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Design and Implementation of Intelligent Traffic-Management System for Smart Cities using Roaming Agent and Deep Neural Network (RAD2N)

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Abstract— In metropolitan areas, the exponential growth in quantity of vehicles has instigated gridlock, pollution, and delays in the transportation of freight. IoT is the modern revolution which pushes the world towards intelligent management systems and automated procedures. This makes a significant contribution to automation and intelligent societies. Traffic regulation and effective congestion management assist conserve many priceless resources. In order to recognize, collect and send data, autonomous vehicles are furnished with IoT powered Intelligent Traffic Management System (ITMS) having a set of sensors. Moreover, machine learning (ML) algorithms can also be employed to enhance the transportation system. Traffic jams, delays, and a high death rate are the results of the problems that the current transport management systems face. In this paper, an active traffic control for VANET is proposed which merges Roaming Agents (RA) with deep neural networks (DNN). The effectiveness of the DNN with RA (RAD2N) routing method in VANETs is evaluated experimentally and compared with the traditional ML and other DL routing algorithms. Several traffic congestion indicators, including delay, packet delivery ratio (PDR) and throughput are used to validate RAD2N. The outcomes demonstrate that the proposed approach delivers lower latency and energy consumption.
Keywords- Deep Neural Network, Intelligent Traffic Management System, Internet of Things, Machine learning, VANET

I. INTRODUCTION

Many modern technologies like autonomous vehicles, adaptive transportation systems, and intelligent highways are directly connected to the Internet of Things (IoT) for Intelligent Traffic Management System (ITMS), improving data transfer and fostering diverse communication. Vehicular ad hoc networks (VANETs) have recently designed to provide safety control and data administration to the users and built with proper mechanism to operate in any condition and adapt the dynamic changes in the network [1]. However, as the number of vehicles increases, both centralized [1] and distributed [2] algorithms must be used to regulate traffic.

The increase in urban traffic results in the raise of jam at junctions, fuel usage, more accidents, and higher pollution levels [3]. Traffic management systems depend heavily on real-time, precise traffic flow predictions. In these situations, the intelligent transportation system (ITS) provides trustworthy traffic control services which inform users about their surroundings by coordinating the network in a safer and more efficient manner. The use of several Information and Communication Technologies (ICT) in ITMS improves traffic and mobility management even more [1].

A widely recognized technique for addressing challenges in the transport management is designing an ITMS. ITMS can improve vehicle traffic and passenger transportation by reducing the gridlock with the help of sustainable development of IoT-based ITMS. The public value of state-of-the-art services is an important key principle of the smart-city administration system [4]. Mobile devices, sensors, and actuators become more intelligent over the past decades, enabling the communication between devices and the

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execution of challenging assignments. Since IoT is made up of embedded systems, smart mobile gadgets, wireless sensors and actuators and practically all other devices, the amont of data created by the IoT devices is growing rapidly along with the number of those devices [5].

Connecting physical objects to the Internet enables the creation of intelligent networks and mobile communication connectivity using cutting-edge system like ITMS. IoT-based vehicle communication is a brand-new information-exchange paradigm that supports ITMS. IoT combines collecting and processing the sensor data in traffic management [6] in order to efficiently manage and support traffic networks.

Implementing ITMS is one of the key agenda in smart city development which can be achieved through the efficient use of smart city development and infrastructure through AI and ML. This focuses on enhancing the quality of resources for the community members while controlling the important attributes and productivity [7]. When traffic is growing exponentially and computational tasks are high, traffic management analysis becomes complex [8]. Advanced intelligent systems are therefore required to provide open and adaptable architecture for smoother transmission of automobiles considering the uncertainty, exponential development, and high computational processes. Hence, we need high-end intelligent systems that use deep learning (DL) algorithms to control the network and manage resource utilization.

Therefore our objectives in this paper include proposing an ITMS which

(i) Utilizes the architecture of the IoT enabled smart signaling system to avoid congestion.

(ii)Using the ML algorithms to automatically manage the traffic control

This paper consists of the following sections: Existing literature is reviewed in section 2; Proposed methodology is described in Section 3; Section 4 provides the experiment results and discussion followed by the conclusion in section 5 with the future research direction.

II. LITERATURE REVIEW

To prevent congestion, ITMS increases the continuously increasing vehicle motion and traffic in highway regions. DL algorithms can be used to examine data in-depth in datasets created as a result of the production of enormous volumes of data by numerous smart gadgets connected to the transport system.

Intelligent traffic prediction can play a vital role in addressing the traffic problems in cities [9]. However, a variety of useful parameters can be considered by those intelligent techniques for anticipating the traffic flow. The use of ML and DL techniques can also be involved in analyzing data and produce more accurate predictions [10].

In recent years many researchers have developed intelligent transportation systems, however traffic control is yet to be improved [11]. In [12], the researchers proved that these techniques can help in forecasting status of the road traffic. Automatic traffic-signal management, route discovery, recognition of neighboring objects or automobiles are the necessary processes to improve the safety and effectiveness of ITMS. Significant traffic surveillance frameworks have been shown by the authors of [13] to enhance the smartness in metropolitan regions. Numerous studies on intelligent traffic management systems based on the IoT methodology have been performed.

2.1 Traffic monitoring

Many researchers are involved in developing intelligent transportation systems, due its complexity in nature. The authors of [14] demonstrated the transformation of smart urban regions by robust traffic surveillance frameworks. Numerous experiments on intelligent traffic-control systems based on the IoT approach have been conducted by the authors.

According to the authors of [14], autonomous traffic detection is essential in urban planning infrastructure and services. Estimating the traffic flow, predicting the congestions and dynamic traffic control are all the capabilities of intelligent network nodes enabled with sensors. When executed properly, this enhances perception, enhancing the resource utilzation and infrastructure in a more efficient manner.

An IoT powered control system was suggested in [15] to obtain, govern and consolidate real-time traffic models. Their main goal is to expand the range of mobility and transmit vital traffic information about traffic bottlenecks and unexpected crashes via the highway signaling system. In [16] the researchers have created a structure to examine the practicality of the traffic model. The experiment outcomes exhibit very low error in highway prediction and good vehicle identification and tracking accuracy.

2.2. Real-Time Traffic Control Based on ML and IoT methods

In [17] real-time data was gathered by the authors using IoT-based connected automobiles. The vehicle-to-vehicle connection enables precision collision avoidance planning by enabling individual vehicle observation.

By utilizing CNN, the authors of [18] seek to forecast the traffic rate and compare the efficiency with the current prediction methods. The CNN is less likely to clatter in traffic data and catches the local interdependence of data. Five input layers are needed for this approach, one of which is for the

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timing data and the other four are for the speed profiles of links from one to four.

Hybrid Multi-Model Deep Learning Framework (HMDLF) is proposed by Du et al [19] with the aim of estimating traffic flow. In order to achieve the properties of correlation between drifts and extended dependencies of each traffic data, this method integrates gated recurrent units (GRU) and one-dimensional CNN. By utilizing big data analytics, Hebert et al. [20] have created a high resolution accident prediction model for predicting the circumstances of an accident in short span of time on the different segments of the road formed by road crossings.

An expressive IoV routing protocol was proposed by the authors of [21], who emphasized the intricate relationships between vehicles, highways, environments, and zebra crossings. Real-time data was collected by the authors of [22] using IoT-based connected automobiles. Vehicle-to-vehicle connections provide accurate collision avoidance planning by supporting individual vehicle observation. In [23], the authors have proposed a refined technique for identifying traffic patterns to setup on congested roadways. The visual signal unit uses alerts, indications, or color combinations to exhibit the present traffic patterns and events.

A dynamic automobile system based on IoT and ML techniques was described in [24]. The image sensor and control panels performed critical roles. The details of the route were mostly recorded by a scene detector with video footage and sent to the next driver circuit. In [25], the researchers have proposed a smart ITM system. The VANET is a particular category of ad hoc network, in which smart automobiles on roads are also thought of as the connecting point to transmit data from crowded routes.

III. PROPOSED MODEL

The design and working principle of IoT based ITMS with ML approach are described in the subsequent paragraphs. We start our discussion with an overview of the IoT architecture followed by the design of the IoT traffic management module.

3.1. Architecture of IoT

IoT connects different "things" that typically include sensors, apps, and other novel techniques to fuse and transport data between platforms and devices through the Web. There are two basic components in IoT. The first is an "item or thing" that people want to connect and make intelligent. The second is the built-in platform that makes the communication possible. The later has a complex structure built with several sensors, actuators, techniques and data-access layers. Interconnectivity between these devices is responsible for building adaptable, wise, and effective interactions with others [26].

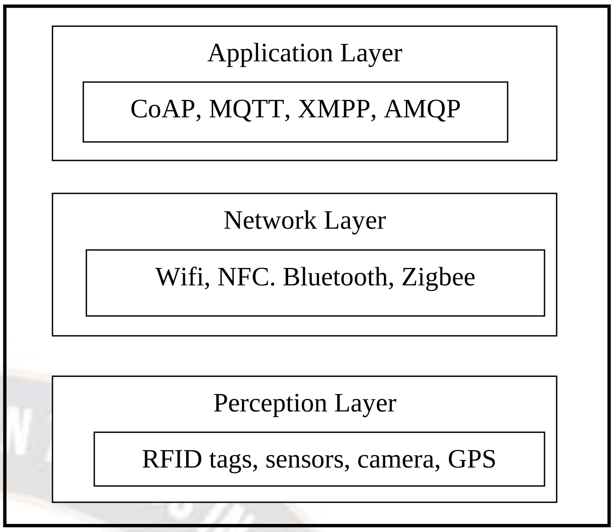

Figure 1. Architecture of IoT

The three-layered IoT architecture is depicted in Figure 1. The bottom most layer is the perception layer, which includes sensors, GPS, RFID tags, and cameras. The network layer or second layer is primarily responsible for representing communication technology and media, including types of internet such as 3G or 4G, channel, and the type of communication. The application layer includes a number of protocols that are useful in the construction of smart architectures such as cities, grids, healthcare, and businesses. The application layer, which represents the ultimate application or end-user seeing the IoT connection, is the top layer.

3.2. IoT based ITMS architecture

The architecture of our ITMS is represented in figure 2. It uses an intelligent transport system's promising methodology to address the real, critical issue with traffic management. The application layer is the top layer and it contains information about the location, accidental tracking, image tracking and message passing of the vehicle. The service layer, or Layer 2, illustrates the process of collecting, storing, and preprocessing data. Layer 3 is the network layer responsible for inter vehicle and vehicle to RSU communication and Layer 4 is liable for sensing and gathering data from the environment.

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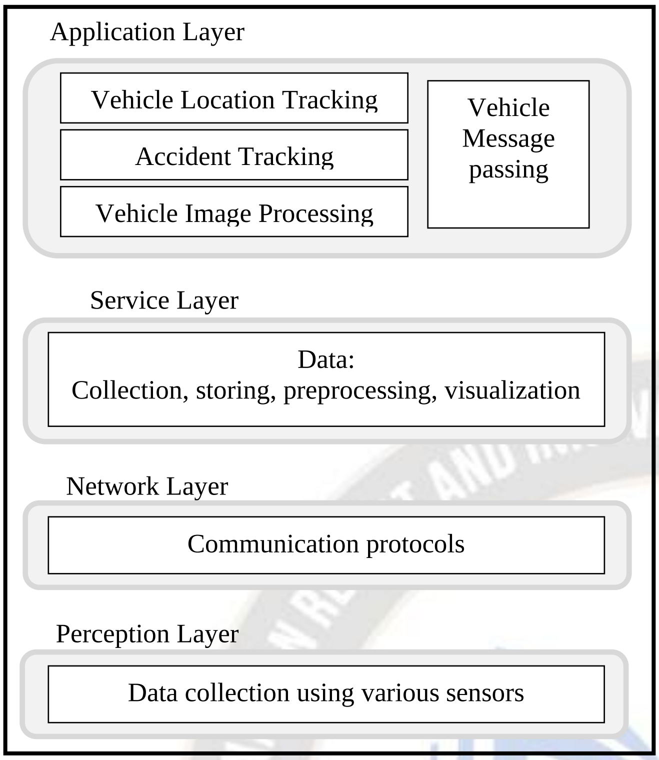

Figure 2. Architecture of the proposed RAD2N –ITMS model

3.3. System Design

As shown in figure 2, the proposed RAD2N –ITMS model contains several layers. Each layer has well defined functionality from data collection to vehicle location tracking, accident tracking and passing messages between vehicles. In the subsequent paragraphs we discuss the functions of different layers in the proposed system.

3.3.1. Tracing the location of a vehicle

The proposed system supports in selecting routes with more precision. The working prototype of the suggested vehicle location monitoring system is depicted in Figure 3. Data are gathered in the first stage with the sensor and camera devices. An essential part of ITMS is the preprocessing of data which is carried out once the data have been captured by a sensors and camera. In this process, missing value estimate techniques are used for correcting the errors in the collected data [27]. The acquired data are processed and the training method is employed to train the ML algorithm.

Roaming Agent (RA)

The RA is a dynamic network unit which actively traverses across VANETs and connects with the Core functioning (CF) module by accessing the automobile units in the proposed VANET architecture. Each RA is assigned a unique id in order to recognize the exclusive data sent by it.

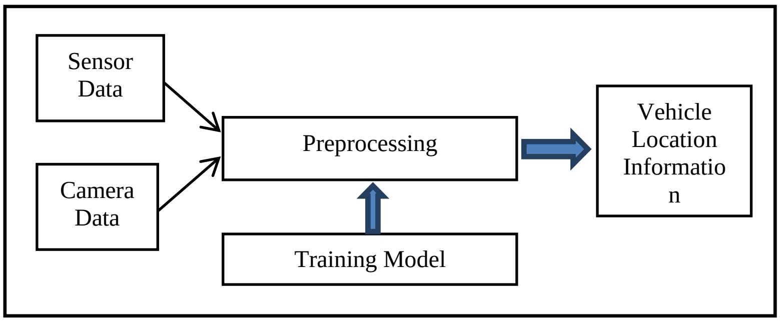

Figure 3. Vehicle location tracking

The RA is composed of four components: (i) Detection module,(ii) Processing module, (iii) Path-finder module, and (iv) data-storage module. The RAs uploads vehicle information to the DNN, in order to send data packets more quickly from source node to destination node via cooperative RAs using specific routing paths.

The executive code stores the data about the current vehicle as it plies on a particular route, which is established by the DNN. After that the data-storage module completely retains the data that was received from the vehicle units. Here, RSU plays a vital role which contains the all the routing paths generated by the DNN [28].

Core functioning (CF) module:

The CF module, which is located at the application layer, uses the vehicle's position, speed, and location to determine the routing path using DNN. As presented in figure 4, the CF module collects control data, comprising the position of the vehicle, speed, and time stamp. Iterative data collecting is employed to guarantee the accuracy of the data. The sensors in IoT based Automation Unit (IoTAU) in each vehicle collect the data and send them to DNN. The DNN receives the input from IoTAU and calculates the routing path. The IoTAU of each vehicle cooperate with the same in other vehicle in order to decide rout to avoid congestion.

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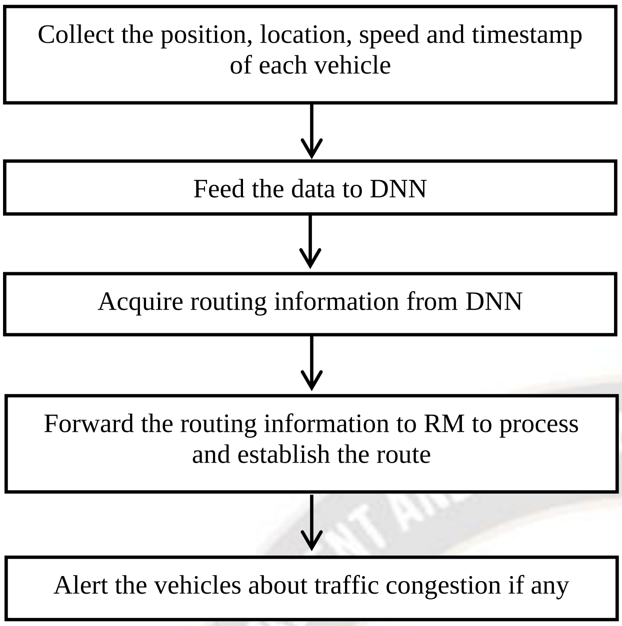

Figure 4. Workflow of CF module

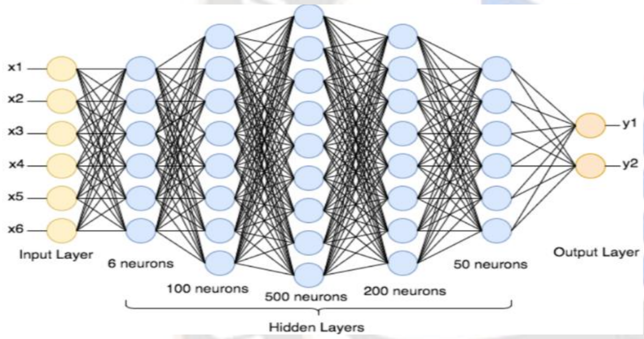

Figure 5. DNN architecture

Figure 5 shows the various layers in the DNN architecture. The DNN and artificial neural network (ANN) models of deep learning that have already been developed were used to validate the proposed model [29 - 35]. Various performance measures, including connection probability, network throughput, PDR, vehicle speed, and network density, were used to validate the average delay and cumulative distribution function (CDF) [36 - 40].

IV. PERFORMANCE EVALUATION

The proposed model is implemented by using python simulator. The simulation parameters are given in Table 1. A machine learning model called ANN [23] and an existing deep learning model called DNN [41] are used to validate the proposed model. The evaluation of average latency, CDF, fuel consumption, PDR and throughput are done using a variety of performance indicators, including traffic type, speed of the vehicle and network density. The proposed RAD2N is compared with DNN and ANN models and the network connection quality is show in figure 6 and 7 with the speed of vehicles at 30 kmph and 40 kmph respectively for comparison. The transmission range may be adjusted between 200 to 500 meters, while the vehicle's arrival speed is maintained from 30 to 50 kilometers per hour. The simulation result demonstrates that as distance between the vehicle and the RSU increases, the probability of connection expiration increases and the link with the vehicle decreases.

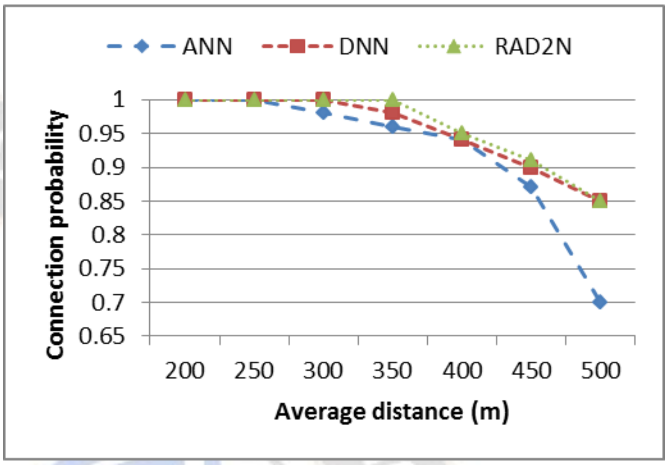

Figure 6. Comparison of connection probability of RAD2N with ANN and DNN at 30 kmph of vehicles

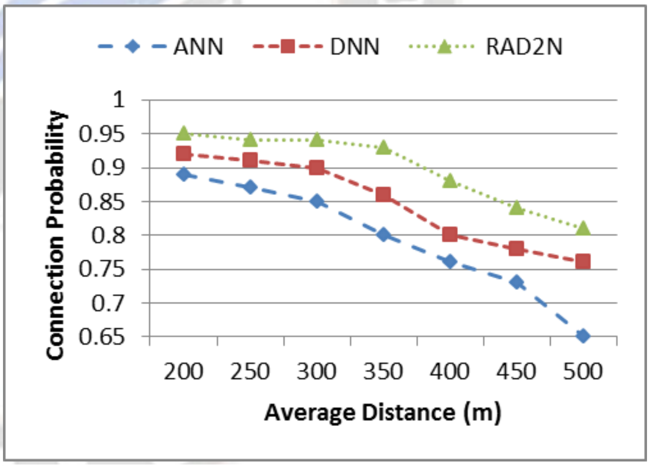

Figure 7. Comparison of connection probability of RAD2N with ANN and DNN at 40 kmph of vehicles

Nevertheless, the long-term connection of the VANETs with vehicles is aided by the deployment of RSU with a distance of 350 m each. The connection probability, on the other hand, continues to be difficult to establish with vehicles that are 300 metres away despite increased network traffic. The network density is rated as high, medium and low for 300, 200 and 100 vehicles respectively. The result demonstrates that, when compared to DNN and ANN models with a low density network, the proposed technique builds longer distance connectivity with vehicles. When the network density rises, there occurs degradation in the system.

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The average delay of data transmission between the automobiles as a function of vehicle velocity is shown in Figure 8. The simulation result suggests that as speed rises, data transmission latency also increases. On the other hand, when network density rises, latency also increases.

Maximum average delay is a result of the combination of increasing vehicle density and velocity. The failure to establish a link for packet forwarding between the vehicles caused by such mobility affects the data transfer. The results of throughput at various data rates are shown in Figure 9.

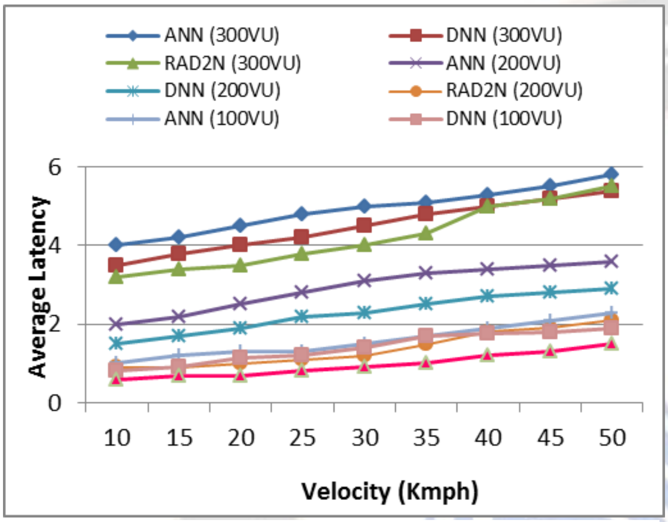

Figure 8. Comparing latency with different numbers of vehicle units

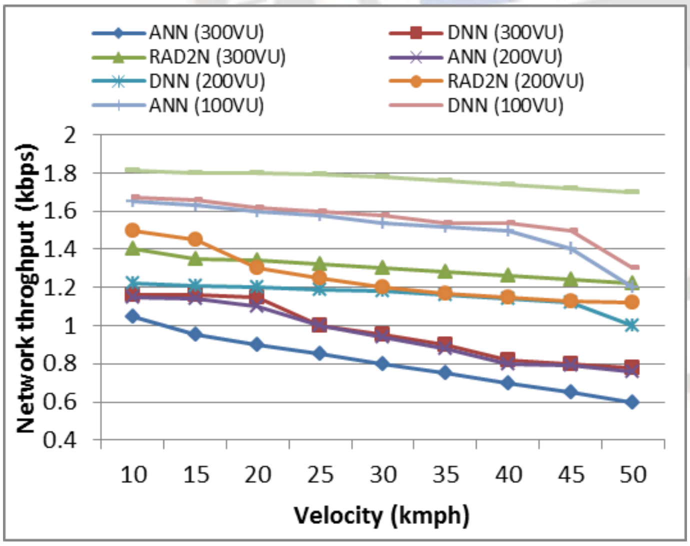

Figure 9. Comparing throughput with various numbers of vehicle units

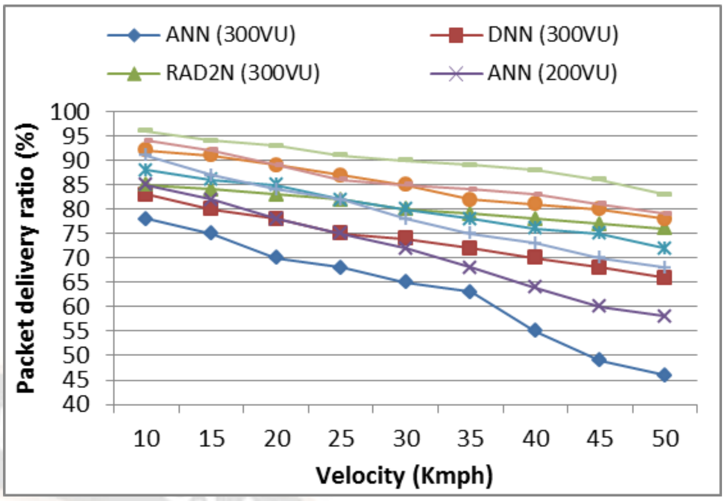

Figure 10. Comparing packet delivery ratio with different numbers of vehicle units

According to the varying speed and density of the vehicles the data rates fluctuate. According to the simulation's results, maximum throughput is attained at the road's edges when the vehicle moves at the slowest possible speed and with the least amount of throughput on both straight and curved road segments. Figure 10 shows the findings of the PDR for various vehicle densities and speeds. As the average delay is indirectly related to the PDR, this has a direct impact on the delivery rate as depicted in Figure 10.

Conversely, simulation results show that the link is successfully created at low vehicle speeds and densities, which significantly reduces the average latency. The effectiveness of RAD2N is enhanced by the inclusion of RA rather than DNN and ANN in terms of minimal average latency rate with decreased failure rate. Compared to DNN and ANN, the RAD2N has a greater packet delivery rate and more functionality, according to the simulation results.

V. CONCLUSION

In this work, RAD2N is used in VANETs to route automobiles in an efficient manner on heavily crowded roads. To determine the location of each vehicle travelling in highways, the deep learning-based RA scans the whole network. When there is increased network traffic congestion, the RAD2N can optimize the routing choice based on the inputs from RA. The DNN efficiently processes the routing option at a quicker pace and offers the network a solution by establishing the ideal pathways so that the congestion is lessened in a shorter amount of time. The routing table at RSU is used to provide frequent updates on the condition of the vehicle, ensuring the best possible vehicle selection. The simulation results demonstrate that the RAD2N model has decreased latency, improved connection, throughput, PDR and end-to-end delay. The RAD2N provides quicker routing decisions than the existing DNN and ANN models, according to the validation under varying velocity, distance, vehicle density, and data and transmission rate. According to the results, the proposed model provides higher data delivery rates since the probability of connection termination is less. Therefore, the traffic density has been maintained in an ideal manner as a result of the streamlined routing decisions made using DNN based on continuous observation by RA, ensuring effective packet delivery to the target nodes.

Future work will incorporate security and energy-efficient systems into the proposed RAD2N system. Instead of using a simulator with live traffic, the proposed solution will be deployed in a real-time setting.

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