ARTIFICIAL INTELLIGENCE SUPPORT FOR 5G/6G-ENABLED INTERNET OF VEHICLES NETWORKS: AN OVERVIEW

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Abstract *– Improving transportation efficiency and on-road safety using Intelligent Transportation Systems (ITSs) has become crucial as road congestion and vehicle complexity increase coupled with ongoing rapid development and deployment of electric vehicles across the globe. Recent advances in computer systems and wireless communications have ushered in more possibilities for smart solutions to road traffic safety, congestion reduction, convenience, and overall efficiency. The evolution and deployment of 5G have opened up new technologies and features that can provide the much needed high-mobility wireless networks for the emerging Internet of Vehicles (IoV). The application of AI consisting of Deep Learning (DL), Machine Learning (ML) and Swarm Intelligence (SI) techniques have emerged in both conventional and vehicular wireless networks with strong promises towards enhancing traditional data-centric methods. Particularly, in the application domains of IoV, big data is frequently generated from various sources within the vehicular communication environment. The collected big data is usually processed and used for both safety and infotainment services including routing, broadening drivers' awareness, traffic mobility prediction for hazardous situation avoidance to improve overall safety and passenger comfort, and general quality of road experience. Applying data-driven methods enables AI to address high mobility and dynamic vehicular communications and network issues facing traditional solutions and approaches like network optimization techniques and conventional control loop design. This study provides a concise review of DL, ML and SI techniques and applications that are currently being explored by different research efforts within the application area of vehicular networks. The paper further discusses the strengths and weaknesses of the proposed AI-based solutions for the IoV networks. Finally, future IoV research directions and open issues that can benefit from the potential of DL, ML and SI were identified.*

Keywords – 5G/6G, artificial intelligence, deep learning, intelligent transportation systems, Internet of Vehicles, Internet of Things, machine learning, swarm intelligence

1 INTRODUCTION

In recent years, the concept of Internet of Vehicles (IoV) has emanated from the emerging Internet of Things (IoT) technology, where smart and autonomous vehicles wirelessly communicate with different aspects of society within an environment. The IoV paradigm is the outcome of developments and convergence of automotive construction, wireless communications, and ITS technologies. Smart vehicles consist of fully semi-autonomous and autonomous driving intelligent vehicles equipped with multi-sensors in the IoV environment. These autonomous vehicles in the IoV paradigms communicate wirelessly to the internal and external environments. In the IoV paradigms, intelligent vehicles communicate with other vehicles, personal devices, roadside infrastructures, pedestrians, sensors and homes. This envisioned era of the IoV will provide seamless wireless connectivity to all aspects of ITS to reduce road accidents, improve overall transport safety, enhance transport comfort, relieve road traffic congestion, and significantly minimize environmental pollution. For efficient communications, it is anticipated that intelligent vehicles in the IoV will be equipped with over 100 multi-sensors [1-2]. The different aspects of wireless communications in the IoV environment, that is, the various Vehicle-to-everything (V2X) wireless communication scenarios [3-4] such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Infrastructure-to-Infrastructure (I2I), Vehicle-to-Personal Device (V2PD), Vehicle-to-Sensor communications (V2S), and Vehicle-to-Cellular Infrastructure communications (V2CI) are presented in Fig. 1 [5]. Currently, the major challenge facing the development and industrial deployment of the various communication scenarios of IoV technology is the continuous and rapid position changes usually demonstrated by fast and dynamic changes in network topology coupled with the relatively short connection times generally associated with vehicular network communications. In the face of these rapid vehicular network topology changes and relatively short connection times, conventional wireless network solutions based on static or low-mobility wireless communication environments become ineffective for IoV paradigms. The emergence of 5G mobile networks with their manifold potential promises several innovative features which can support effective communications, especially in high mobility-oriented IoV environments. These innovative features of 5G/6G can improve vehicular network communications to attain the expanded services' requirements for both safety and infotainment applications in the IoV environment.

Similarly, the latest releases of the digital cellular telecommunication system (Phase 2+), 3rd Generation Partnership Project (3GPP) Specifications (3GPP TR 21.905 version 17.1.0 Release 17) has introduced the emerging radio Vehicle-to-everything (NR-V2X) communication standard [3, 5-6] which further incorporates SideLink (SL) communication technology. 3GPP is currently exploring several other improvements, many of which mainly focus on improving the reliability of communications, reducing latency, guaranteeing wider communication coverage, and power efficiency, particularly for intelligent vehicles and other similar battery-based devices. Within the last 10 years, several vehicular network services have emerged, such as safety applications, driver assistance, infotainment applications, music, and video on demand [7-8]. However, the emergence of these vehicular network extended services has introduced additional challenges for the development and commercial deployment of IoV technology, not only in terms of special Quality of Service (QoS) and high network performance requirements but particularly in terms of cybersecurity, trust and privacy issues.

In the near future, millions of the multi-sensor equipped intelligent, autonomous and semi-autonomous vehicles which will be deployed for fully-fledged operation in the emerging IoV environment. It is expected that each of the intelligent and autonomously driving vehicles will generate more than 25GB of data per hour [70]. The IoV generated big data will generally come in structured, unstructured and semi-structured forms which will require collection, preprocessing, storage, management, as well as analysis to aid informed decision making. Consequently, there has been an increased interest regarding the adoption of AI methods such as Deep Learning (DL), Machine Learning (ML) and Swarm Intelligence (SI) in both academia, industry, and government agencies to proffer solutions to the various challenges facing the emerging IoV. However, adopting AI techniques for efficient IoV communications still requires extensive research given that currently there is limited literature regarding the adoption of AI methods in IoV technology.

The rest of the paper is organized as follows. 5G/6G-enabled IoV communication network structure is presented in Section 2. Section 3 contains the architecture of 5G/6G-enabled IoV. The fusion of ML, DL and SI techniques with 5G/6G-enabled IoV networks is discussed in Section 4. The future challenges and research directions are presented in Section 5. Finally, Section 6 presents the concluding remarks.

1.1 Key research contributions of the study

The key research contributions of this study are shown below:

i. This paper provides a thorough overview of different AI methods and discussion of their suitability and limitations with respect to finding solutions to the several associated challenges and requirements of 5G/6G-enabled IoV technology focusing particularly on its network-centric aspects.

ii. The paper further concentrates on addressing the fusion of AI and 5G/6G-enabled IoV networks for both autonomously driving intelligent vehicles.

iii. Detailed discussion of current challenges and future research directions that require more investigation to facilitate commercial integration of AI with 5G/6G-supported IoV networks.

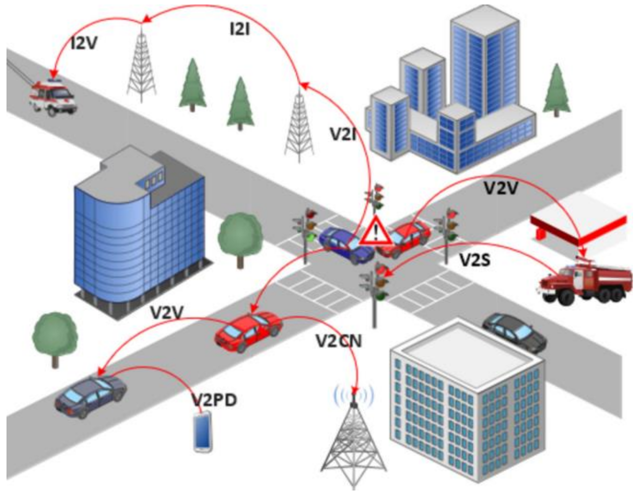

Fig. 1 – Different aspects of wireless communications in IoV environment [5]

2 5G/6G-ENABLED IOV COMMUNICATION NETWORK STRUCTURE

The 5G/6G-enabled IoV communication network is a crucial component of the ITS that supports V2V, V2I, I2V, I2I, V2PD, V2CI, V2X, and NR-V2X communication scenarios for the ITS. As opposed to ordinary IoT communication networks, the V2V and other communication scenarios in the IoV cannot continuously maintain network connection because of the dynamic, high network topology changes and vehicular terminals' high mobility. Although studies have been carried out with the aim of finding solutions to extend vehicular network connection sustainability, there is still a need for further research effort in this area [9]. Adoption of 5G/6G communication technology cannot only extend the communication range of the IoV but also promises to further improve both the vehicular network engineering stability and the overall network connection sustainability of the massive I2V, V2I, I2I and V2X broadcasts in IoV environments. Additionally, application of 5G/6G communication technology in IoV networks can guarantee a stable link and wide bandwidth connection in vehicular networks, and also support the transmission of large-size files [10] across the many IoV communication scenarios.

Unlike conventional Vehicular Ad hoc Networks (VANETs), which is currently based on the IEEE 802.11p protocol, the IoV requires heterogeneous vehicular communication networks [10] through the application of 5G/6G technology to ensure more flexible and wider bandwidth resource, extended communication coverage, and connection stability (see Fig. 2). Several studies have shown the manifold potential of heterogeneous vehicular networks, especially for efficient and improved V2V and V2I communication scenarios [11]-[16]. Yin, et al. [10] proposed a heterogeneous vehicular communication network termed HetVNET, in which the conventional IEEE 802.11p protocol is combined with a Short-range Orthogonal Frequency-Division Multiplexing (OFDM) Wideband Communication (SOWC). Though the benefits of heterogeneous vehicular network in the IoV abounds as mentioned above, these benefits come with a huge cost of a complex network structure, which becomes a challenge to efficient IoV communications. As a solution, several network management and computing technologies, namely Software-Defined Networking (SDN) [32] and edge computing [18] have been introduced in IoV communication scenarios to eliminate the problem of a complex network structure regarding the adoption of heterogeneous vehicular networks in the IoV.

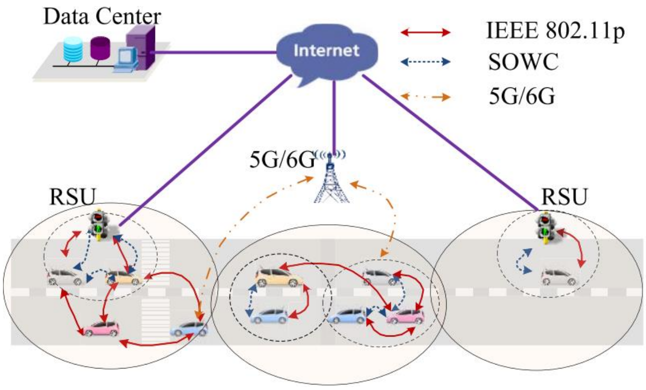

Fig. 2 – 5G/6G-enabled IoV communication network structure [10]

3 ARCHITECTURE OF 5G/6G-ENABLED IOV

The conventional IoV paradigm has a three (3) layer architecture [19]-[20] such as sensory, communication and statistics tools layer based on the intercommunication and cooperation of various technologies involved within the IoV communication network environment. The sensory layer (level 1) of the architecture contains the multi-sensors that make each vehicle an intelligent mobile node and used for gathering environmental data and detection of specific events of interest like road conditions, vehicle situations and driving patterns among others. The communication layer (level 2) provides support for the various vehicular wireless communication scenarios such as V2V, V2I, I2V, I2I, V2PD, V2CI, V2X and NR-V2X communications. Additionally, the seamless connectivity between the emerging and existing networks like Wi-Fi, Bluetooth, LTE, GSM, IEEE802.15.4, IEEE802.11p, among others are supported by the communication layer. Finally, level 3 of the conventional IoV architecture provides support for storage, statistics tools and the corresponding processing infrastructure which forms the IoV intelligence and offers the intelligent vehicles big data-based processing capabilities like content searching, accessing computing resources, available spectrum sharing, etc. Similarly, the third layer is responsible for providing big data storage, processing, analysis, and decision-making with respect to various risk situations associated with safety-related IoV services like dangerous road conditions, traffic congestion among others, and in-vehicle infotainment services. The third layer of the traditional IoV architecture ensures that the different IoV communication modes can make unified decisions supported by the fusion of information generated from various technologies and systems that constitute the IoV, such as vehicular sensor networks, big data, cloud computing, and others.

To further provide additional IoV functionalities, CISCO proposed a four (4) layer-based IoV architecture [21]. The four layers of the architecture are the endpoint (first) layer, infrastructure (second) layer, operation (third) layer, and service (fourth) layer. The first layer covers the software, intelligent mobile vehicles, and the different IoV communication modes through IEEE802.11p, whereas the second layer outlines the different technologies and systems that provide connectivity for various actors of the IoV. Furthermore, the third layer ensures flow-based management and seamless policy enforcement. Finally, the fourth layer defines the services that the different types of cloud computing provide to the intelligent vehicles' drivers based on data centre, subscription or on-demand approach.

Additionally, similar conventional layered IoV architecture was proposed [22]. However, all the proposed traditional layered IoV architectures in [19-22] share common deficiencies in the areas of i) IoV security such as vehicular communication authentication, authorization, accounting, and trust relations; and ii) provision of an IoV architecture layer that can guarantee the integration of vehicular communication intelligence for selecting the best network to transmit and disseminate information or for accessing different services. To address these pinpointed weaknesses of the above-discussed layered IoV architectures, a seven (7)-layered IoV architecture was proposed in [23] which allows seamless connectivity of the different vehicular network components, and provides accounting for the different transactions between the various IoV entities and communication service providers such as WiFi, Direct Short Radio Communication (DSRC) roadside, LTE and 3G, see Fig. 3. In high-mobility vehicular scenarios and dense environments, the DSRC suffers from major deficiencies like limited and poor communication range coverage, unbounded channel access delay, limited QoS guarantees, and low data rate. However, leveraging conventional cellular technologies, 3GPP has been developing a cellular vehicular communications model generally referred to as a Cellular Vehicle to everything (C-V2X) communication network. The C-V2X allows intelligent vehicles to communicate with different entities of a V2X network [71-73]. Although the seven-layered IoV architecture proposed in [23] addressed the weaknesses identified in the IoV architectures proposed in [19-22], it was based on 3G which can hardly support effective vehicular communication in a high mobility-oriented IoV environment. However, the innovative features of 5G/6G will not only address this challenge but can also improve vehicular network communications to satisfy the expanded services' requirements for both safety and infotainment application services in the IoV environment. The envisaged services for a 5G/6G-enabled IoV paradigm are shown in Table 1.

Table 1 – Envisaged services for IoV paradigm

Safety related services	Transport efficiency services	Entertainment/convenience /information services
a) Crash SOS b) Cooperative collision warning c) Cooperative forward-collision warning d) Roadside assistance e) Left turn assistance f) Lane change warning g) Stop sign movement assistance	a) Route guidance and optimization b) Green light efficiency c) Traffic information	a) Content streaming b) Electronic toll collection c) Point of interest notification

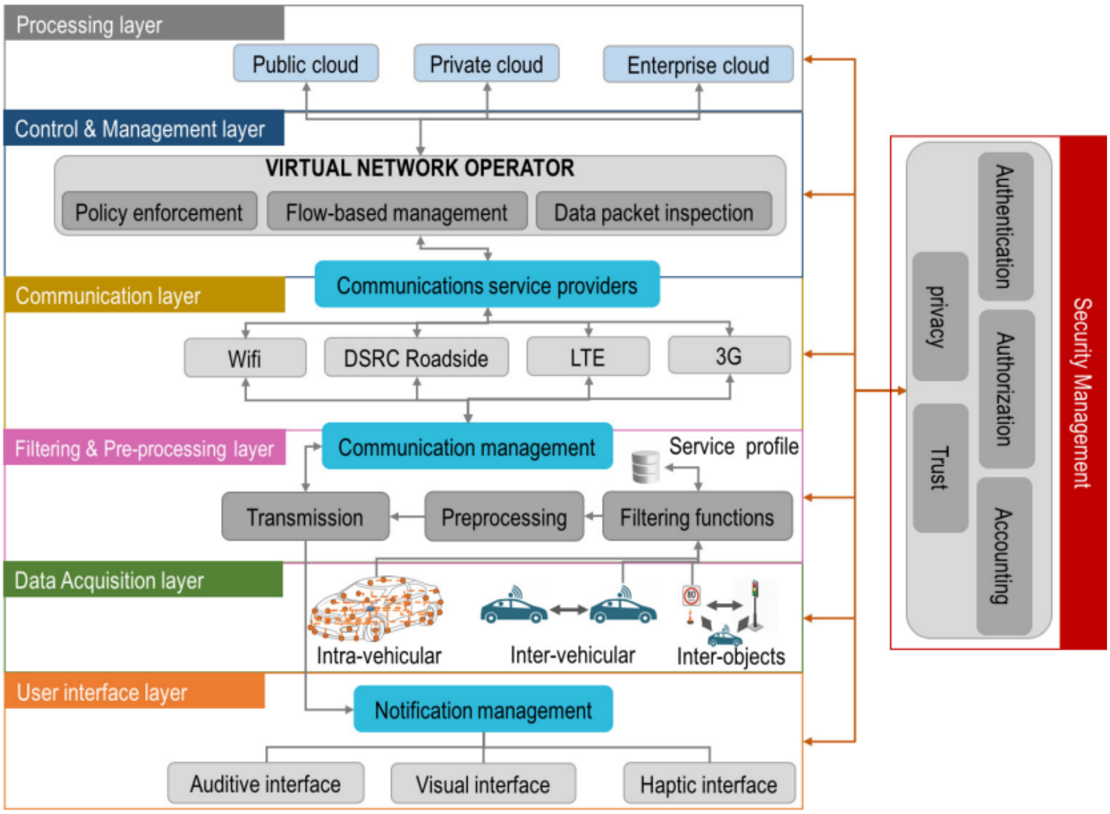

Fig. 3 – Seven (7)-layered IoV architecture proposed in [23] based on [20-22]

4 FUSION OF ML, DL AND SI TECHNIQUES WITH 5G/6G-ENABLED IOV NETWORKS

Over a decade, the conventional VANETs and IoV have remained an active domain of research in academia and industry. Correspondingly, wide-range adoption of AI techniques in different fields, such as intelligent transportation, routing, cybersecurity, health care, medical, robotics, manufacturing, data analytics, engineering, and many others, have been hugely accelerated by the recent advances in computing systems and technologies [24-25]. The emerging 5G/6G-enabled IoV communication networks seek to improve overall road traffic safety and enhance intelligent transport systems efficiency through timely safety and non-safety-related information exchange amongst the smart mobile vehicles, Roadside Units (RSUs), and pedestrians' handheld devices. The support AI techniques such as ML, DL, and SI are discussed in the subsections below with the taxonomy of the AI methods shown in Fig. 4 below.

Similar to 5G/6G-enabled IoV, ML and DL methods are increasingly being applied in several real-life areas in search of improvement and advancement as a result of their computationally efficient algorithms with its associated exceptional problem-solving potential. The application of AI techniques in 5G/6G-enabled IoV promises a great success in the near future due to the availability of big data in vehicular communication networks. Additionally, the adoption of ML and DL in different areas ranging from big data analytics, laboratory exploration, vehicular networks to functional automation have shown significant progress with even more tremendous promises ahead. Furthermore, a concise review of some of the essential AI methods is presented below with emphasis on the identification and discussion of the key applicable areas in 5G/6G-enabled IoV. The following subsections review some of the essential DL, ML and SI techniques, with their key potential identified and main areas of application in 5G/6G-enabled IoV highlighted, as shown in the subsections below.

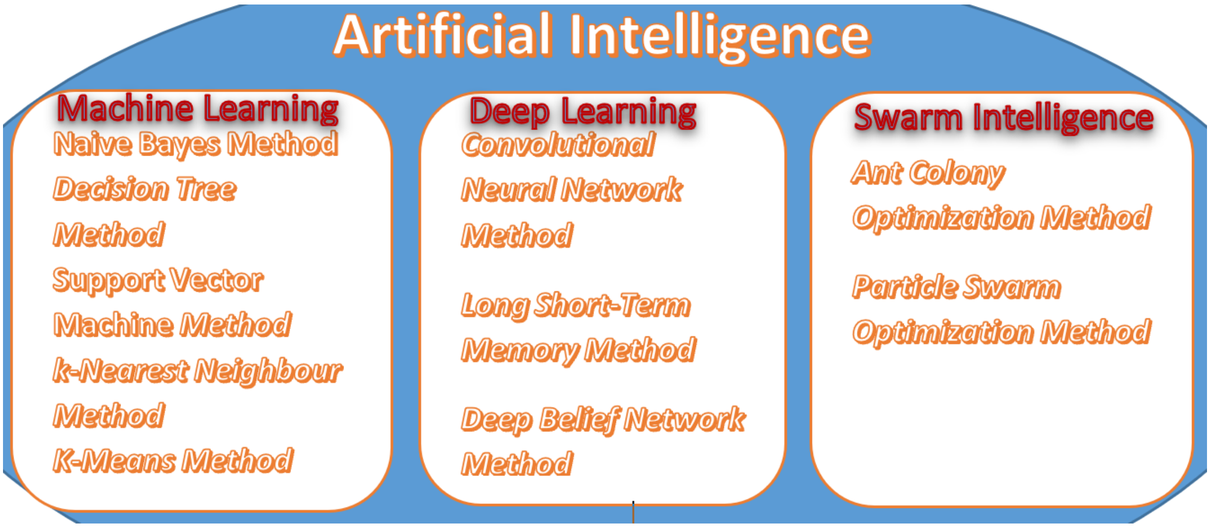

Fig. 4 – The taxonomy of applicable AI methods in 5G/6G-enabled IoV

4.1 Naive Bayesian (NB) method

The Naïve Bayesian (NB) classifier technique is a supervised ML method that performs the classification of a set of observations based on certain predetermined rules by the ML algorithm itself. The working principle of the algorithm is generally based on the assumption that the different categories of the available dataset for training the ML model is known. Consequently, the supervised nature of the Naïve Bayes tool makes it one of the most appropriate techniques for handling different 5G/6G-enabled IoV challenges like packets broadcast storm avoidance, reliable prediction of driver behaviour and misbehaviour awareness [26-27]. This is partly due the simple implementation and training requirements of the algorithm coupled with its robustness in processing irrelevant attributes.

4.2 Decision Tree (DT) method

The DT method is a widely used basic ML classification and prediction mechanism. The popularity and wide applicability of the DT method is largely due to its simplicity. Its mechanism consists of a root station that receives data and the leaf stations. The leaf stations are comparable to a categorization of questions and answers where each of the answers denotes a condition for the subsequent question in the subsequent layer [28-30]. The DT method is a transparent and easy to implement classification and prediction mechanism that can be useful in different 5G/6G-enabled IoV open issues such as intelligent traffic signal management, routing decision, and efficient detection of driver misbehaviour.

4.3 Support Vector Machine (SVM) method

The Support Vector Machine (SVM) techniques also known as Large Margin Separators (LMS) are a category of ML method primarily applied for the forecasting of binary qualitative variable [31]. In the classes of ML techniques, SVM is a supervised learning model with a special learning algorithm usually applied in data analysis for classification purposes as well as regression analysis. The technique was later generalized and defined for the prediction of random independent and identically distributed (i.i.d.) quantitative variables. Furthermore, when it comes to classification of random distichous variables, the process solely relies on identifying the optimal margin hyperplane. Hence, SVM methods are able to correctly classify data while far away from all available observations. Expectedly, the merits of SVM methods rely on their ability to process datasets with a small number of input instances and a vast number of features. With this strength, SVM can be an effective ML technique for cyberattack detection and prevention in 5G/6G-enabled IoV environments and the identification malicious intelligent mobile nodes. Additionally, SVM techniques can be useful in 5G/6G-enabled IoV environments for improving spectral resource allocation and cluster optimization [32-35]. Similarly, Li et al. [36] proposed a vehicular network-based context-aware security framework that applied an SVM algorithm that can automatically differentiate between the normal mobile vehicular stations and malicious vehicular stations, see Fig. 5. The SVM technique has also been applied in conventional VANETs environments for detecting message suppression messages and false message attacks [37]. The authors in [37] proposed a novel scheme comprising of vehicle trust and data trust models where the data trust model adopted the SVM technique for the classification of new messages based on the vehicle attributes and the contents of the messages.

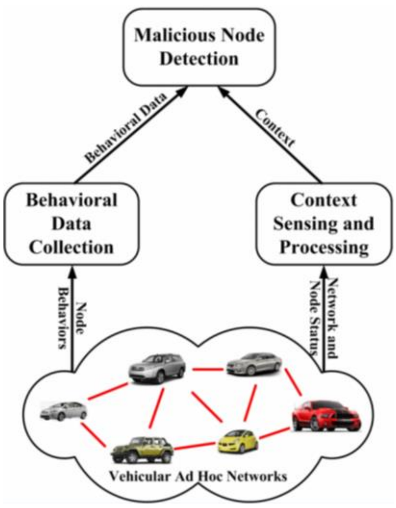

Fig. 5 – SVM based vehicular networks context-aware security framework [36]

4.4 k-Nearest Neighbour (k-NN) method

The k-NN methods belong to a class of supervised ML techniques which are widely applied in both classification, prediction and regression analysis. The k-NN techniques use the complete available dataset to make predictions, and for observations that are not part of the dataset, the k-NN algorithm uses the k instances of the dataset which are nearest to the observations to make predictions [38]. Research has shown that k-NN techniques are efficient with respect to location detection, privacy preservation, intrusion detection and maintaining cluster stability [39], and can be significantly beneficial in a 5G/6G-enabled IoV environment.

4.5 K-Means method

The K-Means methods fall under the category of an unsupervised non-hierarchical ML clustering algorithm. K-Means techniques allow the grouping of observations of the available dataset into K distinct clusters [40-41]. Through the grouping of observations, K-Means techniques ensure that only similar data are located within the same cluster at any given time, that is, exclusive membership of a particular cluster [42-43]. Therefore, dissimilar observations cannot belong to the same cluster, which means that the same observation can never be found in two different clusters. This functionality makes the K-Means technique a useful tool for sensitive information anonymization since labelled data is not required [44]. Consequently, the K-Means ML techniques can be applied for mobile stations congestion detection and is also effective in ensuring clustering stability in a 5G/6G-enabled IoV environment, as well as the application of secured hashing functions for sensitive data transmission.

4.6 Convolutional Neural Network (CNN) method

The CNN, also commonly referred to as ConvNet (see Fig. 6) belongs to a class of DL technique known for low complexity and high scalability [45]. Generally, the DL technique, which has been widely used in diverse areas of research, is a sub-branch of AI whose key goal is to automatically build knowledge and acquire intelligence from the availability of vast amounts of information. The success and potential of a DL technique like CNN have made it popular in several practical application domains. Additionally, CNN is an AI method with high performance efficiency which has made it an effective tool for multimedia data analysis especially with respect to vehicular nodes congestion and intending road accident prediction in 5G/6G-enabled IoV environments. This technique can be mostly helpful with motorway hazard detection, pedestrians and road traffic sign recognition via captured live images. Furthermore, research has shown the applicability of the CNN method for blockchain based cybersecurity solutions through vehicular stations' authenticity, and in 5G/6G resources management via a network slicing approach [46].

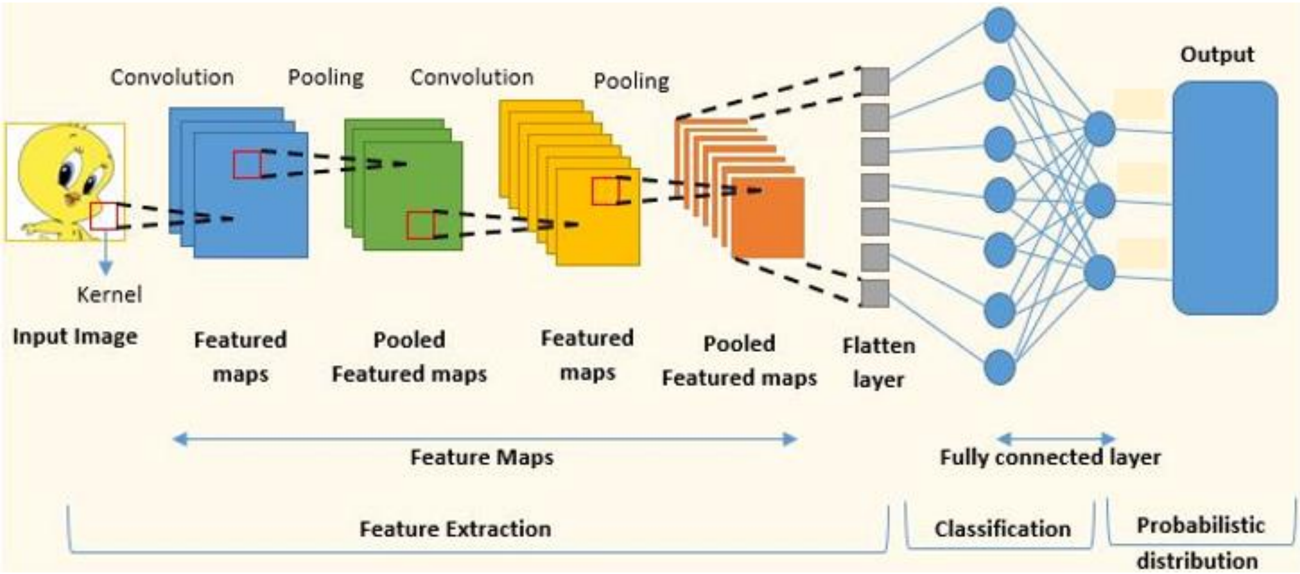

Fig. 6 – Architecture of a typical convolutional neural network

4.7 Long Short Term Memory (LSTM) method

The LSTM techniques are Neural Network (NN) methods belonging to a category of DL technique and generally based on the basic architecture of Recurrent Neural Networks (RNNs). They are a special kind of Recurrent NN (RNN) that have a considerable improvement and which are capable of learning long-term dependencies, hence their advantage compared to other similar artificial neural network algorithms like the Back-propagation Neural Network (BPNN) algorithm, Radial Basis Function Neural Network (RBFNN), Multiple-Layer Perceptron Neural Network (MLPNN), and several others [47]. A typical schematic diagram of a conventional RNN block and deep learning chained LSTM blocks are illustrated by Fig. 7 and Fig. 8, respectively. The previous hidden state is denoted by h_(t-1), the current input sample and current hidden state are represented with X_t and h_t, respectively, the activation tanh function, and current output denoted by h_t.

As shown in Fig. 7, each RNN node generally has the form of a chain repeating units of NNs. The repeating units operate with a very basic structure in typical RNNs such as a single tanh layer only. On the contrary, DL LSTM techniques store information using a set of purpose-built memory cells and maintain a similar chain-like structure with disparate repeating structured units as depicted in Fig. 8. Similarly, Fig. 8 illustrates a DL LSTM unit with four (4) distinct interacting structured layers [53-54]. The formulae presented in equations (1) to (6) demonstrate the calculation processes of the four distinct interacting structured layers in DL LSTM techniques, such as forget gate, input gate, output gate and cell state as depicted in Fig. 8. The equations are as follows:

a) Forget gate equation:

$$F_t = \sigma\left(W_f \times [h_{t-1}, X_t] + b_f\right) \tag{1}$$

where F_t is a vector with values that range from 0 to 1, b_f denotes the bias of the forget gate, W_f represents the weight matrices, and σ represents the logistic sigmoid function. The responsibility of the sigmoid layer is to determine whether new information is relevant for use in updating or irrelevant and discarded. Similarly, the *tanh* function adds weight to every inputted value before deciding their level of importance which usually range from −1 to 1. The same operations are repeated in both the input gate and the output gate as shown below in equations (2) to (5):

b) Input gate equations:

$$I_t = \sigma(W_i \times [h_{t-1}, X_t] + b_i) \tag{2}$$

$$\hat{I}_t = \tanh(W_i \times [h_{t-1}, X_t] + b_i) \tag{3}$$

c) Output gate equations:

$$O_t = \sigma(W_o \times [h_{t-1}, X_t] + b_o) \tag{4}$$

$$h_t = O_t \times \tanh(C_t) \tag{5}$$

d) Cell state equation:

$$C_t = \{(F_t \times C_{t-1}) + (I_t \times \hat{I}_t)\} \quad (6)$$

where W_o and W_i represent the weight matrices, with b_o and b_i representing the DL LSTM neural network's bias vectors of both the input gate and the output gate. *Tanh* denotes the hyperbolic tangent function used by the chained LSTM blocks for adding weights and deciding the importance level of each value.

As opposed to forward propagating DLNN methods, the LSTM technique has feedback connections, which allow it to not only be able to process single data points like images but is also capable of processing complete sequences of data like video or speech datasets. Based on these qualities, research has shown that the performance of DL LSTM techniques improves with increased data availability due to the complex chained structure of the techniques and tend to perform much better with big data availability [55]. The DL LSTM techniques remain one of the most suitable tools for big data processing, classification and prediction. Therefore, in 5G/6G-enabled IoV environments, the DL LSTM technique will be a good candidate for the forecasting of driver (mobility) behaviour, identification of malicious intelligent mobile terminals, detection and prevention of cyberattacks such as intrusion, Blackhole, Sybil, Wormhole and Greyhole attacks. Furthermore, it can be applied for the prediction of intelligent mobile vehicle congestion, efficient detection of intelligent mobile vehicle and road traffic incident locations.

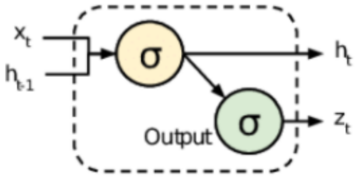

Fig. 7 – Schematic diagram of conventional RNN block

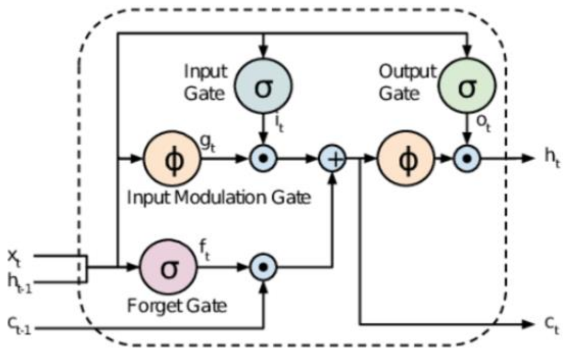

Fig. 8 – Schematic diagram of chained LSTM blocks

4.8 Deep Belief Network (DBN) method

The DBNs are hybrid generative graphical models, which alternatively belong to a category of Deep Neural Networks (DNNs) that consist of multilayers of binary latent variables. The multiple layers do not have connections between units in each layer but usually maintain connections across the multiple layers. The DBN technique as a highly complex generative graphical model applies a deep architecture, see Fig. 9. The key strength of the DBN technique is largely derived from its relatively high depth with respect to the number of hidden layers. This enables the technique to maintain iterative representation of attributes, which makes DBN a suitable tool for providing network security, reliable and high accuracy prediction of intelligent vehicles drivers' emotions and travel time in 5G/6G-enabled IoV environments. Additionally, study has shown that up to 51% of blockchain attacks in emerging vehicular networks can be prevented with the aid of DBN techniques with regards to the reduction of the delivery time of intelligent vehicular packet transmissions and blockchain puzzle computation time, as well as in the identification of trusted and malicious intelligent mobile stations [48].

Furthermore, the study conducted in [49] has shown that DL techniques can be effectively adopted in ITS for vehicular road traffic management, efficient resource allocation, transmission channel access optimization, and efficient relay nodes selection for multipoint routing due to their ability to train 5G/6G-enabled IoV networks in line with the previously acquired data. Secondly, the knowledge acquired from previous motorway road scenarios can be employed to adjust new classifications or the selection of optimal network parameters. The DBN technique cannot only be useful in prediction of the intelligent mobile vehicle's trajectory but can also help in reducing packet transmission latency in 5G/6G-enabled IoV networks. Moreover, the overall reduction in the packet transmission delay will, in turn, result in improved infotainment application performance through an increased rate of data delivery in the network.

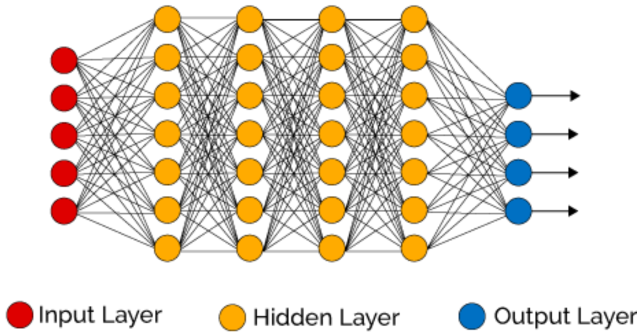

Fig. 9 – A typical architecture of a DBN

4.9 Ant Colony Optimization (ACO) method

The ACO technique belongs to a class of SI, which aims to find near optimal solutions to different problems through a graph optimization approach. In solving difficult optimization problems, ACO techniques usually apply population-based meta-heuristics in finding the near optimal solutions. In other words, the artificial ants in ACO techniques generally tend to follow shortest available paths to their destinations [50]. The ACO technique as a subclass of SI, is mainly characterized as a collective conduct of distributed and autonomous intelligent systems, which in the context of the 5G/6G-enabled IoV paradigm can be represented by a population of intelligent mobile vehicle entities in communication with one another as well as their surroundings. Ordinarily, vehicles adhere to basic road traffic guidelines like the streetlights, maximum allowed speed, and road architecture for their trajectory in the absence of central controllers. Hence, with the aid of ACO techniques, intelligent mobile vehicles can adapt the behaviour of artificial ant colonies to avoid motorway traffic congestion, and detection of malicious intelligent mobile vehicles. Similarly, in 5G/6G-enabled IoV environments, ACO techniques can also help intelligent mobile vehicles in finding near optimal solutions of high quality to challenges of road traffic congestion by combining the exploitation of natural intelligence with shortest paths' discovery and vehicular clustering.

4.10 Particle Swarm Optimization (PSO) method

The PSO technique is a stochastic global optimization method based on the intelligence and movement of swarms. It belongs to a class of SI that solves problems by adopting the concept of social interaction between particles (or artificial agents) which constitutes swarm movement around a particular search space. In other words, the PSO technique applies a stochastic global optimization approach to address problems where a solution can be obtained as a whole surface within an n-dimensional space or a single point. Generally, PSO algorithms ensure that each particle's (or artificial agent's) movement is towards a new position depending on the speed of the artificial agent if the new position is better than the previous one or chooses out of the list of best previously known positions. Then, disparate feasible solutions are plotted within the solution space by applying the initial particle's speed as an input [51-52]. Consequently, with the aid of certain fitness parameters, the artificial agents maintain their movement within that solution space and over time, will progress towards the positions with more excellent fitness attributes. In 5G/6G-enabled IoV environments, the PSO techniques cannot only help in overall network routing optimization but can be used for prevention of routing attacks. The summary of all the discussed AI methods and their application areas in 5G/6G-enabled IoV are presented in Table 2.

Table 2 – Summary of AI methods and their application areas in 5G/6G-enabled IoV

AI methods	Application areas to 5G/6G-enabled IoV
Naive Bayesian method	To improve driver behaviour prediction (mobility) To avoid the broadcast storm in IoV and excessive collisions To detect misbehaving vehicular nodes in IoV
Decision Tree method	To improve routing decision For traffic signal management To detect misbehaviour of malicious intelligent vehicles
Support Vector Machine method	Can be used for the detection and prevention of vehicle misbehaviour, intrusion, Sybil, Greyhole, Blackhole and Wormhole attacks in IoV environments To identify malicious nodes For vehicular nodes' clustering optimization To improve IoV spectrum allocation decision
k-Nearest Neighbour method	For intrusion detection to identify when and how many successful internal intrusion attempts occur To protect privacy, for instance, driver's information and IoV messages exchanged between the intelligent vehicles To maintain stable clusters for IoV cluster-based techniques For intelligent vehicle and incident location detection
K-Means method	Can be used for the anonymization of intelligent vehicle and driver-sensitive information To improve clustering stability for cluster-based IoV techniques Can be used in developing hashing functions for securing vehicular communications For early detection of road congestion
Convolutional Neural Network method	To analyse the multimedia data collected from roadside units or the intelligent vehicle's controlling camera Can be used for accident prediction based on video analysis Can be used for 5G/6G resource management Can be utilized for blockchain-based security
Long Short-Term Memory method	To predict road traffic for improved routing decision To examine and extract time-related features from traffic history for detecting intrusive activities To predict the geographical future position of intelligent vehicles to reduce road congestion
Deep Belief Network method	To secure 5G/6G IoV For the prediction of driver emotions To predict travelling time
Ant Colony Optimization method	For detection of malicious intelligent vehicles (nodes)
Particle Swarm Optimization method	For the optimization of routing protocols

5 FUTURE CHALLENGES AND RESEARCH DIRECTIONS

Different conditions for the adoption of AI techniques in 5G/6G-enabled IoV environments are discussed in this section with respect to the type of challenges that must be resolved to ensure effective deployment such as implementation complexity, time cost, training data, and the differences between several AI approaches. Prior to deciding whether AI should be deployed in 5G/6G-enabled IoV environments, and the types of AI techniques to employ, certain conditions and requirements need be individually researched and thoroughly investigated.

5.1 Challenges associated with 5G/6G-enabled IoV networks

Although some areas of IoV networking such as handover procedures and routing have received significant research effort, advances in other vital areas such as decision-making for 5G/6G-enabled IoV communication network forming and deforming are yet to get sufficient attention from research communities. Several studies on bio-inspired routing algorithms for vehicular networks have been surveyed by Bitam et al [52] where bio-inspired methods have been combined AI techniques to optimize network routing decisions. But one of the major challenges is the fact that the moving speed of nodes in IoV networks is usually higher compared to conventional mobile networks, which further restrains the amount of time required for networks forming and validation. Therefore, future research efforts on application of AI techniques on 5G/6G-enabled IoV environments should focus more on achieving stable network connectivity in IoV communication networks. Similarly, the study conducted by Aljeri and Boukerche [57] has investigated mobility management issues in 5G-enabled vehicular networks focusing on applicable models, protocols, and classification. The vehicular HetNets developed in [57] introduced multiple access technologies for intelligent mobile nodes, RSUs, and Base Stations (BSs) with differentiated services that fit various application requirements and maintain disparate road traffic loads within a specific vehicular environment. Similar ML techniques which have been applied in different recommendation systems can be employed in 5G/6G-enabled IoV environments to learn individual intelligent mobile vehicle behaviour and IoV network traffic loads to identify and make recommendations for suitable networks. Currently, these areas of ML adoption have not received significant attention [58]. Additionally, as shown in [59-61] addressing existing wireless network problems of the IoV concept like inefficiency of spectral resources and the network complexity issue require more research attention to be focussed on combining AI techniques with 5G/6G development roadmaps which already provide a good range of enabling technologies such as software-defined networks, mobile edge/fog computing, network slicing, and network function virtualization. Therefore, in 5G/6G-enabled IoV environments, the application of ML techniques to leverage the benefits of mobile edge/fog computing and network function virtualization to address high network dynamics challenges, and improving latency requires specific attention from both research communities and industrial partners. Although, recent studies in VANETs [62-63] have adopted mobile edge/fog computing and network function virtualization technologies to address these open issues, most of the research did not investigate the adoption of AI techniques.

5.2 Challenges associated with AI support in 5G/6G-enabled IoV networks

All the AI methods discussed in the sections above have many advantages and can be applied to resolving the myriad of issues facing successful development of 5G/6G-enabled IoV networks. However, there are still many challenges that require specific research attention to ensure seamless adoption of AI in 5G/6G-enabled IoV environments. For instance, although the SVM techniques provide many promising directions for 5G/6G-enabled IoV networks, they still face serious bottlenecks due to high SVM models complexity and the choice of kernel optimization. Similarly, the adoption of NB techniques in 5G/6G-enabled IoV networks have their limitations in terms of the NB techniques' specifications which range from the assumption that the existence of a given characteristic in a class is completely different to the existence of any other characteristic to the "Zero frequency" case. Therefore, NB techniques need to individually treat the features and cannot extract useful details from the correlations among its specifications [64]. However, NB techniques can perform correctly in application areas where samples have similar and correlated features. The k-NN techniques can address certain challenges facing 5G/6G-enabled IoV networks but it is worth mentioning that the major limitation of applying this branch of AI in IoV environments is linked to the highly complex and time-consuming process of finding the optimum k value, which normally differs from one dataset to another [65]. It is also useful to note that although the K-Means ML technique can be effective for smart autonomous vehicles' congestion detection, guarantees clustering stability in a 5G/6G-enabled IoV environment and offers secured hashing functions for sensitive data transmission, using these AI techniques is less efficient in comparison with other supervised learning-based AI techniques.

Despite the many promising benefits of applying CNN techniques in 5G/6G-enabled IoV networks, research efforts must focus on how to overcome the high computation overheads associated with these AI techniques. The issue of high computation overheads makes it rather challenging to adopt CNN techniques in a resource-constrained domain like IoV networks, given the amount of vehicular processing and network communications involved. With the DL LSTM technique, there is an inherent weakness of increasing high complexity occurrence with the introduction of additional features to resolving the vanishing gradient issue associated with RNN blocks [66]. Therefore, specific research attention must be paid to this challenge before applying the DL LSTM technique to critical and delay sensitive 5G/6G-enabled IoV networks. Moreover, the DL LSTM technique not only demands higher memory bandwidth but can also often be impaired by the problem of model overfitting. In the case of the DBN technique, the key drawback to its adoption in 5G/6G-enabled IoV networks emanates from its long initialization process because of the considerable number of variables usually processed at the initialization stage.

Generally, the cooperation and communication approach demonstrated by intelligent mobile vehicles in 5G/6G-enabled IoV networks can be easily modelled through swarm behaviour based on bio-inspired methods [52, 67-68]. Furthermore, the application of different SI methods in 5G/6G-enabled IoV networks can provide solutions to various open issues like network scalability, routing, high complexity of safety and non-safety related packets exchanged, as well as minimizing resource requirements. However, application of SI techniques in 5G/6G-enabled IoV environments cannot be successful unless adequate research attention is paid to the unique vehicular network characteristics ranging from the large scale of IoV communication networks and their attendant highly dynamic network topology.

5.3 Interpretability and trust issues for AI in 5G/6G-enabled IoV networks

Humans cannot directly interpret outputs generated by the current decision-making procedures used by DL algorithms, a term generally referred to as the rising blackbox problem [69] for high complex AI techniques, and this can no doubt create risk for security and safety-related services. This may cause trust issues with respect to legal liability and verification confusion at the occurrence of road accidents. Currently, this is another key challenge facing the adoption of AI in 5G/6G-enabled IoV environments. As the application of AI techniques in IoV networks has received some research interest, it has become even more vital to add interpretability to the systems in order to ensure that IoV network operators and the intelligent vehicle drivers understand the overall system behaviour, and introduce possible user-based control, improved performance and justification [69]. Therefore, specific research effort should focus on developing interpretable DL techniques-based systems for 5G/6G-enabled IoV environments to provide the premise for a legal setting with clear interpretability and non-reputability in support of legal judgement when accidents take place. Wang et al [70] conducted a recent study on CNN technique hidden-layer neuron activity visualization system called CNN Explainer, a demonstration of a promising interactive visualization tool designed for supporting non-experts in learning, understanding and examining the deep learning architecture and procedures of CNN. The developed system thoroughly integrates a general overview that summarizes CNN techniques' structure, and dynamic visual explanation, on-demand views that enable non-experts in the AI field to understand and analyse the underlying components of CNN techniques. CNN Explainer helps non-experts to inspect the interplay that exists between low-level mathematical operations and the high-level CNN technique model structures using smooth transitions across different levels of abstraction. A qualitative non-experts' investigation showed that the developed AI-based system enables users to more easily learn, understand and examine the inner workings of CNN techniques. From the point of future research direction, the study in [70] can be a useful example for related research to further improve the interpretability of similar AI-based techniques and help to resolve the potential trust and liability issues regarding application of AI in 5G/6G-enabled IoV networks.

6 CONCLUSION

This paper offers a detailed overview of AI techniques including DL, ML and SI methods' support for 5G/6G-enabled IoV network applications. The study provides a promising solution to the several challenges facing the adoption of AI in 5G/6G-enabled IoV environments. The deployment of AI methods has helped in resolving some of the existing underperformance issues associated with conventional wireless network solutions as a result of high dynamics of heterogeneous communication categories coupled with the disparate Quality of Service (QoS) requirements of IoV communication networks. Notwithstanding the above, it is clear that existing literature has not contributed sufficient research attention to decision-making with respect to how

5G/6G-enabled IoV networks are formed and deformed, although this is an aspect that largely affects vehicular network connectivity and validity. Finally, full adoption of AI in 5G/6G-enabled IoV networks must be preceded by the standardization of research datasets, significant research efforts towards related simulations and testbeds, and the interpretability of relevant AI techniques to provide the necessary premises for legal judgement to resolve any potential trust and liability issues that may stem from the application of AI in 5G/6G-enabled IoV networks.

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