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IMAGE SEGMENTATION BASED ON MACHINE LEARNING FOR AUTONOMOUS VEHICLES

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Abstract: Autonomous vehicles produce and maintain a chart of the surrounding area grounded on the various sensors found in a different region of the vehicle. Radar sensors monitor the position of near vehicles. Videotape cameras detect traffic lights, read traffic signals, track other vehicles, and monitor pedestrians. Light detection and ranging sensor (Lidar) maps into the surrounding area of a vehicle to determine distances, track edges, and identify path signals. In autonomous vehicles, technology image segmentation proved to be a major problem in visual perception. Autonomous vehicles are being used in various applications, including manufacturing, hazardous materials handling, and surveillance. Image segmentation is applied in the visual perceptual functions of observing agents in the environment, identifying road boundaries, and tracking road signals. The purpose of image segmentation is to divide an image into several parts, each representing a different entity. The main aim of this paper is to make the input images into segments using the image segmentation process and Convolution Neural Network method for efficient results of visual perception. The proposed image segmentation method plans to standardize and promote the development of state-of-the-art methods for visual inspection system understanding by using a data-set sample and validation using Python language. Based on the experimental results, an NVIDIA GTX 1050 GPU achieves 73% mean IOU and 90 FPS inference speed.

***Keywords* – Image Segmentation, Deep Learning, Autonomous Vehicles, Convolution Neural Network, k-means clustering.**

I. INTRODUCTION

Self-driving vehicles need object and visual perception technologies. The current status of autonomous vehicles using 6G technology finds the correct location and reduces the area of delay (<1ms). This image segmentation process has multiple applications and is used for the visual recognition of autonomous vehicles (AVs). The vehicle's sensors, such as radar, camera, and an inertial measurement unit (IMU), are used for accurate results, such as those for visual perception. A vehicle's visual system plays the most important role in autonomous driving since AVs make their decisions in all contexts, such as traffic jams, changes on highways, urban roads, and different climates.

In the first stages of self-driving cars, image segmentation was a complex process. It is also called semantic segmentation. With in-depth learning, it is now simple. Image segmentation differs in image layout. As a result of the image segmentation, protests will be automatically grouped with obvious markers such as roads, cars, bicycles, etc., although the image segmentation statistics will be able to distinguish unknown objects as well. Image segmentation of an image takes place on a pixel-by-pixel basis. Image segmentation analyzes an image and divides it into sections with similar characteristics. Photo creation involves arranging the image into one of the various classes described earlier. Self-driving cars require a deeper understanding of their natural properties. To help with this, sensory frames are used to identify all road users with pixel-level accuracy. Using photo-sharing techniques helps to express ideas in pictures.

Machine learning is widely used to solve numerous difficulties arising from the assembly of self-driving cars. During this process, sensory information is used to control the vehicle which makes it vital to improve the use of AI to achieve new tasks. Applications include driver status tests and driving status specifications with data collected from a variety of external and internal sensors, such as Lidar, radars, and cameras. In self-driving vehicles, one of the key responsibilities is the estimation of the distance between objects and the estimation of the K-means Clustering algorithm is to consistently bring normal weather and determine the unimaginable continuity of these natural features to detect an object, object identification, or order of object approval, and object Localization and Prediction of Movement of agents are shown in Fig.1.

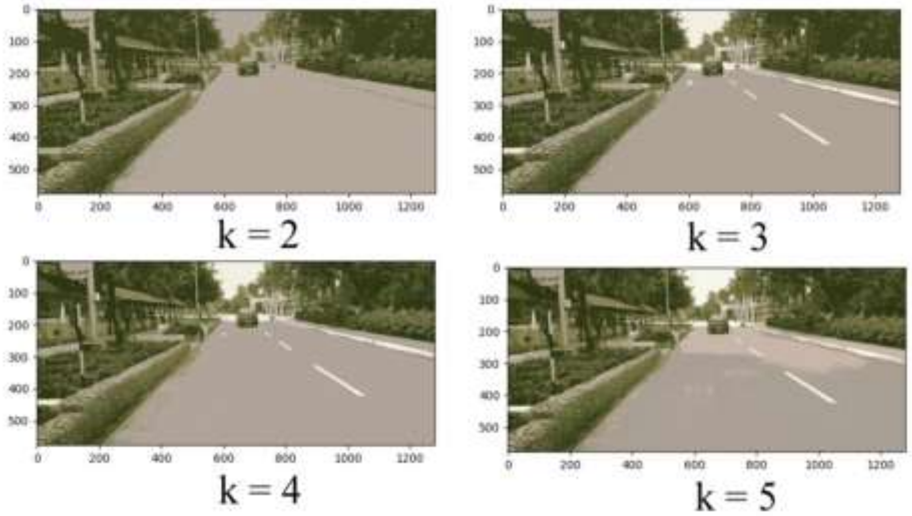


Fig 1. Sample image is classifying the 2, 3, 4, and 5 K-means Clusters

Self-driving can largely be accomplished through deep learning. Artificial Neural Networks (ANN) rely on units that are precise, connected, and equally efficient. The inspiration comes from the nervous system. Sensor recognition is one area of Artificial Intelligence (AI) where it needs to delete data from images. Furthermore, with the great demands of individuals in this field, the beliefs of the past are resurfacing: from object identification, design approval, work acceptance, structured direction, etc., to other papers in Deep Learning and Convolutional Network (Deep CNN). The CNN strategy has many applications in a variety of fields such as image segmentation, artificial intelligence, computer vision, and so forth. In the automotive industry, CNN techniques are widely used for location and computer-based operation as illustrated in Fig 2. Such CNN techniques are used for location and information.

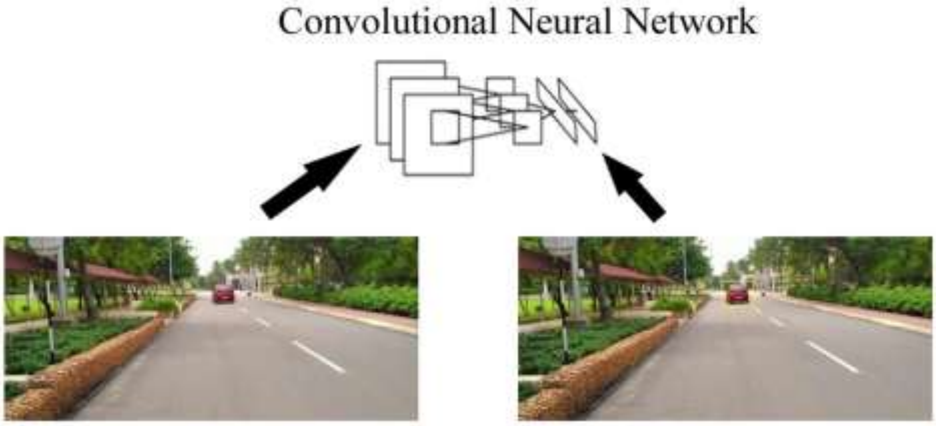


Fig 2. Image features are extracted and identified by Deep CNN. Car Image is identified and marked as a yellow color box.

II. Related to Work

The self-driving car has a few sub-Perception plans and decision-making systems. These sub-programs are detailed as shown in Fig. 3.

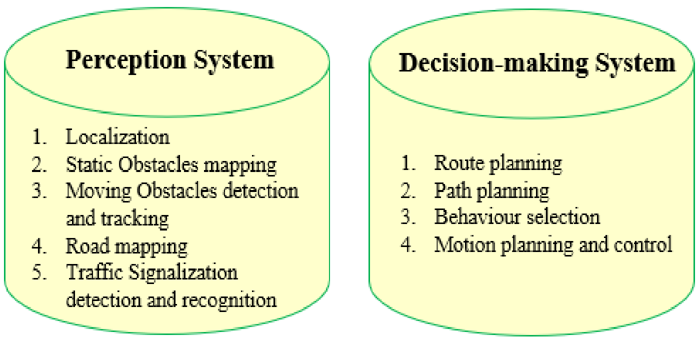


Fig 3. Subsystems of Perception systems and Decision-Making systems

Using Over feat CNN, a neural-based method for the detection of moving agents was proposed. Travel agents and ego car monitoring of a closely related app known as ego track tracking were discussed. Vehicle detection and traffic recognition (Red, Green, and Yellow) are also discussed. Over feat, CNN's proposed work to predict the distance from the current state of the car to the ego cars will be considered. A detailed survey of self-driving cars and decision-making systems was presented.

2.1. Image Segmentation:

The recommended labeling of the real-time CNN-based image segment is based on convolution with uncompressed filters to control image resolution at CNN depth and spatial pyramid pooling (SPP) to separate objects on multiple scales and a combination of DCNN and image models that may be used in the object area with 79.7% of IMoU results. As for the in-depth analysis of multiple models as well as the semantic segmentation of automatic driving, there are challenges, data sets, and existing approaches. The new neural network model of multi-scale feature integration represents an effective semantic image segmentation and use in self-driving vehicles with 74.12% IOU results.

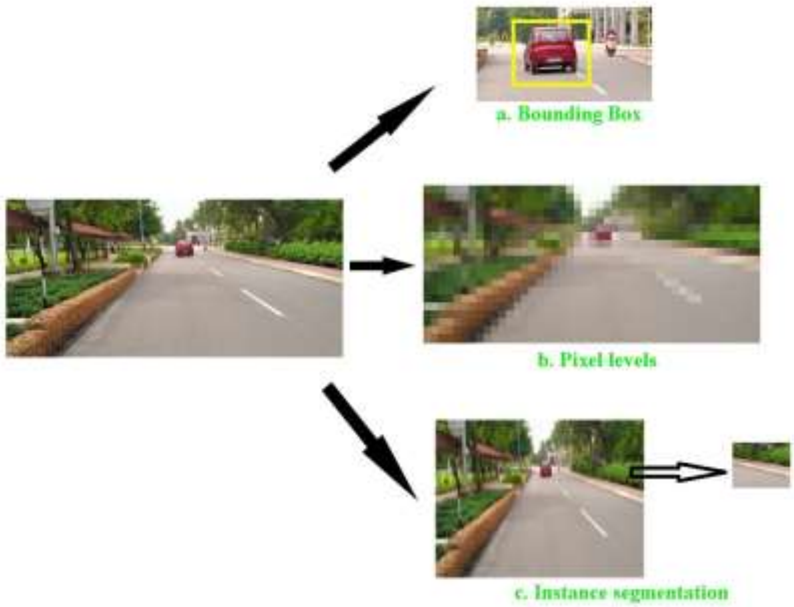


Fig 4. Image segmentation Process a) Bounding Box, b) Pixel level, and c) Instance segmentation

2.2. Convolution Neural Network:

The proposed attention-guided lightweight directed network (AGLNet) uses the architecture of the encoder and decoder to separate real-time semantic components. FPENet is designed for effective accuracy and speed. There are numerous CNN formats including AlexNet, DenseNet, MobileNet, and ResNet. A new architecture of deep image separation networks contains high-level accuracy features.

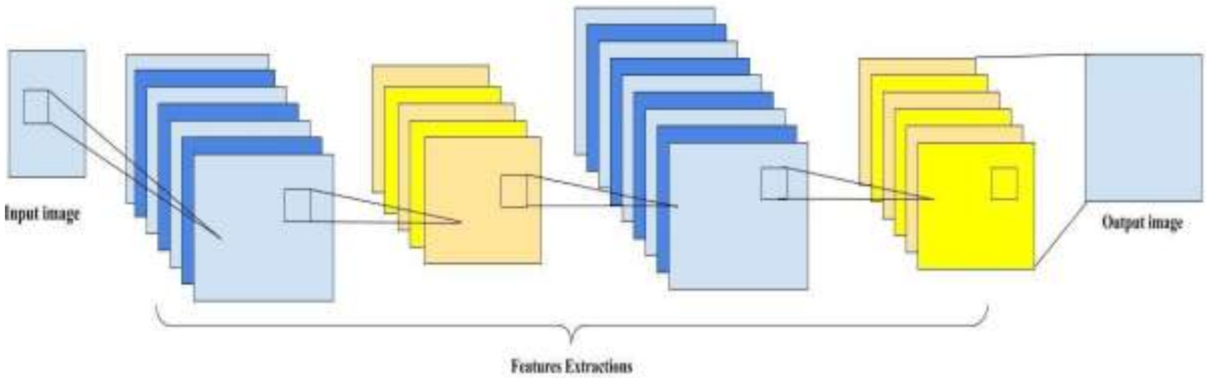


Fig 5. Simple CNN architecture

To summarize the above-related work and the contribution of the framework work as follows:

- The new model utilizes the image segmentation process and the Convolution Neural Network method to create effective visual effects.
- Detailed analysis of the K-means clustering layer, optimization of the model is presented.
- When testing the network model and data sets it accurately describes the results of MOU greater than 100FPS.

III. Frame Work

The framework model consists of seven layers as represented in Fig.6.

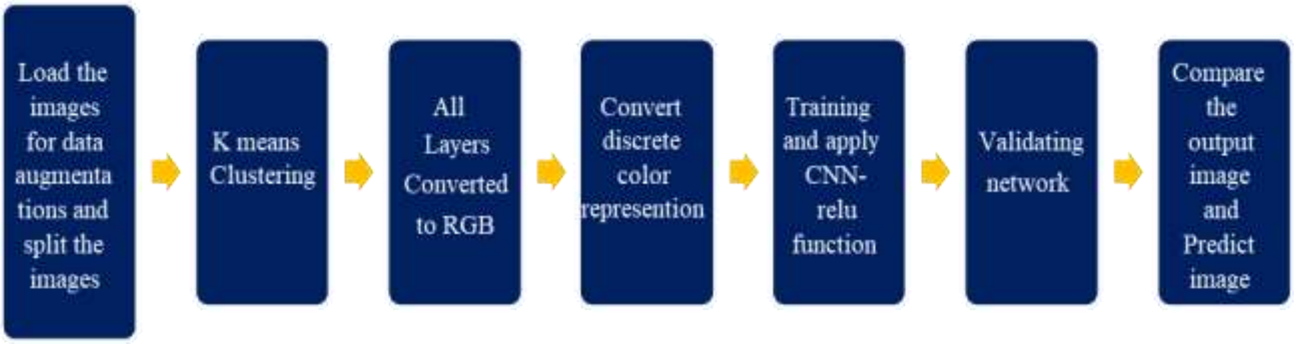


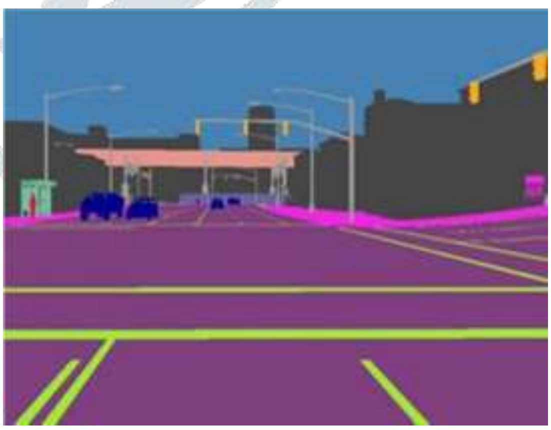
Fig 6. Phases of Our network model

As a first step, the appropriate Python packages are installed, including NumPy, OS, cv2, k means, random, Conv2d, ReLU leak, Adam, and SGD. Next, data sets are uploaded for data addition processes, like scrolling, rotating, and separating images. Following the data addition, the K Means clustering is used to classify the data into color combinations. After the image layers of the merging process have been converted to RGB images, it is time for color representation. After that, the color representation process is divided into classes within the image and assigned a color. A color representation process is then applied to the image to produce data. Productive data is trained by CNN. Then CNN Models trained 1000 times and validated the model. Color segmentation images and real image classes will be shown in Fig. 7.

a. True Image

b. Segmentation Image

c. True Image



d. Segmentation image

Fig 7. True Image and Color Segmentation image

CNN is based in Keras, an advanced API at TensorFlow, and is trained on the NVIDIA GEFORCE GTX 1050 graphics card. Training data and results will be discussed in the next session.

IV. Results and Discussion

Class Intersection over union (IOU) is calculated on the scale of true positive (TP), False Position (FP), and False Negative (FN) as shown in Table 1.

$$F(x , \theta) = [Class\_01, Class\_02, -----, Class\_12]$$

Table 1: Classification Of Segmentation image class Metrics

	Class _01	Class _02	Class _03	Class _04	Class _05	Class _06	Class _07	Class _08	Class _09	Class _10	Class _11	Class _12
TP	4	3	3	3	4	3	3	4	4	3	4	3
FP	0	2	2	2	2	0	2	2	0	0	0	0
FN	2	0	2	0	0	2	0	0	2	2	2	2
IO U	0.6	0.6	0.4	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6

The average mean values of all class values are as shown in Fig 8.

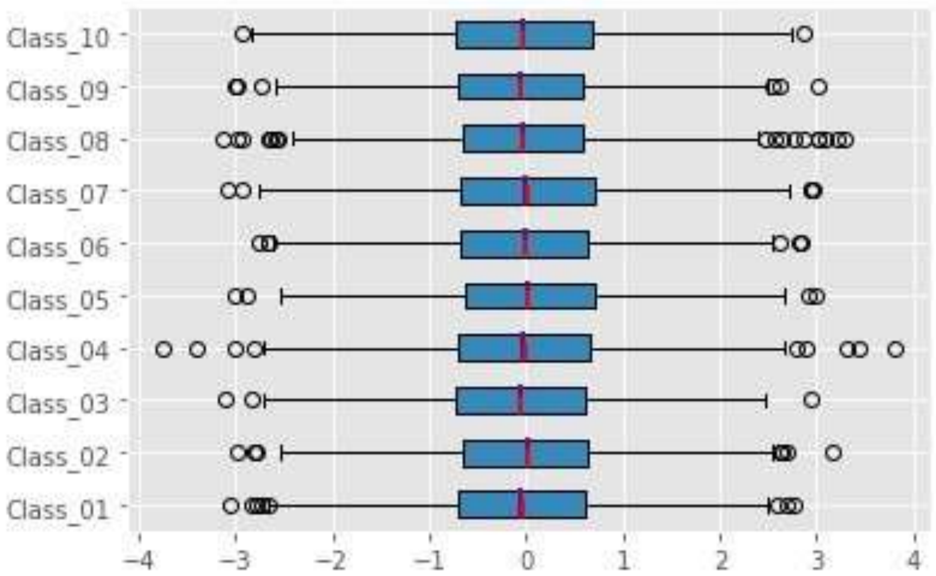


Fig 8. Mean of classes

The values for all classes are compared to other networks, such as CGNet, ENet, ERFNet, FSCNet, FSCNN, and DABNet. Except for class_04, the rest of the values are higher than the current network values shown in Table 2. The parameters of Param, FPS, and MIoU are also compared to the other models which numbers are shown in Table 3.

Table 2: Accuracy results of individual classes and comparison with other networks

Method	Class _01	Class _02	Class _03	Class _04	Class _05	Class _06	Class _07	Class _08	Class _09	Class _10	Class _11	Class _12
CGNet	90.8	79.8	28.1	95.3	81.9	73.2	41.6	32.9	81.3	52.9	53.9	68.4
ENet	92.4	75.1	24.2	93.5	74.5	96.7	31.2	21.5	78	42.6	46.2	64.1
ERFNet	91.6	77.45	26.15	94.4	78.2	84.95	36.4	27.2	79.65	47.75	50.05	66.25
FSCNN	68.7	58.09	19.61	70.80	58.65	63.71	27.30	20.40	59.74	35.81	37.54	49.69
DABNet	69.4	72.61	24.52	88.50	73.31	79.64	34.13	25.50	74.67	44.77	46.92	62.11
Our Model	93.2	82.1	58.4	85.1	90.2	95.1	55.4	68.2	90.8	62.1	70.2	82.78

Table 3: Comparison with other networks

Method	Param	FPS	MIoU
CGNet	0.57	97.5	65.7
ENet	0.34	92.4	57.5
ERFNet	2.12	142.5	69.2
FSCNN	1.16	247.6	55.6
DABNet	0.72	138.2	66.8
Our Model	1.47	92.4	72.4

By assuming that image classification is done as X-sections, we can improve our CNN model. A sample of output probability is that,

$$P = [P, P, \_\_\_\_\_, P] \quad (1)$$

When the ground truth label index is g_n, the output probability as,

$$Where, P^* = [P^*, P^*, \_\_\_\_\_\_, P^*] \quad (2)$$

$$p^* \{ 1 \; if \; x == g \; , 0 \; other \; wise \} \quad (3)$$

V. Conclusion

In this paper, a network of semantic image segmentation is presented. The model's sensitivity to image elements and effects is illustrated by its functionality. The development details of the network model are discussed as well. Compared to other network models, this CNN model's mean IoU is 72.4 with a segmentation speed of more than 100FPS, which is better than accuracy, making it ideal for visual work in self-driving cars.

References

[1] M. Aladem and S. A. Rawashdeh, "A Single-Stream Segmentation and Depth Prediction CNN for Autonomous Driving," in IEEE Intelligent Systems, vol. 36, no. 4, pp. 79-85, 1 July-Aug. 2021, doi: 10.1109/MIS.2020.2993266.

[2] A. Novozámský et al., "Automated Object Labeling For Cnn-Based Image Segmentation," 2020 IEEE International Conference on Image Processing (ICIP), 2020, pp. 2036-2040, doi: 10.1109/ICIP40778.2020.9191320.

[3] A. Sagar and R. Soundrapandiyan, "Semantic Segmentation With Multi Scale Spatial Attention For Self Driving Cars," 2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW), 2021, pp. 2650-2656, doi: 10.1109/ICCVW54120.2021.00299.

[4] L. C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, “DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 40, no. 4, pp. 834–848, 2018, doi: 10.1109/TPAMI.2017.2699184.

[5] B. Chen, C. Gong and J. Yang, "Importance-Aware Semantic Segmentation for Autonomous Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 1, pp. 137-148, Jan. 2019, doi: 10.1109/TITS.2018.2801309.

[6] J. He, K. Yang and H. -H. Chen, "6G Cellular Networks and Connected Autonomous Vehicles," in IEEE Network, vol. 35, no. 4, pp. 255-261, July/August 2021, doi: 10.1109/MNET.011.2000541.