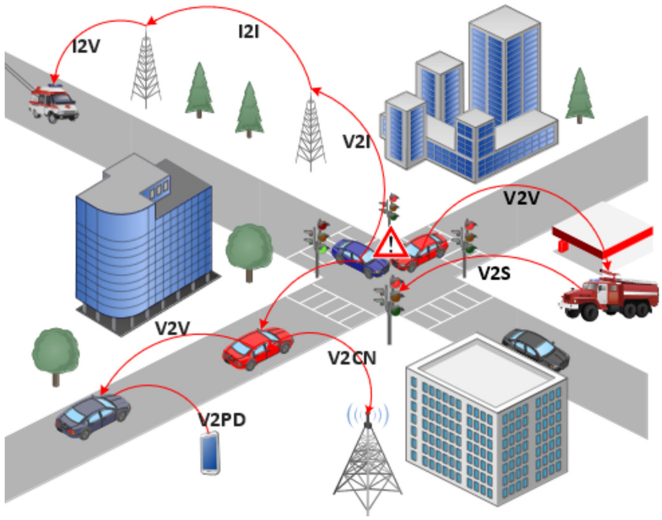

Fig. 1. Communication in VANET: Vehicle to Vehicle (V2V), Infrastructure to Infrastructure (I2I), Vehicle to Infrastructure or vice versa (V2I or I2V), Vehicle to Sensor (V2S) Vehicle to Personal Device (V2PD), and Vehicle to Cellular Network (V2CN).

Fig. 2 presents some of The major research topics in VANET that have been studied in the last decade, range from applications to routing and security/privacy as well as mobility management. Resource allocation and the design of novel integrated architectures with emerging technologies such as Internet of Things, cloud computing, fog and edge computing have also received a lot of attention from researchers in academia and industry [5].

Another recent trend is the surge in interest in the deployment of Artificial Intelligence (AI) techniques in many application domains including cybersecurity, data analytics, routing, healthcare, robotics, and so on [6]. It is not surprising that we are also currently witnessing increased attention being paid to the use of AI techniques (such as basic Machine Learning (basic ML), Deep Learning (DL), Swarm Intelligence (SI)) in emerging VANET solutions to solve various VANET challenges. However, applying AI methods to vehicular communications still need further research.

1.1. Research contributions of this work

The main contributions of this work include:

- We have reviewed several AI techniques and discussed their suitability as well as their limitations in addressing several VANET challenges and requirements.
- We also discuss future research opportunities that need further investigation to enable the full integration of AI with VANET.

We organize the rest of the paper as follows. Section 2 presents some background information on VANET and AI. Section 3 discusses VANET challenges and areas that can benefit from the use of AI techniques. Section 4 discusses future research opportunities that will enable the full potential of AI to be reaped by VANETs. Finally, section 5 makes some concluding remarks.

2. VANET and AI: background

VANET has been an active area of research for over a decade. Similarly, recent advances in computing technologies have accelerated the adoption of AI techniques in many fields (medical, transport, engineering, manufacturing, healthcare, and several others) [7]By exchanging information among cars, pedestrians, and road side infrastructures, vehicular networks seek to improve the safety and efficiency of transport systems. Fig. 3 presents a basic taxonomy of AI tools. We describe the techniques: ML, DL, and SI below.

Today, in several real–world scenarios, AI techniques are being used due to their exceptional problem-solving capabilities. In addition to advances in computationally-efficient algorithms, the recent success of AI techniques has also been motivated by the availability of big data. Over the recent years, basic machine learning and deep learning have progressed considerably, ranging from laboratory exploration to functional automation with comprehensive critical applications [8]. Next, we present a brief review of some of the most important AI techniques and we identify and discuss key VANET areas where they can be applied to.

2.1. Basic machine learning

In this section we review some of the popular basic Machine Learning (basic ML) techniques which include supervised, unsupervised, semi-supervised and reinforcement [9]. We identify their key benefits and highlight VANET areas where they can be applied.

a) Decision Trees (DT) The decision tree is a classification and prediction tool, and its popularity is largely based on its simplicity [10]. A decision tree is made up of a root node through which data enters and leaf nodes which correspond to a classification of questions and answers. Each answer represents a condition for the following question in the next layer [11]. It is a transparent and a simple classification tool that can be very useful in vehicular network to handle routing decision, traffic signal management and detect misbehavior [12]. Fig. 4 shows a simple illustration of DT and SVM mechanisms.

b) Support Vector Machine (SVM) Support Vector Machines (SVM), often referred to as Large Margin Separator, are a class of learning algorithms originally defined for discrimination, that is, the prediction of a binary qualitative variable [13]. They were then generalized to predict a quantitative variable. In the case of the discrimination of a dichotomous variable, they are based on the search for the optimal margin hyperplane which, when it is possible, classifies or separates data correctly while being as far away as possible from all observations. The strength of this technique relies on its capability to handle data with a large number of features and a small number of input instances. Therefore, it may be an effective approach for attack prevention and detection in the VANET environment as well as for identifying malicious parties. It is also useful for cluster optimization and improving spectrum allocation [14]. Fig. 4 shows a simple illustration of SVM mechanism.

c) Naive Bayes (NB) The Naive Bayesian classification method is a supervised machine learning algorithm that classifies a set of observations according to rules determined by the algorithm itself [15]. The naive Bayesian classifier assumes that the classes of the training dataset are known, and hence the supervised nature of the tool. Due to its robustness with respect to irrelevant attributes, its easy implementation and simple training requirements, Naive Bayesian is an appropriate method for handling several VANET issues such as driver behavior prediction, broadcast storm avoidance, and even misbehavior awareness [16].

d) k-Nearest Neighbor (KNN) The K-NN algorithm is a supervised learning method. It can be used for both regression and classification. To make a prediction, the K-NN algorithm uses the entire dataset. Indeed, for an observation, which is not part of the dataset, that we want to predict, the algorithm looks for the K instances of the dataset closest to our observation [17]. Then, the algorithm uses the corresponding images of these K neighbors to calculate the value of the output of the observation that we want

Fig. 2. Major research topics in VANET: Security, applications, mobility management, routing, resources allocation, and novel integrated architectures.

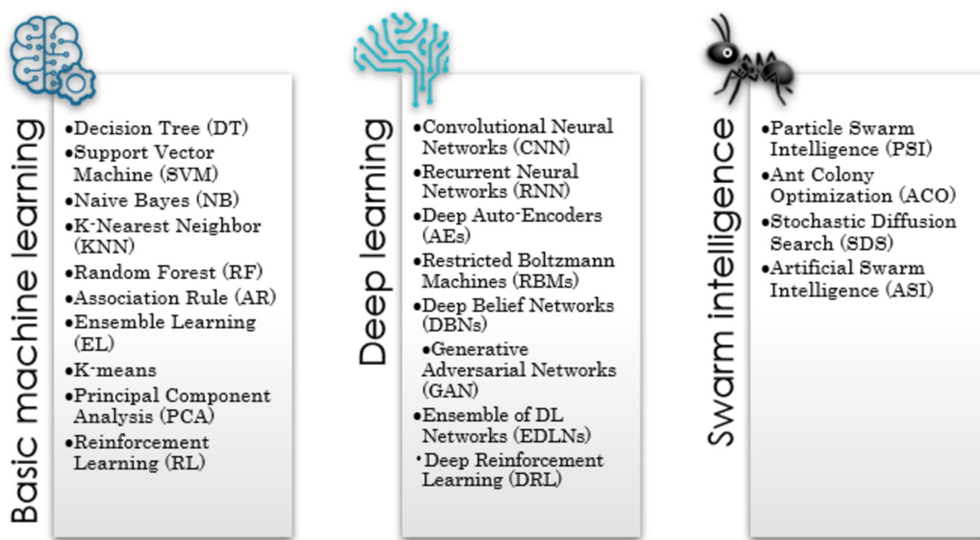

Fig. 3. Taxonomy of AI techniques.

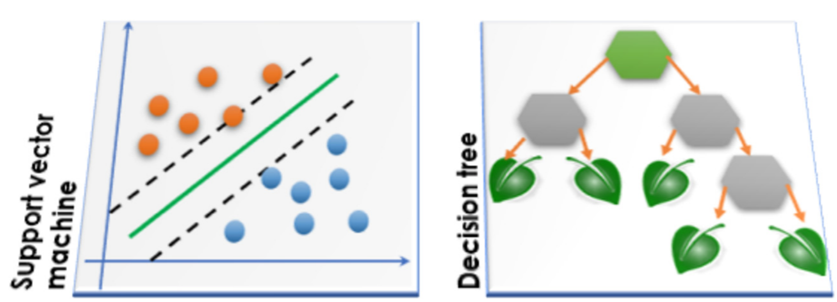

Fig. 4. Basic machine learning tools: illustration of SVM and DT.

to predict. KNN is efficient for intrusion detection, preserving privacy, maintaining cluster stability, and location detection [18].

e) Random Forest (RF) Random forest is fairly intuitive to understand, quick to train, and it produces generalizable results. A random forest is made up of a set of independent decision trees [19]. Each tree has a fragmented view of the problem due to a double random selection. Random forest can handle over-fitting, and circumvent the selection of features. It only requires a few input values. These advantages make it a good technique in solving congestion prediction, performing handover especially for multimedia data dissemination and for managing channel allocation [20].

f) Association Rule (AR) Association rules belong to both the disciplines of data mining and machine learning because they involve both performing data processing operations and uncovering recurring patterns within data to predict future behaviors [21]. The simple correlation discovery enables association rules to be efficient in detecting road accidents, and for generating paths and maps traversed by vehicles [22].

g) Ensemble Learning (EL) Ensemble techniques are meta-algorithms that incorporate many machine learning techniques into one predictive model to minimize uncertainty, bias or enhance predictions [23]. Ensemble learning is a technique that is robust to over-fitting and it is able to decrease variance by working more effectively as an adapter (that transforms irregular data into a uniform representation) than a classifier. Ensemble learning's characteristics as a machine learning techniques makes it efficient in misbehavior awareness, vehicular positioning accuracy, and handover decision [24].

h) K-Means K-means is an unsupervised non-hierarchical clustering algorithm. It enables the observations of the data set to be grouped into K distinct clusters [26]. Thus, similar data will be found in the same cluster. In addition, an observation data can be found in only one cluster at a time (exclusive membership) [27]. The same observation cannot therefore belong to two different clusters. It is useful for anonymization of sensitive information as it does not need labeled data and, thus, it can ensure VANET clustering stability, securing hashing functions during sensitive data transfer and may also be applied for congestion detection [28].

i) Principal Component Analysis (PCA) Principal Component Analysis PCA is one of the key techniques for feature extraction which is the process of extracting new and more significant features from existing ones. Given an input dataset having "n" predictor variables. An $n \times n$ matrix, called covariance matrix, can be obtained after centering the predictors to their respective means. This matrix is then decomposed into Eigenvalues and Eigenvectors. So, PCA is the process that includes a Covariance matrix to quantify how one variable is related to the others, Eigenvectors identify the directions of the spread of the data, and Eigenvalues highlight the relative importance of these directions [29]. In a VANET context, this AI technique can be exploited in security risk prediction as well as caching optimization because of its ability in reducing the dataset dimension which decreases the complexity of the optimization algorithms [30].

j) Reinforcement Learning (RL) Reinforcement Learning (RL) refers to a class of machine learning problems, the goal of which is to learn, from successive experiences, what to do in order to find the best solution. Reinforcement learning differs fundamentally from supervised and unsupervised learning in terms of the interactive and iterative aspect: the algorithm tries several solutions (exploration), observes the reaction of the environment and adapts its behavior (the variables) to find the best strategy [31]. Therefore, RL is very useful in handling offloading for 5G/6G enabled networks, spectrum allocation, and proactive radio resource management wireless resource management and optimizing data processing distribution under network slicing paradigm [32]. Table 1 summarizes the key benefits of the various machine learning algorithms along with VANET areas where they can be most beneficial.

2.2. Deep learning

Deep learning (DL), derived from machine learning, is a sub-branch of artificial intelligence that aims to automatically build knowledge from large amounts of information. The success of these techniques has made them popular in many practical applications. Next, we present the main deep learning techniques, their advantages, and possible applications to the VANET environment.

a) Convolutional Neural Network (CNN) Convolutional Neural Network (CNN or ConvNet) is known for its scalability and low complexity [33]. It is an AI technique with high efficiency enabling it to be very effective for multimedia data analysis such as video analysis for congestion and accident prediction thanks to computer vision CNN based systems. Indeed, it helps in traffic sign recognition and pedestrians or hazard detection through captured images. However, it can also be applied to 5G/6G resources management through the application of the network slicing technique and blockchain based security solutions by enabling vehicular nodes' authenticity [34]. Fig. 5 presents a basic illustration of CNN and GAN mechanisms.

b) Recurrent Neural Network (RNN) Recurrent Neural Networks (or RNNs) are particularly suited to applications involving some context, and especially the processing of temporal sequences such as learning and signal generation (i.e., when the data forms a sequence and is not independent of each other). RNNs achieve best performance with discrete and sequential data and are an excellent tool for sharing intelligence for collaborative edge, fog, and cloud computing. They may also provide a good approach for mobility prediction by measuring the probability that a vehicle may enter a certain region in the near future time based on its present trajectory and by using the knowledge obtained from theoretical analysis of input data. RNN can be useful for determining when to perform handovers by predicting the upcoming quality of the received signal sequence. Moreover, RNN can be a helpful tool for resource reservation by extracting resource availability patterns based on the frequency band utilization time [35]. Besides, the detection of obstacles on the road can be performed using RNN based methods by analyzing road images captured.

c) Long Short Term Memory (LSTM) Long Short Term Memory (LSTM) is a Recurrent Neural Network (RNN) architecture used in the field of deep learning. Unlike forward propagating neural networks, LSTM has feedback connections. In addition to being able to process single data points (such as images), it can also process complete sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as non-segmented or connected handwriting recognition or speech recognition. LSTM networks are well suited for classification, processing, and forecasting based on time series data, as there may be lags of unknown duration between important events in a time series. LSTMs were developed to address the vanishing gradient problem (This issue makes it difficult to learn large data sequences. The gradients convey information that is used in the RNN variable update, and as the gradient decreases, the parameter updates become minor, implying that no meaningful learning is taking place.)

d) Gated Recurrent Units (GRUs) RNN suffers from the disappearance/explosion of gradients and does not remember states for a very long time. The GRUs [36], are an application of multiplicative modules which attempt to solve these problems. This is an example of a recurring network with memory. Gated recurrent neural networks have been developed to solve the problem of the disappearance of the gradient that can be caused by regular recurrent neural networks. They can be considered to be a variation of short-term long-memory recurrent neural networks because they are similar in design and produce identical results in some cases.

e) Deep Auto-Encoders (AEs) The auto-encoder is a technique that can extract the characteristics "relevant" to the entry data collected from the network in an unsupervised way. The basic idea here is to train a neural network at a hidden layer to predict its input at its output, a task called reconstruction. Thus, the goal is to minimize the reconstruction error [37]. AEs are useful for learning features,

Table 1
Basic machine learning techniques: key advantages and VANET areas where they can be beneficial.

ML technique	Key advantages	Application areas of ML technique to VANET
Decision Trees (DT)	Transparent, simple to use	-Improves routing decision -Traffic signal management -Detecting misbehaviors of malicious vehicles
Support Vector Machine (SVM)	Handles data with a large number of features and a low number of input variables instances	-Vehicle misbehavior, intrusion, Sybil, Greyhole, Blackhole, and Wormhole attacks prevention and detection - Identifying malicious nodes - Vehicular nodes' clustering optimization - Improves VANET spectrum allocation decision
Naive Bayes (NB)	Robust (irrelevant attributes are ignored or eliminated), easy to implement, and simple training requirements	-Improves driver behavior prediction (mobility) - Avoids the broadcast storm in VANET and excessive collisions -Improves the detection of misbehaving vehicular nodes
k-Nearest Neighbor (KNN)	Efficient classification based on votes	-Intrusion detection: identify when and how many successful internal intrusion attempts occur -Protects privacy (e.g., driver's information and VANET messages exchanged among vehicles) -Can help maintain stable clusters for VANET cluster-based techniques -Vehicle and incident location detection
Random Forest (RF)	Handles over-fitting, circumvents the selection of features, and only requires a few input values	-Prediction of vehicular congestion -Improves handover support for multimedia data dissemination among vehicular nodes -Control channel allocation
Association Rule (AR)	Simple correlation discovery	-Can detect road accidents -Can generate paths and maps
Ensemble Learning (EL)	Robust to over-fitting, decreases variance, works more effectively as an adapter than a classifier	- Can detect misbehaviors of malicious vehicles -Provides better vehicle positioning accuracy information in vehicular networks -Improves handover decisions from vehicle to roadside units
K-Means	Useful for anonymization of vehicle and driver sensitive information (such as personal data or internal status of the vehicle) because it does not need labeled data	-Improves clustering stability for cluster-based VANET techniques -Helps in developing hashing functions for securing vehicular communications -Can help with early detection of road congestion
Principal Component Analysis (PCA)	Useful for reduction of data dimensionality	- Can achieve a reduction of dimensionality and therefore decreases the computational complexity of voluminous vehicular data -Can identify driving risks and predict Denial of Service (DoS) attack -Vehicular multimedia data caching optimization in Vehicle-to-Everything (V2X) communications
Reinforcement Learning (RL)	Learn from trial and error	- Very effective for hard vehicular mobility and driving prediction and routing decision problems -Can improve intelligent vehicular tasks' offloading in V2X communications for heterogeneous 5G/6G enabled vehicular networks -Can improve dynamic and fair management of spectrum allocation for multiple access over vehicular channels -Proactive radio and wireless remote resource management in edge and cloud-based VANET -Can improve network slicing for V2X communications: developing vehicular partitioning algorithms for safety services slices, traffic management slices, infotainment slices and autonomous driving slices

extraction, and reducing dimensions by ignoring or eliminating irrelevant data attributes. Therefore, they can be applied to traffic prediction by learning temporal correlations of a vehicular network, and thus predicting traffic congestion. Deep auto-encoders help in intrusion prediction and detection by reducing the size of the traffic datasets to obtain the most relevant features. These features can be then used as input for classifiers to distinguish normal behavior from intrusions. Deep auto-encoders can be useful for estimating vehicular speeds by sequentially evaluating the new speed of the vehicle based on the given previous speed values [38].

f) Restricted Boltzmann Machines (RBMs) A restricted Boltzmann machine is an algorithm used for dimensionality reduction, classification, regression, collaborative filtering, feature training, and keyword training. It is possible to stack several layers of restricted Boltzmann machines to create deep networks that are more efficient. RBMs use unsupervised learning with feedback technique. A restricted Boltzmann machine may be efficient for network traffic prediction because it is useful in the restitution the historical information of the traffic datasets input superposition, and supervised nonlinear approximation. RBMs are useful in detecting intrusion in

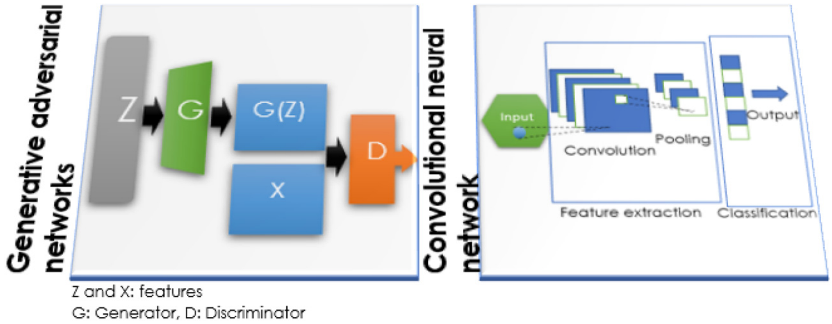

Fig. 5. Deep learning tools: Simple illustration of Convolutional neural networks and Generative adversarial networks.

vehicular networks because it can fit the features of the vehicles from the input data samples when unsupervised learning classifier is used. This process can be regarded as an additional step in feature extraction (of vehicular historical behavior and characteristics) from the previously extracted features from previous input samples. Accident duration may have important temporal and spatial correlations with the traffic flow and thus decreases the road capacity. Therefore, RBMs can be used as accident duration prediction technique by handling continuous traffic variables and building a prediction pattern based on the classification according to the duration [39].

g) Deep Belief Networks (DBNs) Deep Belief Networks have relatively high depth (i.e., a high number of hidden layers). The key advantage of DBNs is their iterative representation of attributes making them a strong tool for securing 6G VANET, where security is much more crucial than traditional VANET, predicting driver emotions, as well as predicting travel time. Indeed, traffic data collected from the road scenario, can be decomposed into the input space of many intrinsic. Next, each part of data entries is trained by a DBN and finally, its forecasting results can be summed up as the output of the ensemble model. DBNs also help in preventing 51% blockchain attack in vehicular communications in terms of the numbers of vehicular good nodes and malicious nodes, the delivery time of the messages exchanged among vehicles, and the blockchain puzzle computation time [40].

h) Generative Adversarial Network (GAN) A GAN is an artificial intelligence technique that can be used to create perfect imitations of images or other types data. GANs use a predefined number of iterations to construct samples and can therefore reduce communication latency and improve infotainment applications' efficiency. This can be achieved with more efficient resource allocations by adjusting the allocated resources according to each vehicular application's needs. GAN can improve trajectory prediction by using approximate semantic spaces (the contextual concept vector is formed by projecting the context information into a semantic space using the deep learning model), and capturing semantics such as merging and turning in a way that mimics the predicted distribution of vehicles, and controlling each vehicle's trajectory [41]. Fig. 5 presents a simple illustration of GAN mechanism.

i) Ensemble of DL Networks (EDLN) Several deep learning models can operate cooperatively to perform better than when deep learning algorithms applied separately [42]. By combining discursive, exclusionary or hybrid models, EDLNs can be achieved. EDLNs are also used to manage complex problems with high-dimensional characteristics and uncertainties [43]. An EDLN consists of layered different classifiers, either homogeneous or heterogeneous (within the same family). EDLNs commonly support diversity and generalization of the model [44]. They are, therefore, appropriate for intrusion detection, mobility prediction, and even accurate GPS location given that a simple model does not always succeed to solve such complex problems efficiently in real vehicular scenarios.

j) Deep Reinforcement Learning (DRL) Reinforcement learning can represent functions applied on an input data space with high size by automatically extracting a hierarchy of descriptors [45]. The decision is made through a process of trial and error. In each state of the state space, the agent selects an action from the set of possible actions. DRL does not need to have prior knowledge about the input data and is effective even with adversary conditions (i.e., data attributes creating some semantic or logical conflicts). It is an effective technique for traffic control, resource allocation, optimizing channel access and relay selection for multipoint routing because it can train the network according to the previously sensed data and adjust the new classification or selection parameters based on the knowledge gained from previous road scenarios [46]. Table 2 and 3 presents the key advantages of each deep learning techniques and the VANET areas that can benefit from such techniques.

2.3. Swarm intelligence

Swarm intelligence can be characterized as the collective conduct of systems that are autonomous and distributed. Swarm intelligence in the context of the vehicular paradigm is represented by a population of vehicular entities that communicate with each other and with their surroundings. Without any central controller, the vehicles obey basic guidelines such as the road architecture for their trajectory, the maximum allowed speed, and the lights. Swarm intelligence include the behavior of ant colonies, bacterial germination, bird groups, fish schools, and microbial cognition.

a) Particle Swarm Optimization (PSO) The PSO is an approach for global optimization which can be used to address a problem where the solution can be identified as a single point or a whole surface in n-dimensional space. The PSO algorithm guarantees that each particle selects one of the best previously experienced positions or moves toward a new position using the particle's speed if the new one is better [47]. Then, different possible solutions are plotted in this solution space using an initial speed as input [48]. With some fitness parameters, the particles travel over that space, and over time, they progress toward those areas having better fitness attributes. Fig. 6 presents a simple illustration of the PSO and ACO mechanisms.

b) Ant Colony Optimization (ACO) ACO seeks near optimal solutions to various problems with graph optimization. The ants in ACO attempt to follow the shortest path as stated in [49]. Fig. 6 illustrates the ACO mechanism.

c) Stochastic diffusion search (SDS) SDS was first introduced as a population-based mapping algorithm which employs direct inter-

Table 2
Deep learning techniques: key advantages and VANET areas where they can be applied.

DL technique	Key advantages	VANET areas where the deep learning technique can be applied
Convolutional Neural Networks (CNN)	Scalable and less complex, highly efficient	- Analysis of multimedia data collected from road side units or vehicle's controlling camera - Accident prediction based on video analysis - 5G/6G resource management - Blockchain-based security
Recurrent Neural Networks (RNN)	Best performance with discrete and sequential data	- Sharing intelligence with collaborative edge, fog and cloud computing - Improves mobility prediction - Efficient handovers - Internal(vehicle) and external (Road Side Unit (RSU), edge, cloud) resource reservation - Obstacles detection
Long Short-Term Memory network (LSTM) & Gated Recurrent Unit (GRU)	The ability to learn long-term dependencies	- Predicting road traffic for routing decision - Examining and extracting time-related features from traffic history for detecting intrusive activities - Predicting the geographical future position of vehicles to reduce road congestion
Deep Auto-Encoders (AEs)	Useful for learning and extracting features from high volumes of vehicular data, reduce the number of dimensions of the data	- Traffic prediction - Can perform intrusion prediction and detection - Can estimate speed of vehicles
Restricted Boltzmann machines (RBMs)	Unsupervised learning with feedback technique	- Can predict network traffic density - Can detect intrusions - Can predict road occupation or unavailability (time and space) after an accident
Deep Belief Networks (DBNs)	Iterative representation of attributes	- Securing 6G VANET - Can predict driver emotions - Can prevent 51% blockchain attack - Can predict traveling time
Generative Adversarial Networks (GAN)	Pre-defined number of iterations to construct samples	- Reduces communication latency - Can predict the trajectory of a vehicle - Improve the performance of infotainment applications by increasing the data delivery rate and reducing the transmission delay
Ensemble of DL networks (EDLNs)	Supports diversity and generalization of the model	- Can detect DDoS and 51% Blockchain attacks - Can predict the mobility of vehicles - Can provide accurate GPS information for better data routing

Table 3
Deep learning techniques: key advantages and VANET areas where they can be applied (Part II).

DL technique	Key advantages	VANET areas where the deep learning technique can be applied
Deep Reinforcement Learning (DRL)	No need for restricted prior knowledge, effective with adversary conditions	- provide efficient traffic road management (number of vehicles, route congestion) - Internal (vehicle On-Board Unit (OBU)) and external (RSU, cloud, edge, and so on) resource allocation - Can optimize access of VANET users to the physical communication channel - Improves the relay selection for multipoint routing by learning from the routing history under different road constraints

action patterns to evaluate the discovery and aggregation hypothesis of all possible paths, such as collaborative movement identified across social insects [50].

d) Artificial swarm intelligence (ASI) Driven by the natural Swarm Intelligence (SI) concept, ASI links distributed communities of integrated human subjects into a real-time system that is modeled with natural swarms and moderated with AI algorithms. This approach uses real-time networks and AI algorithms to construct a "hive mind" of human actors, allowing teams to converge on solutions that are far more relevant than individuals can accomplish on their own [51].

Almost all swarm intelligence techniques do not require any hypotheses about optimizing the problem. Also, swarm intelligence helps to find solutions of high quality by combining paths' discovery with the exploitation of natural intelligence. In addition, swarm intelligence is known for its simplification and ease of implementation compared to other artificial intelligence techniques. Swarm intelligence is commonly applied to enable routing optimization such as shortest path determination, geocast routing, and clustering algorithms [52]. It may also be deployed for handling traffic congestion and the detection of malicious nodes. Table 4 presents the main characteristics of each swarm intelligence technique and the VANET areas where the techniques can be applied.

2.3.1. Summary

In this section, we reviewed some of the most popular AI techniques. We have highlighted their key advantages and discuss some of the potential areas of VANET where each can be used (as Table 1 shows). As we have mentioned earlier, machine learning methods provide promising and powerful algorithms domains that are being extensively used in various application domains. However, in order to represent data at various levels of abstraction, deep learning techniques give a computational structure that incorporates many processing levels (layers). Deep learning methods have significantly improved state-of-the-art technologies in comparison to conventional machine learning methods. Deep learning algorithms have the ability to remove the need for the manual processing of features whilst delivering high classification precision. Swarm intelligence techniques have also proven useful in many VANET areas such as routing optimization and solving security issues. Empowered by their deployment simplicity, the swarm intelligence techniques in this branch of AI have demonstrated remarkable efficiency.

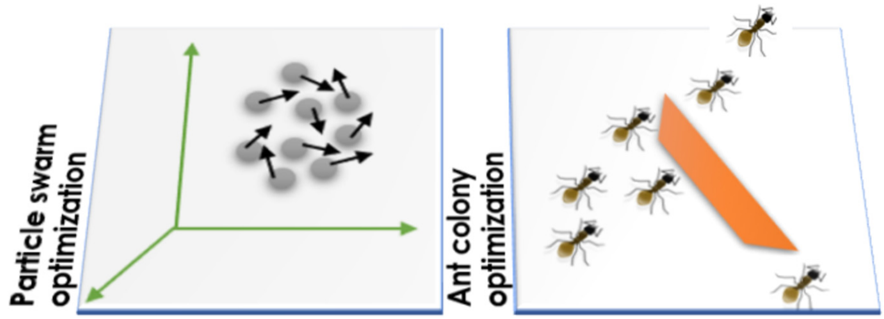

Fig. 6. Swarm Intelligence tools: Simple illustration of Particle swarm optimization and Ant colony optimization.

Fig. 7. Challenging issues in different VANET areas including applications, routing, security, resources allocation and access technologies, mobility management and integrated architectures.

Table 4
Swarm intelligence techniques: key advantages and VANET areas where they can be applied.

Swarm Intelligence (SI) technique	Key advantages	VANET areas where SI techniques can be applied
Particle Swarm Intelligence (PSI)	-No hypotheses required about optimizing the problem,	- Can optimize routing protocols (shortest path, geocast, clustering)
Stochastic Diffusion Search (SDS)	-Can find solutions of high quality by combining paths' discovery with exploitation of natural intelligence	- Handles traffic congestion
Ant Colony Optimization (ACO)	-Gradient information not required for problem optimization (i.e., gradient-free)	- Can detect malicious nodes
Artificial Swarm Intelligence (ASI)	-Simple and easy to implement	Helps to prevent routing attacks, can help in routing optimization

3. AI solutions for VANET

In this section we analyze six areas namely, applications, routing, security, resource allocation and access technologies, mobility management, and integrated architectures (as Fig. 7 shows) that can benefit from AI technologies. Table 5 highlights the specific issues that can be addressed in each of these aforementioned areas using AI solutions.

3.1. Applications

One of the most popular VANET applications aims is to send early alerts and ensures timely responses to specific situations to ensure safe travel. We can categorize VANET applications into three major categories [8].

- **Safety applications**: by disseminating information about threats and obstructions, these VANET applications are used to avoid car crashes. Crash prediction is possible using a random forest algorithm [20]. For a driver, there are several factors that must be considered when selecting a route. These include of traffic signals, pedestrians, and other cars, and in many cases guidance instructions from the Global Positioning System (GPS). This makes it challenging for a driver to focus on all these activities simultaneously. Therefore, studying driver's behavior becomes an important issue in this context. A Support Vector Machine can help in identifying the road conditions because of its ability to provide information accurately and on-time. Convolutional Neural Networks are useful in predicting drivers' behaviors and actions to avoid unsafe maneuvers [54]. In addition to warning signals, safety applications are often used for safe lane change management, navigating and applying automatic emergency breaks to prevent collisions [55]. These applications can be enabled by taking advantage of the Principal Component Analysis technique because of its ability to extract relevant input data based on the driver attributes, car features, and the environment's characteristics [56]. If an incident occurs, we can apply Naive Bayes which is a classifica-

Table 5
Opportunities for solving VANET issues with AI.

VANET area		Issues	Applicable AI techniques
Application	*Safety*	- Accident prediction and alert dissemination, driver behavior prediction and motion detection -Reduce congestion after accident	- Random forest for crash prediction [19] - Principal Components Analysis for driver assistance [29] - Support Vector Machine for driver's behavior identification [53] and Convolutional Neural Networks for driver's behavior prediction [54] - After a road accident Naive Bayes [57] and Decision Tree can help in decision for reducing congestion [58]
	Traffic	Lane change, speed, traffic congestion control	- Predict traffic scenarios and reduce congestion with Convolutional Neural Networks [63] or Artificial Neural Networks [64]. Traffic volume prediction using GRU [65] - Predict vehicular speed and density according to hours of the day with K-Nearest Neighbors [68] - Reinforcement learning for smart management of traffic lights [67] - Include weather and road conditions broadcasted by road side units in traffic management [60] - Decrease traffic congestion with Ant Colony Optimization [61] and LSTM [62]
	Infotainment	Multimedia data dissemination, Video quality, QoS support for real time applications	QoS-aware video compression with Convolutional Neural Networks [73] Intelligent multimedia data encoding with Convolutional Neural Networks [75] and Deep Auto-Encoders [76] Travel path guidance with Particle Swarm Optimization [77]
Routing		- Vehicles' speeds - V2V communications link disruption - Obstacles - Message forwarding nodes' selection	- Support Vector Machine for vehicular nodes classification according to their suitability for better message forwarding [81,1] - Convolutional Neural Networks for route prediction [82] - Decision Tree [7], and Naive Bayes for routing decision [84] - Particle Swarm Optimization for vehicle's neighborhood exploration to recognize the identity and number of neighbors [86] - Ant Colony Optimization for determining shortest routing paths [78] - Traffic flow prediction for trusted routing decision with LSTM [85] - Geocast (data dissemination to a subset of vehicles in a predefined geographical area) with Particle Swarm Optimization [86]
Security	*Physical layer*	Malicious nodes DDoS attacks [90] Auth and trust management	- K-means for vehicular nodes' clustering according to their trust level [25] and GRU for in-vehicle intrusion attack detection [92]. - Artificial Neural Networks for detecting misbehaving nodes [93] - Intrusion detection using Convolutional Neural Networks [94]
	Network layer	SQL injections	- Support Vector Machine [96] and Reinforcement Learning for trust management [97]. GRU [98] for robust vehicular communication against jamming.
	Application layer	Detection and prevention of intrusions	- Particle Swarm Optimization for DoS prevention [99] and LSTM for malware traffic detection on On Board Units (OBUs) [100]
	Cloud layer	Hardware attacks	Artificial Neural Networks for detecting hardware intrusions [93]
Resource and access technologies	*- Resource management* *- Access technologies*	-Delay-sensitive applications - Vehicular applications' reliability -Crucial resources of the vehicle's on board units and road side units -Heterogeneous technologies (IEEE 801.11p, 4G LTE, 5G and 6G)	-Deep Reinforcement Learning for task scheduling and offloading -Network slicing algorithms with Support Vector Machine [106]. -Intelligent cloud resources' allocation with Particle Swarm Optimization [102] - Reinforcement Learning based PHY access [105] -Deep Reinforcement Learning for 5G and LTE management of heterogeneous data generated from V2X communications [103]
Mobility		- Mobility models - Communication under high mobility - Communication link disruption	-Driver behavior management with Convolutional Neural Networks [111] and Artificial Neural Networks [108] - K-Nearest Neighbors for predicting vehicles' mobility [109] - Driver intention prediction and recognition with GRU [110]
Integrated architecture	*- Cloud, fog and edge*		
	- 5G, 6G	- Communication delay with external entities - Seamless integration of emerging technologies	- Deep Reinforcement Learning for cloud [116], fog, and edge integration - Convolutional Neural Networks [125] and Support Vector Machine [124] for V2X communication management -Generative Adversarial Networks (GAN) can be implemented to reduce data transfer latency between the integrated architectural layers [117]

tion model with strong probabilistic independent assumptions among the variables of the predictor (a predictor of a language is a property of the objects of the domain considered (the universe of discourse) expressed in the language in question) [57]. Decision Tree-based solutions [58] are highly robust and practical can also help in this case by enabling timely decisions which can help reduce congestion on the road [15].

- **Traffic management applications**: The primary objective of traffic control and management is to improve traffic flows, reduce traveling time by preventing traffic jams or assist drivers with updated road conditions on the best route [59]. This may require the use of certain devices on the roadside, such as sophisticated traffic lights and e-sign panels which can be managed through reinforcement learning techniques [60]. GRU [65] as a sub-type of RNN is distinguished by its simpler structure of gating and relatively lower computational complexity which can help in predicting the local volume of road traffic flow. LSTM [63], can also be applied in this context and can achieve better traffic prediction because it outperforms standard time series networks in terms of prediction accuracy. In addition, LSTM fit data more efficiently and quickly than standard time series models, and it can cope with bigger data sets better than traditional time series models. Knowledge about possible road congestions can help alleviate congestion and enhance road capacity. ACO swarm intelligence may be applied as a decision making technique to guide traffic flows in order to minimize traffic congestion [61]. However, for better predictive capabilities that reduce congestion, we can apply CNN [63] or ANN [64] based approaches because these two models have high prediction accuracy due to their highly interconnected processing components (neurons) [66]. Predicting vehicular speed and different vehicular densities which vary at different times of the day is one of the possible applications of KNN in the vehicular context [67]. KNN can outperform the tree model and the linear regression of the input data while maintaining a minimal error rate [68]. Weather and many other road conditions are relevant factors in traffic management that can be considered when using machine learning techniques to optimize traffic management applications.
- **Infotainment applications**: Comfort and entertainment application services are also popular for VANETs in addition to road safety applications. These applications provide users with convenience and amusement [69]. Infotainment provides services such as exchanging multimedia content, movies, and music among network vehicles. Ubiquitous Internet access today has become a reality with the emergence of many enabling technologies [70,71]. The VANET environment is no exception to this as it also provides continuous Internet connectivity to VANET users [71] when integrated with these technologies too. Infotainment applications provide travelers with convenience, such as advertisements, parking availability, and highway tolling. Nevertheless, a minimum level of QoS is required to achieve these objectives and enhance the Quality of Experience (QoE) [72]. CNN is well-suited for handling image and video data [73] since it can optimize the image resolution to provide a clearer output image to the driver [74]. It is useful to achieve a high quality data compression for infotainment applications [75]. Here, a deep auto-Encoder for multimedia data intelligent encoding can be used [76] because it has a robust learning of nonlinear vehicular data representations and their subsequent reconstruction. Travel path guidance is considered one of the sophisticated infotainment services that can be handled with PSO technique due to its ability to search the near-optimal path (travel path) based on given search space (road map) [77].

3.2. Routing

Routing plays a vital role in VANETs because all supported services, unicast or multicast, rely on multi-hop communications for the routing of data [78]. Unicast communications are typically used in convenience applications such as file transfer and gaming [79]. Multicast communications are used in security and traffic management applications such as collision warning and platooning [1]. One of the major issues related to routing in VANET is the speed of the vehicles which varies in urban and highway environments. Variations in speed often result in frequent link disruption, thus making the maintenance of continuous communication between vehicles a challenging task. Prompt lane changing and obstacles are other challenges that must be addressed [80]. For almost all routing protocols, especially those based on multi-hop communications, the most crucial step is the selection of the set of quasi-optimal relays. In this context, using the Random Forest technique for exploring the vehicle's neighborhood along with an SVM classifier for the classification of nodes based on their ability to forward messages, can improve the design of routing protocols [81] in the vehicular environment. Using LSTM [85] can guarantee the trust level of vehicles in the routing decision thanks to its ability to predict the traffic flow in a stochastic way and retain vehicle information for a longer time. In [82], the authors studied driver behavior, and they showed that CNN is a suitable technique for predicting driving routes and thus avoid the consequences of rapid changes if a route to the destination fails. ACO is one of the best methods for determining the quasi-shortest path in data routing but DT and NB can also be utilized in routing decisions [83]. As a bioinspired technique, ACO has the advantage of self-organization and resilience to errors during the search of the near-optimal solution. For geocast protocols (broadcasting the message to a subset of vehicles in a predefined geographic area), PSO may play an important role in locating neighboring vehicles and localizing them in a specific area or zone [86]. Indeed, in the PSO process, the movement of each particle, is influenced by its local neighbors, but it is also driven toward the best known areas of the search space, which are modified as better positions are discovered by other particles. The swarm is supposed to shift toward the semi-best solutions as a result of this.

3.3. Security

Security in VANET has been extensively studied over the last decade [87–89]. In VANETs, messages are constantly being exchanged among vehicles and between vehicles and roadside infrastructures. The integrity, authenticity, privacy, and confidentiality of these messages must be protected as many of them contain sensitive information. Additional considerations must be given to the data consistency (the trust level and the relevance of this data of the messages generated by other vehicles and the real-time requirements of safety-related applications [89]. As we have mentioned earlier, often vehicles share safety information through VANETs, and based on the information collected from neighbors, a vehicle makes critical decisions (such as route or lane change, message broadcast). If this information is not correct, unwanted consequences may occur endangering the lives of the occupants of the vehicles. Additionally, misinformation regarding vehicle conditions, environmental incidents and road conditions can be harmful to the VANET users [2]. A particular vehicular node could falsify or manipulate the traffic information for its personal gain such as in the case of a Sybil attack wherein the Sybil nodes create a false sense of traffic congestion. Malicious nodes, DDoS attacks, authentication and trust management, Structured Query Language (SQL) injections, intrusion prevention and detection and hardware attacks are the main security concerns in the vehicular context at the physical, network, application and cloud layers [91]. Generally, a node clustering algorithm is needed during the preliminary phase to detect a malicious node and the k-means algorithm is well-suited for this purpose due to its adaptability to the highly dynamic topology of VANET [5]. In-vehicle attacks and particularly, CAN bus attacks, are also an important type of intrusions that have to be accurately handled. The use of GRU [92] as a recurrent neural network can help detect such intrusions but, generally, it has to be combined with other deep learning methods. GRU can develop a distributed cooperation framework to assess network conditions and make real-time judgments on whether to protect the network against a jamming attack, enabling vehicle nodes to avoid communication holes caused by jamming attacks [98]. The ANN technique is also useful for misbehavior detection as it classifies nodes based on their historical behavior [93]. In contrast, CNN, a deep learning method, can be a useful tool for extracting spatio-temporal vehicular attributes from a two-dimensional dataset, long with the common back-propagation algorithm [94]. LSTM [100] can help in intrusion detection by automatically detecting the malware traffic on the OBU using time-dependent traffic flow information. In the area of trust management, many approaches [95] have been proposed in the literature to ensure the trustworthiness of the information and nodes in the VANETs. In a vehicular network, a vehicle may evaluate the trustworthiness of messages exchanged based on a variety of variables, including neighbor perceptions, vehicle credibility, and previous interactions with the communicating vehicle. However, communication is short-lived and unstable due to the high mobility of cars. It is highly challenging and complex to assess the trustworthiness of a vital message (such as emergency alerts) in a short time interval. In VANETs, SVM and RL may be applied to establish trust strategies related to vehicular nodes or third parties' behaviors. On one hand, for various non-linear classification scenarios, SVM is a reliable machine learning technique [96]. This makes it an appropriate tool for developing trust models by supplying relevant parameters such as the vehicle's inputs (such as the position, velocity and neighbors' identity) and attributes, and its efficiency has been demonstrated in various vehicular environments. On the other hand, the Reinforcement Learning technique [97] can handle the massive data generated in vehicular environment, and thus, provide a powerful tool to analyze the historical vehicles' behaviors and make trust decisions. DoS is a well-known attack that needs be detected and mitigated. PSO may play a significant role in mitigating DoS attacks by interpreting vehicular groups behavior [99]. Indeed, the concept of PSO is based on the behavior of the particles (vehicles in the case of VANETs) in the search space. Then, the particles are adjusted in the search space according to their historical behaviors (historical road scenario). It is a heuristic technique that simulates the movements of birds flocks that aim to find food (here the attacked node).

3.4. Resource allocation and access technologies

Resources in VANET include radio resources (such as frequency bands, transmit power levels), road infrastructure resource (such as RSUs, RSU storage) and external resource (such as cloud infrastructure resource). Ensuring the fair distribution of resources in VANETs is a challenge [101] due to a variety of inherent limitations. This includes erroneous and congested wireless channels (due to high mobility or lack of coordination channel-access), progressively fragmented and congested spectrum, hardware flaws, and the continuous growth of vehicular communication devices [102]. The heterogeneous aspect of different access technologies deployed in VANETs makes their integration with each other and with external networks even more challenging [103]. However, employing DRL can be effective in addressing some of the aforementioned issues through the implementation of intelligent cloud resource allocation algorithms. Indeed, DRL can handle high dimensional input data and decide the best action for each input [104]. DRL can also help in performing better task scheduling and efficiently handle offloading of tasks from internal (vehicle) to external (RSU, cloud) resources. A RL based PHY access is an approach for reducing congestions on the physical channel [105] thanks to the capability of RL to make decisions under uncertain constraints. Moreover, the implementation of DRL-based data management algorithms increases the efficiency of resource management [when dealing with 5G and LTE heterogeneous technologies in VANET [103]. The heterogeneity for resource allocation is of high complexity but can be addressed using DRL (with different layers) by decomposing the problem into multiple sub-problems. Another new paradigm related to vehicular context is network slicing which is an emergent architectural model that allows virtualized and separate logical networks to be multiplexed on the same physical network infrastructure. SVM technique can be used to develop effective and innovative solutions for network slicing [106]. Indeed, after the collection of required network slicing data, SVM can perform features' extraction and then slicing classification.

3.5. Mobility management

Mobility in VANETs is directly linked to the behavior of drivers and their reactions to obstacles in different and complex situations encountered at road structures (such as intersections and traffic signs) or at roadside base stations (infrastructures) on highways or within a metropolitan area. These constraints greatly affect the mobility model and the quality of radio transmissions [107]. High mobility is one of the main characteristics that distinguishes vehicular networks from other classes of wireless networks, because vehicle speeds vary depending on the environment [108]. Although the movement of vehicles is relatively predictable, the impact of mobility on connectivity and network topology remains one of the major challenges of vehicular networks. For example, a node can join or leave the network in a very short time making topology changes very frequent. We need to develop driver behavior management methods in order to address mobility issues. CNN and ANN are suitable AI techniques because they can analyze vehicle mobility models, driver behavior, and road traffic. ANN can also be used for mobility prediction especially for Software-Defined Networking (SDN) based vehicular networks where the SDN controller is the entity performing the prediction [111] by developing mobility models based on probability of the movement models of users. Predicting the mobility of vehicles and lane changes are possible by using the KNN algorithm because it is based on the proximity of each vehicle to other vehicles with similar features (such as different positions in the same direction or the same lane) [109].

3.6. Integrated architectures

The implementation and deployment of VANET applications require wide range of networking and computing capabilities. Emerging technologies such as cloud, fog, edge, and 5G are being integrated with VANETs applications [113,114,112]. The integration of these heterogeneous infrastructures and hybrid architectures brings about many challenges especially those related to data processing latency and security risks [115]. The data, while transmitted over the different architectures integrated into VANETs, goes through various processing operations. Here, Deep Reinforcement Learning (DRL) is an efficient technique that can help handle heterogeneity during data migration because of the flexibility of its convolutional layers [116]. Generative Adversarial Networks (GAN) can be implemented to reduce data transfer latency between the integrated architectural layers because it has a fixed pre-defined number of iterations for constructing a representation model independently of the data size or structure [117]. For intrusion detection, KNN is an appropriate technique due to its high accuracy for node classification (in supervised learning) as well as regression (in unsupervised learning). However, the use of Ensemble of Deep Learning Networks (EDLN) may achieve better intrusion detection efficiency because of its support for data source diversity and data type heterogeneity [118]. For instance, we present here a sample scenario where an intrusion can be detected through the cloud-VANET data flow. In the first stage, two different Ensemble of Deep Learning Networks (EDLN) can be trained on historical normal flows and attacks already stored. Then another classifier can be used to learn the feature vector representation of the data flows [119]. After that, at the predictive stage, the model used can predict and detect new signs of malicious activities. Thus, it is possible to quickly filter malicious data, stop abnormal activities or block malicious vehicles before the occurrence of a new attack. Additionally, these VANET architectures integrated with emerging technologies are also incorporating new technologies such as the traditional Dedicated Short Range Communication (DSRC), IEEE 802.11p and LTE standards [120,121]. New communications modes such as V2X (Vehicle to everything), C-V2X (Cellular V2X) and LTE-V-Cell enabled by the 5G generation services have been developed in the last few years [122]. To integrate and administer these technologies, vehicular networks need advanced solutions [123]. SVM and CNN are two powerful AI techniques that can help in better channel management and spectrum allocation in heterogeneous environment since they can handle various data types such as structured, unstructured, and semi-structured data. Both SVM [124] and CNN [125] are able to perform non-linear classifications and clustering when input data is not labeled, which is a common situation in heterogeneous VANET environments [126].

4. Future challenges and research opportunities

4.1. Basic machine learning

Most of ML techniques can be applied to the VANET environment. DT can be used to address several issues but it also suffers from limitations such as large storage requirement and complexity issues when many DTs are needed [127]. SVM presents a promising direction for VANETs. However, it faces challenging issues such as the choice of the optimized kernel and models complexity. Furthermore, it is hard to develop SVM-based models.The limitations of adapting NB to VANETs include NB specifications (such as the assumption the presence of a particular feature in a class is unrelated to the presence of any other feature and the "Zero frequency" case). Indeed, NB is unable to extract valuable clues from the interrelationships among its specifications because it treats features individually [128]. But, in applications where samples have related and similar characteristics, it can function correctly. The issues of using KNN in a vehicular network is linked to the optimum value of k which usually varies from one dataset to another so it can be a time-consuming and complex method to find the optimum value of k [129]. RF can address VANET challenges but it is worth noting that RF focuses on the construction of several DTs. Therefore, in specific time-sensitive applications (e.g. safety applications) where the test data defined is large, this may be inefficient. One of drawbacks of AR algorithms is their high processing times. An AR algorithm assumes that there is no order of items and the amount of computation required to apply the algorithm depends critically the minimum specified coverage of the generated association rules. In many instances, as in safety applications such assumptions are not valid. The main difficulty of using EL is its time complexity which is higher than another single classifier-based technique. When using K-Means we need to know that this scheme is less efficient compared to supervised learning techniques, especially in the detection of common threats. PCA is a feature reduction technique that can be used in conjunction with other machine learning techniques as refining tool to develop a better approach of optimization in vehicular networks. RL requires a large amount of data and an intensive processing [130]. Furthermore, the burden of dimensions limits the application of reinforcement learning to actual physical systems. (Table 6.)

Table 6
Summary of machine learning techniques and their limitations when applied to VANET.

Basic machine learning technique	Limitations pertaining to VANET
Decision Trees (DT)	- Requires large storage - Complex when many DTs are needed
Support Vector Machine (SVM)	- Optimized kernel choice is a challenge - It is hard to comprehend and perceive SVM-based models.
Naive Bayes (NB)	- Treats features individually and is therefore unable to extract valuable clues from the interrelationships among them (it can operate effectively in applications where samples have similar characteristics)
k-Nearest Neighbor (KNN)	- The optimum value of k typically differs from one dataset to another; thus, finding the optimum value of k can be a difficult and time-consuming process
Random Forest (RF)	- It is based on the construction of many DTs; therefore, this might be inefficient particularly for time sensitive applications (e.g., safety applications) where the specified test data is large
Association Rule (AR)	- The processing time of these algorithms is high. These algorithms use basic assumptions for between parameters (case series and occurrence). In many instances, such assumptions are not valid particularly for safety applications
Ensemble learning (EL)	- The time complexity of the EL process is significantly higher than a single classifier based scheme
K-Means	- K-Means is less efficient compared to supervised learning techniques, especially for detecting common threats
Principal Component Analysis (PCA)	- This is a feature-pruning technique which must be used along with other machine learning techniques to develop a high performance approach for it
Reinforcement Learning (RL)	- Reinforcement learning requires a large amount of data and a lot of processing. Also, the large number of features can be a serious issue for reinforcement learning when it is deployed in actual physical systems

4.2. Deep learning

Deep learning can be useful in addressing some VANET challenges. When CNN is used to deal with some challenges, we need to consider that CNNs have high computation overheads. This makes deploying them on resource-constrained devices (such as vehicles) to sustain vehicular processing and communication challenging. In contrast, when RNN is applied to the field of VANET, it the problem of gradients exploding or bursting which occurs during the training phase linked to high updates to neural network due to the accumulation of large error gradients [131]. The main drawbacks of LSTM and GRU, especially when applied on critical and delay sensitive VANET situations, include their increasing complexity when adding more features to solve the vanishing gradient problem of RNN. Moreover, they also require high memory bandwidth and they can be easily affected by overfitting. To leverage

Table 7
Limitations of Deep Learning Techniques.

Deep learning technique	Limitations pertaining to VANET
Convolutional Neural Networks (CNN)	- CNNs have high computation overheads; hence, it is difficult to deploy them on resource-constrained devices (such as vehicles) to support vehicular systems
Recurrent Neural Networks (RNN)	- The main drawback of RNN is the problem of gradients exploding or bursting (which is a problem that occurs during the training phase linked to high updates to neural network due to the accumulation of large error gradients)
Long Short-Term Memory network (LSTM) & Gated Recurrent Unit (GRU)	- The main drawback of LSTM and GRU is their increased complexity when more features are added to solve the vanishing gradient problem of RNN. Also, they require high memory bandwidth and they can be easily affected by overfitting.
Deep AutoEncoders (AEs)	- AEs incur high training times. AEs can efficiently learn how to identify the attributes of the training sample. However, AEs may hinder the learning process instead of conveying the aspects of the training data. This occurs when the training data does not give accurate representations of the test dataset
Restricted Boltzmann machines (RBMs)	- RBMs have high training times which make it difficult to apply for highway scenarios in VANETs.
Deep Belief Networks (DBNs)	- DBNs have a long initialization stage caused by a large number of variables
Generative Adversarial Networks (GAN)	- GAN learning is complex to adapt to VANET contexts. Training to produce discrete data using GAN is a challenge
Ensemble of DL networks (EDLNs)	- The entire system's computation cost is high when diverse hybrid models are integrated
Deep Reinforcement Learning (DRL)	- DRL relies on many assumptions which are hard to achieve in practice

AEs to address VANET issues, we need to know that AEs have high training time. Although AEs can learn how to classify the characteristics of the training sample productively, AEs can actually obstruct the learning process instead of communicating the aspects of the training data if the test dataset is not correctly represented. The adaptation of RBMs, as a DL technique, to vehicular networks is also challenging because of its high training time. Meanwhile, the main limitation in the use of DBNs stems from its lengthy initialization stage which makes use of a large number of variables during the initialization stage. Adapting GAN learning is unreliable and difficult to implement for VANETs because of the specific characteristics of VANETs. Thus, GAN must be adapted before using it with such a network [132]. Also, it is difficult to produce discrete data using GAN. The main limitations regarding the use of EDLNs in VANET are that the entire system processing can increase quickly when diverse hybrid models are integrated [133]. Another DL technique that can be used to solve the VANET data communication problem is DRL which relies on many assumptions that are difficult to achieve in practice. This makes DRL unsuitable for VANET environments. (Table 7.)

4.3. Swarm intelligence

VANET cooperation and communication methods can be modeled by swarm behavior based on bio-inspired techniques [47]. Various swarm intelligence techniques can be applied to address different challenges (such as routing, vehicular network scalability, minimizing resource requirements and complexity of messages exchanged) in VANETs. However, before applying swarm intelligence we need to take into consideration the specific VANET characteristics such as the highly variable network topology and the large scale of the network. The use of Particle Swarm Optimization (PSO) also faces security issues in VANET which is a non-monitored network. PSO is based on the efforts of many entities (e.g., the velocity of the vehicles, the positions of the vehicles, the messages generated by the vehicles) [134], and therefore any non-trusted intrusion to VANET can affect the results of the application of the PSO algorithm. PSO needs many other metaheuristics to be combined [135], which is difficult to do in VANET because of its highly dynamic topology. If we want to apply Ant Colony Optimization (ACO) in VANET, we have to provide the required processing capacity for its execution. Indeed, ACO incurs a high processing time to generate multiple solutions [136]. Finally, Artificial Swarm Intelligence (ASI) uses real-time networks and AI algorithms to construct a “hive mind” of human actors [137]. In real-time networks, the time criterion is central because delays can usually occur in VANET which does not have a pre-defined topology and does not guarantee reliable communications. (Table 8.)

Table 8
Limitations of Swarm intelligence techniques.

Swarm intelligence technique	Limitations pertaining to VANET
Particle Swarm Optimization (PSO)	- If we apply PSO to VANETs, it requires the cooperation of many vehicles. As a result, the security of communications as well the identification of vehicles need to be enforced
Stochastic Diffusion Search (SDS)	- It needs to combine several other metaheuristics but the highly dynamic topology of VANETs can affect SDS.
Ant Colony Optimization (ACO)	- ACO incurs high processing times in order to generate multiple solutions.
Artificial Swarm Intelligence (ASI)	- The application of ASI is linked to the computing delays which is a challenge due to the size of the vehicular network as well as the highly dynamic topology.

An important challenge facing the application of AI techniques on VANET is their adaptation to the new standards [138] introduced for V2X communications. As noted in [3], the 3GPP latest release introduced many techniques for improving vehicular communications at different levels (physical, network, and so on) but did not consider any artificial intelligence techniques. AI techniques can be proposed to enhance the new V2X communication paradigm such as integrating road and weather condition for task scheduling, prediction algorithms, and resource allocation thereby improving the overall QoS factors under new standards. However, at this advanced standardization level, the use of AI needs to be adopted with caution and this remains a challenge for future research efforts that are focusing on AI techniques and VANET integration.

5. Conclusion

In this work, we have presented a comprehensive survey on the relevant AI techniques that can be applied to VANETs. We have described different AI techniques. AI-driven algorithms can improve the performance of vehicular applications over traditional algorithms. In general, the performance optimization problem in many studied fields faces many challenges related to various factors that interfere with each other. Therefore, ML, DL and SI areas of AI can support each other to achieve optimal solutions that can address the limitations of ML, DL, and SI. In general, AI algorithms have higher computation costs and resource requirements. These resources may not be embedded into vehicles or the road side units. However, the recent emergence of new integrated architectures and access technologies (such as fog, edge, and so on), the computation burden of artificial intelligence algorithms can be alleviated by migrating some of the computations to external computation and storage servers located at the edge, fog, or cloud. We have discussed how some of the benefits of AI techniques that can be leveraged in the VANET environment despite some of the limitations some of the AI techniques are associated with.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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