# Road Segmentation using Semantic Segmentation Networks for ADAS

**JongBae Kim**

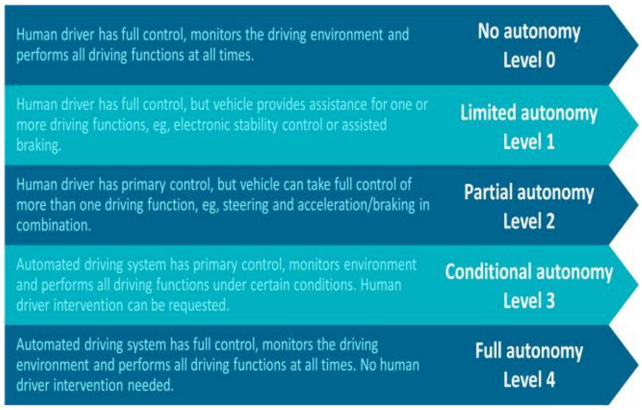
***Abstract*: *In this paper, we propose a method to automatically segment the road area from the input road images to support safe driving of autonomous vehicles. In the proposed method, the semantic segmentation network (SSN) is trained by using the deep learning method and the road area is segmented by utilizing the SSN. The SSN uses the weights initialized from the VGC-16 network to create the SegNet network. In order to fast the learning time and to obtain results, the class is simplified and learned so that it can be divided into two classes as the road area and the non-road area in the trained SegNet CNN network. In order to improve the accuracy of the road segmentation result, the boundary line of the road region with the straight-line component is detected through the Hough transform and the result is shown by dividing the accurate road region by combining with the segmentation result of the SSN. The proposed method can be applied to safe driving support by autonomously driving the autonomous vehicle by automatically classifying the road area during operation and applying it to the road area departure warning system.***

***Index Terms*: *road segmentation, line detection, ADAS, deep learning, semantic segmentation.***

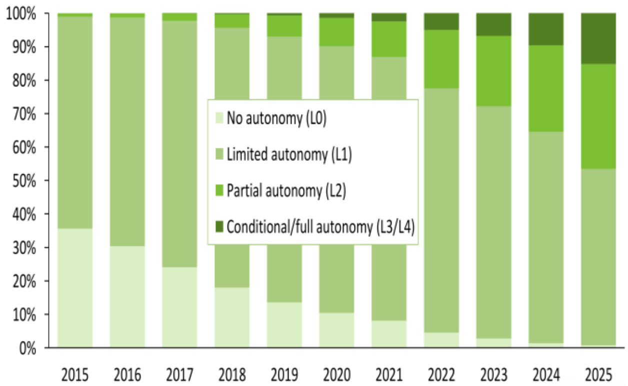
## I. INTRODUCTION

Recently, autonomous-driving technology development is rapidly increasing, and the market size of autonomous vehicles will increase from $ 42 billion in 2025 to $ 77 billion in 2035 [1]. However, there are still many technical issues that need to be addressed in order to develop a completely unmanned autonomous vehicle that does not require a driver. The most important issue is the safety of autonomous vehicles. It is very difficult to automatically determine the road conditions and to automatically drive a vehicle in a road environment that is difficult to predict and a myriad of obstacles such as real roads. Recently, artificial intelligence-based image processing technology and situation judgment technology have emerged and when the high-performance processing device is developed, it plays a role as a driving assistance system sufficiently. For example, a lane departure warning system, front collision warning, and pedestrian detection system are installed in vehicles and are being adopted as driver 's safe driving assistance system.

In the development stage of autonomous driving vehicle (Figure 1), there are 0 stages of non-automatization, 1 stage of driver assistance function, 2 stages of partial autonomous driving, 3 stages of conditional autonomous driving and 4 stages of autonomous driving. At the present time, most of them are the partial autonomous driving stage, that is, the driver performs the direct driving operation. In recent years, commercial vehicles have been equipped with various Information Technology devices to support safe driving, and some have legally obliged to install safety driving support systems such as drowsiness prevention devices and black-boxes system. According to the recent analysis survey [2], most of the autonomous driving stages, that is, the driver is directly driving, but the lane departure and the front collision warning are performed automatically and occupy more than 70% in order to support safe driving. In 2025, in a restricted environment such as a highway, which is a conditionally autonomous driving stage, it is expected to occupy more than 50% of the roads in which autonomous driving is possible without driver intervention.




**(a)**




**(b)**

**Figure 1. Autonomous vehicle technology development stage and application status [2], (a) level of autonomous vehicle, (b) application status of autonomous vehicle technology by year.**

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Various technologies have been developed to support safety during driving in autonomous vehicles. Especially, vehicles equipped with safety support technologies such as lane departure detection, forward collision detection, and pedestrian detection are being introduced. Especially, the most important factor during driving is the technology to prevent large traffic accidents that may occur due to the deviation of the road area while driving. It is required to clarify the boundary with respect to the road area in the autonomous vehicle so as to prevent a case of departing from the road area during traveling.

In previous researches, there have been studies using a morphology operation and a threshold method to segment the road area [3]. However, their method has limitations in applying to various outdoor road environments. There is a limitation in adaptively changing the threshold value change to the road environment, and the morphology operation also has a problem of providing robust performance only in a limited environment. M. Valente, et al.,[4] proposed a road segmentation method based on vanishing point detection and seeded region growing algorithm. Their research is to set the boundary of the road area to vanishing point detection and then use the SRG algorithm to improve the accuracy of the road boundary. This method presents robust performance on polluted roads and curved roads, but has a somewhat higher speed of execution. S. Yadav, et al.,[5] proposed a method of dividing the road area using CNN and using the color lines model to distinguish the road boundary area. Then, the final road area is segmented by combining the road area segmentation result and the road boundaries detection result. The proposed method is a way to distinguish the non-pavement road area from various lighting environment changes. There is a problem that their method requires a lot of learning images for non-paved road learning and also takes long learning time.

## II. PROPOSED METHOD

In order to quickly segment the road area in the input image, it is necessary to quickly learn a number of pre-learning images. As the number of learning images decreases, the performance of the road segmentation becomes lower. In the proposed method to reduce the learning time of the training images, the output layer is modified so as to classify into two classes in the previously learned SegNet CNN network [6]. And the result of the road segmentation based on the learning machine generated with a small number of training images, the boundary part of the road area is not clear. Therefore, in order to distinguish the boundary of the road area relatively accurately, the proposed method segments the road boundary line using Hough transform. Finally, we propose a method to segment the road area boundaries by semantic segmentation networks and to segment the road area boundaries by using Hough transform to distinguish only the road area from the segmented results. In the proposed method, the training image labeled in the road image is used. The training images are a labeled image designated by only two classes, a road area and a non-road area. The SSN used for road area learning is based on the VGG-16 CNN model. The SSN generates a multi-level pyramid image using the convolutional and ReLU layers of the input image. As shown in Figure 2, the SSN divides the image by enhancing the classification function of the pixel region into the corresponding class by down-sampling and up-sampling the input image. Through the SSN, the segmentation result of the road area and the non-road area is obtained, and the boundary line of the road area obtained through the Hough transform is obtained. Through the combination of these two results, the road region having the optimal region is extracted as the segmentation result. Figure 3 shows a flow chart of the proposed method.

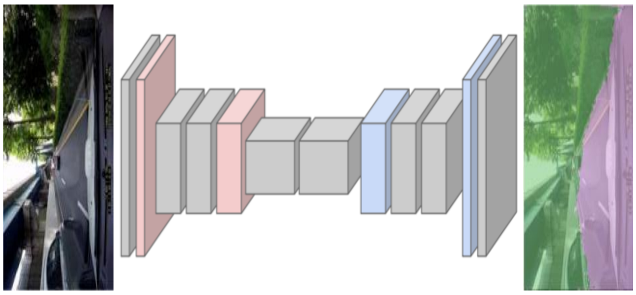


**Figure 2. Structure of semantic segmentation network.**

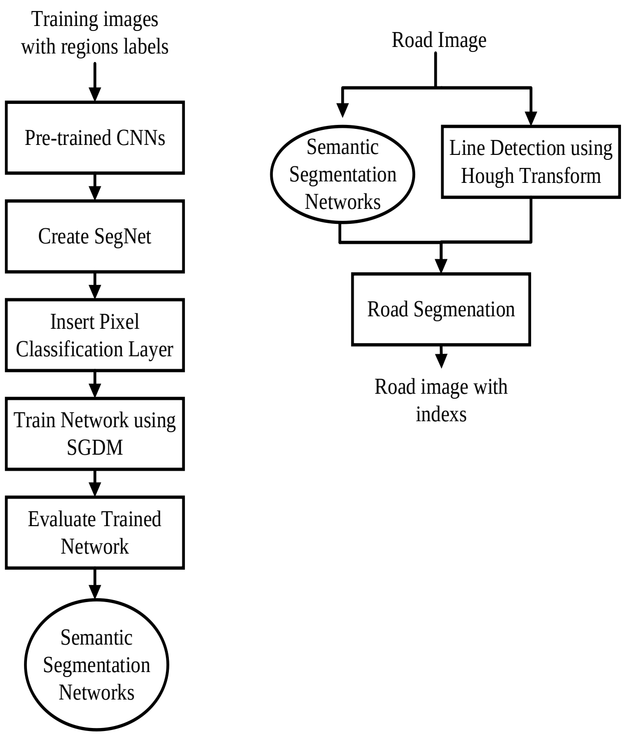



**Figure 3. Flowchart of the proposed method.**

In order to apply the proposed method to road segmentation, road images are acquired in a black-box device installed in the vehicle. However, vehicle black box images have HD resolution and it takes much time to apply them to learning. Therefore, the input image is reduced to 1/4 size for learning the road image. Figure 4 is the result image which is labeled for training road area.

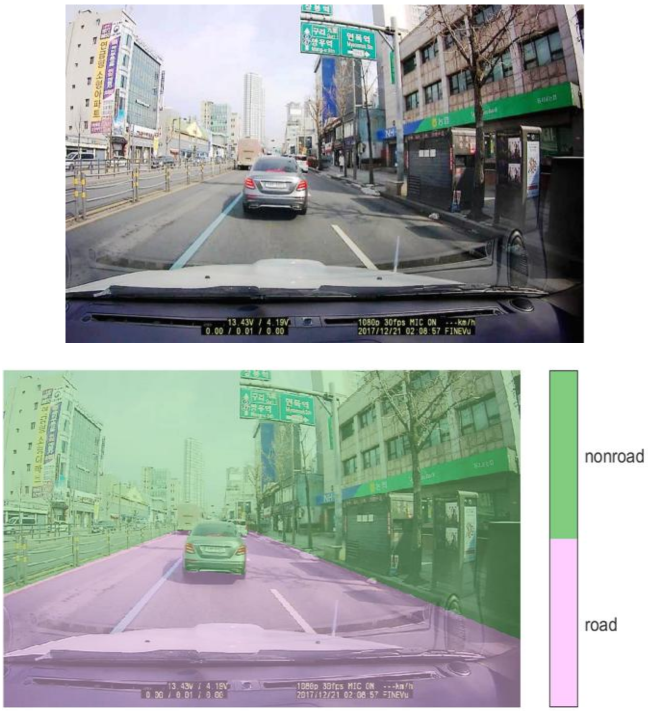



**Figure 4. Result of road image labeling.**

In the proposed scheme, the previously learned VGG-16 [7] is used to segment between the road area and the non-road area in the road image. The VGG-16 consists of 41 layers. There are 16 layers with learning weights, 13 of which are layers and 3 are full connection layers. In order to create the SSN structure shown in Figure 5, the VGG-16 layer for down-sampling the input image and the Vgg-16 layer for up-sampling the result of down-sampling layer are constructed to output the image segmentation result.

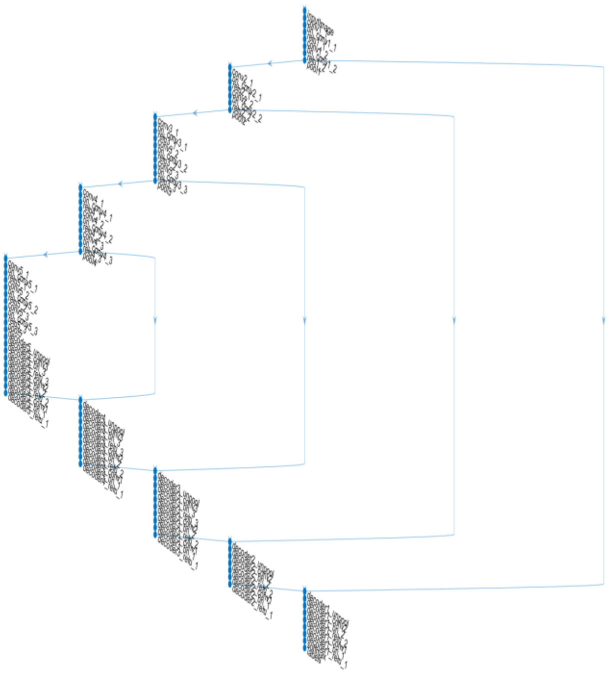
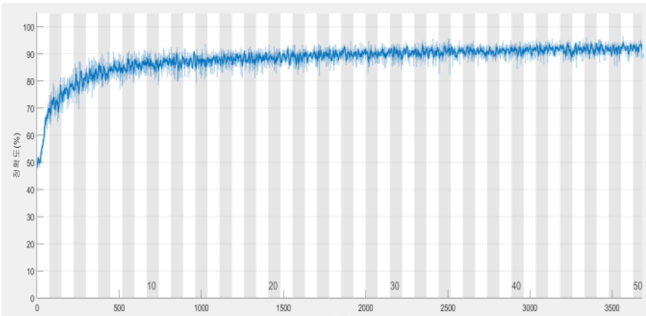


**Figure 5. Structure of SSN training layer.**

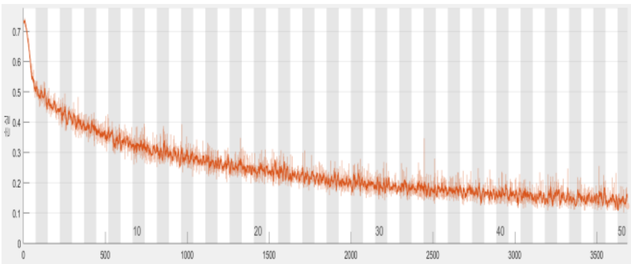
The road area is divided through the SSN classifier in the input road image. Then, a straight-line component is extracted from the input road image through Hough transform. The straight line to be extracted using the Hough transform detects a pair of straight-line components from the bottom of the image to the center of the image.

## III. EXPERIMENTAL RESULTS

In the proposed method, we experimented with Matlab on Windows PC (3.2GHz, Hexa core, 48G RAM, Dual GPU) to experiment on the road segmentation process. The experimental images used for learning SSNs were 1920×1080 pixel size images acquired from a vehicle black-box and the labeling was applied to the road images obtained from 1800 different locations using ground-truth method. The training images were obtained at various places such as city roads and highways. For down-sampling used in SSNs learning, set it to 2 and reduce the input image by 2 times. The training option is SGDM (stochastic gradient descent with momentum), and the network is trained by setting the initial learning rate to 0.01 and the maximum number of epochs to 50. Then, the slope of the straight line was set to [-60:60] and the canny edge detection method was used for straight line detection to detect the straight-line component extending to the center of the lower part of the image through the Hough transform. Figure 6 shows the results of pixel classification success rate and failure rate in the SSN learning process. And Figure 7 shows the image segmentation confusion matrix.



(a)



(b)

**Figure 6. Image segmentation accuracy and error rate reduction graph during SSN learning process.**

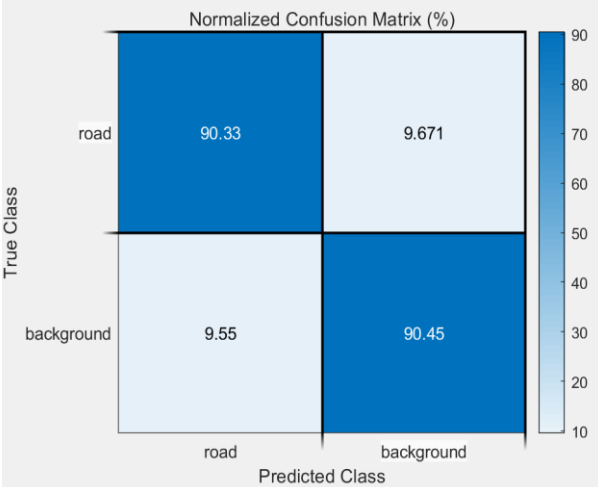



**Figure 7. Image segmentation confusion matrix.**

The final road image segmentation result is shown in Figure 8. Experimental results show that although the results are somewhat lower through the performance comparison with the user-defined road area, the results are mostly satisfactory for the criteria for judging whether the actual road area is included or not. The average accuracy and processing time of the proposed method are 90.4% and 0.43sec. It can be applied to the autonomous vehicle. However, the proposed method has limitations in the application to curved roads and unpaved roads other than straight roads. In order to solve this problem, it is necessary to acquire more learning images and to apply color, texture, etc.

## IV. CONCLUSIONS

In this paper, we propose a road segmentation method that can be applied to autonomous vehicles. The proposed method segments the road area based on the SSN and extracts the road boundary using the Hough transform, and determines the road segmentation result belonging to the inside of the pair of straight lines as the road area. As a result of applying the proposed method to various road environments, the road segmentation accuracy showed the result of 90.4% and the execution time of 0.43sec. However, there are some limitations on non-pavement roads and curved roads, and further research will be conducted to research more robust road area detection methods.

## ACKNOWLEDGMENT

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**Figure 8. Results of road segmentation.**

## AUTHOR PROFILE

Jong-Bae Kim received the B.E. degree in computer engineering from Busan National University, Miryang, Korea in 2000, and received the M.S. and Ph.D degrees in computer engineering from Kyungpook National University in 2002 and 2004, Deagu, Korea. He joined a visiting researcher of University of Münster, Münster, Germany in 2003 and the School of Electrical and Computer Engineering of the Georgia Institute of Technology, Atlanta, GA, USA in 2004, respectively. He served a full-time researcher at the Digital Manufacturing Information Technology Research Center in the University of Ulsan, Ulsan, Korea in 2005. His is currently working a professor at the Department of Computer and Software in the Sejong Cyber University, Seoul, S. Korea. His research interests include the ITS, ADAS and Computer Vision.