Applying Deep Convolutional Neural Network (DCNN) Algorithm in the Cloud Autonomous Vehicles Traffic Model

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Abstract: *Connected and Automated Vehicles (CAVs) is an inspiring technology that has an immense prospect in minimizing road upsets and accidents, improving quality of life, and progressing the effectiveness of transportation systems. Owing to the advancements in the intelligent transportation system, CAV plays a vital role that can keeping life lively. CAV also offers to use to transportation care in producing societies protected more reasonable. The challenge over CAV applications is a new-fangled to enhance safety and efficiency. Cloud autonomous vehicles rely on a whole range of machine learning and data mining techniques to process all the sensor data. Supervised, Unsupervised, and even reinforcement learning are also being used in the process of creating cloud autonomous vehicles with the aim of error-free ones. At first, specialized algorithms have not been used directly in the cloud autonomous vehicles which need to be trained with various traffic environments. The creation of a traffic model environment to test the cloud autonomous vehicles is the prime motto of this paper. The deep Convolutional Neural Network (CNN) has been proposed under the traffic model to drive in a heavy traffic condition to evaluate the algorithm. This paper aims to research an insightful school of thought in the current challenges being faced in CAVs and the solutions by applying CNN. From the simulation results of the traffic model that has traffic and highway parameters, the CNN algorithm has come up with a 71.8% of error-free prediction.*

Keywords: *Cloud computing, neural network, prediction model, resource selection.*

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1. Introduction

Vehicles make use of machine vision algorithms that play an essential role in cloud autonomous vehicles by gathering or capturing, preparing training data sets. With the help of sensors, the raw images on road signs, traffic lights, and moving objects have been given training both their recognition and decision-making things to detect and categorize the objects ahead of them. Since the time required to accomplish the entire process of prediction must be done in a fraction of seconds, the success of cloud autonomous is rely on better machine learning through artificial neurons. Moreover, the advancement of automated vehicles needs clarity to differentiate between self-driving and cloud autonomous vehicles. A fully cloud autonomous vehicle can be self-aware and proficient in creating its individual preferences. For example, if we speak “ride me to work” but the vehicle decides to take you to the park instead. But, an entirely automated vehicle, however, would go after orders to ride itself are termed self-driving and often used interchangeably with cloud autonomous. The 5 levels of cloud autonomous vehicle are as follows

- Level 1 needs driver assistance.
- Level 2 is nothing but partial automation.
- Level 3 indicates conditional automation.
- Level 4 means high automation.
- Level 5 is meant for full automation.

The navigation scheme procedure of the cloud autonomous vehicle is used for the following steps:

- Localization of the vehicle on the map
- Observation of the sensors to inform the 3D record with images in the front of the vehicle
- Navigation, which choose the route of movement

Cloud autonomous vehicles create and maintain a map of their surroundings based on the information from a variety of sensors situated in different parts of the vehicle. Radar sensors monitor the position of nearby vehicles. Video cameras detect traffic lights, read road signs, track other vehicles and look for pedestrians. Moreover, the three key functional components of a cloud autonomous vehicle are to sense, map, and negotiate its place on the road. While a human mind expects definite circumstances along a travel path, a driverless vehicle only responds to input and its response as there has been no concrete thought process of expectation or insight. So, there have been so many fatalities and accidents with driverless vehicles. The motivation of this paper has come from the Challenges to produce level 5 cloud autonomous vehicles as defined below.

- To implement fully cloud autonomous vehicles for the road.
- To design building blocks of a fully cloud autonomous vehicle.
- The ability to sense traffic environment using multiple sensors.
- The ability to perceive their surroundings.

The three main cloud autonomous vehicle sensors such as camera, radar and LiDAR work together to render the vehicle images of its surroundings in addition to the speed and distance of nearby objects in three-dimensional shape. Then the cloud autonomous vehicles do communicate by gathering data by various sensors built-in and the message is sent back to the cloud through wireless communication. During the drive, vehicle must answer following questions which are illustrated. During the drive, car should answer then above questions.

- Where is vehicle's current location?
- Where is everyone else?
- How do I get from point A to B?
- What's the driver up to?

The vehicle should get a vision and for that CNN is used to recognize objects on the road. So it is a tough task to choose the machine learning algorithm according to the need and suitability of the environment. The contributions of this paper are twofold: Firstly, a traffic model is proposed to create in a cloud autonomous environment. Secondly, we propose a deep CNN algorithm, where a dynamic approach is needed. Figure 1 shows the Sensors used in Cloud autonomous Vehicles. Sensors have been inevitable in the development of self-driving to monitor its environment. The sensors provide a message to a computer that unites the sensor data with high-definition map information to pinpoint the vehicle. This envisages the object's future motion pedestrians and the movements of other vehicles. The computer manages with the sensor commands for the actuators that control the steering, throttle, brake, and drive unit. Figure 1 shows the Sensors used in Cloud autonomous Vehicles. Sensors have been inevitable in the development of a self-driving to monitor its environment. The sensors provide message to a computer that unites the sensor data with high-definition map information to pinpoint the vehicle. This envisages the objects future motion pedestrians and the movements of other vehicles. Computer manages with the sensor commands for the actuators that control the steering, throttle, brake, and drive unit. Figure 1 show the Sensors used in cloud autonomous vehicles.

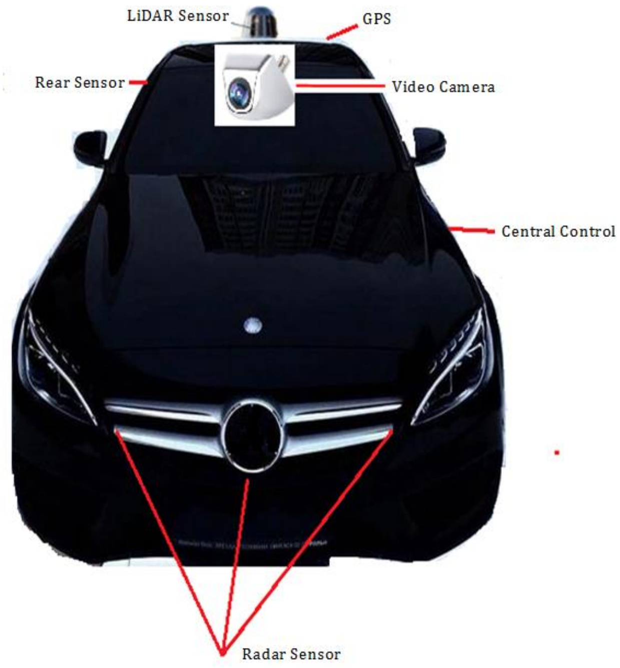

Figure 1. Sensors used in cloud autonomous vehicles.

- LiDAR offers an extremely accurate response using laser measurements for both static and mechanical objects to compute the distance to a target by illuminating the target with pulsed laser light and finding the reflected pulses with a sensor.
- The Lidar uses an electromagnetic pulse to look after solid objects that have low light reflectivity.

- **Assessments of cloud autonomous vehicles**: The performance of cloud autonomous vehicles has been assessed as per the following procedure defined.
  - Observe the environment around it in all sides and angles, bright and dark
  - Recognize pedestrians in a crosswalk
  - Categorize vehicles in all positions including bicyclists
  - Watch out for an object dashing unexpectedly into its lane, and react for that reason
  - Plan through structure like cones
  - Succumb to critical situation vehicles React to keep away from accidents
- **The perception of CAVs and communication protocols in an Environment**: LIDAR is the 3-Dimensional mapping technology influential in allocating AVs to determine the space of objects and carefully watch the road using its pair of eyes using the algorithms that power self-driving systems. The affordability, ease to manufacture, ability to measure the velocity of objects in dark times, compatibility with any self-driving software makes LIDAR an efficient one.

This paper presents a contribution to analyzing Preliminary Studies, the Role of deep Learning

Algorithms for Connected and Automated Vehicles (CAV)'s, Machine learning algorithms, and communication protocols for CAVs, Proposed Cloud Autonomous Vehicle Algorithm Based Convolution Neural Networks (CNN) with experimental results and outcome and conclusion with discussion.

2. Preliminary Studies

This section focuses on the literature survey on functional operation, protocols and communication systems, design Challenges, performance Evaluation of CAV's. The survey also imports attention to the role of machine learning and artificial intelligence in the successful enhancement of CAV's Performance. In addition, various deep learning methods will also be researched.

Shladover [19] examined the outset of connected and automated vehicle systems has been examined with the help of artificial intelligence. Federici *et al*. [7] surveyed architecture for CAV have been introduced. They also focused on improving energy efficiency and provided an overview by comparing existing algorithms. Elliott *et al*. [6] discussed both passive and active, mechanisms for collision-free, maneuverability, vehicle connectivity, control complexities, motorcycles for pedestrian detection sensor, radar, and computer vision-based techniques by creating connections among the subjects. Do *et al*. [5] stated a study on the literature review of the simulation-based connected and automated intelligent vehicle and summarized the intelligent vehicle, various models. Kuutti *et al*. [13] discussed the challenges for smart cities with connected and CAV's. In addition; they highlighted the literature on the intelligent transportation system. Zhao and Malikopoulos [22] summarized the research directions of cloud autonomous vehicle systems. Seuwou *et al*. [17] studied the merits and demerits of deep learning methods by comparative analysis in terms of computation and architecture selection of autonomous vehicles. Lim and Taeihagh [15] highlighted the ethical and technical causes of algorithmic decision-making in AVs by exploring the decisions through predictions. Kocic *et al*. [12] attained cloud autonomous driving with the aid of a deep neural network for the deployment of embedded automotive platforms. The shortcomings in the current methods of cloud autonomous vehicles in terms of safety measures by considering AI have been interrogated by Cunneen *et al*. [3] Al-Qizwini *et al*. [1] initiated a robust framework and algorithm for cloud autonomous driving. First, they analyzed the 3-CNN models for feature extraction and assess their efficiency by a deep learning-based algorithm. The opportunities and challenges of incorporating deep learning for self-driving cars have been offered by Rao and Frtunikj [16]. The applications in the field of image recognition and the trends of deep learning-based cloud autonomous driving have been explained by Fujiyoshi *et al*. [9]. Tian *et al*. [21] deliberated and evaluated a systematic testing tool called Deep Test to detect erroneous behaviors of Deep Neural Network-based vehicles that can lead to fatal crashes. The demand in rural mobility and the vehicle population has been presented by Li *et al*. [14]. The state of the art on deep learning methodologies like CNN and RNN neural networks used in cloud autonomous vehicles have been surveyed by Grigorescu *et al*. [10]. A review of the state of the art on smart driving systems which rendered a large number of research areas has been presented by Figueiredo *et al.* [8]. Guanetti *et al*. [11], explored Intelligent transport Systems which depicted the mechanism for a structured study and testing. Advancement in transportation systems to enhance the accuracy of the system has been initiated by Sumalee and Ho [20]. The characteristics of cloud autonomous systems and their exploited technologies have been analyzed by Andersen and Sutcliffe [2].

From the literature survey, it is identified that the contemporary algorithms, methods, protocols used in Cloud autonomous vehicles do have some deficiencies in terms of object tracking, reorganization, and prediction. Further, the existing methods have not utilized the deep learning algorithms to improve the accuracy in terms of the performance of prediction and decision making of cloud autonomous vehicles. Our proposed algorithms filled these gaps to meet out the objectives under the traffic model to drive in a heavy traffic condition.

3. Role of Deep Learning Algorithms for CAV's

Cloud autonomous transport systems have been intimately connected with Internet of Things (IoT) which is shared with essential technologies like machine learning, artificial intelligence, local computing to build them work without drivers taking control of the wheel utilizing a lot of sensors, actuators, and controllers. The software controls the end devices in the form of Electronic Control Units (ECUs). Machine learning software plays a big part in this set [2]. One of the main duties of any machine learning algorithm in the self-driving car has been an uninterrupted interpretation of the nearby situation and the forecast of probable modifications to those surroundings. These tasks have been essentially separated into four associate tasks:

- Entity Identification or recognition Object classification through intelligent recognition and classification algorithms
- Entity localization and prediction of movement through prediction algorithms
- The process of detection, identification, classification and prediction tasks can be carried out

by the machine learning algorithms namely regression algorithms, pattern recognition, cluster algorithms, and decision matrix algorithms. The important part of any intelligent transport system is to possess efficient policy learning for the vehicles to take speedy action against immediate situations based on the sensing environment and understandings. In such challenging situations, deep learning comes in to take place in CAVs. Particularly deep learning can be the best choice based on neural network t from the experience in terms of reducing the distance errors and velocity to optimize the fuel consumption. A range of sensors has been used in cloud autonomous vehicles. Each sensor is generally linked to its algorithms, whose outputs may nourish a system that makes the final decisions. Some of these algorithms are Machine Learning techniques. To give an example, an early system used an ML algorithm with its visual inputs. Cameras that showed the driver's view was the inputs to a neural network that had three digitized outputs: steering-wheel turn, brake-pressure, and gas-pedal pressure. The system was trained to imitate a human driver's steering, braking, and gas in response to visual input over hours of training. The neural-net learned to contest the human's answer to very high levels of accuracy after examining them over miles and miles of training. The machine learning algorithms are summarized as follows.

4. Machine Learning Algorithms and Communication Protocols for CAVs

- **Regression Algorithms**: In cloud autonomous transport systems, images (radar or camera) occupy a significant role in localization and actuation. Building up an image-based model for prediction and feature selection has been the major confrontation. Bayesian regression, neural network regression, and decision forest regression are the kinds of regression algorithms used for cloud autonomous cars [4]
- **Pattern Recognition Algorithms (Classification)**: The sensors are capable of possessing environmental image data followed by filtering to recognize occurrences of an object grouping by preventing the inappropriate information points. To classify the objects, it is important to recognize the pattern in an informal group for which data reduction algorithms have been much useful. Line segments are aligned to edges up to a corner and then a new line segment is started. Circular arcs are robust to sequences of line segments that approximate an arc. The image features are combined in various ways to form the features that are used for recognizing an object. The Support Vector Machines (SVM) with Histograms of Oriented Gradients (HOG) and Principal Component Analysis (PCA) are the most common recognition algorithms used in ADAS. The Bayes decision rule and K Nearest Neighbor (KNN) are also used [10].
- **Clustering**: It has been a difficult task to detect and locate objects if the captured images are blurring which brings the system will be failing due to a lack of accuracy. The clustering algorithms are centroid-based and hierarchical and the best option at determining arrangement from information points. K-means, Multi-class Neural networks are the popular clustering algorithms in practice.
- **Decision Matrix Algorithms**: As the name suggests systematic identification, analysis, and evaluation of the presentation of the relationship between sets of standards and assessment matrix alg. have been the best choice. Since a sudden decision may be required at any time during the vehicles start running in the form of taking a left turn to put a brake has been dependent on the algorithms by the classification, recognition, and prediction of the dynamic movement of objects. Hence, it is mandatory to have composed of multiple decision models independently trained to make the overall prediction with absolutely non-possibility of errors in decision making. Gradient boosting and Ada-Boosting are the important kinds of decision matrix algorithms. The Protocols for connected vehicles are as follows. Vehicle-to-everything (V2X) permits vehicles to be in touch with touching parts of the traffic system around them [12].

  - Vehicle-to-everything (V2X) permits vehicles to be in touch with touching parts of the traffic system around them.
  - Vehicle-to-Vehicle (V2V) communications have a wireless mesh network where movable parts transmit information to each other about what they have been doing.
  - Car2X, smart wireless vehicle networking which is designed for local vehicle communication to make it possible to send static and dynamic data in real-time.
  - A connected Vehicle represents the knowledge that links a vehicle to its nearby environments.

5. Proposed Cloud Autonomous Vehicle Algorithm Based Convolution Neural Networks (CNN)

This section illustrates the proposal of the CNN algorithm for cloud autonomous vehicles. This algorithm has two main parts namely Feature Extraction and Classification. In the feature Extraction part, the three operations that have taken place are Data/Image captured on all sides of the cloud autonomous vehicle, filtering to create a map, and

Convolution and Pooling Operation. In the first part of the CNN algorithm, feature extraction is done. After capturing the image or data from the sensors of all in the cloud autonomous vehicle are given into the filtering process followed by the intended convolution and pooling operation. At the end of this extraction process, the characteristic of the object like width, edge, height, and depth have been extracted. In the second part of the CNN algorithm, the extracted features of the objects are needed to classify for better prediction.

In the above proposed CNN algorithm which is shown in Figure 2, the convolution is done utilizing a kernel or filter. Logically the formation of layers aimed with 3 Dimensional views of calculating width, height, and depth. Though the formation of the layers called convolution and pooling in the CNN do have the uniqueness of neuron connections from one layer to another layer in a limited way which means that all the neurons from the previous layer will not be connected to the next layer neurons but rather than the portion of neurons. The high amount of prediction accuracy is here possible owing to its final output with a single vector of probability. The intention of producing a traffic situation that takes account of the traffic model and its performance parameters has the proven merits of the proposed CNN algorithm for cloud autonomous vehicles to improve the precision in decision making compared with traditional approaches [18].

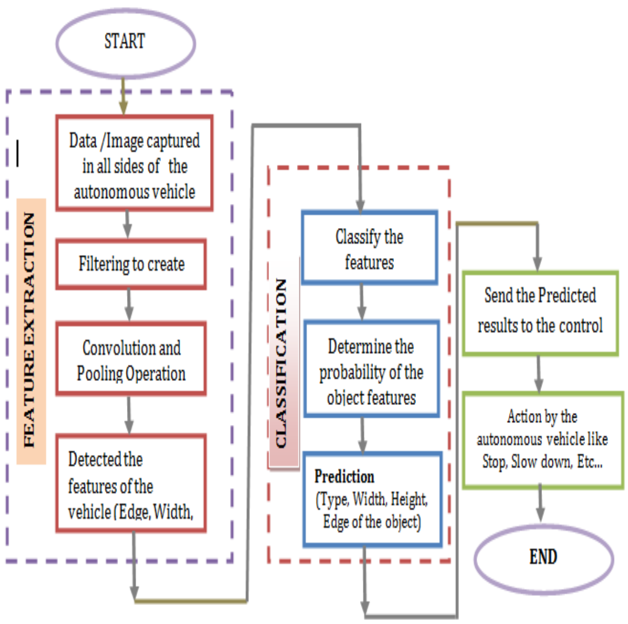

Figure 2. Proposed CNN algorithm flow-graph.

6. Experimental Results and Outcome

A traffic model has been created using Tensor Flow Open Simulator using Python language. In that highway traffic for different parameters has also been installed. The parameters used to represent a highway h are as follows.

- No. of highway paths, X, which does not comprise the previous path Size of the highway path Y, in which the number of tracks in each highway path.
- No. of Previous highway path, P: in the previous path, should be assumed as 0
- Previous path size, Ps: no. of tracks of every previous path.
- The gap size of the path, Gs: no. of tracks of successive previous paths

The following are the traffic parameters that we used to experiment with the traffic model in our simulation.

- No. of Highway paths X > 0; L 2 N
- Size of the highway path Y > 0; C 2 N
- No. of Previous highway path P _ 0; E 2 N
- Previous path size Ps > 0; Se 2 N
- The Gap size of the path, Gs > 0; Ss 2 N
- collapse period Cp > 0; Tf 2 N
- Traffic Volume _ 2 [0; 1]
- The highest speed of the vehicle Hspeed > 0 - 2N
- Vehicle’s top acceleration _Top > 0; _Top 2 N
- Rider's Logic Sense ;l € [0,1]

With the above parameters, simulation experiments have been done to analyze the performance of cloud autonomous driving using the CNN algorithm by correlating the outcome with the throughput. The performance parameters are listed as follows.

- No. of Highway paths=4
- Size of the highway path=60
- No. of Previous highway path=3
- Previous path size=4
- The Gap size of the path=8
- Collapse period=8
- The highest speed of the vehicle=4
- Vehicle’s top acceleration=2

- **Algorithms used in CNN**: The reinforcement learning algorithm has been presented based on Q Learning. The calculation used here is to guess Q-values and compact with the harms being faced out during an incessant action. The perception learning of CNN is presented as Algorithm (1). In this weight, the vector is updated for the incorrect data point.

Algorithm 1: Perception training

For a target function
Initialize weight=0
While {
misclassified values do
Pick a misclassified point x_n
Weight= weight+ x_n *} end*

The order of preference is defined in the below - proposed Algorithm (2) where the accelerations and directions have been combined to produce the optional movements ahead of other vehicles.

Algorithm 2: chosen Moves (Entry and Exit)

Chosen moves → null
Chosen accelerations Get Chosen Accelerations ()
For {all acceleration in chosen accelerations do
chosen instructions Get Choseninstructions(acceleration)
for {
al l directions in chosen directions do
insert (direction, acceleration) in chosen move
} } end
if right path is exit path then
for { all acceleration in chosen accelerations do
insert (RIGHT, acceleration) in chosen moves
} } end

Algorithm (3) proposes the movement and behavior unexpectedly of vehicles.

Algorithm 3: Get Chosen Moves Exit

Chosen moves NULL
Chosen directions Get Chosen Directions Exit ()
For {every direction in chosen directions do
Chosen accelerations Get Chosen Accelerations Exit (direction)
For {every acceleration in chosen accelerations do
Insert (direction, acceleration) in chosen moves
} } end

Algorithm (4) called opting option is illustrating the unfortunate move of vehicles around the cloud autonomous vehicle. In such a case, the action required must be taken very immediately to avoid crashing by taking the best move.

Algorithm 4: Opting Action

Prefer the chosen progress according to the condition
Finest Colliding move
While {move source Collide do
Prefer next chosen move is best
if {move causes less \frontage" Collides than best Colliding move or less collides in overall then
Colliding move is best
}} if {move does not cause collide then
decide move action
else {
decide best Colliding move}
} end

Algorithm (5) is provided with an additional called irrationality where the driver by himself can take any decision randomly without thinking too much with its previous training.

Algorithm 5: Irrational

If {irrational, with possibility
Random action is taken
Else {
Find Action ()
}} end

The proposed Algorithm (6) explains about the vehicle to generate traffic circumstances utilizing the speed, acceleration intensity, and the level of the brake.

Algorithm 6: Create Traffic

For {all highway do
if { highway's preliminary location is free then
if { random value< T, with probability T then
Arbitrarily initialized by driver
Driver goes into highway path
}}} end

The aim of creating such a traffic environment that includes traffic models, highway parameters, and performance parameters is to explore the advantages of the proposed CNN algorithm for cloud autonomous vehicles to enhance accuracy. While undergoing experiments, three assessment parameters namely target, non-target and collide have been taken into account to analyze the traffic model under a cloud autonomous environment.

- The target indicates that the cloud autonomous driver accomplishes the mission of the successful outcome.
- Non-Target indicates that the cloud autonomous driver does not accomplish the mission.
- Collide means that the cloud autonomous driver could not take the decision appropriately that resulted in a crash.

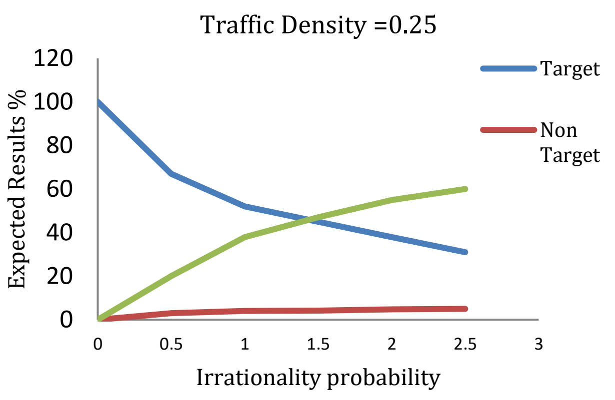

Figure 3. Outcome percentage depending on the drivers' irrationality (Traffic Density =0.25).

In our proposed traffic model, the outcome proportions namely Target, Non Target and, Collide have been shown in Figures 3 and 4 based on the irrationality probability for two traffic density

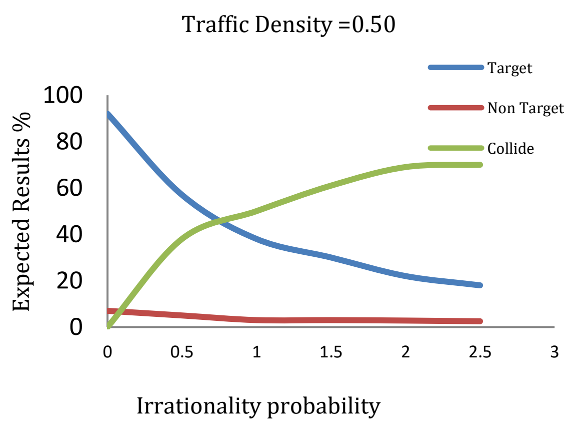

Figure 4. Outcome percentage depending on the drivers' irrationality (Traffic Density =0.5).

Table 1. Drivers' Irrationality (Traffic Density =0.5&0.25).

Irrationality probability	**Traffic Density =0.25**			**Traffic Density =0.5**		
	Expected results					
	Target	Non target	Collide	Target	Non target	Collide
0	100	0	0	94	7	0
0.5	67	5	20	56	4	42
1	52	6	38	36	3.5	50
1.5	44	4	46	30	3	61
2	38	4.7	54	24	2.5	68
2.5	31	4.9	60	16	2	70

Figures 5 and 6 illustrate the number of cars that enter and exit the highway paths based on the irrationality probability for dissimilar values of the traffic density values 0.25 and 0.50. It is studied that the number of vehicles that enter the highway path is directly proportional to the traffic density.

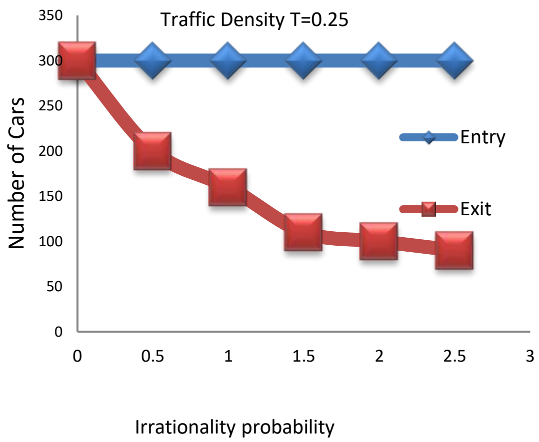

Figure 5. Throughput depending on the drivers' irrationality (Traffic Density =0.25).

On the other hand, it is seen that when the irrationality probability expands, this number will go decreased. By using the proposed CNN calculation, it is derived that the cloud autonomous driver could be ready to make the choice or decision through precise prediction in a pretty way upon the traffic model. Table 1 explains the drivers' irrationality with the Traffic Density of 0.5 and 0.25.

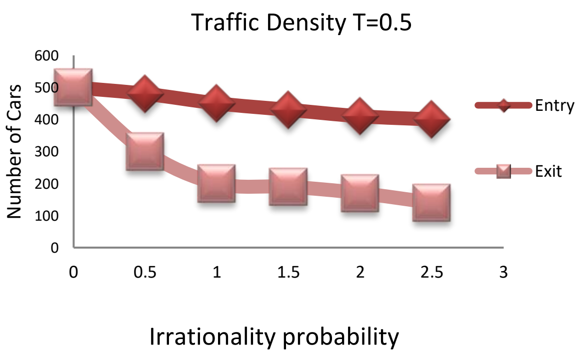

Figure 6. Throughput depending on the drivers' irrationality (Traffic Density =0.5).

The results are highly beneficial irrespective of traffic density and irrationality probability expansion, using the proposed CNN calculation in the cloud autonomous environment to ease the decision-making upon the traffic model. The outcome of this study would be more helpful for the researchers who focus on developing autonomous vehicles traffic models as a critical area to overcome the existing challenges and the elucidation by using CNN with no errors. From the proposed model, a conclusion has been arrived using three assessment parameters namely target, non-target, and collide to examine the traffic model in cloud autonomous background.

7. Discussions

As we know, Deep Learning (Convolution neural networks) plays a vital role in classifying images. Vehicle detection is tightly coupled with Image detection, Thus, Deep Learning gives better results than traditional algorithms. Reinforcement learning is the one that outperformed all other existing algorithms in the case of Self-driving cars. In the case of reinforcement learning, the model is trained with the concept of Rewards and punishments. If Vehicle is detected correctly, using the Feedback mechanism, the model is rewarded with value 1 else model is punished with value 0. It is understood that the Convolutional Layers have made an effective functioning in Deep Learning Neural Networks. In CNN, convolutional layers have been acting as the key blocks. The filters are doing the convolution part as a feature map that uses the detected features in the form of images as activations. Furthermore, the prediction can be done by the effective probability of extracted features of the object. It is observed that the effective way of filter application to make a feature map, learning the filters aimed at prediction and determination of convolutional layer by dimension feature map are the typical things to accomplish the accurate results of CNN in cloud autonomous vehicles. The limitations of the proposed works are using High-technology vehicles and equipment that are expensive on one end and the other hand, safety and possible security concerns concerning Non-functional sensors. The assumption we included is the lack of uniformity in road signage and stoplights that could also prove to be a hurdle for the autonomous car.

8. Conclusions

This paper in its initial sections the role of deep learning, the general principles of operations of Cloud-based CAVs, challenges, the various deep learning algorithms for enhancing the performance, and the communication protocols that play a key portion have been discussed. On the other side, the machine learning techniques for cloud autonomous vehicles have been studied. From the perspective of taking advantage of deep learning that focuses on creating artificial neurons, a convolutional neural network for cloud autonomous vehicles has been proposed. To simulate the traffic model the proposed CNN algorithm has been applied and correspondingly the assessments were done. After feature extraction and classification in cloud autonomous vehicles by case studies, it is concluded that the CNN simply outperforms the other machine learning methods in terms of 71.8% of error-free prediction (accuracy and performance). This paper focuses mainly to extract the merits of CNN by specialty of self-learning the filters in high numbers that result in attractive outcomes towards smart and speedy assessment of decision making and hence the cloud autonomous vehicles could increase its knowledge to avoid accidents. In future work, RNN of deep learning will be proposed by applying various case studies like the three-dimensional environment.

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References

[1] Al-Qizwini M., Barjasteh I., Al-Qassab H., and Radha H., "Deep learning Algorithm for Autonomous Driving Using Google Net," *in Proceedings of Intelligent Vehicles Symposium*, Los Angeles, pp. 89-96, 2017.

[2] Andersen J. and Sutcliffe S., "Intelligent Transport Systems (ITS)-An Overview," *IFAC Proceedings Volumes*, vol. 33, no. 18, pp. 99-106, 2000.

[3] Cunneen M., Mullins M., and Murphy F., "Autonomous Vehicles and Embedded Artificial Intelligence: The Challenges of Framing Machine Driving Decisions," *Applied Artificial Intelligence*, vol. 33, no.8, pp. 706-731, 2019.

[4] Dhaya R. and Kanthavel R., "Accomplishment of Intellectual Supply Managing Algorithm for Ubiquitous Cloud Computing," *Gedrag and Organisatie Review*, vol. 33, no. 3, pp. 236-246, 2020.

[5] Do W., Rouhani O., and Miranda-Moreno L., "Simulation-Based Connected and Automated Vehicle Models on Highway Sections: A Literature Review," *Journal of Advanced Transportation*, vol. 2019, pp 1-15, 2019.

[6] Elliott D., Keen W., and Miao L., "Recent Advances in Connected and Automated Vehicles," *Journal of Traffic and Transportation Engineering*, vol. 6, no. 2, pp. 109-131, 2019.

[7] Federici T., Albano V., Braccini A., D'Atri E., Sansonetti A., *Information Technology and Innovation Trends in Organizations*, Physica-Verlag HD, 2011.

[8] Figueiredo L., Jesus I., Machado J., Ferreira J., and Martins de Carvalho J., "Towards the Development of Intelligent Transportation Systems," *in Proceedings of ITSC IEEE Intelligent Transportation Systems Proceedings*, Oakland, pp. 1206-1211, 2001.

[9] Fujiyoshi H., Hirakawa T., and Yamashita T., "Deep Learning-Based Image Recognition for Autonomous Driving," *IATSS Research*, vol. 43, no. 4, pp. 244-252, 2019.

[10] Grigorescu S., Trasnea B., Cocias T., and Macesanu G., "A Survey of Deep Learning Techniques for Autonomous Driving," *Journal of Field Robotics*, vol. 37, no. 8, pp. 1-39, 2019.

[11] Guanetti J., Kim Y., and Borrelli F., "Control of Connected and Automated Vehicles: State of the art and Future Challenges," *Elsevier Annual Reviews in Control*, vol. 45, pp. 18-40, 2018.

[12] Kocic J., Jovicic N., and Drndarevic V., "An End-to-End Deep Neural Network for Autonomous Driving Designed for Embedded Automotive Platforms," *Sensors*, vol. 19, no. 9, pp 1-22, 2020.

[13] Kuutti S., Bowden R., Jin Y., Barber P., and Fallah S., "A Survey of Deep Learning Applications to Autonomous Vehicle Control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 2, pp. 712-733, 2021.

[14] Li J., Cheng H., Guo H., and Qiu S., "Survey on Artificial Intelligence for Vehicles," *Automotive Innovation*, vol. 1, pp.1-20, 2017.

[15] Lim H. and Taeihagh A., "Algorithmic Decision-Making in AVs: Understanding Ethical and Technical Concerns for Smart Cities," *Sustainability*, vol. 11, no. 20, pp. 1-28, 2019.

[16] Rao Q. and Frtunikj J., "Deep Learning for Self-Driving Cars: Chances and Challenges," *in Proceedings of ACM/IEEE 1st International Workshop on Software Engineering for AI in Autonomous Systems*, Gothenburg, pp. 35-38, 2018.

[17] Seuwou P., Banissi E., and Ubakanma G., *Digital Twin Technologies and Smart Cities*, Springer, 2019.

[18] Shukla A., Kumar S., and Singh H., "ANN Based Execution Time Prediction Model and Assessment of Input Parameters through ISM," *The International Arab Journal of Information Technology*, vol. 17, no. 5, pp. 683-691, 2020.

[19] Shladover S., "Connected and Automated Vehicle Systems: Introduction and Overview," *Journal of Intelligent Transportation Systems Technology Planning and Operations*, vol. 22, no. 3, pp. 190-200, 2017.

[20] Sumalee A. and Ho H., "Smarter and More Connected: Future Intelligent Transportation System," *IATSS Research*, vol. 42, no. 2, pp. 67-71, 2018.

[21] Tian Y., Pei K., Jana S., and Ray B., "DeepTest:

Automated Testing of Deep-Neural-Network-Driven Autonomous Cars," *in Proceedings of the International Conference on Software Engineering*, Gothenburg Sweden, pp. 303-314, 2018.

[22] Zhao L. and Malikopoulos A., "Enhanced Mobility with Connectivity and Automation: A Review of Shared Autonomous Vehicle Systems," *IEEE Intelligent Transportation Systems Magazine*, pp. 1-14, 2020.

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