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5G Vehicular Network Resource Management for Improving Radio Access Through Machine Learning

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ABSTRACT The current cellular technology and vehicular networks cannot satisfy the mighty strides of vehicular network demands. Resource management has become a complex and challenging objective to gain expected outcomes in a vehicular environment. The 5G cellular network promises to provide ultra-high-speed, reduced delay, and reliable communications. The development of new technologies such as the network function virtualization (NFV) and software defined networking (SDN) are critical enabling technologies leveraging 5G. The SDN-based 5G network can provide an excellent platform for autonomous vehicles because SDN offers open programmability and flexibility for new services incorporation. This separation of control and data planes enables centralized and efficient management of resources in a very optimized and secure manner by having a global overview of the whole network. The SDN also provides flexibility in communication administration and resource management, which are of critical importance when considering the ad-hoc nature of vehicular network infrastructures, in terms of safety, privacy, and security, in vehicular network environments. In addition, it promises the overall improved performance. In this paper, we propose a flow-based policy framework on the basis of two tiers virtualization for vehicular networks using SDNs. The vehicle to vehicle (V2V) communication is quite possible with wireless virtualization where different radio resources are allocated to V2V communications based on the flow classification, i.e., safety-related flow or non-safety flows, and the controller is responsible for managing the overall vehicular environment and V2X communications. The motivation behind this study is to implement a machine learning-enabled architecture to cater the sophisticated demands of modern vehicular Internet infrastructures. The inclination towards robust communications in 5G-enabled networks has made it somewhat tricky to manage network slicing efficiently. This paper also presents a proof of concept for leveraging machine learning-enabled resource classification and management through experimental evaluation of special-purpose testbed established in custom mininet setup. Furthermore, the results have been evaluated using Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Deep Neural Network (DNN). While concluding the paper, it is shown that the LSTM has outperformed the rest of classification techniques with promising results.

INDEX TERMS Future internet architectures, machine learning, network reliability, privacy, resource management, security, software defined networks, vehicular networks.

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I. INTRODUCTION

Substantial technological improvements lead to a pervasive growth of smart things enabling communications among

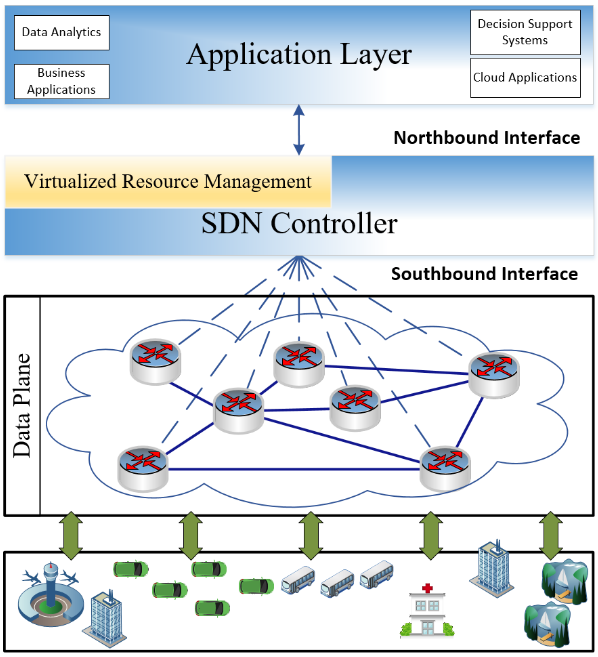


FIGURE 1. **SDN architecture depicting various components and their respective roles.**

entities from mobile devices to fast speed vehicles envisioned in smart cities [1], [2]. The intercommunication demands for quality of services (QoS) and quality of experience (QoE) to realize the associated benefits such as fast communication, low latency, high reliability, maximized throughout, etc. These requirements made networks more challenging in a dynamic vehicular environment [3].

In recent years, the proliferation of intelligent vehicular networks has captured the attention of industry and academia. The substantial benefits associated with intelligent vehicles can benefit an urban society in terms of traffic regulation, resource management, and accident reduction among others. A fast stride is observed in the development and implementation of Autonomous Driving Vehicles (ADVs), e.g., Waymo by Google, Tesla self-driving cars, Aptiv, Audi A8, Ericsson's 5GCAR project, etc. ADVs are more complex in nature due to multiple integrated sensors, automotive control, and ultra-fast communication capabilities. ADVs are anticipated to be in the market till 2020 [4], and 25% ADVs are expected on the roads by 2035.

Traditionally, wireless technologies provide infrastructure for vehicular communications, which can play a significant role in efficient resource management as well as transportation for the provisioning of QoS and QoE [5]. The Third Generation Partnership Project (3GPP) is among the incorporating standards for reliable communications among Vehicles-to-Pedestrian (V2P), Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and futuristic Vehicle-to-Everything (V2X) [2]. The enhancement in V2X services enables multiplexing resources across vehicular networks. However, the communication of wireless cellular networks is a bit expensive in terms of latency for time-critical scenarios in a vehicular network. 3GPP is a de-facto standard for LTE-V2V communication standard protocol that allows communications by directly exchanging messages with the LTE infrastructure involvement [6].

In this paper, we proposed a resource allocation framework for autonomous vehicular networks that may provide optimization of resource allocation in a vehicular network, as shown in Figure 2. Vehicles may communicate with other vehicles or infrastructure. The proposed policy optimizes flow requests from vehicles and a priority is assigned based on the criticality of the application demand. Flows grouped-based on application scenarios, such as applications for road safety, infotainment applications, and/or applications for comfort indicators. The flow slices are classified using Traffic Classifier (TC). The elements of privacy and security are very crucial in affecting the performance and utilization of vehicular networks. Thus, confidentiality, authenticity, encryption, and other security features are all assumed to be parts of the overall environment.

The rest of the paper is organized as follows: starting with Section II, we present the background and related studies of SDN-based autonomous vehicular networks. In Section IV, a framework for resource allocation in SDN-based networks is presented. Section V discusses the achieved throughput and response time of the proposed framework in addition to compare the efficiency of machine learning techniques. Finally, Section VI concludes the study and gives future directions.

II. BACKGROUND AND RELATED WORK

The widespread use of large networks over the Internet has proved to be hindering in giving users an optimal quality of service. Traditional network architectures prove cumbersome in terms of energy efficiency, dynamic network configuration, agile network measurement, and flexible network deployment [7]. Due to the unchanged architecture of legacy networks for the past few decades, software defined networks (SDN) have envisioned as an emerging approach providing programmability, adaptiveness, and flexibility. As SDN architecture provides a global network overview, logical centralization, and strengthening a network, it also introduces problems of resource management, some of which have been addressed and brought forward by Khelifi *et. al* [8].

The joint initiative between the European Commission and European ICT industry for 5G Public Private Partnership Group (5G PPP) advocates the use of multiple technologies for pervasive computing that enables multiple radio access technologies (RATs) [9]. The advocates of 5G claim for the provision of mobility, high flexibility, low latency, high reliability, security, privacy, and maximized data rate in a highly dynamic environment [10], [11]. The 5G METIS project [12] provides a flexible architecture and service management in wireless communications between a V2X network where a vehicle communicates with other vehicles or an external environment leveraging the existing and futuristic wireless networks.

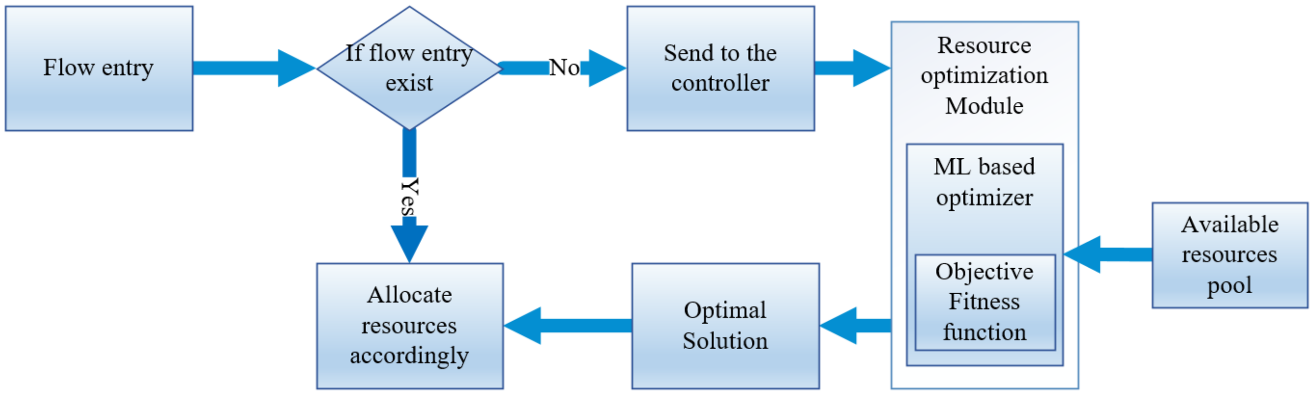


FIGURE 2. Machine learning-based optimization high-level view for resource allocation.

The SDN is a well structured and layered architecture consisting application layer, control plane, and data plane, as shown in Figure 1. As evident from the architecture, SDN controller is responsible for resource management through slice management. This enables SDN to orchestrate the 5G network through network functions virtualization (NFV), which is considered as the key enabling technology for 5G networks while considering resource management [13]. The control plane and data/forwarding plane are separated in SDN, enabling centralized management, greater flexibility, and network programmability with a global view of the overall network. The centralized control provides network intelligence for resource orchestration. The SDN can also benefit vehicular networks in terms of efficient resource allocation and network management by providing fine-grain traffic steering [14].

The data plane comprises data forwarding entities, vehicles, physical infrastructure, e.g., base station (BS) or access points (APs), of different RAT technologies such as 5G LTE, Wi-Fi, WiMAX, etc. The V2X communication is also held on this layer of the SDN network. Similarly, the control plane is the decoupled entity from the rest of the distributed forwarding devices. It is logically centralized on a server that controls the overall functionality of the network functions. The control plane can program forwarding devices through southbound API interfaces. In addition, control plane also defines rules/instruction sets for forwarding devices. Hence, it is known as the *network brain* where all control logic resides in the applications and controllers, which form the control plane.

The SDN was initially designed for carrier infrastructure, i.e., wired network, and it proved its success in data centers. However, its implications are demonstrated in other network scenarios such as mesh networks, wmSDN, sensors network management, SDN-based Wi-Fi networks, and wireless domain [15]. The SDN-based vehicular network implementation gets attention in recent years. In the same way, SDN-based cellular network's support for vehicular networks is being investigated by academia, but mostly architectural layout and theoretical work remain a focus. Despite the fact of SDN associated benefits, there are certain overheads involved in the dynamic network management in vehicular networks. Resource allocation is critical due to the profoundly changing network dynamics because of high mobility and less reliable wireless link capabilities.

Xie *et. al* [16] have proposed a blockchain-enabled infrastructure for Internet of Things (IoT) that provides security and trust in SDN-enabled 5G VANETs. This definitely puts additional burden on the overall network processing. One optimal solution for the mitigation of resource management is to adopt AI-based resource management techniques [17]. This paper aims to implement a secure deep learning-based API for the detection of diverse and sophisticated resource demand in SDNs [18], [19].

Generally, VANETs are sub-forms of mobile ad-hoc networks wherein vehicles communicate using V2V or V2I fashion with other vehicles and roadside units (RSUs) [8]. A VANET comprises highly mobile vehicles, supporting infrastructure, and wireless communication. The communication between vehicles is done using Dedicated Short-Range Communication (DSRC), which is considered as the defacto standard for vehicular communications. Beside DSRC, different wireless technologies are also used for vehicular communications such as Wi-Fi, WIMAX, and LTE. Wireless technologies are advanced and sophisticated in the context of providing a plethora of applications from road safety applications, cooperative driving to autonomous human-like driving, and provisioning of high bandwidth-demanding video streaming access in a fast mobility environment. For supporting a multitude of applications, various heterogeneous RAT technologies are getting attention from the research community [20], [21].

An SDN based architecture (SDVN) for vehicular networks is proposed in [22], which incorporates vehicles and RSUs that act like SDN switches. The SDN-based architecture supports V2V, V2I, and vehicular-to-cloud (V2C) communications. The data plane is constructed using an overlay network where all forwarding devices behave like SDN switches. The vehicle status information is collected and monitored by the SDN controller. The status policy update is done using trajectory-prediction, which reduces the frequency of status updates.

The SDN-based autonomous transportation system is presented in [23] in which V2X communications of the ADV network is presented. The RSU maintains local information about the surrounding environment and communicates with the ADV. This architecture is based on time division multiple access (TDMA) for a four-lane infrastructure. The SDN-enabled eNodeB (eNB) facilitates local vehicular networks. The RSU controller in the proposed SDN architecture is responsible for the incorporation of data forwarding by receiving it on the southbound interface and processes it towards the northbound interface. This provides multiple services to users, vehicles, and the complete infrastructure, where the V2I communication is done using a wireless link.

A software-defined in-vehicle networking (SDIVN) architecture is proposed for the autonomous vehicle resiliency, robustness, and timely message delivery in [24]. In [25], authors present a resource allocation mechanism ADVs by combing mobile edge access computing (MEC) and SDN in autonomous AVNETs. Resources are stored on the MEC to get short response delay where the NFV is used to efficiently manage resources among different MEC servers. The MEC servers are placed on the edge, which help in gaining scalability and efficient resource utilization.

Zheng *et al.* [26] proposed Soft-defined heterogeneous Vehicular nEtwork (SERVICE) framework for radio resource virtualization in LTE for VANETs. In this framework, stochastic learning is used for the estimation of delay and optimization of virtual resource scheduling. The framework has two stages for resource virtualization, i.e., macro and micro virtualization resource allocation, known as MaVRA and MiVRA, respectively. The large and small time scale variables are used to categorise services such as traffic density operated in MaVRA and network state, and queue state operated in MiVRA time scale. The controller acts as a proxy service fulfilling user requests in a hierarchical control architecture. Two layers of the controller are the primary controller– responsible for the global SERVICE network, and the secondary controller–that acts as a regional controller.

The integrated architecture of SDN and Fog Computing (FC) for VANETs, named SDFC-VeNET, is proposed in [27]. The control layer and forwarding layer reside on edge consisting of multiple controllers in the control layer. The controller provides a control function and resource management. The FC provides a cache mechanism for reducing the access time of the services. Two types of resource allocation policies are used in SDFC-VeNET architecture, i.e., macro resource allocation policy and micro resource allocation policy leveraging CSI and QSI. The proposed scheme used sparse code multiple access (SCMA) and full-duplex to support massive communications in VANETs and uses OFDM and half-duplex for V2I communications. It provides centralized scheduling for a mixed SCMA/OFDMA scheme for virtual resource allocation.

In the last few years, SDN integration in wireless and cellular networks gained much attention. Different studies are proposed for the incorporation and implementation of SDN in autonomous VANETs, as depicted in 3. Software-defined vehicular ad-hoc network (VANET) is proposed that provides V2V communications using central SDN controller. It leverages cellular communications for control transmissions by incorporating stationary SDN RSUs. Resources are allocated statically by using different wireless radio technologies such as WiMax, WiFi, etc.

III. RESOURCE ALLOCATION IN AUTONOMOUS VEHICLES

In vehicular networks, autonomous vehicles need to communicate with other vehicles, i.e., V2V communication, and with the roadside infrastructure wherein reliable communication is stringent, needs to collect real-time information such as speed, direction, and location. Moreover, the increasing demand for data services and high bandwidth under increasing vehicular density, dynamic traffic conditions, and distributed RSUs across the infrastructure become challenging objectives in an autonomous vehicular network. Traditionally, DSRC is used for V2V communications and RAT technologies. However, these technologies have their limitations, such as radio access in LTE uses orthogonal frequency multiple access, which suffers from spectrum limitations and intrinsic delay incur in communications between vehicles. In the case of safety applications, this delay response can cause disaster. Moreover, limited spectrum restrains from massive connectivity as anticipated in 5G networks.

Autonomous driving needs to precisely monitor the traffic conditions in both safety and non-safety scenarios. Despite, ADV comprises sensitive sensors, artificial intelligence algorithms, and high-speed communication gadgets; several challenges still encounter efficient management.

- Communication capabilities with the neighboring vehicle to monitor the exact traffic situation.
- Inefficient network utilization
- Frequent information updates due to high mobility
- Optimal resource allocation based on the intermittent traffic condition

IV. PROPOSED SDN-BASED VEHICULAR NETWORK FRAMEWORK

In this study, we propose a policy framework for resource allocation in SDN-based 5G cellular networks for autonomous vehicles and suggested architecture, as shown in Figure 3. The overall network is composed of several key components. The main module is the SDN controller, which is responsible for providing network hypervisor services. Moreover, the global scheduler is responsible for keeping records of all requests in the queue and thus enables the resource optimizer to use machine learning enabling resource management on the control plane.

The SDN-based 5G cellular network consists of two main parts. The SDN core network and the SDN-enabled wireless data plane. A fine-grained decomposition of the front haul

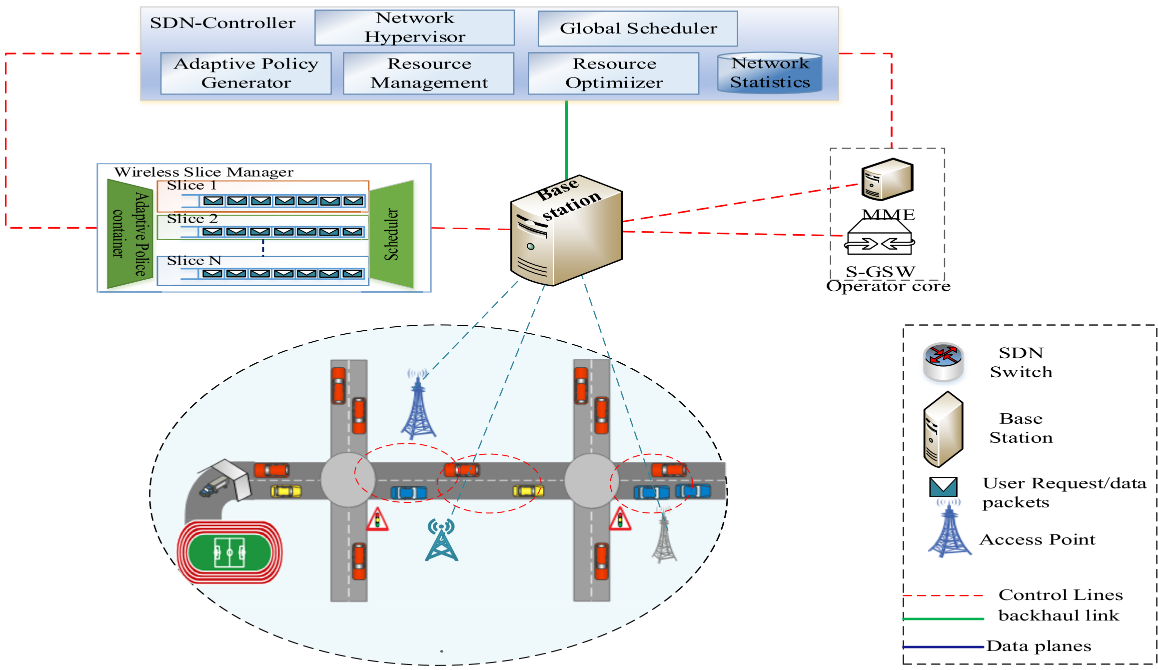


FIGURE 3. SDN-based 5G architecture for VANET service provisioning.

network of the wireless part in the SDN cellular network is achieved by implementing a wireless slice manager. The wireless slice manages allocation and schedule resources on the instruction of global scheduler in the SDN controller. Wireless slicing is a virtualization concept to enable a single network to behave in a manner similar to multiple logical virtual networks. Thus, enabling granular controller and fine-grained management of resources. The backhaul network of this architecture is sliced based on the flow request from mobile virtual network operators (MVNO). The network-level slicing is handled by the hypervisor that acts as a network virtualized engine, which flexibly slices network infrastructure and radio resources based on the MVNO demands of resources and traffic types.

This policy can dynamically adjust its behavior in response to changes and QoS requirements. We define an optimal policy for network bandwidth allocation and queue management at the cellular BS. The optimized policy considers the queue-length resource allocation in the wireless slice manager to bridge the gap between resource demands at the BS and bandwidth allocation at the controller.

The network hypervisor, i.e., FlowVisor, centrally manages the SDN cellular network and is responsible for handling virtual slice manager at the BS, i.e., wireless hypervisor instance, and allocates bandwidth as per the requirement to achieve fairness. The virtual slice manager at each BS serves as the local controller. This local controller reduces the communication overhead at the centralized controller. The overhead is computed in terms of time computation and processing for allocating resources dynamically. The virtual manager logically partitions physical resources into slices and assigns resources based on adaptive policies.

A. SDN-BASED VANET ARCHITECTURE

The basic architecture consists of the following modules in the control plane.

1) ADAPTIVE POLICY GENERATOR

The adaptive policy generator is responsible for creating network policies based on predefined rules agreed by InPs and MNOs. The ADP module collects network statistics and SLA from the NSM module and generates an adaptive policy for resource allocation based on the resources available and allocated capacity to each network slice.

2) RESOURCE MANAGEMENT MODULE (RMM)

The resource management module (RMM) calculates the available resources in the network and analyzes real-time network information in addition to generate global resource management in the SDN controller. The RMM executes resource allocation algorithm for optimization and allocation of resources to different network slices. We used the cuckoo search optimization algorithm for achieving the optimization state of resource allocation.

3) TRAFFIC ADAPTIVE SCHEDULING (TAS)

The traffic adaptive scheduling (TAS) is a module in the SDN controller, which is responsible for the collection of network information. The TAS can envision a global view because of centralization of the controller, which possesses insight into the global network information. Network slices span all resources of the whole network. The TAS classifies the QoS flow classes by using the traffic classifier module.

4) TRAFFIC CLASSIFIER

The QoS is an important parameter to get enhanced performance. Network QoS enforced by applying different QoS parameters thresholds and techniques. One method to ensure QoS is the classification of traffic based on some predefined criteria. This traffic classification is used to do effective scheduling in the network. Queuing mechanisms are vital techniques to prioritize the overall traffic in the network elements. The efficient use of these queuing techniques ensure bandwidth for different traffic classes and control the congestion.

In the proposed framework, we consider three different queues in each port of the OpenFlow-enabled device: (i) Priority Queue (PQ), (ii) Bandwidth sensitive Queue (BQ), and (iii). No strict queue (NSQ). The most prioritized traffic buffered in the PQ. The traffic prioritization is based on sensitivity of the application and user requirement with intensive delay boundaries. The threshold value is defined for high priority traffic. If the traffic required delay is less than the defined threshold, it is inserted in the PQ.

B. OPTIMIZED RESOURCE ALLOCATION PROCEDURE

The SDN-based cellular network management and bandwidth allocation policy use virtualization manager at the centralized controller and the BS for core and wireless virtualization. It provides a flow-based queue-length resource allocation in the wireless domain. The overall flow management is performed on the controller level. It can dynamically adjust its behavior in response to changes and QoS requirements due to the presence of a virtual slice manager at each BS and a local controller in addition to allocate resources to the incoming flow. The scheduling granularity is achieved by identifying QoS flows in the network flow.

The flows are categorized as safety flow and non-safety flows. The safety flows get more priority ratio based on the criticality, and the non-safety flows get less priority. In the proposed framework, bandwidth allocation is the main fairness allocation criterion, i.e., fair allocation of bandwidth so that to achieve rate maximization for different application/services flow in the SDN. For the optimal solution, we use the Cuckoo search algorithm.

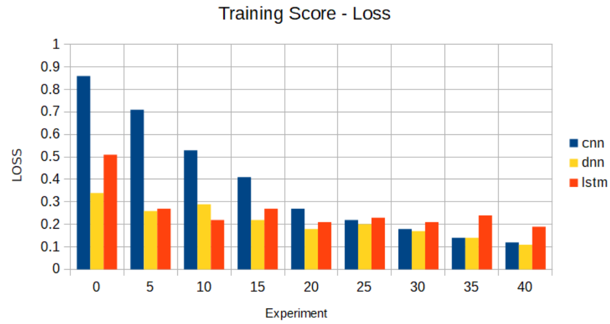
V. PERFORMANCE EVALUATION AND DISCUSSION

For the simulation purpose, we use a light-weight fork of mininet emulator, version 2.3.0d1, mininet-wifi running on the Ubuntu virtual machine of version 18.04 LTS. Mininet is considered as a standard emulator for experimenting the SDN concepts. Mininet-wifi provides large functionalities of the wireless networks from propagation models to mobility scenarios, as shown in Figure 1. The car node, implemented in [28], provides a vehicular architecture to offer the proof-of-concept of a vehicular network in SDN scenarios. It is one such example that we have leveraged to achieve the video content request from the cloud.

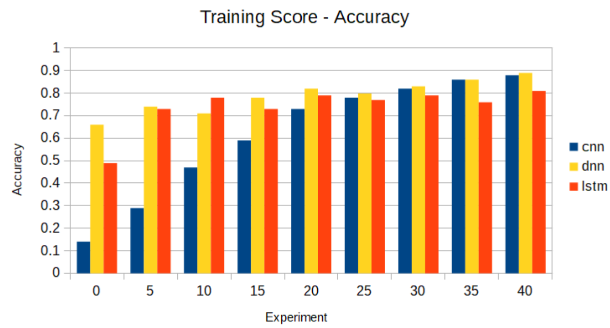
In the proposed scenario, we have considered an infotainment application, which is deployed at the application plane. The core mechanism of the application service is

TABLE 1. Training results for machine learning models adopted for the experiment.

	Loss			Accuracy		
	CNN	LSTM	DNN	CNN	LSTM	DNN
0	0.86	0.51	0.34	0.14	0.49	0.66
5	0.71	0.27	0.26	0.29	0.73	0.74
10	0.53	0.22	0.29	0.47	0.78	0.71
15	0.41	0.27	0.22	0.59	0.73	0.78
20	0.27	0.21	0.18	0.73	0.79	0.82
25	0.22	0.23	0.20	0.78	0.77	0.79
30	0.18	0.21	0.17	0.82	0.79	0.83
35	0.14	0.24	0.14	0.86	0.85	0.86
40	0.12	0.19	0.11	0.92	0.94	0.93



(a) Training score (Loss) of the machine learning algorithms used for the training dataset.



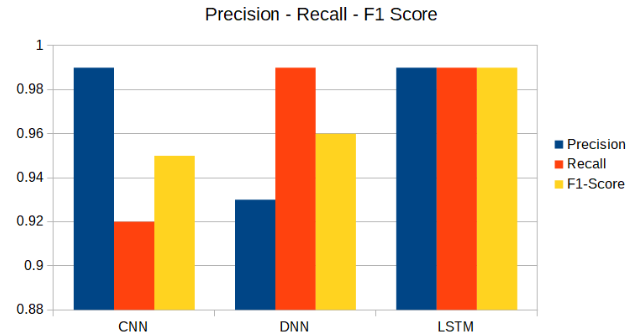
(b) Training score (Accuracy) of the machine learning algorithms used for the training dataset.

FIGURE 4. Training score (Accuracy and Loss) for the dataset generated by the mininet-wifi for traffic generation and floodlight as the SDN controller.

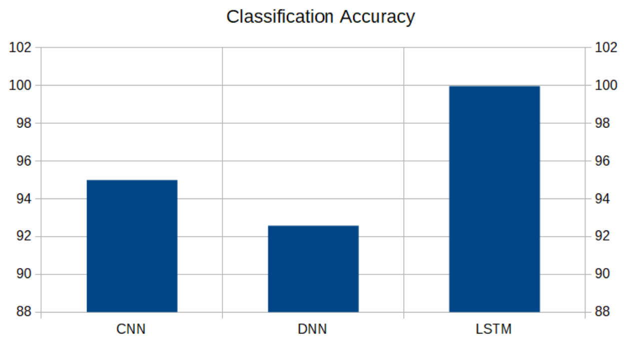
to receive data. We have conducted V2X simulations using mininet-wifi where multiple RSUs can communicate with each other and vehicles can perform V2V and V2I communications. The SDN default controller is used for simulating the transmission of video from a vehicle to a client. The resource allocation in vehicular networks is managed by the SDN controller in an efficient manner.

The overall simulation was run multiple times using stochastic process in order to mimic realistic scenarios. The dataset that we gathered includes information about the requests, which are generated from client nodes at the data plane. We have used deep learning techniques to train the system using historical data of the network. The historic network data consists of both standard and tagged signatures.

We have used long short-term memory (LSTM), convolutional neural network (CNN), and deep neural



(a) Precision, Recall and F1 score for the experiment of the proposed machine learning based resource management



(b) Accuracy of CNN, LSTM and DNN compared for resource management using machine learning model on experimental data

FIGURE 5. Classification accuracy of CNN, LSTM, and DNN compared for resource management using machine learning model on experimental data.

network (DNN) models for predicting results and have compared them for the best suitable solution. The CNN essentially is a neural network variation mainly used for computer vision with hidden layers. Similarly, the DNNs are feed forwarding neural networks, which basically leverage many layers to successfully classify regions of interest in a data.

Moreover, the LSTM being a break through in machine learning techniques ensures to avoid this layer's Independence issues. The LSTM by remembering things between layers achieves a great feat of promising results specially in text and speech analysis. In our case, we feel that all three of these have promising results. The experimental data is divided into train and test sets for training and testing the system, respectively. The training data, which is 80% of the dataset, is fed into learning algorithms. These algorithms train themselves on the data and predict the test set, which is 20% for results, as shown in Table 1.

In the experiments, we use the SDN Floodlight controller as a development environment. We split data into 80:20 for training and testing. For LSTM, we use Scikit-learn[1] library for the implementation using parameters relu/sigmoid, 64, 20 and Adam for activation, batch size, epochs, and optimizer, respectively. Whereas the hidden layers are (50,250,1).

[1]Scikit-learn - classification, regression, and clustering algorithms library https://scikit-learn.org

For the implementation of CNN, we use Keras[2] library using relu, 64, 40 and Adam for activation, batch size, epochs, and optimizer, respectively. While the layers used are convolutional, pooling, dropout, and flatten. For DNN, we use Keras for the implementation with parameters relu/sigmoid, 16, 30, Adam for activation function, batch size, epochs, and optimizer, respectively. Whereas the layers are (256,128,32,11,1).

The training loss and score of LSTM, CNN, and DNN are calculated in the run-time during the training of the system, which is illustrated in Figure 4. This shows that the overall model is trained well, especially in the case of 4a. Detection accuracy is the prime evaluation metric for the performance evaluation of the system. The detection accuracy of LSTM, CNN, and DNN on testing data is shown in Figure 5. Here it is noticeable that LSTM shows the most accurate averaging at 99.36%, where the CNN obtained an accuracy of 95% and the DNN achieved 92.58%.

VI. CONCLUSION

Software defined networks (SDN) have proved the performance gain in the data centers as well as carrier networks. The SDN provides flexibility in wireless and cellular networks even for highly dynamic networks such as VANETS. In this paper, we proposed a resource allocation policy framework for SDN-based vehicular networks in the context of 5G connectivity. We proposed a novel resource allocation scheme based on state-of-the-art deep learning algorithms: CNN, DNN, and LSTM on the basis of SDNs using mininet-wifi-based setup with floodlight as SDN controller. The proposed policy framework can optimize resource allocations according to the changing demands and network dynamics in vehicular networks.

The experimental results showed that the LSTM outperformed in detection accuracy with 99.36%, followed by CNN and DNN with 95% and 92.58%, respectively. The LSTM lacks marginally in resource allocation time, where the CNN performs better in the detection time, whereas it is just behind the LSTM in the detection time. The DNN, on the other hand, shows a deficiency in performing better in terms of both resource allocation time and resource allocation accuracy. These limitations can be evaluated as part of the future work, where we intend to implement other deep learning models such as Gated Recurring Units (GRU) and bidirectional LSTM as they produce better throughput. Moreover, we also intend to evaluate the performance of machine learning based resource management on real traffic.

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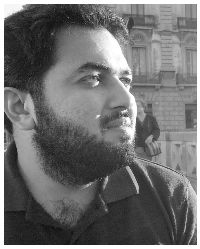

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