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Real-time lane departure warning with cascade lane segmentation

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ABSTRACT

Lane departure warning (LDW) is one of the safety innovations in autonomous cars that provides vehicle position monitoring. This technology will alarm if the vehicle moves out of the lane. Lane detection and lane measurement is the main part of LDW. The novelty of this research is the method can measure different lane marks. Very important to know the lane mark that can and cannot be passed. We use semantic segmentation to segment lane mark solid, lane mark dashed, and road. After extracting road and lane marks, we use inverse perspective mapping (IPM) to help calculate the measurement between the car and lane mark. The data is that 374 images were collected from several roads in Makassar City. The model was evaluated using intersection over union (IoU), reaching 79.8% accuracy. The developed system also estimates the measure between the vehicle and lane marks. The lane measurement estimation system's test results were evaluated using the root mean square error (RMSE) method to reach between 0.025254 and 0.134345.

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1. INTRODUCTION

The car industry's development in recent years has been increasing rapidly and has become a concern for academics and the industry. Many innovations have been developed, such as how vehicles can run by themselves without human intervention. The direction of car innovation has changed. It is no longer a matter of high-speed or powerful machines but a matter of safety. Safety aspects such as adaptive cruise control (ACC), lane departure warning (LDW), and automatic parking system are several features that new cars are included. Therefore, autonomous car research is still a big innovation and has the potential to become successful in the market [1].

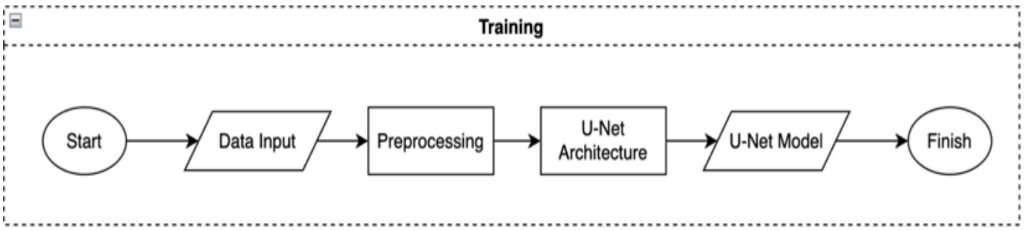
For the last few years, traffic accidents constantly increase in Indonesia. Three categories cause traffic accidents, human factor, vehicle factor, and environmental factor. The major traffic accidents caused by human factors are 88%, vehicle factors 3%, and environmental factors 8%. Numerous human factors are caused by unruly behavior (46%) and careless driving (32%). Surprisingly drowsiness (2%) and alcohol (1%) contribute small factor of traffic accidents [2]. The LDW was made to reduce traffic accidents and improve safety caused by human factors. LDW is a system that gives monitors the position of the vehicle. The system will generate an alarm if the vehicle approaches the line departure. The systems can warn drivers with unruly behavior or careless driving to stay on the path, reducing traffic accidents [3]. The LDW has two main parts: lane detection and lane measurement. There are various methods for lane detection, such as the Hough transform.

Mahersatillah *et al.* [4] use Hough transform and edge detection to extract lane on structured and unstructured roads in Indonesia. This method performs well on a straight road but poorly on a curve road. Muthalagu *et al.* [5] use linear regression to improve the detection for curve road. But those methods can't classify the type of lane mark. We know there are two-lane marks. First is lane solid, which serves as a no lane change. Second is lane dashed, which is the car can change lanes [6]. Classifying the type of lane marks is very important for LDWs, to know where the car can change lanes.

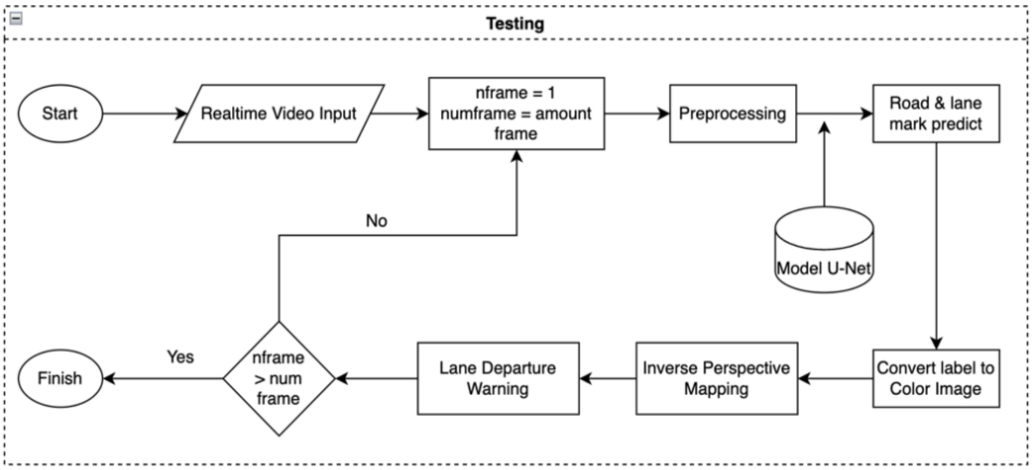
This paper proposes semantic segmentation to extract road and classify lane marks for LDW. The use of semantic segmentation is very broad, such as in agriculture [7], biomedical [8], [9], and smart city [10]. Babaali's research use semantic segmentation to extract road from remote sensing image. Semantic segmentation can deal with different varieties and complex types of roads. Semantic segmentation is the process of classifying each pixel of an image as a class label to understand the image at the pixel level. The class label is the class objects, such as cars, roads, humans, and others, so vehicles can recognize their surroundings [11]–[13]. For lane measurement, we use inverse perspective mapping (IPM) to generate bird's eye view images to support calculation. Compared to the original image, lane measurement has two advantages: first, each processing results in the bird eye view image associated with its actual world to help calculation more accurately; and second, to take out unimportant features for our calculation for lane measurement. The novelty of this paper is that we propose a cascade approach for lane detection and lane measurement in two main parts of LDW. Our method is to detect road and classify lane marks with semantic segmentation and then calculate the estimation of lane measurement based on pixel coordinates with the support of IPM.

2. METHOD

In designing the system, we are divided into two parts: training and testing. In the training stage, we use u-net architecture. After pre-processing, the input data is entered into the u-net architecture to be trained, producing a model. In general, Figure 1 shows the whole process of the system in this study, which consist of the training dan testing stage flowcharts shown in Figures 1(a) and (b), respectively. The testing stage is a real-time process to calculate measurements between the car and the lane mark using video. The data will go through pre-processing same as the training stage. The real-time data are then predicted based on the model that has been trained. The prediction output is a label converted into a color image. The image then goes through the IPM stage to help calculate LDW. Then go for the next image. The Testing stage is shown in Figure 1(b).



(a)



(b)

Figure 1. Flowchart of lane detection system (a) training and (b) testing stage

2.1. Data collection

The data used in this research is primary data or self-collected data. Obtained at several street points in Makassar City, South Sulawesi. The camera used was a dashcam with a 2,560×1,600 pixels resolution and a view angle of 140°. The camera installation is placed on the car's front windshield, as shown in Figure 2. The data used is Makassar City road data which has gone through the annotation stage manually and consists of 374 images.

Figure 2. Camera installation

2.2. Data pre-processing

Images were created using data video that was captured with a dashcam. After that, the dataset was manually annotated and translated in accordance with PASCAL visual object classes challenge (PASCAL VOC). Four categories make up the data: background, road, solid lane mark, and dashed lane mark. In order to hasten the learning process when training the data for our model, data that was initially very huge in size was subsequently reduced to 128×128 pixels. Two pictures dataset example in Figure 3, an RGB image as the original data in Figure 3(a) and ground truth as the annotated data in Figure 3(b).

(a) (b)

Figure 3. Dataset example (a) RGB image and (b) corresponding label (ground truth)

2.3. Semantic segmentation architecture

The u-net is an architecture network that was originally made for biomedical image segmentation. According to the original paper [11], the architecture uses various layers: convolutional layer, rectified linear unit (ReLu) activation function, max pooling layer, deconvolutional layer, Softmax activation function, and pixel classification. In several research studies, u-net is not only implemented for biomedical imaging but can also be used for many conditions [14]–[18]. The u-net showed great performance due to segmenting different image conditions. The u-net is based on convolutional neural network (CNN) with a U-shaped structure in Figure 4. The input data will be trained to learn parameters to predict the output as closely as possible by ground truth data [19].

The structure of u-net consists of an encoder and a decoder. This network is made of 23 convolution layers. Each block consists of repeated two convolutional layers with a 3×3 size filter followed by ReLU activation function and 2×2 max pooling operation with stride 2 for down-sampling. At each down-sampling step, we double the number of feature channels. Every step in the expansive path consists of an up-sampling of the feature map followed by a 2×2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3×3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer, a 1×1 convolution is used to map each 64-component feature vector to the desired number of classes [11].

The most ingenious aspect of the u-net architecture is skip connections. The skip connections between the encoder and decoder path concatenate features from both sides, which force the model to capture local and global information. The output of the convolutional each level layer on the encoder side is transferred to the decoder. These feature maps are then concatenated with the output of the decoder operation. These skip connections allow the network to retrieve the spatial information lost by pooling operations [16], [20], [21]. The architecture is illustrated in Figure 4.

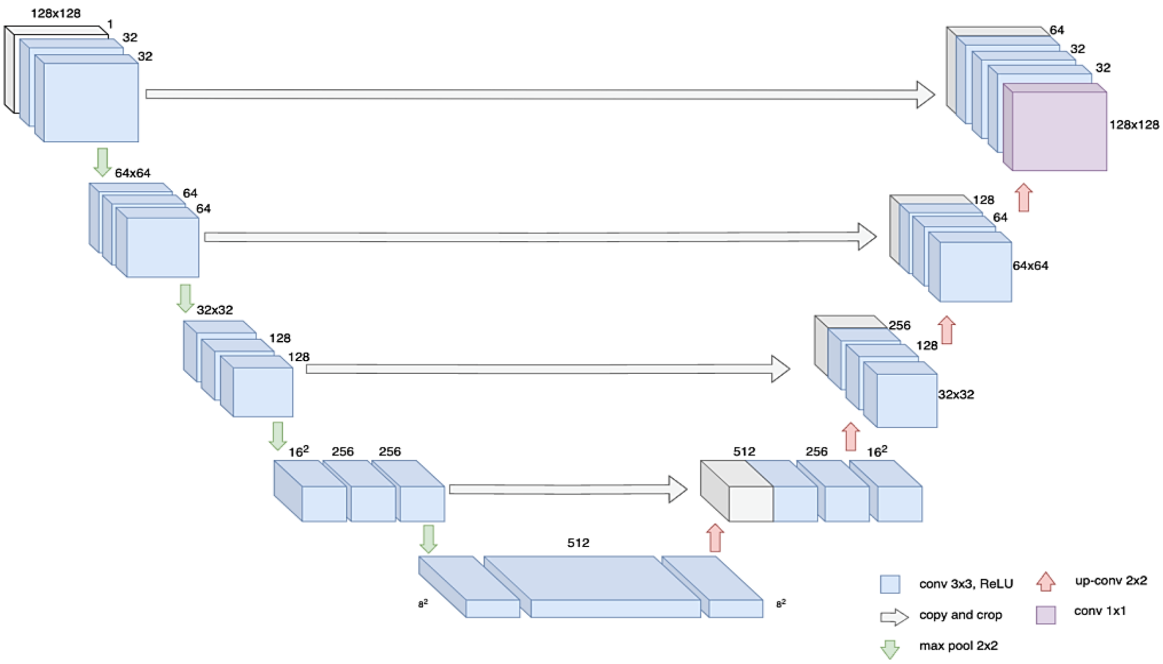


Figure 4. U-net architecture

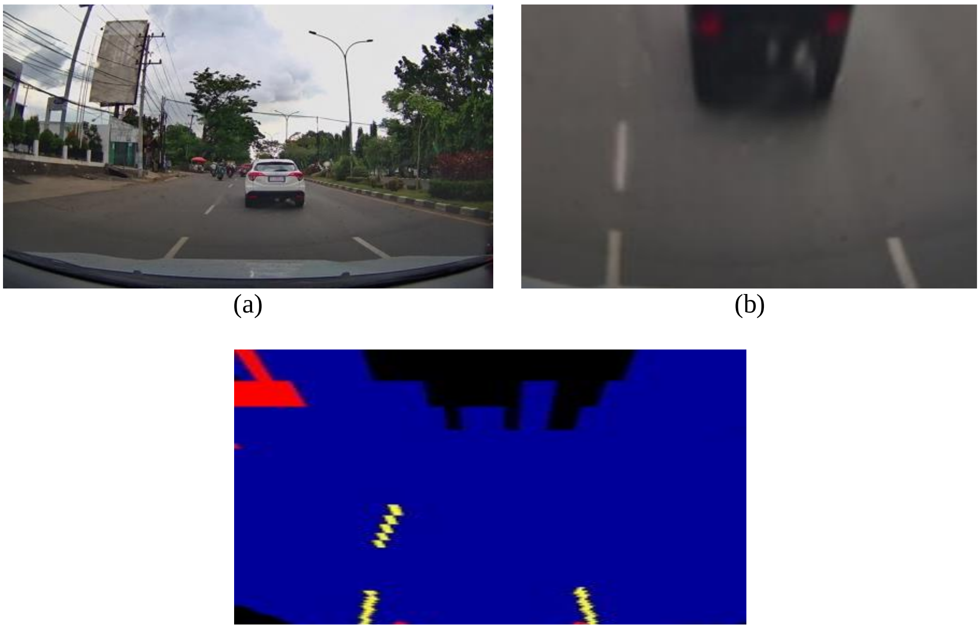
The ground truth dataset was an RGB image and then converted to a label. For background is set by 0, for road set by 1, for lane mark dashed set by 2, and for lane mark solid set by 3. Each label represents each category. For multiclass segmentation in this research, we use categorical cross entropy [22] for the loss function. The function p_{ic} is used to determine whether the *i*th training pattern belongs to the *c*th category. The target p_{ic} can be understood as true, while the output y_{ic} represents the predicted probability distribution indicating the likelihood of the *i*th observation belonging to class *c*. The formula for categorical cross entropy (E_{CC}) is as follows.

$$E_{CC} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C}(p_{ic}\log(y_{ic})) \quad (1)$$

2.4. Inverse perspective mapping

After the road is extracted, we use IPM to help measure the distance between the car and the lane mark. Understanding the 3D layout of a scene from a single perspective image is one of the fundamental problems of computer vision. Generating a bird eye view of the scene plays a part in this understanding as it allows the perspective distortion of the ground plane to be removed. This rectification of the ground plane allows the scene geometry on the ground plane to be measured directly from an image [23]–[25].

IPM is an image transformation method to remove perspective effects from images based on the intrinsic and extrinsic parameters of the camera, which has several applications, such as distance detection, road mapping, and parking assistance systems [26]. The purpose of implementing IPM is to reduce features from other lane marks (if the road has more than one lane departure) so we can estimate the distance of vehicles and lane marks. Besides reducing features, generating bird's eye view will be more simplified when estimating the distance of lane marks. IPM is widely used for road environmental understanding [27], [28]. Therefore, IPM is critical for the large number of automated tasks that must be handled by intelligent vehicles. IPM works under three core assumptions: the road must be a flat surface, there must be a rigid body transformation from the camera to the road, and the road must be clear of obstacles. Figure 5 illustrates the application of IPM. In Figure 5(a), real-time video data is transformed into frames prior to IPM implementation. An instance of IPM application is shown in Figure 5(b). Subsequently, in Figure 5(c), semantic segmentation is implemented following the IPM process.



(a) (b)

(c)

Figure 5. Example of IPM (a) before applying IPM, (b) after applying IPM, and (c) after semantic segmentation

2.5. Lane departure warning

The LDW feature is one of the safety features found in the latest cars. This LDW helps keep vehicles in the lane and ensures that no vehicle changes lanes unsafely. Vehicle lanes are marked with road markings. The results of detecting road lanes using the semantics were then carried out by measuring the position of the distance between the tires and the markings. The size of the IPM results is 400×600 pixels which can be seen in Figure 6. To find out the position of the marker marked in yellow in Figure 6, we take all the *x* and *y* pixel coordinates where the yellow color is located. Then convert the pixel coordinate to a data array. We separate left and right by looking at the *y* coordinates of the image. If $y > 200$, the marker is included in the array of right markers, while $y < 200$ is included in the array of left markers. After all lane mark included in array, set tire coordinate.

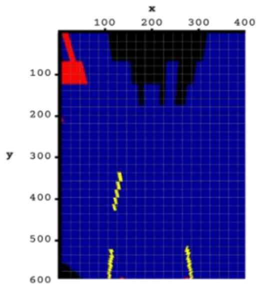


Figure 6. Result of semantic segmentation

The example of tire coordinate is shown in Figure 7. The determination of tire coordinates for measurement is placed in front of the tire by 2.5 m shown in Figure 7(a). The predetermined tire coordinates are entered into the system marked with the TC symbol in Figure 7(b). After the tire coordinates are determined, the deviation between the tire coordinates and the road markings is calculated. The deviation result in pixel form is then converted into meter (m) form according to the real world.

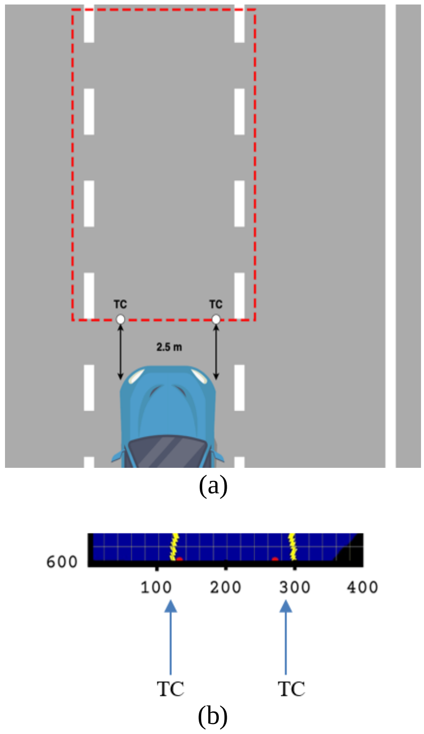


Figure 7. Illustration of tire coordinate (a) in real-world and (b) in the system

2.6. Evaluation metrics

There are two metric used to evaluate the proposed system, namely intersection over union (IoU) and root mean square error (RMSE). The formula of IoU and RMSE is shown in (2) and (3), respectively [29].

$$IoU = \frac{A \cap B}{A \cup B} \quad (2)$$

where A is the predicted image and B is the ground truth in this paper.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - o_i)^2} \quad (3)$$

where f is the actual data, o is estimation data, and N is number of data.

3. RESULTS AND DISCUSSION

3.1. Testing and evaluation

This chapter presents a discussion of the results of two system scenarios. First, the results of the detection test of the road, lane mark solid, and lane mark dashed using the u-net architecture and tested by the IoU method. Second, the distance test results between the lane markings and the coordinate of car tires were tested using the RMSE value. The overall accuracy obtained for testing the system using the u-net architecture is 79.8% using IoU. While the accuracy of each class obtained is shown in Table 1. The IoU calculations are carried out entirely automatically. Model testing was also carried out on several roads in the city of Makassar, which was carried out in real-time with a frame rate is 12 frames per second (fps). Figure 8 shows the example of the data input in Figure 8(a), the ground truth results in Figure 8(b), and the predicted results in Figure 8(c).

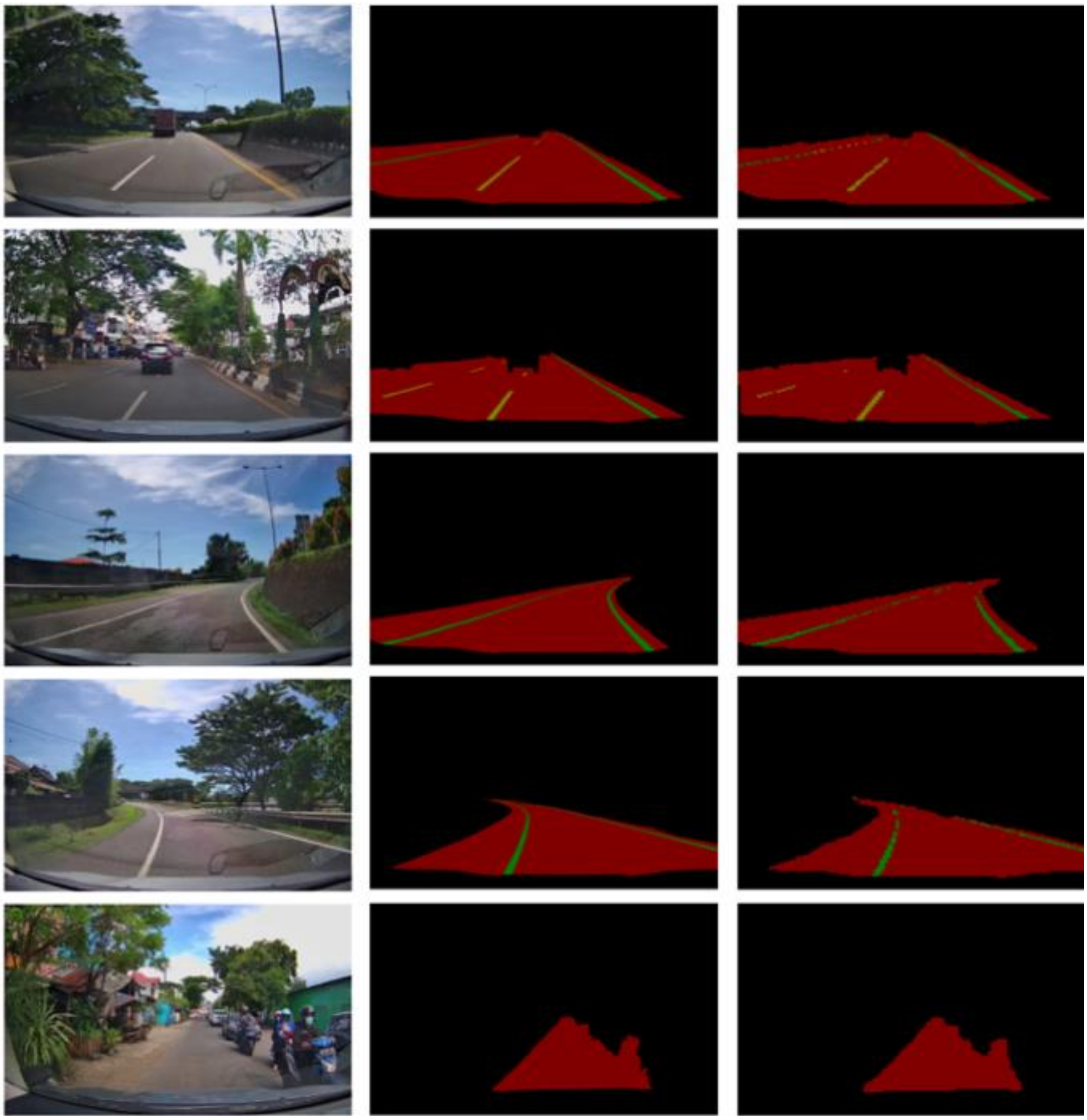
Table 1. Accuracy of each class

Class	IoU
Background	98.6%
Road	93.3%
Lane mark solid	75.3%
Lane mark dashed	54.8%

Four scenarios with actual distances of 0 m, 0.5 m, and 1 m were performed, with each distance being evaluated five times, to determine the distance between the tire and the line markers. The four scenarios are:

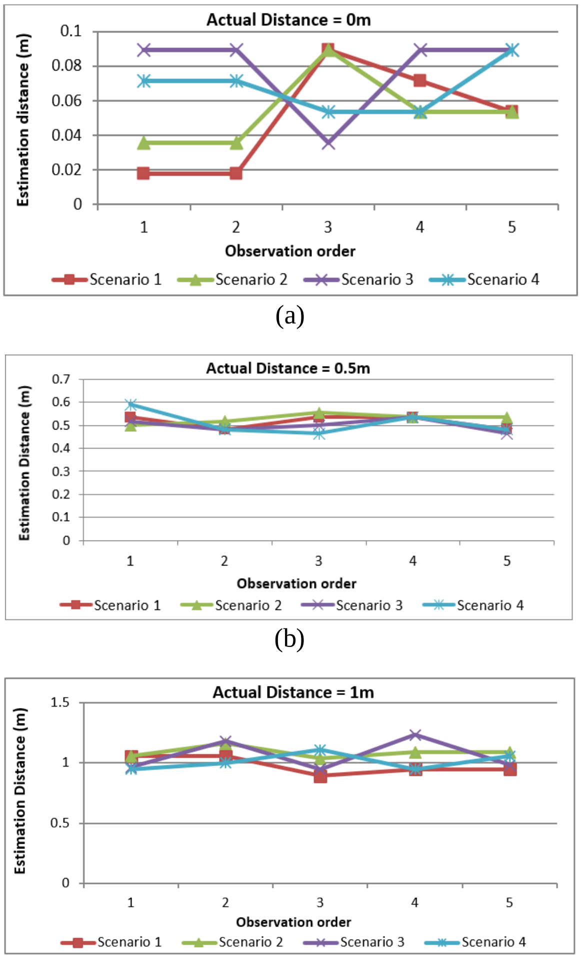
– Scenario 1: distance between the lane mark solid and the right tire.
– Scenario 2: distance between the lane mark solid and the left tire.
– Scenario 3: the distance between the lane mark dashed and the right tire.
– Scenario 4: the distance between the lane mark dashed and the left tire.

Figure 9 showcases outcomes across four scenarios, featuring actual distances of 0 m in Figure 9(a), 0.5 m in Figure 9(b), and 1 m in Figure 9(c). These results are evaluated through Table 2 RMSE values, revealing a range between 0.025254 and 0.134345, providing a comprehensive measure of accuracy assessment. The findings from Table 2 underscore the system's performance across diverse scenarios.



(a) (b) (c)

Figure 8. Example result (a) data input, (b) ground truth, and (c) prediction



(a) (b) (c)

Figure 9. The results of estimation distance with actual distance (a) 0 m, (b) 0.5 m, and (c) 1 m

Table 2. RMSE value of four scenarios

Actual distance (m)	Scenario 1	2	3	4
0	0.057588	0.057031	0.081441	0.06916
0.5	0.029881	0.033882	0.025254	0.047246
1	0.067763	0.095831	0.134345	0.063387

4. CONCLUSION

A real-time lane detection and lane measurement system for autonomous cars can be implemented using the semantic segmentation method with the u-net architecture IPM application. The training process uses epoch parameters of 10,000. The image size is 128×128 pixels and consist of four objects, namely background, road, lane mark dashed, and lane mark solid. Real-time performance of the semantic segmentation technique utilizing the u-net architecture is quite good. With IoU, the system’s performance evaluated at 79.8% and 12 fps. With the use of IPM, the system for measuring the distance between the lane marking and the vehicle produces positive results. The findings demonstrated that determining object distances had a good performance with an RMSE value between 0.025254 and 0.134345.

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