

The Reputation of Machine Learning in Wireless Sensor Networks and Vehicular Ad Hoc Networks

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ABSTRACT

It's difficult to deal with the dynamic nature of VANETs and WSNs in a way that makes sense. Machine learning (ML) is a preferred method for dealing with this kind of dynamicity. It is possible to define machine learning (ML) as a way of dealing with heterogeneous data in order to get the most out of a network without involving humans in the process or teaching it anything. Several techniques for WSN and VANETs based on ML are covered in this study, which provides a fast overview of the main ML ideas. Open difficulties and challenges in quickly changing networks, as well as diverse algorithms in relation to ML models and methodologies are also covered in the following sections. We've provided a list of some of the most popular machine learning (ML) approaches for you to consider. As a starting point for further research, this article provides an overview of the various ML techniques and their difficulties. The comparative examination of current state-of-the-art ML applications in WSN and VANETs in this paper is outstanding.

Key words: Business intelligence (BI), Intelligent Systems (IS), VANETs, Wireless Sensor Networks (WSN), Machine Learning (ML), Taxonomy

INTRODUCTION

Wireless sensor networks (WSN) count on on the collection of data and the transmission of that data to base stations for further processing. Insufficient quality of service (QoS), brittle vehicle-to-infrastructure and connection (V2I), channel access latency, congestion, and data packet loss are just a few of the issues that WSN solutions must contend with. Many concerns are raised by the complexity and quick change of these challenges, which necessitates a significant amount of effort to solve their constraints. The 3GPP (3rd Generation Partnership Project) has taken the initiative to investigate how to assist V2X vehicle-to-everything services in the next 5G cellular systems and the long-term evolution network LTE (Long-Term Evolution Network) networks. In addition, graph-theoretic tools, as well as numerous effective protocols, are being developed for resource management in automotive technology. Machine learning is establishing its roots in the advancement of 5G, LTE, and other associated advanced technologies, enabling them to deliver desired and more effective results more efficiently.

Meanwhile, a wide range of sensors are being integrated into intelligent cars to assist them in completing a number

of jobs as well as collecting data from the surrounding environment and monitoring intended operations in real time, among other things. These sensing techniques are transforming automobiles into intelligent computing systems capable of data processing and networking functions from a simple transportation facility, thanks to these advances. Varied purpose networks (VANETs) regard all nodes to be self-sufficient systems that are capable of conducting specialized activities without the assistance of any preceding data. VANET requires an Access Point (AP) in order to be able to connect to the network in general. The vehicle serves as the nerve center of the transportation system. V2V distance, functional ratio, and V2I access point are all determined by the VANET protocol. For speech/image evaluation and data communications between V2V and V2I, Artificial Intelligence (AI) techniques have been introduced into VANETs. AI is successfully overcoming the various limitations and challenges associated with VANETs. AI is successfully overcoming the various limitations and challenges associated with VANETs. Furthermore, the success of pattern recognition techniques connected to machine learning (ML) is a determinant of the success of



data-driven approaches. These tools are now focused on the backpropagation of the Expectation-Maximization (EM) algorithm, Q-learning, and adaptive learning rate schedules, among other things. A great deal of attention has been focused on machine learning and deep learning (DL) in recent years as a result of their outstanding performance in Intelligent Systems (IS) to work in real-time and complex environments. There have been a large number of successful and effective applications for classification and dealing with robotics.

WSN and VANETs are briefly discussed in this work, as well as other essential topics in machine learning that are briefly discussed. In this review, we will look at some ML and WSN applications. This paper has examined and highlighted various open research topics and limits associated with machine learning (ML) in VANETS and WSNs. ML algorithms and their mapping to various WSN and VANET approaches and models form the basis of Section V of this document.

LITERATURE REVIEW

Data-generating, communication, and data-sharing in vehicular networks are all made possible by machine learning (Madding et al., 2020), which provides useful tools for WSNs and VANETs. It also assists the network in making data-driven judgments that are well-informed. There are four types of machine learning methodologies (Adusumalli, 2018), which are supervised learning (SL), semi-supervised learning (SSL), unsupervised learning (UL), and reinforcement learning (RL). Supervised Learning (SL) is used in applications that are supported by a sufficient amount of pre-established datasets as well as other information, such as channel decoding and email spam classification, to name a few examples. Additionally, classification and regression can be used to characterize the data. In regression, labels are numerical, whereas in classification, labels are categorical. Other techniques mentioned are k-nearest neighbours (KNN), Neural Networks, Bayesian classifier, Support Vector Machine (SVM), and decision trees, amongst other things (Adusumalli, 2019).

Unsupervised Learning (UL) is a type of machine learning that works exclusively with unlabeled data having inputs, i.e. data that has no assigned output. Clustering is a term used in supervised learning to refer to the process of grouping samples. The same clusters were clustered together with more links than the samples in the other clusters were grouped together (Fadziso et al., 2018). Hierarchical clustering, spectrum clustering, and k-means are all examples of standard clustering techniques.

Reinforcement learning (RL) is applied to problems involving sequential decision making in which the learner connects with the environment by sequentially taking measures (outputs) on the source of its interpretations (inputs) and then receiving feedback related to each

selected action. Reinforcement learning (RL) is a type of machine learning in which the learner learns by doing (Rahman et al., 2019). These algorithms are used in a variety of applications, including robotics, route finding, and gaming. Using Semi-Supervised Learning, it is possible to work with both unlabeled and labelled data, and it is important to do clustering with both types of data. It is advantageous for dimensionality reduction with labeled data and regression with unlabeled data, for example (Pasupuleti, 2017). For real-time applications such as natural language processing, SSL is a good choice. Moreover, wireless sensor networks (WSNs) are employing SSL for the learning process to handle difficulties such as failure detection and localization technique.

Deep learning works by learning data representations from both supervised and unsupervised data sets (supervised and unsupervised). Reinforcement learning has made significant advancements in a variety of machine learning tasks that can be used to WSNs and VANETs. Machine learning techniques are employed in a variety of applications, including traffic resource routing, vehicle-to-vehicle communication, gaming, and speech recognition, among others. For action space and a larger state, the Q learning algorithm is used in conjunction with the Q learning algorithm. With reinforcement learning, complex deep reinforcement learning is used (Adusumalli, 2021; Pasupuleti, 2018).

An explanation of four major machine learning categories with their subtypes, classification, and associated methodologies and applications is provided in the form of a taxonomy for machine learning approaches (Miah et al., 2021). This study is devoted to providing a thorough explanation of all of the categories and classification. However, just a handful of these are taken into consideration for discussion in the following parts (Pasupuleti, 2020). WSN and VANETs are discussed in detail in this study, including open research problems and the mapping of machine learning algorithms on WSNs and VANETs.

MACHINE LEARNING APPLICATIONS FOR WSN AND VEHICULAR NETWORKS

The vast amount of data generated and accumulated in the vehicular network makes data-driven solutions suitable for decision making and network dynamicity. Machine learning is a powerful method for securing massive data sets in WSNs and VANETs. Here are some ML applications in WSNs and VANETs.

NetSecurity: In the pre-processing stage of the intrusion detection system, deep neural networks are used to set the parameters. Using these methods, the network can detect and recognize abnormalities with great precision. It also predicts the next word from each car.

Predicting Vehicle Path: Machine learning is helping advanced driving assistance systems (ADAS) avoid accidents and collisions. It is also used in link scheduling, vehicle routing, and handoff control protocols. Moreover, utilizing variation GMM and Gaussian mixture models (GMM), probabilistic trajectory prediction can estimate the vehicle's direction.

Estimation Accuracy: Finding accuracy in today's wireless communications networks is difficult. Vehicle networks have quickly changing topology, short channel contacts, and large Doppler shifts. The accuracy of wireless channels is determined by time and frequency domain correlational time, multipath delay spread, and vehicle speed position. These data can be used to create a dynamic database to store the values of communication channels. Deep learning and Bayesian learning are useful ML methods for data prediction, channel accuracy, and more reliable channel estimates for existing vehicular links.

Predicting traffic flow: VANETs have constantly changing traffic conditions. ML work for real-time traffic data and sensor data. Machine learning is effective at predicting traffic performance and responding in real-time. This approach uses stacked auto encoders to learn general features from changing traffic flow. Training is also done in a greedy layer-wise way.

Load Balancing WSN: Due to the frequency of WSN data, the network must manage various patterns and transitions. In this case, learning-based approaches for WSN load balancing can be a good alternative. User organization with load balancing is already developed online.

Location and Scheduling Routing: Placement and timing Routing ML ensured expected dynamics for networking protocol architectures. The HMM predicts the vehicle's future locations based on past mobility data and VANET mobility using V2I and V2V links.

Decongestion: WSN and VANET congestion is a major issue. This issue is exacerbated by network density, e.g. in congested urban areas. When a large number of cars try to access the same communication channel, it generates data collision, packet loss, and bottleneck circumstances. Using k-means clustering, ML can effectively control data congestion.

Wireless Management: The difficulty is in forming appropriate heterogeneous wireless and vehicular links. Reinforcement learning interacts with the dynamic environment to maximize successful signaling ratio.

Routing Methods: The difficulty originates from the necessity for multiple routing approaches. VANETs are subject to random and rapid change. It is still challenging to create a design or model that works in all contexts. Despite huge efforts to meet WSN and VANET environmental standards, a uniform strategy to routing remains lacking.

OPEN RESEARCH CHALLENGES

Due to its distinct nature, Machine Learning has made significant progress in WSN and VANET. The existing ML techniques can now be used in vehicle networks. Finding a suitable ML approach for a task is difficult, the open issues are:

Placement: However, real-time applications necessitate three-dimensional localization techniques. Improved localization algorithms are required for mobile/static VANETs and WSNs.

Security Issues: Machine learning helps against cyber-attacks, which undermine VANET security. Because ML-based schemes can produce unexpected outcomes, they are not secure. While ML has made great strides in WSN, much more work is needed to improve the security and robustness of ML-based algorithms.

Difficulty: Conventional ML methodologies and techniques necessitate feature design effort. Deep neural networks, on the other hand, generate best results by acquiring characteristics directly from raw input. Thus, compared to other methods, deep neural networks may be more effective. So, few models should be built to relieve the computation resource constraint.

Coverage and Connection: In WSN applications, sensor node deployment is unexpected, resulting in network coverage gaps. Finding the coverage gap is tricky.

Error Detection: Anomaly detection is an application-specific approach. Many ML-based algorithms exist to detect anomalies, making it difficult to select one for heterogeneous wireless sensor networks. So choosing anomaly detection strategies for heterogeneous WSNs is difficult. Actions for anomaly detection require more investigation.

Avoiding Congestion: Because VANETs and WSNs have limited energy and memory, a simple congestion control mechanism is necessary at each node to minimize transmission delays. To avoid congestion in VANETs, better traffic assessment protocols are needed to categorize rapidly changing route circumstances.

QoS: WSN QoS seeks to meet user and application needs. Its standards vary depending on the application and requirements. Thus, defining QoS criteria for various requirements is problematic.

High Energy & Computer Need: Machine Learning applications require a lot of computational power to run complicated models and approaches. High mobility nodes and traffic in WSN and VANETs necessitate high energy consumption. To fulfill high energy demands, WSN and VANETs require lightweight and energy-efficient ML models.

ML ALGORITHMS MAPPING ON VARIOUS WSN AND VANETS TECHNIQUES AND MODELS

Supervised Learning

Supervised learning uses machine learning techniques like SVM, Naive Bayes, and K-Nearest Neighbours to analyze WSN and VANET systems. Machine learning-based solutions improve WSN and VANET safety, dependability, and efficiency.

SVM (SVM): SVM is a statistical learning model. It is a machine learning approach for classification that minimizes empirical error. Surprisingly, SVM minimized the structural dangers of over-learning with. For connectivity and coverage, there is the SVM-based localization technique and the Naive convex hull algorithm (Pasupuleti et al. 2019). For secure routing, there is another SVM classification method and an Efficient SV based clustering protocol. SVM is the best choice for VANET malware detection.

Bayesian: The Bayes theorem uses elementary probability theory to predict traffic crashes and collisions. For example, the three-level hierarchical prior model and the NBC Naive Bayes classifier are frequently used Connectivity and Coverage Techniques. There is also a Bayesian network model based sensor defect detection technique and a Nave Base Cluster Head Node.

K-neighbors (KNN): KNN work well for classification and regression problems. Their interpretation is simple and saves time. KNN is employed in K-NN based intrusion detection systems. Anomaly detection (KNN-based AD) and data aggregation Bovel (NN) imputation method are important (Pasupuleti & Adusumalli, 2018).

Random Wood: Classification is a big aspect of Machine Learning. Classification of observations and predictions is critical in VANET and WSN applications. The Random Forest classifier is important because it can intelligently analyze clusters (crowds). Massive traffic bottlenecks and busy roads are better dealt with random forest.

DSA: Discriminant analysis can reduce dimensionality and classify data. Discriminant analysis is the best method for detecting vehicle communication intrusion. It plays an important part in secure communication because to its quick detection of harmful vehicles. The Intelligent Intrusion Detection Scheme employs Discriminant Analysis to detect DoS and black hole attacks on VANETS (Williams, 2018).

Neural Nets: Using radial basis neural networks, it is feasible to identify malicious nodes by displaying anomalous behavior. Neural networks also assist drivers operate their vehicles intelligently and detect accidents and obstructions.

Trees: Decision Trees help analyze road structure, traffic conditions, and flows, reducing time delays, congestion,

and reporting potential collision situations. The fuzzy detection tree model is utilized for traffic signal optimization.

DL: Deep learning is revolutionizing WSN and VANET intrusion detection systems. Deep learning-based distributed technique is widely adopted to suppress inter-vehicle attacks and malicious nodes detection. DNN-based distributed data mining and IP-based node degree of WC are further fault detection and routing techniques.

Unsupervised Learning

Unsupervised learning in WSNs and VANETS is presenting an algorithm that can categorize networks into groups based on their characteristics (clusters). Unsupervised clustering is more suited since it allows you to compare different cluster formations without having to resort to supervised clustering. This element increases the reliability of VANETS and the ease with which they may be maintained (Pasupuleti & Amin, 2018).

Hidden Markov Model (also known as HMM): The Hidden Markov Model is useful in modeling complex end-to-end vehicular and network relationships in situations when nodes/vehicles are changing often and in unpredictable ways. The PRHMM (Predictive Routing based on Hidden Markov Model) Hidden Markov Model is one example of this type of model, which is particularly focused on the communications between vehicles and between vehicles and infrastructure, and which is influenced by the density of vehicles and the speed of vehicles.

Hierarchical and Gaussian Mixtures: The importance of hierarchical and Gaussian mixtures can be attributed to their tractable analytical features. It makes it possible to communicate smoothly in a distributed environment. They make direct and indirect contributions to applications for smart cities that are based on Intelligent Transportation Systems (ITS). One such example is cooperative positioning with GPS assistance in wireless sensor networks and virtual area networks (Williams, 2020).

The SVD, the ICA, and the PCA: In VANETS and WSNs, machine learning approaches such as Singular Value Decomposition (SVD), Independent Component Analysis (ICA), and Principal Component Analysis (PCA) are proving to be useful.

Reinforcement Learning

Reinforcement Learning is crucial in the selection of authentication nodes and settings in order to reduce application learning time while simultaneously improving performance and reducing costs.

Q-learning: Q-learning is a type of learning in which questions are asked and answers are given. Q-learning is useful in traffic-aware routing models since it allows for faster response times. Q-learning has experimented with

high dynamicity and complicated network architectures in order to improve its performance. QTAR (Q-learning-based Traffic-Aware Routing) is a routing protocol that uses dynamic selection for packets being sent between different nodes and vehicles. QTAR is a subset of QTAR. Q-learning has successfully overcome the unicast problem across WSNs and VANETs by the use of targeted neighbour intersections, as demonstrated in the video below.

Markov Decision Process: The second method is the Markov Decision Process. By utilizing Q-learning, the Markov Decision Process (MDP) assists in the formulation of basic assumptions for the resolution of complicated network connectivity difficulties. Using MDP-based transmission regulations, such as Rate and Power (MDPRP), network congestion can be avoided by maximizing channel use while also ensuring secure performance for safety-critical applications.

CONCLUSION

All in all, we have discussed the fundamentals of machine learning in a concise manner and highlighted the ML-based problems, constraints, and unresolved concerns that exist for WSNs and VANETs in this work. We also talked about the latest breakthroughs in machine learning (ML) for tracking the dynamics of vehicular surroundings, as well as wireless sensor networks (WSN). Different machine learning algorithms are mapped onto some unresolved challenges that require a great deal of attention based on their level of complexity. Despite the fact that research in this field is still in its early stages, we have attempted to map existing information in order to explore new vistas of possibilities. Many of the challenges associated with the research gap have yet to be studied and will be fully defined in the future. Through the explanation and examples provided above, we can conclude that Machine Learning is successfully giving solutions to many technical challenges linked to WSNs and VANETs that were previously regarded to be difficult to do in the past.

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