Distributed Traffic Congestion Classification in Intelligent Transportation Systems based on SDN and Fog Computing

Naserali Nourani
Department of Computer Engineering
Ferdowsi University of Mashhad
Mashhad, Iran
alinoorani517@mail.um.ac.ir

Seyed Amin Hosseini Seno
Department of Computer Engineering
Ferdowsi University of Mashhad
Mashhad, Iran
hosseini@um.ac.ir

Sina Samadzad Etehadi
Department of Computer Engineering
Ferdowsi University of Mashhad
Mashhad, Iran
samadzad@um.ac.ir

Mahsa Hosseinpour
Department of Computer Engineering
Ferdowsi University of Mashhad
Mashhad, Iran
mahsa.hosseinpour@mail.um.ac.ir

Mohammad Hossein Yaghmaee
Department of Computer Engineering
Ferdowsi University of Mashhad
Mashhad, Iran
hyaghmae@um.ac.ir

***Abstract*—In recent years, in addition to the significant growth in intelligent transportation systems with new concepts such as SDN (Software Defined Networks), fog computing, and new machine learning methods, the advancement of communication technologies and automotive industries has been considerable. Vehicular Adhoc NETworks (VANETs) can effectively detect traffic congestion, which can be classified into Repetitive Congestion (RC) and Non-Repetitive Congestion (NRC). In particular, NRC in an urban area is mainly due to accidents, congested areas with high loads, special events, and weather conditions. This paper presents a new architecture using two concepts, SDN and fog computing, called SDN and Fog computing-based VANET (SFVN), to classify the causes of congestion in VANET. This architecture is proposed for distributed and real-time congestion classification, considering its components in an urban road network in VANET. The proposed scheme has been evaluated with CCSANN, FogJam, C4.5 classification tree, and the Naïve Bayes method, which indicates the effectiveness of the proposed method. By knowing the leading causes of congestion, this scheme can help transport companies develop effective policies to reduce urban congestion.**

***Index Terms*—classification, traffic congestion, fog computing, SDN, VANET**

I. Introduction

With recent developments in telecommunications and automated industries, we have seen a growing trend in intelligent transportation systems, of which vehicular ad hoc networks are a significant component. As a significant component of intelligent transportation systems, VANETs suffer from many problems, including architectural inflexibility, wireless communication instability and communication range limitation, frequent topological changes due to rapid vehicle movement, congestion, etc. One of the primary challenges in intelligent transportation systems is the occurrence of traffic congestion. Congestion can be classified into recurrent (RC) and non-recurrent (NRC) congestion. Recurrent congestion is regularly occurring and is usually caused by intentionally created factors, such as traffic lights. Accidents, special events, and adverse weather conditions mainly cause non-recurrent congestion in an urban network. Existing NRC detection methods require extensive data sets and must be collected and processed in realtime. In this case, valuable information can be transferred to drivers and traffic management centers according to the identified NRC effects so that appropriate preventive strategies can be set to restore traffic conditions to normal. Therefore, solving non-recurrent congestion problems requires continuous and realtime monitoring [1], [2].

With the help of SDNs and fog computing, it is possible to provide suitable solutions for existing challenges.

SDNs can provide advantages for VANETs via the flexibility and programmability of networks through a centralized logical control unit with a general view of the network. However, initially, SDN was proposed only for use in fixed networks; its adaptation to function in VANETs requires modifications to regard the specific characteristics of scenarios, such as the high mobility of nodes. SDN provides solutions for these problems by virtualizing network functions and centralized control. By reducing the complexity of the network by separating the data layer from the control layer, SDN has gained flexibility and programmability. As a result, it can solve significant challenges in transportation networks [3], [4].

On the other hand, fog computing is an emerging technology that brings data processing, storage, and analysis closer to end users. It includes some features of cloud computing, but it can be distinguished from the cloud due to its proximity to end users, geographical distribution, and mobility support. Fog computing allows some data to be analyzed and managed at the network's edge, thereby supporting applications that require very low and predictable latency [1], [4], [5].

This paper considers a set of unique features for different types of NRC and extracts features from the data to infer the occurrence of NRC. To this end, we elaborate on SDN and fog computing technologies. Data can be collected to detect congestion at the network's edge with low latency in real time using fog computing. With the global vision that the SDN controller will provide us, we can detect the occurrence of congestion and set appropriate strategies to manage and control congestion. After that, machine learning models are used to identify the specific type of NRC. In particular, incidents and work areas are characterized by problem points. We evaluate the route's travel time, speed, and distance in bad weather. Specific events are characterized by the area of influence and increased demand.

The rest of paper organized as follows: In section II, the relevant literature reviewed is presented. The system framework is presented in section III. Section IV explains the simulation and obtained results. Finally, the conclusion and future directions are given in section V.

II. Related Work

Many works on congestion detection through VANET use machine learning to classify traffic congestion state or free flow. In this section, some cases of congestion management in vehicular ad hoc networks have been examined.

One of the critical needs of Intelligent Transportation Systems (ITS) is to understand and predict the future traffic situation (e.g., travel time, travel flow, and traffic congestion). However, accurate traffic situation prediction is challenging due to the stochastic characteristics and nonlinear nature of the traffic flow. SDN is one of the key concepts in networking that has attracted much attention in recent years. The tremendous advancement in SDN equipment has introduced a new networking paradigm called Software Defined vehicular networks (SDVN). In the paper [6], Bhatia et al. proposed a data-driven approach to implement an artificial intelligence model to predict vehicle traffic behavior. They combined the flexibility, scalability, and adaptability employed by the SDVN architecture with machine learning algorithms to model traffic flows efficiently. The training and implementation of various intelligent computing models were based on the distributed VANET model, focusing on detecting and predicting traffic congestion and then analyzing it using an SDN controller in a centralized cloud architecture. An architecture consisting of RSU and OBU is proposed, which is monitored by an SDN controller connected to a suitable cloud infrastructure for real-time data storage and high computing capacity. Finally, the results showed that the proposed method can predict future traffic jams with an accuracy of 97% on the general data set that provided the necessary information to manage and control traffic jams.

The rapid development of urbanization has contributed to traffic events such as accidents and traffic delays. It is difficult to detect and solve highway traffic congestion in time using traditional methods. Therefore, it is necessary to introduce advanced technologies to solve these challenges. Deep learning is one of the most critical technologies for detecting and evaluating traffic congestion, which enables accurate diagnosis of highway traffic congestion, traffic congestion assessment, and possible traffic congestion prediction. In [7], Y Liu et al. proposed a framework based on deep learning for traffic management. The framework selects traffic density indicators to build an index model and then builds a deep learning model based on self-encoding. It predicts and classifies highway traffic environment data. Once the traffic data is classified, a prediction model based on SoftMax is developed to detect and predict traffic congestion. The proposed framework is evaluated using data collected from highway and street monitoring scenes, and the results showed that 98.6% of the data can be correctly recognized and classified. However, using the SoftMax-based prediction model for highway vehicles during peak hours, the obtained accuracy was 92%. This framework is a promising solution for the next generation of highway traffic management and provides accurate and timely detection and assessment of traffic congestion.

In a vehicular network, information is collected periodically to update and discover vehicular congestion. The use of cloud computing to support the massive amount of traffic data received from multiple vehicles significantly increases the network traffic. Peixoto, M. et al., in the paper [8], proposed FogJam, a Fog service to detect traffic congestion directly at the edge of the vehicular network. FogJam uses sampling and clustering-based methods to reduce the data flow of traffic transmitted by vehicles to the cloud. The simulation results show that FogJam is very accurate in detecting traffic congestion at a low cost, even in the scenario of high vehicle congestion. Furthermore, using clustering-based methods, FogJam can reduce the network utilization impact by about 70% compared to sampling methods while providing an acceptable level of congestion detection accuracy [8].

As the urban renewal process becomes faster and faster, there are more and more vehicles in the city, and urban traffic congestion is becoming more severe daily. In the article [9], a model of traffic congestion prediction is built using machine learning classification algorithm-random forest to build a traffic congestion prediction model. The random forest algorithm has the characteristics of high robustness, high performance, and high practicability. Weather conditions, time periods, special road conditions, road quality, and holidays are used as model input variables to create a road traffic predicting model. Finally, the results show that the traffic prediction model created using the random forest classification algorithm has a prediction accuracy of 87.5%, and the generalization error is low and can be effectively predicted. In addition, the calculation speed is quick and has a more robust application for predicting congestion conditions [9].

Managing the ever-increasing road traffic congestion due to the enormous growth of vehicles is a substantial concern worldwide.

Severe air pollution and loss of time and money are expected intelligent consequences of traffic congestion in urban areas.

The intelligent transportation system based on the Internet of Things (IoT) can help manage road traffic congestion efficiently. Estimating and classifying the traffic congestion situation of different road sections is essential to intelligent traffic management. The paper [10] aims to estimate and classify the state of traffic congestion in different sections of a city's road by analyzing traffic data taken by fixed sensors inside the road. The Artificial Neural Network (ANN) system is used to classify traffic congestion states. Based on Traffic congestion, ITS automatically updates the traffic regulations, such as changing the queue length at the traffic signal and suggesting alternative routes. It also helps the government to set policies regarding the construction of flyovers/alternative routes for better traffic management.

III. System Model

Vehicle ad hoc network (VANET) is a technology developed to achieve inter-vehicle communication, road safety, emergency warnings, entertainment, etc. Nowadays, research in vehicle networks has received lots of attention due to issues related to intelligent transportation. The main application of VANET is intelligent transportation systems. Vehicular ad hoc networks can effectively detect traffic congestion, which can be classified into repetitive and non-repetitive congestion. In this paper, the main focus is on non-repetitive congestion. In particular, NRC in an urban network is mainly caused by incidents, work zones, special events, and adverse weather. In the rest of this section, the main problem is explained, and then the proposed plan is offered.

A. Problem Definition

Although the understanding of total congestion caused by NRC for highway and urban traffic has been thoroughly studied in intelligent transportation systems, problems still need to be solved. In this context, NRC's duration, time, and place are very different in an urban road network. Therefore, it becomes difficult to monitor traffic in real-time or continuously with cameras and mobile vehicle mechanisms that are expensive to deploy and maintain over large coverage areas. Cost-effective and flexible alternative solutions are needed to ensure better road traffic monitoring at different levels. The existing NRC detection methods require extensive data sets and cannot be obtained in real-time. Valuable information regarding the identified NRC effects can help drivers, and traffic management centers set appropriate preventive strategies to restore traffic conditions in real-time. Finally, NRC detection methods should be able to determine the cause of an NRC event after detection and also classify the root cause of NRC. We will use SDN and fog computing technologies to achieve such a goal.

B. The proposed Architecture

In this study, we consider a set of unique features for each type of NRC and extract such features from the data to infer the NRC. For this purpose, a three-layer architecture consisting of SDN and fog computing is proposed. As shown in Figure 1, a three-layer architecture is designed for NRC collection and detection in VANET. This architecture considers parked vehicles as Fog Computing (FC) nodes. It will also use the SDN controller for network management. The proposed architectural layers from bottom to top are as follows:

- *Vehicles layer*: Any vehicular network in a city consists of numerous parked vehicles and vehicles moving at different speeds. These vehicles have storage and wireless communication capability and use Vehicle-to-infrastructure (V2I) connection mode to connect to the Roadside Unit (RSU) and Base Station (BS) via WAVE and LTE interfaces, respectively.
- *Fog computing (FC) layer*: consists of a set of fog nodes, including parked vehicles, BSs, and RSUs located in a geographical area. In this layer, all fog nodes have processing and storage capabilities and support the OpenFlow communication protocol to connect to the SDN controller. Fog nodes and the SDN controller can communicate with each other to exchange data. We assumed that BSs and RSUs use LTE and WAVE interfaces to communicate with vehicles.
- *SDN controller layer (SDN_C)*: It is the highest layer of the SDN controller and is responsible for network management, which is connected to the lower layers using the OpenFlow protocol. The lower layers often send updates about network conditions; Thus, SDN_C has complete and updated information about all network links and locations of BSs, RSUs, vehicles, and traffic conditions. In addition, it performs functions such as minimum-latency tree construction, NRC occurrence decision-making, and NRC occurrence mitigation coordination.

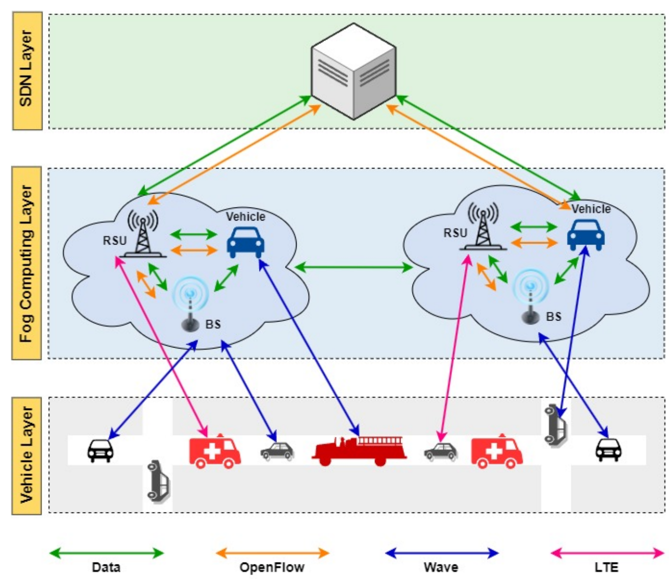

Fig. 1. The Architecture of the proposed scheme

We utilize fog nodes for data collection. The proposed architecture uses RSUs, BSs, and vehicles as fog nodes spread throughout urban areas. With fog nodes, data can be collected and processed in real time with low latency at the network's edge. We evaluate adverse weather conditions, travel time, vehicle speed, and route distance to collect data. This information will be sent to SDN_C for aggregation and evaluation to identify the occurrence of NRC. After that, machine learning models will be implemented to identify the specific type of NRC in SDN_C, and specifically, the working areas will be identified as problematic points. After receiving information from fog nodes, SDN_C can consider all the details and determine the cause of NRC about the global view of the network.

The overall process of our framework is divided into two steps: feature extraction and classification model.

1) Feature Extraction: To specify the features, we need to collect information locally, which is done by distributed fog nodes at the network level. The communication features of a VANET are based on a message called BEACON, sent by each vehicle every 0.1 seconds, and data such as speed, position, direction of movement, origin address, destination address, etc., are gathered by fog nodes. After executing primary features, the classification model is extracted and sent to SDN_C. In the following, we will offer the features that define NRC.

The observed travel time of a vehicle ($TT_{observed}$) along a road section may consist of recurrent delay ($Recurrent_{delay}$) and non-recurrent delay ($Non\_Recurrent_{delay}$).

$$TT_{observed} = Recurrent_{delay} + Non\_Recurrent_{delay} \quad (1)$$

$Recurrent_{delay}$ is the recurrent historic travel time $TT_{historic}$ that depends on the specific location and time. Non-recurrent delay is formed due to incident characteristics ($incident\_delay$), work area ($workload_{delay}$), weather ($weather_{delay}$) or delays caused by The specific event ($specific\_event_{delay}$).

$$\begin{aligned} Non\_Recurrent_{delay} = {} & incident\_delay + workload_{delay} \\ & + weather_{delay} + specific\_event_{delay} \end{aligned} \quad (2)$$

The observed travel time along a part can be easily obtained by VANET vehicles. If $TT_{Observed}$ is higher than a threshold [11], determined by multiplying the congestion factor c by the expected recurrent delay, the travel time is considered excessive.

$$TT_{Observed} > (1 + c) * TT_{historic} \quad (3)$$

F fog computing allows real-time traffic flow data to be collected along the vehicle path and other road parts. From these data, understandable statistical spatial and temporal characteristics can be extracted to help infer the component causing excessive delay.

Incidents are characterized by problematic spots (PSpot) [12]. We use geolocation data to extract these points in VANET. If part of the road is blocked, no vehicle position coordinate is recorded between the PSspot start and end positions. This feature also takes into account the temporal aspect of observed problematic spots. If the event lasts more than an hour, it is a good indicator of NRC caused by an incident.

NRC caused by lousy weather affects travel time ($Path_{TravelTime}$), speed on the path ($Path_{Speed}$) and path gap ($Path_{Gap}$). $Path_{TravelTime}$ measures the maximum travel time along the vehicle path and compares it to the expected travel time of the corresponding trip. $Path_{Speed}$ is to measure the speed data of vehicles on the path. $Path_{Gap}$ collects and calculates the minimum distance between vehicles in adverse weather conditions as drivers try to maintain a minimum safety distance to handle longer stopping distances caused by slippery roads.

Special events are identified by their impact region ($Impact\_Region_{Specific_{e}vent}$). Each part of the network path is labeled as inside or outside an influential zone [13]. We assume that if a vehicle experiences an NRC caused by a particular event, then the vehicle is necessarily located in the event's impact area.

Using the speed-flow relationship and knowing the average observed speed in each area and the flow density, we can estimate and compare the flow with the maximum flow.

Finally, the feature $TT_{Current}$ classifies the observed travel time during a part as usual or excessive according to (3). We only focus on NRC and do not consider frequent densities. An accident, work zone, special event, weather, or no specific event may cause any event in the network. These features are input to classification models to infer the cause of NRC.

2) Clssification Model: Classification is one of the essential topics in the field of machine learning. There are various classification methods, such as decision trees, neural networks, etc. Among decision tree algorithms, ID3 and C4.5 are the most effective algorithms. C4.5 is the next generation of the ID3 algorithm that uses the inference method in the decision tree. This paper uses VANET architecture based on SDN and SFVN fog computing to extract features and build a decision tree using the C4.5 method. This method is based on the concept of entropy. At each stage of tree construction, Gonavon features are inspected, and features that reduce the amount of disorder are selected.

We also use the Naïve Bayes method in SFVN to evaluate the classification. Simple Bayes is a probabilistic algorithm that uses Bayes theory for classification. In Bayesian classification, the main goal is to find posterior probabilities, which can be expressed as follows with the help of Bayes theorem.

$$P(c|x) = \frac{(x|c)P(c)}{P(x)} \quad (4)$$

In (4), c represents the class in question; x represents the features that each one should be calculated separately. $P(c|x)$ is the posterior probability of class c having predictor x; $P(c)$ is the probability of class. $P(x|c)$ is a measure of likelihood that shows the probability of predictor x having class c. $P(x)$ is the prior probability of the predictor of x.

Posterior observable features $X = x_1, x_2, ..., x_i$ to the density component of class c are calculated using Bayesian rules:

$$P(c|X) = \frac{P(x_1|c)P(x_2|c)P(x_3|c)...P(x_i|c)}{P(x_1.x_2.x_3....x_i)} \quad (5)$$

With the help of the simple Bayesian method, using probability rules, the cause of congestion in different urban areas can be classified.

IV. Simulation Results

The network topology was created using the actual urban environment with the help of OpenStreetMap (OSM) and SUMO urban traffic simulation software, and the NS2.35 [14] simulator was used for simulation and performance evaluation. SUMO, a traffic simulator for simulating urban mobility [15], is developed under extensive scenarios to model typical traffic conditions, including weather, accidents, work zones, and special events. The SUMO simulator requires two inputs: the network of a part of Tehran city road, imported from the OpenStreetMap database, and the traffic requests, which are based on the car trips dataset. The output of SUMO is the movement of vehicle nodes in an extensive urban network and data such as acceleration, density, flow, gap between vehicles, and other microscopic parameters at the vehicle level. We extract features that constitute a sample of the sequence data set from the simulation data collected by each vehicle. To obtain a realistic environment for simulating vehicle communication, we will use the scenarios developed in SUMO to generate a vehicle trace file in NS2. The simulation parameters are shown in the Table I. We demonstrate the effectiveness of our scheme

TABLE I
Simulation parameters

Parameters	Values
Simulation area	$3000m * 2000m$
Number of nodes	$50 - 75 - 100 - 125 - 150$
Protocol	$AODV$
Mac protocol	$802.11p$
Traffic type	CBR
Packet size	$512byte$
Communication range (R)	$250me$
Transmission rate (r)	$0.1Mbps$
Propagation speed (c)	$3 * 10^8$
Simulation Time	$300s$
Number of simulation runs	20

by investigating the performance of classification accuracy, detection accuracy, detection rate, and detection speed of NRC in an urban network. We use colab. Google to generate a classification tree. The simulation results of SFVN proposed in this paper are compared to the CCSANN [10], FogJam [8], and standard VANET architecture.

A. Evaluation

A sensitivity analysis has been performed on the model's features to obtain the significance of a feature for some of our classifications. We show in Figure.2 the sensitivity of each feature on the accuracy of the C4.5 and BN methods in the structure of the proposed SFVN architecture, standard VANET architecture, FogJam, and CCSANN. As can be seen, SFVN is more accurate than other methods. Based on the accuracy of

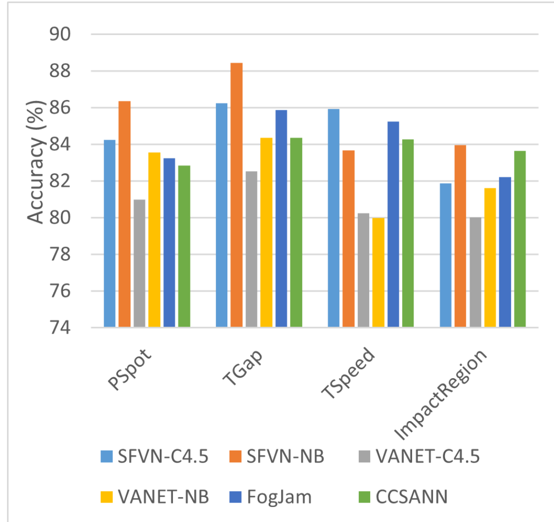

Fig. 2. Accuracy in SFVN and VANET models

features and probability models in each of the simple Bayesian and tree construction methods, the cause of the congestion will be determined. We have divided the classification classes into six categories: Normal, Incident, WorkZone, SpecialEvent, Weather, and Recurrent. Finally, we show that vehicles over VANET can identify the cause of NRC. We have analyzed the percentage of correct detection of the cause of congestion in Figure.3. As illustrated in Figure.3, the SFVN method detects the cause of congestion in different classes more accurately. The reason for this is that in the SFVN method, data and features are extracted using fog nodes in real-time and with higher accuracy, and by using the global and intelligent vision that the SDN controller adds to the network, the classification can be done more comprehensively that help to determine the cause of the congestion. The classification evaluation of the

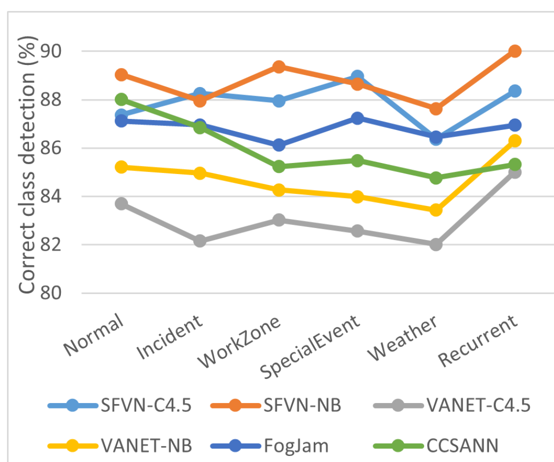

Fig. 3. Comparison of the correct class detection

proposed method in terms of the number of vehicle nodes is presented in Figure 4. As can be seen, with the increase in the number of vehicles, the detection rate of the cause of congestion has increased. Also, according to Figure 5, this rate has increased proportionally with time. The reason for the growth in the detection rate proportional to time is that more vehicles were present in the simulation scenario with the increase in the simulation time. As a result, the congestion was heavier, and the detection rate was also higher. By reaching the end of the simulation and reducing the number of vehicles, the detection rate has also decreased. Figures 4 and 5 present

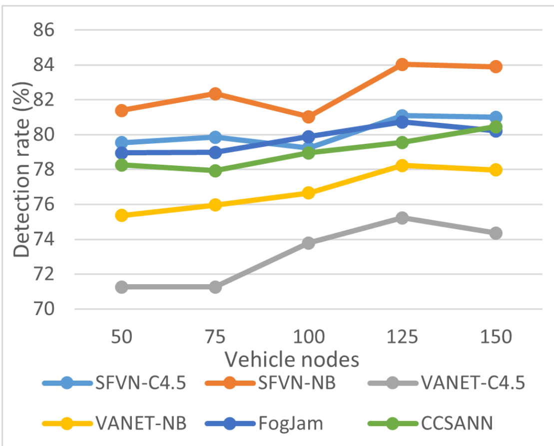

Fig. 4. Comparison of detection rate (considering vehicle nodes)

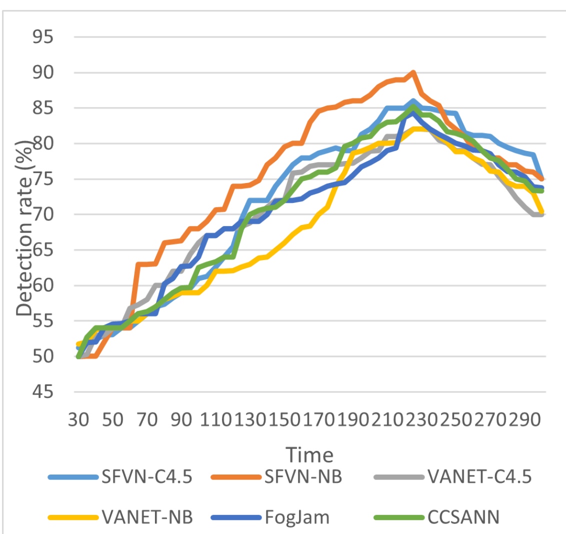

Fig. 5. Comparison of detection rate (considering time passing)

that the congestion detection rate in SFVN-based classification methods was higher than others. The reason is that, with the increase in vehicles, the SDN controller performs network management and data collection better and more completely using its global view. The management performance of RSU, BS, vehicle, and fog nodes for collecting and extracting features is better in the SFVN architecture with many nodes. As a result, with the growth in vehicle nodes, the classification methods have also performed better in the SFVN architecture.

V. Conclusion

The duration, time, and location of Non-Recurrent Congestion (NRC) in an urban network vary greatly, and real-time traffic monitoring is complicated with conventional methods. We have used SDN and fog computing technologies for distributed congestion classification, and we have proposed using these two technologies as a cost-effective and flexible solution to ensure better monitoring of road traffic in VANET networks. The proposed framework aims to exchange traffic flow data through vehicles and fog nodes located at the edge of the network to infer the cause of NRC. The simulations show that the prediction accuracy of the proposed scheme for C4.5 and simple Bayesian methods is higher than the standard VANET architecture.

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