# New Approaches To Increase Safety In Autonomous Vehicles

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## I. INTRODUCTION

Nowadays, as major technological developments take place, the human factor seems to fade away in many sectors, like transportation. Due to vehicle autonomy advancements, soon people will not be driving as much. AVs are significantly important since any failure in safety measures would mean tragic accidents. In recent years, Tesla's AVs were involved in some accidents and have proven to people how important safety is. In this paper, to increase this AV's safety, security, and robustness, we propose two main approaches: Improving new sensor-based detection systems, and new deep-learning-based applications.

## II. NEW DETECTION METHODS FOR RADAR AND LIDAR

Sensors collect all the data required for AVs. The safety of AVs directly depends on how well the sensors work. Each sensor has its own merits. Not all sensors are suitable for every use. The quality of the received data can be enhanced by improving the sensors. However, developing sensors is not always the best option due to higher costs. Developers can obtain higher-quality data using different strengths of different sensors to increase the safety of AVs.

### A. RADAR

#### 1) 79GHz Polarimetric Radar

One of the biggest challenges to remain in autonomous driving is to detect the environment properly. Polarimetric radar technology is a helpful tool to overcome this challenge. There are two main advantages to use circular polarization for environmental analysis: being able to distinguish different numbers of ray bounces within each scattering center and the high probability of detecting a target. This makes the vehicle possible to differentiate targets such as a complex target, a vehicle, and a complete environment. Figure 1 exemplifies a vehicle turning left as a radar image (Polarimetric Data).

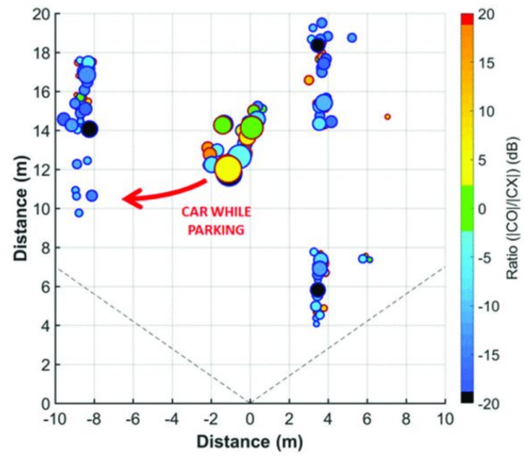



Figure 1. Polarimetric Data Image

Another powerful method is Micro-Doppler analysis giving an overall impression of the vehicle. The Micro-Doppler effect is also present with other targets like humans when arms and legs are in motion. Another benefit of polarimetric technology is its ability to measure street conditions in a precise way. Polarimetric radar images provide characteristic images on a pixel basis. An asphalt road's polarimetric radar image is given below.

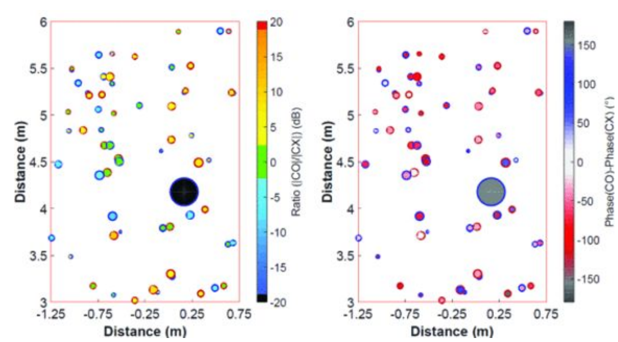



Figure 2. Polarimetric Radar Image of the Asphalt Road

Local maxima are shown as circles in Figure 2. The traffic cone (which is the circle with the highest radius) is detectable with the strongest signal which has a polarimetric ratio < -20 dB. Here, the potential uses of polarimetric radar technology are presented. Some main ideas discussed are as follows: Doppler analysis, classification, and street condition measurements. Every one of the areas discussed has infinite other applications and more aspects to be researched. All reasons discussed make polarimetric radar technology to be key in future applications for autonomous driving.

*2) 77GHz Radar Target Classification*

Radars are one of the many important sensors in autonomous vehicles. The authors explain the dataset for RCS of different objects gives researchers enough data for target classification. Traffic targets may be divided into three groups: vehicles, pedestrians, and stationary targets. According to these different targets, a huge dataset of RCS is created. The target for the dataset includes every type of individual, vehicle, signs, bus stops, trees, and animals like cats, horses, deer, etc.

Examples of the RCS images for a pedestrian, a horse and, a tree are given below.

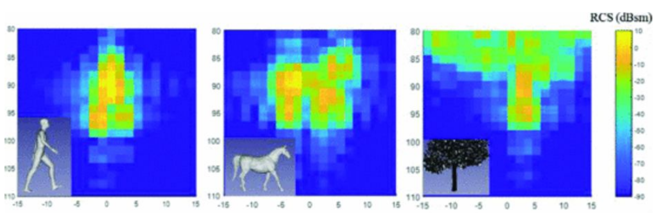



Figure 3. RCS Images of Various Targets

In this paper, two types of classification are explained: Classification based on statistical parameters of RCS and classification based on RCS image. Around a thousand pairs of parameters are compared, and an artificial neural network tool is applied to implement the target classification. 60% of the data are randomly selected, 20% is used as validation and the rest is used as test data. The results are given below for 50, 75, and 100 m.

Table 1. Results

| | | Include all data | | | Exclude Veh. | |
|---|---|---|---|---|---|---|
| **True positive rate** | *Range* | *Ped.* | *Veh.* | *Sta. Obj.* | *Ped.* | *Sta. Obj.* |
| | *50 m* | 92.8% | 89.7% | 56.1% | 97.8% | 90.0% |
| | *75 m* | 94.7% | 91.8% | 63.3% | 96.1% | 93.3% |
| | *100 m* | 90.3% | 90.6% | 61.7% | 93.3% | 91.9% |

Nearly 3,000 RCS images are created for many different targets having the same range but different aspect angles. The classification algorithm is implemented by ANN. The results are below, with range 10m the recognition accuracy is more than 99%.

Table 2. Other Results

| | | Include all data | | |
|---|---|---|---|---|
| **True positive rate** | *Range* | *Ped.* | *Veh.* | *Sta. Obj.* |
| | *10 m* | 99.0% | 99.7% | 99.6% |
| | *20 m* | 91.5% | 92.8% | 91.0% |
| | *30 m* | 88.3% | 90.2% | 84.3% |

The accuracy decreases with range since RCS image is harder to be recognized. This study proves that applying the ANN method and considering only RCS values is enough to get very good target classification performances.

*B. LIDAR*

*1) 2D LIDAR In Obstacle Detection*

2D and 3D LIDAR are more popular and preferred than RADAR in AVs' safety due to their close-range object detection feature. Although 2D LIDAR is not as efficient as 3D LIDAR to detect and classify objects, its low cost gives a chance for use. Catapang and Ramos examine the object detection performance of 2D LIDAR [3].

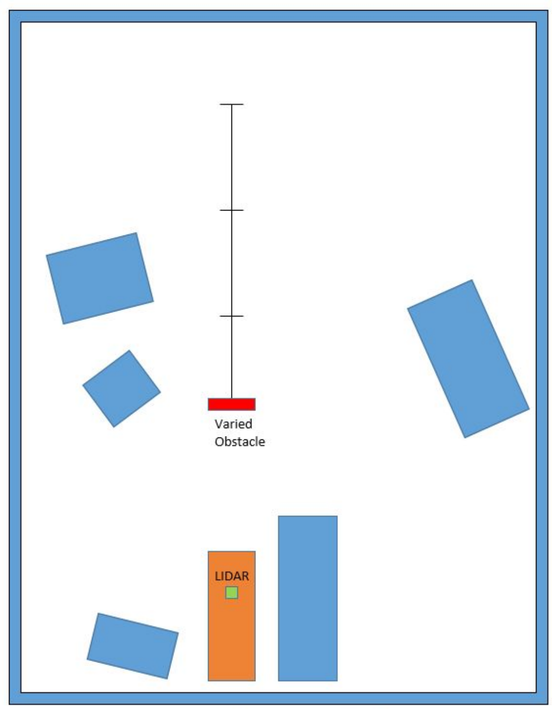



Figure 4. Test Area Sample

Catapang and Ramos's testing area is represented in Figure 4. The AV sample is shown as orange and at the top of that, the LIDAR system (green) is located at a height of 1.5m. A rectangular obstacle with 2.2m height and 1.36m width are shown in red. Distance between obstacles and the AV is gradually increased. Table 3 shows the obstacle detection and shape classification results of 2D LIDAR.

Table 3. Results for the Testing of the LIDAR using a 2.2m x 1.36m Rectangular Obstacle

| True Distance | Trial | Obstacle Detected? | Shape Classification | Measured Distance |
|---|---|---|---|---|
| 430 cm | 1 | YES | LINEAR | 439 cm |
| | 2 | YES | LINEAR | 434 cm |
| | 3 | YES | LINEAR | 441 cm |
| | 4 | YES | LINEAR | 437 cm |
| | 5 | YES | LINEAR | 438 cm |
| 826 cm | 1 | YES | CIRCLE | 836 cm |
| | 2 | YES | CIRCLE | 830 cm |
| | 3 | YES | CIRCLE | 836 cm |
| | 4 | YES | CIRCLE | 842 cm |
| | 5 | YES | CIRCLE | 830 cm |
| 1230 cm | 1 | YES | CIRCLE | 1152 cm |
| | 2 | NO | - | - |
| | 3 | YES | CIRCLE | 1237 cm |
| | 4 | NO | - | - |
| | 5 | YES | CIRCLE | 1242 cm |
| 1626 cm | 1 | NO | - | - |
| | 2 | NO | - | - |
| | 3 | NO | - | - |
| | 4 | NO | - | - |
| | 5 | NO | - | - |

According to results, researchers developed equations to determine LIDAR's measuring capacity.

- Equation 1 shows the 100% detectability condition.
- Equation 2 shows the stochastically detectable condition.
- Equation 3 shows the proper classification condition.

$$d < \frac{w}{[4\sin(r)]} \quad (1)$$

$$d < \frac{w}{[3\sin(r)]} \quad (2)$$

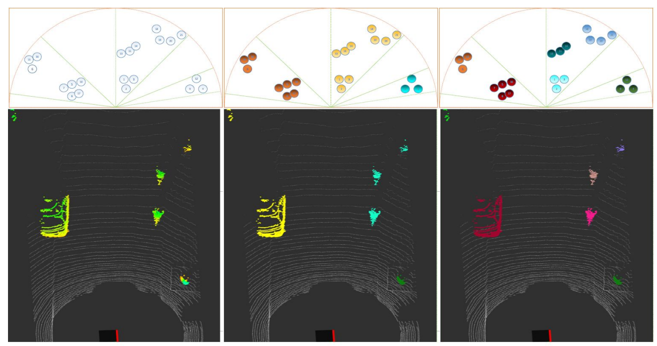
$$d < \frac{w}{[8\sin(r)]} \quad (3)$$

where $d$, $w$, $r$, represents the distance limit, obstacle width, and stepper motor resolution, respectively.

According to the equations, 2D Lidar roughly detects a 1.36m wide obstacle below 10.82 m, precisely detects under 8.82m, and classifies under 5.5m. Results and calculations show that although 2D LIDAR is useful in obstacle detection at short distances, it is not effective in classification. As a result, using only 2D LIDAR is not enough for AVs' safety because 5.5m classification distance is inadequate since 3D LIDAR offers better measuring distances.

*2) 3D LIDAR and Camera Fusion In Object Detection*

3D LIDAR is more popular than 2D LIDAR because it offers better measuring distance due to its precise depth measurement feature. Although 3D LIDAR is more effective, it has a distance limit and cannot detect tiny objects well enough. Since each sensor has different weaknesses, developers try to combine the sensors to decrease the disadvantages. For example, Zhao et al. combined 3D LIDAR and camera to solve 3D LIDAR's lack of tiny object classification. Detection and classification steps are shown in Figure 5.



(a) (b) (c)

Figure 5. Illustration of Classification Steps: (a) Normal Classification; (b) Angle Dependent Classification; (c) Advanced Classification with Camera

They also examined the performance of 3D LIDAR and camera fusion in "car" and "pedestrian" detection. Table 4 shows a comparison with the existing state-of-the-art methods. Their method achieved 89.04% average precision (AP) for cars and 78.18% AP for pedestrians, with an average runtime of about 67 ms at a moderate difficulty level which is highly competitive.

Table 4. Comparison Results

| **Approach** | **Sensor** | **Cars** | | | **Pedestrians** | | | **RunTime (ms)** |
|---|---|---|---|---|---|---|---|---|
| | | Easy | Moderate | Hard | Easy | Moderate | Hard | |
| LHAU [48] | L | 87.03 | 77.15 | 76.95 | / | / | / | 169 |
| Complexer-YOLO [18] | L | 91.92 | 84.16 | 79.62 | 42.16 | 36.45 | 32.91 | 60 |
| F-ConvNet[49] | L | 95.85 | 92.19 | 80.09 | 83.63 | 72.91 | 67.18 | 470 |
| F-PointNet [50] | L+C | 95.85 | 95.17 | 85.42 | 89.83 | 80.13 | 75.05 | 170 |
| AVOD-FPN [35] | L+C | 94.70 | 88.92 | 84.13 | 67.95 | 57.87 | 55.23 | 100 |
| Our method | L+C | 95.58 | 89.04 | 80.35 | 86.65 | 78.18 | 70.04 | 67 |

This study shows that the lack of one sensor can be improved with the help of another sensor, like solving the 3D LIDAR's inability to detect tiny objects with the help of the camera. This is a great achievement for AVs' safety. However, 3D LIDAR and camera fusion loses its accuracy after 60m due to 3D LIDAR's detection limit. The 60m detection range is not enough for AVs' safety, especially at high speeds. The detection range can be developed by combining different sensors for effective solutions at longer distances and AVs can be made safer.

## III. NEW DEEP REINFORCEMENT LEARNING APPLICATIONS

Even though radars and sensors have a crucial role in the safety of AVs, processing of those radars, cameras, and other sensor's data and making decisions using deep learning algorithms and methods also has a considerable role in the safety of AVs. Recently, an increasing number of studies about deep reinforcement learning algorithms such as DQN increase the deep learning improvements in AV. Especially, those methods help the car to make a decision such as changing lanes or accelerating. Deep reinforcement learning is not just used in making decisions, it also contributes to identify the traffic lights or objects better. Hence, using new deep reinforcement learning applications improves the safety of cars.

### *A. Combination of Deep Learning and DAS*

In contrast to previous knowledge, K. Min et al. propose [5] an autonomous driving framework using conventional Driving Assistance Systems (DAS) and deep reinforcement learning. The driving policy operates based on camera images and LIDAR data.

In this study, three deep reinforcement learning algorithms and network architectures were used. Those are Deep Q Network (DQN), Double DQN (DDQN), and Dueling DQN.

"DQN is a technique that combines the convolutional neural network (CNN) and reinforcement learning." Double DQN reduces the overestimation problem of the action value found by DQN and Dueling DQN is a convolution part of the DQN.

In simulations, those reinforcement learning algorithms (DQN, DDQN, Dueling DQN) are combined to find the optimal driving policy. Because the proposed algorithm uses two different inputs at the same time, the convolutional layers of the original DQN structure are changed to analyze the multi-input. After conjoining of these two refined data, data is used to determine action by obtaining Qvalues.

By Table 5, when using both LIDAR sensors and cameras the values are optimal compared to only lidar and camera inputs.

Table 5. Results of The Experiment

| Input Configuration | Average Speed (km/h) | # of Average Lane Change | # of Average Overtaking |
|---|---|---|---|
| Camera only | 71.88 | 16.8 | 35.8 |
| LIDAR only | 69.48 | 18.4 | 32.2 |
| Multi-Input | 73.54 | 30.2 | 42.2 |

An autonomous driving framework using conventional Driving Assistance Systems (DAS) is proposed in this study guarantees safety in most cases. It can be easily seen by observing the decreasing number of unnecessary lane changes and using more than one input data source because it increases the precision of data. Further studies should focus more on high safety in high performance.

### *B. Deep Q Network-Based Simulated Autonomous Driving Systems*

Similar to the previous knowledge, A.R.Fayjie et al. present a DRL and Deep Q Network-based autonomous driving plan for the urban environments [6]. However, the further step is the usage of the reward-based car training and the car simulation systems in the driving plans. Lidars and radars are used in the car prototypes to simulate the deep q network algorithm.

As shown in Figure 6, every algorithm action, aiming to maximize the positive rewards and minimize the negative rewards, has a reward value. This approach is used in several video games and car training. Using this approach helps the cars to decide properly to act according to the rewards.

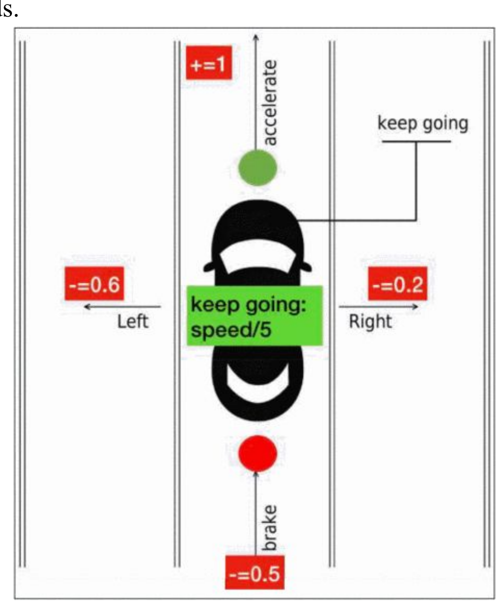



Figure 6. Action Definition of The Car

Another experiment focuses on DNN. This system, seen in Figure 7, involves 3 convolutional layers and 4 dense layers. Lidar data and front camera images are the data types, developing the detection systems, for these layers.

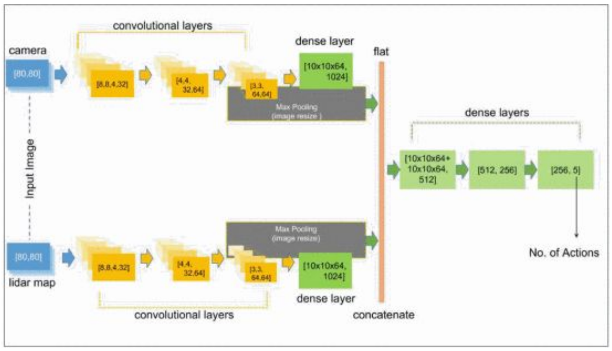



Figure 7. DQN architecture: The deep neural network is based on a fully-connected convolutional neural network.

To strengthen the DQN-based automated systems more, this study furthers the knowledge about AV driving systems by simulating an urban environment and the car behaviors by using the Unity Game Engine.

The study [6] aims to improve automated systems by reducing traffic light candidates. It uses the data concatenations, simulations, reward functions, car auctions, and prototypes to address this issue. The study results indicate that deep neural networks and deep Q network are developed steps to improve autonomous cars by some training and suitable decisions. In the future, researchers can optimize these algorithms by creating more efficient functions to them.

### C. *Image Processing And Deep Learning-Based Traffic Light Detection Systems*

Rather than using Deep Q Network-based systems, J.Wang et al present a deep learning and high dynamic imaging-based traffic light recognition system. This system, decreasing car accidents, detects the traffic lights from imaging and estimates the light signal situations. This study focuses on dealing with imaging and lighting situation difficulties.

High Dynamic Range (HDR) cameras involving several channels corresponding to the different values are used. The channels are 2 types: low exposure and high exposure. The detection by using low exposure channels, used for detection, is robust to the environment. In the high exposure channels, light recognition is easy because two channels can be reached within around 40 milliseconds. Moreover, these systems, seen in Figure 8 showing the tracking technology development, are capable of deep learning and tracking.

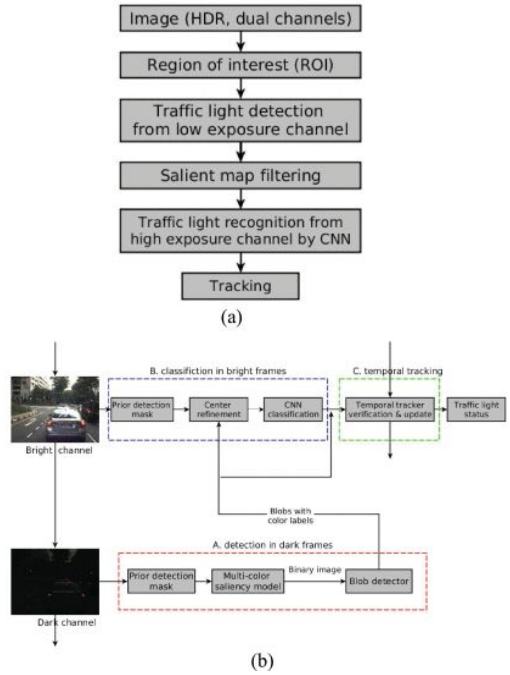



Figure 8. (a) Flowchart of our traffic light recognition system; (b) Diagram of the proposed dual-channel traffic light recognition system.

In the tracking-based temporal trajectory analysis, the salient map filtering, CNN systems, and region of interest are used for verifying and decreasing the traffic light candidates. The trajectories are classified according to the RGB space and stability flag. By using the RGB space, the image variance and brightness calculations are done with formula 4 and 5.

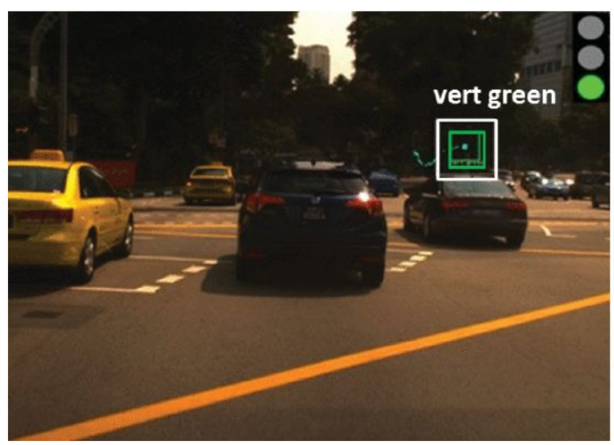



Figure 9. Plot the trajectory of the traffic light (marked in green) onto the current frame.

$$I = 0.2126*R + 0.7152*G + 0.07221*B \qquad (4)$$

$$V = |R-I| + |G-I| + |B-I| \qquad (5)$$

The results indicate that the traffic light recognition systems, using both bright and dark images, are more efficient to increase the automated system accuracies. Researchers can collect more training data to reduce the current false positives and increase automation reliability.

### D. Autonomous Vehicles Diagnosis Platform

Unlike the previous study about traffic light recognition systems, Kim et al. focus more on a platform constructed by deep learning and helps cars to take action [8]. Autonomous Vehicles Diagnosis Platform (AVDP) represents a significant shift in how safety can be improved with AVDP based on deep learning and loopback. AVDP consists of the On-board gateway Module (OGM) and a Self-diagnosis Module of Part (SMP) (Figure 10).

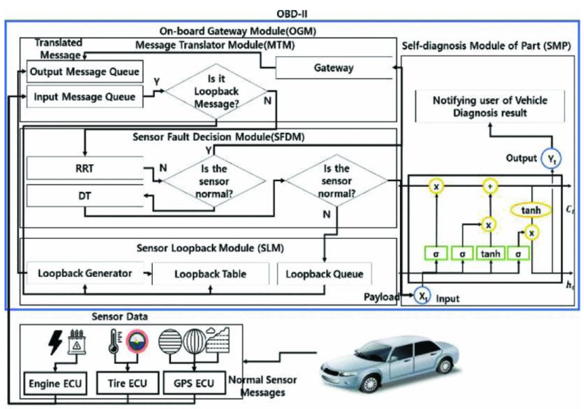



Figure 10. AVDP graph

OGM has three submodules: Message Translator Module (MTM), Sensor Fault Decision Module (SFDM), and Sensor Loopback Module (SLM). The main purpose of MTM is to provide communication between protocols. SFDM detects if there is a malfunction in sensors. SLM determines the cause of the malfunction SFDM detected.

SMP is based on LSTM which is an algorithm for the self- diagnosis of a vehicle`s parts. OGM continuously sends data to SMP and SMP transfers those data to LSTM to diagnose parts relative to the data. LSTM has Cell and Hidden States and Input, Output, and Forget Gates.

Experiments' results (Figure 11) show that this process's accuracy is higher than other common methods such as CNN and MLP in more test data sets under the same experimental conditions. Accuracy improvement proportionally increases car safety. However, as shown in Figure 11, accuracy varies for each case. So, further studies should work on a method having more steady and higher accuracy regardless of the data sets' number.

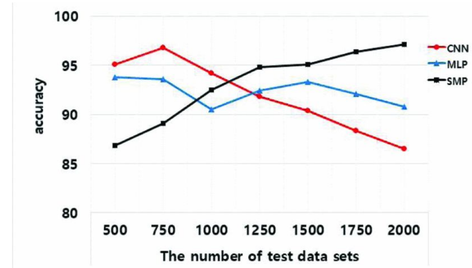



Figure 11. Graph about the accuracy of 3 methods

## IV. CONCLUSION

Eventually, sensors and deep learning systems are crucial for the safety of AVs. Sensor quality is important but each sensor has an individual benefit. So, by the improvement of each sensor and usage of the different sensors, the detection results will be more precise. Therefore, obstacle detection works better and AV becomes safer. On the other side, improvements in traffic light recognition, obstacle detection, diagnosis, and simulation systems using deep reinforcement learning algorithms also increase the safety of AVs. In the future, to prevent the safety problem more, researchers should improve the sensors and the functions of the deep learning algorithm more.

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