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PRECISION IN MOTION ENHANCING AUTONOMOUS DRIVING WITH ADVANCED LANE RECOGNITION USING HIGH RESOLUTION NETWORK

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ABSTRACT

Autonomous cars are revolutionizing transportation by navigating roadways without human intervention using digital technology and artificial intelligence. However, reliable lane recognition is a big barrier in this endeavor. Lane identification is a complex topic that presents significant challenges to computer vision and machine learning systems. Accurate lane line detection can be challenging due to real-world driving conditions, resulting in negatively impacts steering angle prediction. In response to this difficulty, our research proposes a novel strategy to improving lane detection and steering control accuracy. To recognize lanes with better precision, we use computer vision techniques, namely semantic segmentation. Semantic segmentation allows the vehicle's internal artificial intelligence system to classify each pixel in an image as belonging to a given object class, such as road lanes. The precise lane detection required for secure and dependable navigation is addressed by this suggested methodology, which addresses a crucial part of autonomous driving technology. In this paper we have improved the accuracy and robustness of autonomous vehicles, preparing them to face the difficulties of real-world road conditions, by using HR-Net architecture.

I. INTRODUCTION

An autonomous vehicle is a vehicle that travels without human inputs using a mix of sensors, cameras, radar and artificial intelligence. Autonomous vehicles are in-charge of observing their environment, keeping an eye on critical systems and exercising control, including steering, lane monitoring etc. It can maneuver itself maintaining its lane, dodging hazards in a swift and smooth manner. A pivotal role of autonomous vehicles is lane detection, which employs computer vision to identify lane markings. However, due to the dynamic road conditions that can be experienced while driving, lane detection becomes a difficult task. As a human driver it is hard to remain in the correct lane for an extended period. Humans are prone to tiredness, sleepiness, inattention, and driver fatigue. Besides that, using smartphones, entertainment and navigation system can interrupt the driver and jeopardize the safety. Therefore, the cost of road accidents to society are significant both in terms of harm to people and financial loss.

For [1] Increase in safety and reducing road accidents, saving lives of people are one of great interest in the context of Advanced Driver Assistance Systems. However, the complex and challenging structure of roads and vehicles needs to be detected for the safety of the people and the autonomous vehicles. There are several factors that affect lane detection in real time, for example [2] the lane markings are detected mainly based on basic gradient changes due to real-time limitations which leads to slow processing speed. Autonomous vehicles have a variety of methods for detecting lanes. According to [3], to recognize lane markings on the road, color thresholding is used, which involves filtering out pixels with values below a certain threshold. However, this technique can also identify other white areas that are not lanes, therefore it might not completely fix the issue. [4], Regardless of many approaches have been put out to increase precision while expediting speed, various hindrances, including lane markings variations, lighting fluctuations, and shadowy conditions, demands the development of robust detection system. In lane-detection, model-based and learning-based approaches are the two most used approaches. Model based methods afford rapid computation speeds, while learning-based methods extend robustness amidst complexity.

According to [5] Lane detection minimizes the possibility of accidents caused by lane departure by assisting in maintaining the car in its selected lane. Additionally, it aids in the detection of roadblocks and other cars, enabling the car to react appropriately to prevent crashes. Highly accurate lane marking identification is possible with lane detection algorithms, which facilitates vehicle navigation [4]. This is especially helpful when there is low visibility or other obstructions that prevent the driver from seeing the lane lines. According to [5] Comparing Lane detecting algorithms to other sensor technologies like lidar and radar, they are comparatively less expensive. As a result of this, they are a desirable choice for makers of autonomous vehicles trying to cut expenses.

According to [6] Manufacturer adoption of lane detecting algorithms is facilitated by their easy integration with current ADAS systems. This is very helpful for adding ADAS capability to older vehicles. Overall, lane detection is an essential technology for autonomous vehicles, providing a number of benefits that raise the standard for accuracy, cost-efficiency, and safety. Lane detection should become even more dependable and robust in the future as researchers continue to create novel algorithms and sensor technologies.

This paper [4] discusses over a number of lane detection techniques, such as using ridge detectors to identify road lanes in aerial photos. The study emphasizes the difficulties in lane recognition and the growing need for more reliable and precise algorithms. An algorithm for lane recognition that can manage intricate road conditions and dynamic surroundings is presented in paper [7]. The program tracks and detects lane markings in real-time using a combination of edge detection, Hough transform, and Kalman filter. Although, the proposed algorithm's imperfections such as its susceptibility to noise and occlusion, which may impair its effectiveness in practical situations, are not covered in the paper.

HR-Net stands out by its capacity to concurrently record high-resolution data at several scales. HR-Net retains fine-grained information in contrast to conventional methods that down sample the input image, enabling a more thorough comprehension of the scene. This capacity to extract features at many resolutions comes in handy in situations where lane markings are indistinct or dispersed. We incorporate HR-Net into the lane detection procedure in our trials. We make use of a large dataset with challenging circumstances like urban environments, highways, and inclement weather. By using HR-Net's benefits in managing even the tiniest aspects, the installation has been modified to enhance efficiency.

Our research results demonstrate how effective HR-Net can be with lane detection tasks. Even in scenarios in which conventional techniques might struggle, the model performs exceptionally well at precisely drawing lanes and predicting the steering angle of the vehicle. HR-Net consistently outperforms other lane detection algorithms in comparison analyses conducted against a variety of datasets.

II. THEORETICAL REFERENCE

II.1 HIGH RESOLUTION NETWORK

The HRModule is responsible for processing features concurrently at various resolutions. Let's define X for the input tensor and Xi for the i-th branch. This represents the output of each branch at a distinct resolution. The following is a representation of the operations:

$$Xi=fi(X), \quad i=1,2,...,n \tag{1}$$

Where the function corresponding to the i-th branch applies is denoted by f i. Typically, activation functions, normalization, and convolutional layers are used in this function.

II.2 STAGED AGGREGATION

Connecting features across different resolutions is the ultimate objective of staged aggregation. When X i is the result of the X i-th branch and A i represents the aggregated characteristics at the X i-th stage, the aggregation can be expressed as follows:

$$Ai=gi(X1,X2,...,Xi), \tag{2}$$

where Fg_i = f_i* is a function which incorporates features from F_1 X 1 to F_i X 1. The network can benefit from context learned at coarser resolutions in addition to high-resolution details according to this aggregation process.

II.3 TASK SPECIFIC HEAD

The final stage involves a task-specific head for the particular application (lane detection, for instance). Let Y represent the output predictions and H as the features following the staged aggregation. The head for the task at hand can be shown as:

$$Y=h(H), \tag{3}$$

where h is a specific to the task function that might involve activation functions, completely linked layers, and maybe other actions customized for the application.

II.3 LOSS FUNCTION FOR TRAINING

A loss function termed L is used to figure out the extent to which the model's predictions deviate from the ground truth during training. Usually, the criteria for the work specify the loss. For instance, the mean squared error (MSE) loss is frequently selected for lane detection:

$$L=N1\sum i=1N(Yi-Y\hat{}i)2, \tag{4}$$

where N is the number of samples, Yi is the predicted output, and Yi is the ground truth.

III. MATERIALS AND METHODS

Implementing a high-resolution network is one method of lane detection. High spatial resolution image processing is a feature of this kind of network that is critical for identifying minute details like lane markers due to the fact that high resolution networks can learn complicated properties from the input images, they usually contain several layers and many parameters. Pre-processing the input image is the initial stage in incorporating a high-resolution network for lane detection. This entails enhancing the features—such as edges and colour gradients—that are relevant for lane detection through the application of various filters and transformations. After that, the network receives the pre-processed image and uses a number of convolutional layers to process it. An array of probability maps demonstrating the probability of each pixel being a lane marker are the network's output. The actual lane boundaries are subsequently extracted via postprocessing from these probability maps. This entails using a variety of methods to eliminate noise and outliers and smooth the borders.

The potential of a high-resolution network to handle a variety of road and lighting situations is one benefit when employing it for lane detection. The network may be trained to recognize lane markings in a variety of lighting scenarios, including direct sunshine and dimly lit environments. Additionally, it is capable of handling various road surfaces like gravel, concrete, and asphalt. The capability of a high-resolution network to detect many lanes at once is another benefit. This is crucial when driving on multilane roads since you have to stay in your own lane and keep vehicles out of the surrounding lanes. One of the most significant features of autonomous driving systems is steering angle prediction; this function can be made more accurate by utilizing a high-resolution network such as HRNet.

In conclusion, a high-resolution network for lane detection is a potent method for autonomous driving. It can recognize numerous lanes at once and handle a wide range of road and lighting situations. High resolution networks are probably going to become more crucial as autonomous driving technology develops in order to guarantee safe and effective driving.

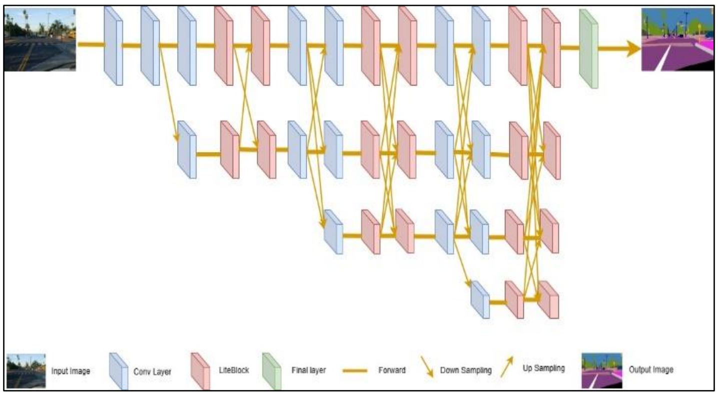

Figure 1: HRNet Architecture.
Source: Authors, (2024).

A detailed illustration of the HRNet architecture is provided in Figure 1, providing a clear understanding of its composition and design. This figure shows the more complex aspects of HRNet's network architecture and provides an illustration of how it handles the segmentation task. Figure 1 provides a visual aid that enhances understanding while making simpler to understand HRNet's functioning in the context of segmentation activities by outlining the essential elements.

IV. RELATED WORKS

Safety is the main objective of every road lane detection system. Lane detection techniques have been proposed in a number of literary works. The real-time lane recognition approach that the authors of this work devised in [8] has an accuracy of 88% and can identify lane signs on the highway in near-real time. However, under different lane detecting settings, these methods exhibit poor accuracy [9]. Only 80% of the time could lane borders be accurately identified utilizing the RANSAC-based boundary detection technique that the authors of [10] presented. The authors of the paper [11] said that their suggested model had an accuracy of 88%. Numerous obstacles must be overcome, including perspective distortions, generalization, lane structure variability, and the detection of both lane boundaries. The potential of the model to predict the lane effectively is essential in the very promising subject of lane identification. The algorithm used in [12] has a major drawback when it comes to addressing false positive and false negative rates in lane detecting. While false negatives can lead to lane markings being missed, false positives can result in unnecessary alerts or incorrect decisions. The management of edge conditions, like fading intermittent lane markings, which are critical to the system's dependability, is not covered by the authors in [13].

Real-Time Lane Detection Networks for Autonomous Driving: A real-time lane detection technique called LaneNet has been developed [14]; however, its accuracy is limited to 86%. In contrast, the UNet model achieved 90% accuracy, while Segnet obtained 89% accuracy when compared to U-Net [15] and SegNet [16]. The purpose of the paper [17] is to conduct picture segmentation without requiring detailed pixel-level annotation by presenting a weakly supervised semantic segmentation technique. Depending on how well-made and efficient the procedure is, the created pseudo-labels by picture masking may or may not be accurate. The segmentation performance of the model may be lowered by noisy or inadequate pseudo-labels produced by poorly masked areas. The multi-layer deep convolutional neural network used in the research [17] is called the VGG11 encoder, and it can capture features at different scales and degrees of abstraction. The model is able to comprehend both high-level semantic context and low-level features thanks to its hierarchical representation, which makes the segmentation model more reliable and accurate. TernausNet may be applied to a variety of photo segmentation challenges due to its adaptability and flexibility. Semantic segmentation and object recognition are two medical imaging applications where the U-Net design has proven to be effective. Squeeze U-SegNet is utilized for brain MRI segmentation utilizing the techniques described in paper [15]. This model might be affected by variations in MRI data, such as different imaging protocols, scanning equipment, or patient demographics.

Deep neural networks have been employed by the paper's author [18] to detect lanes in continuous driving scenes. While lane detection in complicated road scenarios like crossings, construction zones, or busy urban surroundings can be naturally more difficult, the algorithm utilized is intended to be robust under harsh conditions and has limited generalization to unexpected and extreme scenarios. In these circumstances, the model's performance can be jeopardized. Sensing Image Semantic Segmentation is achieved by a number of alternative techniques, including pseudo-labelling in [16]. The drawback of this approach is that it may cause the model to become unduly confident in its predictions during training, even when those forecasts turn out to be inaccurate. This problem could lead to poor generalization and make it difficult for the model to adapt to novel or complex settings. TernausNet and Attention-Aware RCNN have been combined to bring the strengths of both architectures, resulting in enhanced accuracy for brain tumor segmentation and classification. The authors of paper [19] used this combination to segment and classify brain tumors in MRI images. By helping the model focus on important regions, the attention processes reduce false positives and improve accuracy. The authors of the paper [20] used a technique by using front-view images to ensure improvements in the accuracy and operating speed. DSUNet-PP from the paper [21] performs more effectively than UNet-PP. In lateral error tests carried out in a real car on a real road, DSUNet-PP performs better than a modified UNet. These findings demonstrate the effectiveness and efficiency of DSUNet for autonomous driving's lane detection and path prediction. The authors of paper [22] used image augmentation and the identification of driving lanes on motorways, we employ a CNN. Edge extraction and line detection are typically the initial steps in the lane detection procedure. Prior to lane detection, a CNN can be used to improve the input images by eliminating objects and noise that do not have effect on the edge detection outcome. However, a large dataset and a significant amount of processing power are needed to train traditional CNNs. The study in [23] proposes a real-time lane detection method that takes advantage of deep learning capabilities by using a lightweight convolutional neural network model as a feature extractor. The generated model is trained using a dataset of 16 × 64 pixel-sized image patches, and to facilitate quick inference, a non-overlapping sliding window technique is used. Subsequently, a polynomial is fitted to the clustered predictions in order to model the lane borders.

IV. RESULTS AND DISCUSSIONS

IV. 1 DATASETS

TuSimple dataset [24] and Udacity dataset has been used to analyze the suggested technique. TuSimple dataset contains 6,408 road pictures of resolution 1280 x 720 resolution. Udacity dataset contains custom images of a custom track which is used to predict the steering angle. The dataset was gathered in a variety of daytime hours and traffic situations during fair to moderate weather. There are 34,680 photos in the dataset for testing and 88,880 for training. Context-based annotations are included with curved splined. Additionally, this dataset records the state of the roads under many circumstances, including normal, congested, night, shadow and arrow.

IV. 2 PERFORMANCE ANALYSIS

The ratio of correctly classified instances to the total number of instances, as indicated by formula (5), is the measure of accuracy. The terms that are related include:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + False\ Negative + True\ Negative} \quad (5)$$

Several instances of true-positives (TP) represent situations in which actual events are accurately predicted to be true. True-Negatives (TN): In circumstances in which real false cases are precisely called false.

False-Positives (FP): Whenever true cases are mistakenly anticipated to be false based on real false cases.

Instances when true instances are inaccurately predicted as false are known as False-Negatives (FN).

The experiments were carried out using Python libraries like NumPy, Keras, TensorFlow, Flask, Socketio, and OpenCV on a local computer and Google Colaboratory. The following are the specifications of the local machine:

- 11th generation Intel Core i7 processor,
- 16GB RAM,
- 1TB SSD,
- Nvidia GeForce RTX 3060 graphics card

To achieve solid and trustworthy findings, the model was run through twenty rounds of execution

IV. 3 RESULTS

The implementation of HRNet architecture in the research's lane detection and steering angle prediction showed outstanding results, with a remarkable accuracy of 93.2%. Compared with various architectures, this performs more effectively: UNet recorded an accuracy of 84.3%, while ResNet34 achieved 85.3% on TuSimple Dataset. The foundation for HRNet's improved accuracy is that it can extract more complex lane features and, in return, predict steering angles with greater precision due to the fact it can record high-resolution spatial information at various scales. The results of this study demonstrate the effectiveness of HRNet in lane detection and steering angle prediction tasks, highlighting its potential to enhance autonomous vehicle performance and safety through reliable and accurate environmental perception. Table.1 tabulates the performance analysis of the HRNet with two other deep neural architectures such as UNet and ResNet34.

Table 1: Performance of architectures on TuSimple dataset.

Model	Accuracy	FP	FN
Unet	84.30%	0.09	0.09
ResNet34	85.30%	0.1	0.12
HRNet	93.20%	0.1	0.11

Source: Authors, (2024).

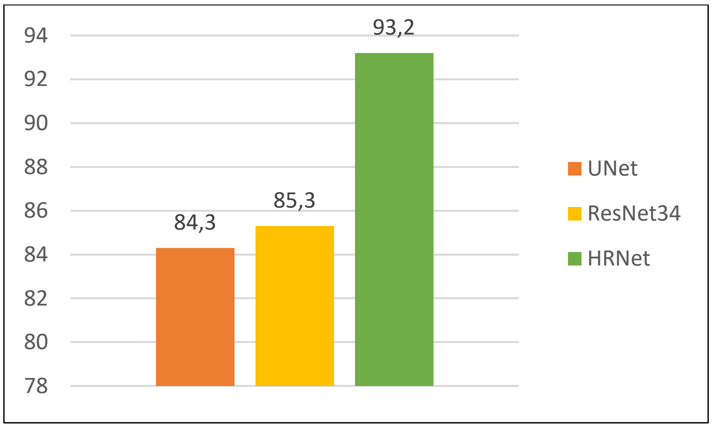

Figure 2: Performance results of deep neural architectures on TuSimple dataset.
Source: Authors, (2024).

The provided images in Figure 3 gives visual evidence of the model's ability to identify lanes. These images, which were captured using the steering angle prediction and lane recognition system in place, clearly demonstrate the ability of the model to recognize and define lane boundaries. The lanes stand out clearly, demonstrating how well the HRNet design captures fine-grained spatial features. The 93.2% accuracy rate of the model's successful lane detection in these images not only validates its accuracy but also highlights its practicality in real-world situations. The model's capacity to improve environmental perception-a crucial component in the development of sophisticated driver-assistance systems and autonomous vehicles is strongly illustrated by these visual results.

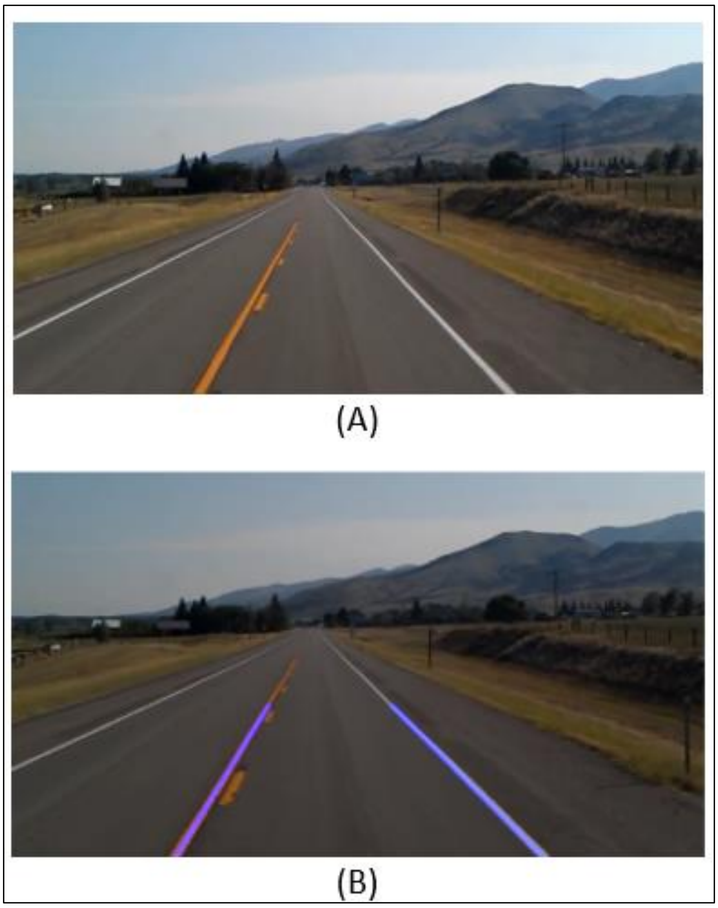

Figure 3: (a) Shows the road image (b) denotes the model detecting the lane.
Source: Authors, (2024).

V. CONCLUSION

In conclusion, the development of autonomous vehicles, driven by advancements in computer vision, artificial intelligence, and sensor technologies, demonstrates a revolutionary change in the transportation industry. Lane detection is vital for the secure and efficient functioning of self-driving vehicles since it helps keep lanes in order, avoid impediments, and improve navigation in general. However, sophisticated lane detecting systems are required as a result of the difficulties caused by changing lighting circumstances, dynamic road conditions, and the requirement for real-time processing. The computational speed and robustness of traditional lane detection approaches, such color thresholding and simple gradient modifications, are constrained. These issues are addressed with the emergence of high-resolution networks, such as HR-Net, which capture fine details and make it feasible to recognize various lanes in a variety of situations. With its task-specific heads and staged aggregation, the HR-Net architecture offers a flexible framework for lane detection, especially in situations where other methods might not be as successful.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: P.Santhiya and S. Kiruba Karan.
Methodology: P.Santhiya and S. Kiruba Karan.
Investigation: P.Santhiya, Getzi Jeba Leelipushpam Paulraj and S. Kiruba Karan.
Discussion of results: P.Santhiya, Getzi Jeba Leelipushpam Paulraj, Ebenezer, S.Kiruba Karan.
Writing – Original Draft: Ebenezer.
Writing – Review and Editing: Ebenezer.
Resources: Immanuel JohnRaja Jebadurai.
Supervision: Immanuel JohnRaja Jebadurai.
Approval of the final text: Immanuel JohnRaja Jebadurai.

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