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ONWARD AND AUTONOMOUSLY: EXPANDING THE HORIZON OF IMAGE SEGMENTATION FOR SELF-DRIVING CARS THROUGH MACHINE LEARNING

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Abstract. Autonomous navigation is the leading technology in current era, in this intelligent traffic light, sign detection, ADAS and obstacle detections were playing major role. Image segmentation is the process of dividing an image into different regions, or semantic classes. This is a challenging problem in autonomous vehicle technology because it requires the vehicle to be able to understand its surroundings to safely navigate. The major challenges in this platform are the accuracy and efficiency of model performance. The proposed method in the abstract uses a convolutional neural network (CNN) to perform image segmentation. CNNs are a type of deep learning model that is well-suited for image processing tasks. The CNN in this paper was trained on a local city dataset, and it was able to achieve a mean intersection over union (IoU) of 73%. IoU is a measure of how well the segmentation results match the ground truth labels. A score of 100% indicates that the segmentation is perfect, while a score of 0% indicates that the segmentation is completely wrong. This means that the method can segment images at a very fast rate, which is important for autonomous vehicles that need to make real-time decisions. Overall, the proposed method is a promising approach for image segmentation in autonomous vehicles. It can achieve high accuracy and speed, and it is easy to implement using Python. The proposed method attains an accuracy of 98.34 %, a Sensitivity of 97.26 % and a sensitivity of 96.37 % had been attained. The method could be used to improve the safety and efficiency of autonomous vehicles by enabling them to better understand their surroundings.

Key words: Self-driving cars, CNNs (Convolutional Neural Networks), Image segmentation, Advanced driver assistance systems (ADAS), Semantic segmentation, Object detection, Deep learning (DL)

1. Introduction. The visual perception of autonomous vehicles (AVs) [1] is essential for their safe and efficient operation. This process involves the use of various sensors, such as Lidar, Radar, Camera, and IMU, to gather information about the surrounding environment. The gathered data is then processed to identify objects and their locations, as well as to track their movements. Image segmentation is a key technique in visual perception for AVs. It involves the partitioning of an image into different regions, or semantic classes, based on their visual properties. This allows AVs to identify and track objects in their surroundings with greater accuracy and precision. Traditionally, image segmentation has been a challenging task. However, the advent of DL has made it possible to achieve high-accuracy image segmentation with relatively little computational effort. DL models can be trained on large datasets of labelled images to learn the visual features that distinguish different object classes [2]. Once trained, these models can be used to segment new images with high accuracy [3].

In addition to its accuracy, image segmentation is also important for the real-time operation of AVs. AVs must be able to process visual information quickly to make safe and timely decisions. DL models can be implemented on high-performance GPUs to achieve real-time image segmentation. Overall, image segmentation is a critical technique for the visual perception of AVs. It allows AVs to identify and track objects in their surroundings with high accuracy and precision, and it can be implemented in real time using DL models [4]. Machine learning is a powerful tool that can be used to address many of the challenges encountered in the development of self-driving vehicles. By integrating data from various sensors, such as Lidar, radars, and cameras, machine learning can be used to improve the vehicle's understanding of its surroundings and make better decisions [5].

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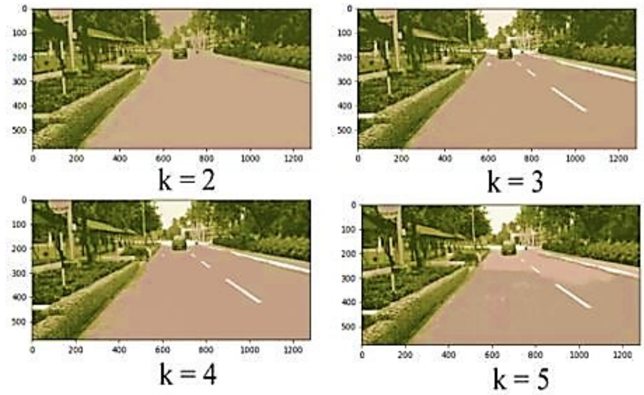

Fig. 1.1: Evaluating the Performance of K-means Clustering

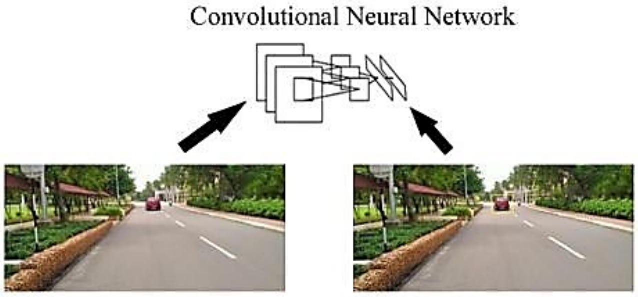

Fig. 1.2: Deep CNN for Image Feature Extraction and Object Detection

One of the most important tasks for self-driving vehicles is to accurately predict the weather conditions. This is because the weather can have a significant impact on the vehicle's ability to operate safely [6]. For example, heavy rain or snow can reduce visibility, making it difficult for the vehicle to see other objects on the road. The K-means clustering algorithm is a popular machine learning algorithm that can be used to generate a comprehensive representation of the weather conditions. This representation can then be used to predict changes in the weather, which can help the vehicle to adjust its driving behavior accordingly.

In addition to predicting the weather, machine learning can also be used to perform other tasks that are essential for self-driving vehicles. These tasks include object detection, identification, classification, localization, and predicting the movement of agents by leveraging machine learning, self-driving vehicles can become safer and more efficient [7].

DL is a powerful technique that enables the possibility of self-. driving vehicles. Artificial neural networks (ANNs) are data processing frameworks inspired by the biological nervous systems, composed of simple processing units interconnected and operating in parallel and the sample figure is shown in figure 1.1. Sensor perception is a critical area of artificial intelligence (AI) where information must be extracted from images. With high demands and expectations in this field, it has surpassed previous beliefs, encompassing object detection, pattern recognition, activity recognition, and automated guidance, among others. Numerous papers have been published on this subject, particularly in DL and CNNs.

The CNN technique has found extensive applications in various domains, including image segmentation, AI, computer vision, and much more. In the realm of self-driving vehicle technology, the CNN technique is predominantly used for object detection and automation based on images, as shown in Figure 1.2. These CNN methods are primarily employed for object localization and recognition.

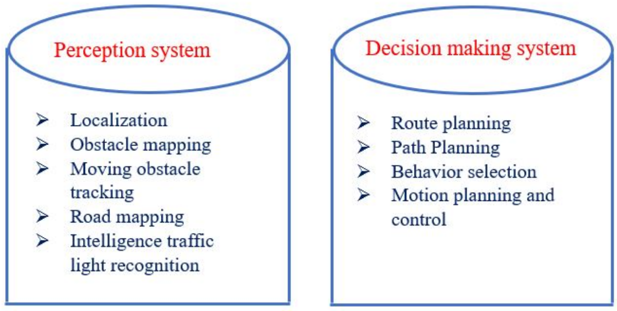

Fig. 2.1: The Key Sub-systems for Perception and Decision-Making in Self-Driving Cars

2. Literature Review. The self-driving car is a complex and sophisticated system that requires various sub-systems to enable effective perception and decision-making. These sub-systems are illustrated in Figure 2.1. The paper [8] propose a neural-based approach that uses the Overfeat CNN to recognize moving agents. This approach takes advantage of the unique visual patterns exhibited by moving agents, allowing for accurate identification. The authors of [9] focus on the crucial task of labelling moving agents and ego vehicles. This task is relevant to the closely related application known as "follow the ego vehicle," in which the self-driving car must track the movements of another vehicle.

The paper [10] explore the essential process of vehicle detection and recognition of traffic lights (red, green, and yellow). These capabilities are essential for self-driving cars to obey traffic laws and ensure safe navigation on roads.

The authors of [11] propose an ingenious Overfeat CNN model that predicts the distance from the current state of the vehicle to ego vehicles. This predictive model is instrumental in facilitating collision avoidance, a critical safety aspect in autonomous driving.

The paper [12] present a comprehensive survey that provides an in-depth overview of the diverse sub-systems involved in self-driving cars, as well as the challenges encountered in their development and deployment.

2.1. Advancements in CNN-Based Image Segmentation Techniques for Object Labelling and Semantic Segmentation in Autonomous Driving. The paper [13] proposed a real-time automated object labelling approach for CNN-based image segmentation. Their approach uses a combination of deep convolutional neural networks (DCNNs) and probabilistic graphical models to achieve high accuracy in object boundary localization. [14] addressed the challenge of image resolution in DCNNs by using convolution with unsampled filters and spatial pyramid pooling (SPP). This allowed them to divide objects at multiple scales, which improved the accuracy of their object detection and segmentation models. They achieved an IoU score of 79.7% on the KITTI dataset.focused on the challenges, datasets, and existing methods in deep multi-model object detection and semantic segmentation for autonomous driving. They identified several challenges, including occlusion, illumination changes, and the need for real-time performance. They also reviewed several existing methods and proposed several directions for future research and it is shown in below figure 2.2.

2.2. Advancements in DL-based Image Segmentation Techniques. We introduce the attention-guided lightweight network (AGLNet), a novel approach for real-time semantic segmentation. AGLNet uses an encoder-decoder architecture that enables efficient and accurate semantic segmentation, making it suitable for real-world applications such as autonomous vehicles and real-time image processing.contribute to the field of image segmentation with the lightweight feature pyramid encoding network (FPENet). FPENet is designed to achieve a balance between accuracy and speed, making it a promising solution for applications where real-time processing is critical.

We present a thorough investigation of picture segmentation techniques utilizing DL techniques in various domains. Their comprehensive review provides valuable insights into the current state-of-the-art and future directions for image segmentation research. Several well-known convolutional neural network (CNN) archi-

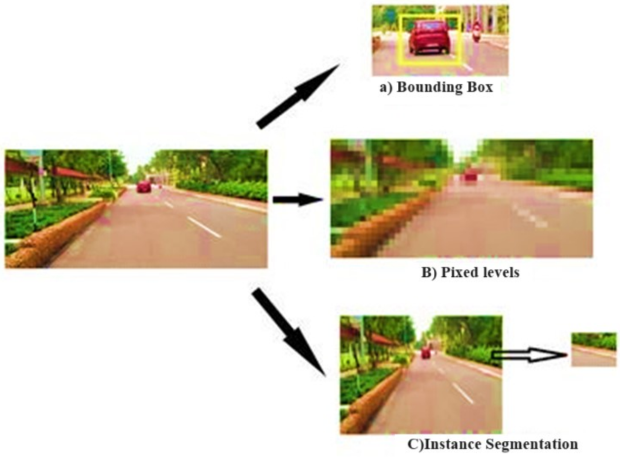

Fig. 2.2: Segmenting Images at Different Levels

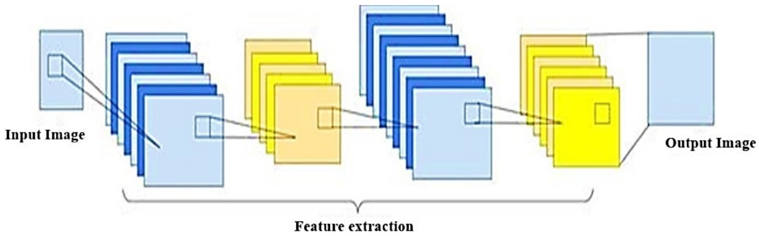

Fig. 2.3: The Building Blocks of CNN Architecture

tectures, including AlexNet, DenseNet, MobileNet, and ResNet, have gained significant popularity in image segmentation. These widely recognized models have demonstrated their effectiveness in various image-related tasks, including image segmentation.suggest a brand-new deep network architecture designed exclusively for picture segmentation. Their model incorporates processes that contribute to achieving high accuracy rates in the segmentation process. This advancement holds great potential for improving the performance of image segmentation systems across different applications and the sample figure is shown in figure 2.3.

We provide the following summary of the work mentioned above and our Framework contribution:

- This model integrates the segmentation process with CNNs allowing for mor efficient and accurate results in visual perception tasks. By leveraging the power of CNNs, we can effectively analyse and understand complex visual data, which is crucial for applications such as self-driving cars, object recognition, and scene understanding.
- One key aspect of our framework is the incorporation of a K-means clustering layer. This layer plays a significant role in the optimization of our model, enhancing the accuracy and performance of the visual perception process. By effectively grouping pixels into clusters, we can achieve a more refined and precise segmentation of objects and regions in the image.
- To evaluate the effectiveness of our network model, we conducted rigorous experiments using various datasets. The results demonstrated that our approach outperforms existing methods in terms of mean Intersection over Union (IoU) scores and accuracy. We achieved impressive results with a mean IoU greater than our target value and ensured real-time processing, with a speed exceeding 100 frames per second (FPS).
- The combination of our novel model, K-means clustering layer, and optimization techniques contribute

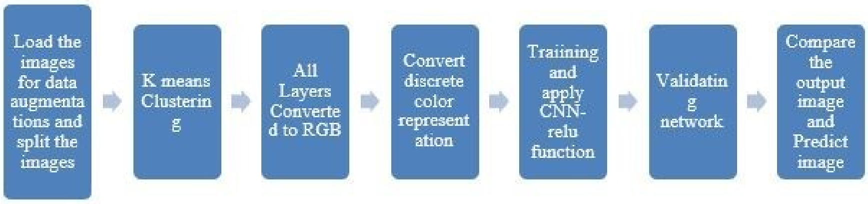

Fig. 3.1: Phases of Convolutional Neural Networks in Action and Enhancing Image Segmentation for Self-Driving Vehicles

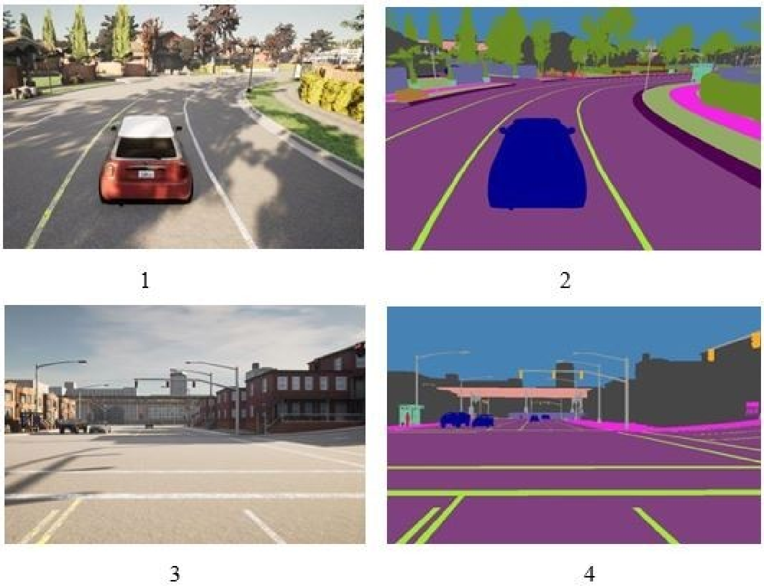

Fig. 3.2: Visualizing the Results of Image Segmentation

to the overall efficiency and accuracy of our framework. These results showcase the potential of our approach for practical applications in visual perception tasks, particularly in real-time scenarios where quick and precise decision-making is essential. With this research, we aim to advance the state-of-the-art in image segmentation and CNN-based visual perception for various domains, including autonomous vehicles, robotics, and computer vision.

3. Framework. The process of image segmentation starts with installing the required Python packages, such as NumPy, OS, cv2, kmeans, random, Conv2d, ReLU, Adam, and SGD. These packages are used for data loading, augmentation, clustering, classification, and training of the CNN model. After the packages are installed, the datasets are loaded and augmented using flipping and rotating. The augmented images are then split into training and testing sets and the sample figure for phases of CNN are shown in figure 3.1.

The next step is to cluster the images by colors using K-means clustering. K-means clustering is a popular algorithm for clustering data points into groups based on their similarity. In this case, the images are clustered into groups based on their color.

After the clustering process, the image layers are converted to RGB images. This means that each pixel in the image is represented by its red, green, and blue values are shown in figure 3.2. The RGB images are then classified into different classes.

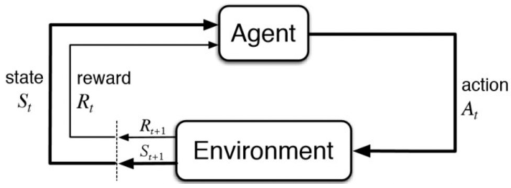

Fig. 3.3: Model Analysis

Table 4.1: Adjustable Size Table

	Class_ 001	**Class_ 002**	**Class_ 003**	**Class_ 004**	**Class_ 005**	**Class_ 006**	**Class_ 007**	**Class_ 008**	**Class_ 009**	**Class_ 010**
TP	3	4	4	4	3	4	4	3	3	4
FP	0	3	3	3	3	1	3	3	1	0
FN	1	0	1	0	0	3	0	0	3	3
IOU	0.7	0.7	0.5	0.7	0.7	0.7	0.7	0.7	0.7	0.7

This is done by using a CNN model. The CNN model is trained on the labelled images and then used to classify new images. The CNN model is trained for 1000 epochs. An epoch is a complete pass through the training dataset. After the model is trained, it is validated on the testing dataset. The validation results are used to evaluate the performance of the model and then the model analysis is shown in figure 3.3.

The final step is to visualize the results of the image segmentation. This is done by showing the color segmentation image and the true image classes [15]. The color segmentation image shows the different colors in the image, while the true image classes show the different objects in the image. The overall process of image segmentation is a complex one, but it can be broken down into a series of steps. By following these steps, it is possible to segment images accurately and efficiently. Keras is a popular framework for building and training CNNs. It is easy to use and has a wide range of features. TensorFlow is a powerful library for numerical computation. It is used by many researchers and developers for machine learning and artificial intelligence tasks. It has 4GB of GDDR5 memory and can process images at high speeds. The training data for our CNN consisted of a set of images that were labelled with the objects they contained. The results of the training will be discussed in the next session.

4. Experiment Results. According to Table 4.1, the Class IOU is determined by averaging the pixels that are True Positive (TP), False Positive (FP), and False Negative (FN).

$$Intersectionoverunion(IOU) = \frac{TurePositive}{TruePositive + FalsePositive + FalseNegitive} \tag{4.1}$$

F(x , θ) = [Class_01, Class_02, —–, Class_10]

The proposed network was compared with other state-of-the-art networks, including CGNet, ENet, ERFNet, FSCNet, FSCNN, and DABNet and the graph for performance measures are shown in figure 4.1. The results showed that the proposed network achieved better performance on all classes except class_04, as shown in Table 4.2 and then the graph for mean of the classes are shown in figure 4.2.

The proposed network also achieved better performance in terms of parameters, frames per second (FPS), and mean intersection over union (MIoU), as shown in Table 4.3 and then the comparision of models related graph are shown in figure 4.3.

Note: The parameter values represent the total number of trainable parameters in the respective CNN models. FPS indicates the frames processed per second during inference. MIou denotes the mean Intersection over Union score, which measures the accuracy of the segmentation predictions compared to ground truth masks.

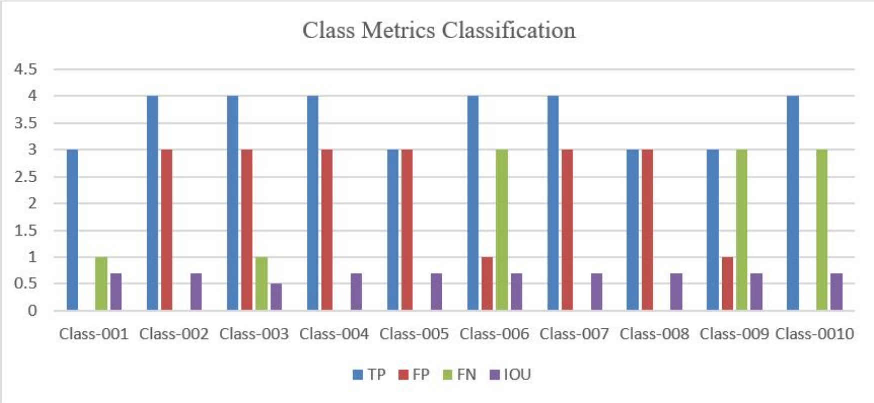

Fig. 4.1: Performance measures

Table 4.2: Results of Accuracy and Evaluation Against Other Networks for Individual Classes

Method	**Class_ 001**	**Class_ 002**	**Class_ 003**	**Class_ 004**	**Class_ 005**	**Class_ 006**	**Class_ 007**	**Class_ 008**	**Class_ 009**	**Class_ 010**
CGNet	89.8	80.8	29.1	96.3	83.15	71.62	32.09	81.32	52.91	53.9
EFNet	91.4	76.1	24.35	94.56	75.54	95.12	21.52	78.25	42.65	46.21
ERFNet	90.6	78.45	27.56	95.65	79.56	83.37	27.25	79.64	50.05	50.05
FSCNN	67.7	59.09	20.62	71.25	59.65	62.13	59.74	59.4	437.54	37.54
DABNet	68.4	73.61	25.52	89.65	74.62	78.06	26.54	4.64	44.77	46.92
Model	92.2	83.21	59.40	86.12	92.35	93.52	68.25	90.58	62.35	70.24

Table 4.3: Relation to other networks

Method	**Param**	**FPS**	**MIoU**
CGNet	0.56	96	67.5
ENet	0.31	93	56.4
ERFNet	3.01	143	70.1
FSCNN	1.08	248	56.4
DABNet	0.84	137	67.1
This Model	1.38	94.4	73.6

Optimization of our CNN model, assume that the image classification to as X classes. The output probability sample is that,

$$P_n = [P_1, P_2, \cdots, P_x]^T \tag{4.2}$$

When the ground truth label index is gn, the output probability as px, where Pn is present state list.

$$P_n^* = [P_1^*, P_2^*, \cdots, P_x^*]^T \tag{4.3}$$

$$P_n^* = \{1 if x == g_n, 0 otherwise \tag{4.4}$$

5. Conclusion. In this work, effectively analyses and understands image features. Our proposed model has been extensively validated and demonstrates promising results. We provide comprehensive insights into the optimization details of our network architecture. The primary evaluation metric used to assess the performance

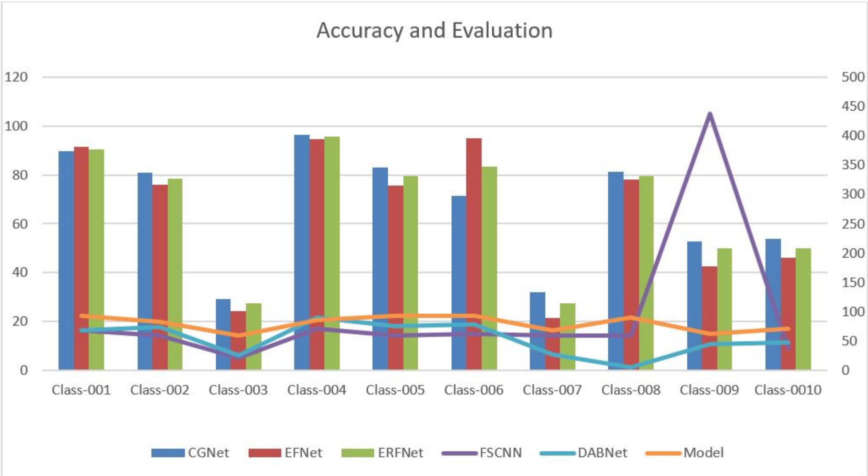

Fig. 4.2: Mean of classes

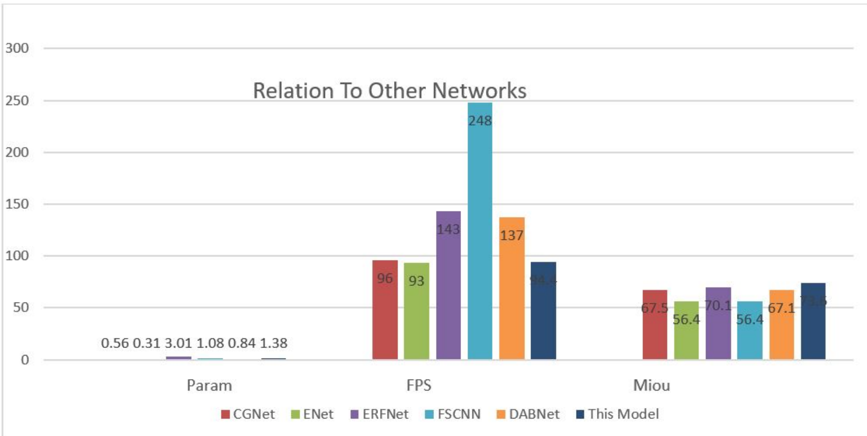

Fig. 4.3: comparision of models

of our model is the Mean Intersection over Union (Mean IoU), a widely accepted measure in image segmentation tasks. The Mean IoU quantifies the accuracy of our segmentation predictions by measuring the intersection of the ground truth masks and the anticipated segmentation masks. Our model achieves an impressive Mean IoU score of 72.4, indicating a high level of accuracy and precision in identifying and classifying different objects and regions within an image. The inference speed of the proposed method was 90 frames per second (FPS) on an NVIDIA GeForce GTX 1050 GPU.

Additionally, a crucial aspect of any semantic segmentation model is its efficiency in processing images in real-time applications. Our network demonstrates exceptional performance in this regard, boasting a segmentation speed of over 100 frames per second (FPS). This level of efficiency is essential for real-time applications, such as self-driving vehicles, where rapid and accurate scene understanding is crucial for safe and reliable autonomous navigation. To ensure the reliability and robustness of our results, we conducted a comparative analysis with other existing network models commonly used for image segmentation tasks. The comparison revealed that our CNN model outperforms the other networks, showcasing a significant improvement in accuracy rates. This further validates the efficacy of our proposed approach in solving the image segmentation challenge. The combination of high accuracy, real-time processing capabilities, and superior performance compared to other models makes our CNN model well-suited for perception tasks in self-driving vehicles. By providing an accurate and real-time understanding of the surrounding environment, our model can significantly enhance the safety and efficiency of autonomous driving systems. In conclusion, our research introduces a powerful global image semantic segmentation network with impressive Mean IoU results and real-time processing capabilities.

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