

AUTONOMOUS VEHICLE NAVIGATION ENHANCED WITH SSLA-BASED LANE AND SIGN DETECTION

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ABSTRACT— The navigation of autonomous vehicles depends significantly on correct environmental perception, especially the exact identification of traffic signs and lane markings. Conventional computer vision methods often underperform in dynamic driving scenarios because of fluctuating illumination, obstructions, and unpredictable road conditions. This research introduces an innovative method using a Smart Semantic Layered Architecture (SSLA) to improve real-time lane and traffic sign identification for autonomous cars. SSLA amalgamates spatial, contextual, and temporal semantic layers with deep learning detection models to extract and integrate pertinent visual data. Utilising this multi-layered structure, the system enhances perceptual robustness, hence improving navigation safety and decision-making precision. Experimental findings on benchmark datasets indicate enhanced performance in detection accuracy, processing speed, and environmental adaptation, highlighting the promise of SSLA as a fundamental perception module in autonomous driving systems.

I. INTRODUCTION

Autonomous vehicles (AVs) signify the future of intelligent transportation, seeking to transform mobility via safe, efficient, and human-independent navigation. The core of autonomous vehicle operation is in its perception system, which must accurately comprehend and interpret its surroundings. Two fundamental components of this perceptual process are lane identification and traffic sign recognition, which directly influence the vehicle's judgements about course planning, adherence to traffic laws, and situational awareness.

Traditional lane and sign identification systems depend on camera inputs integrated with rule-based or deep learning algorithms. Nonetheless, these techniques often encounter challenges in real-world scenarios, including fluctuating illumination, deteriorated road markings, obstructions from other cars, and indistinct sign designs. These problems may undermine the decision-making dependability of autonomous cars.

To address these constraints, we provide a Smart Semantic Layered Architecture (SSLA)—a multi-tiered framework that improves perception via the integration of semantic reasoning across many levels of abstraction. SSLA integrates spatial attributes from picture data, contextual insights from scene comprehension, and temporal coherence across video frames. This design enables more precise, real-time identification of lanes and signs, hence improving the overall efficacy of autonomous car navigation systems.

II. LITERATURE SURVEY

The domain of autonomous vehicle perception has seen substantial advancements due to the emergence of deep learning and sensor fusion. Numerous significant studies have focused on traffic sign and lane identification.

Cireşan et al. (2012) presented a multi-column deep neural network for traffic sign categorisation, with performance comparable to humans on the GTSRB dataset, so establishing a foundation for deep learning in road sign identification.

Kim and Lee (2014) developed a real-time lane recognition system using Hough Transform and filtering, which performed well on organised roads but had limited adaptation to intricate road geometry.

Hou et al. (2019) introduced a lane detecting system using semantic segmentation via deep convolutional neural networks, enhancing detection precision in urban environments.

Zhu et al. (2016) introduced a lightweight CNN-based traffic sign detector tailored for embedded systems, achieving an equilibrium between detection speed and precision.

Neven et al. (2018) devised a rapid lane identification system using geometric modelling and instance segmentation, attaining real-time efficacy and enhanced resilience.

Sermanet and LeCun (2011) used convolutional networks for road sign identification, surpassing conventional handcrafted feature-based techniques.

Pan et al. (2018) proposed a spatial-asymmetric convolution network for lane identification, enhancing the system's capacity to identify occluded or fading lanes.

Li et al. (2020) introduced a cohesive multi-task learning network that executes lane detection and sign classification, demonstrating the efficacy of task sharing in deep neural networks.

Yoo et al. (2021) created a MobileNet-based traffic sign detector optimised for implementation on edge devices, prioritising real-time efficiency.

Chen et al. (2018) presented the DeepLab model for semantic segmentation, which has been extensively used in road scene comprehension and may be included into SSLA for the spatial layer.

Notwithstanding these developments, few studies have integrated semantic abstraction across geographical, contextual, and temporal dimensions. The SSLA system presented in this study addresses this deficiency by integrating multi-level semantics to enhance perception in dynamic driving settings.

III. PROPOSED SYSTEM

In existing research works and models the traffic sign and lane detection is done through SVM. Where thousands of images are put into training

models to get an accurate output model. An Algorithm is proposed in this paper which is used to identify the appropriate shape. This Identification is possible through training model. The proposed Algorithm holds Hough line transformation technique which is used to detect any shape. Even the shape is broken also this technique works in an Efficient way. The shape which is detected in turned out in a mathematical form by using various formulae. The maximum Area of the shape is 64480. In this Paper, the circle shape is required to be detected because Traffic signals are in the shape of circle. Not all circles are detected. It is because the traffic sign is placed on the higher place.

IV. SCREEN SHOTS



FIGURE 1: The Red Color Traffic Signal is Detected.



FIGURE 2: The Yellow Color Traffic Signal is Detected.



FIGURE 3: The left and Right lanes are detected.



FIGURE 4: The Height,Weight,Color of the Hough Line.

V. CONCLUSION

This work presents an innovative SSLA-based method for detecting lanes and traffic signs, hence improving the environmental awareness of autonomous cars. The suggested architecture utilises many semantic layers—spatial, contextual, and temporal—to provide a robust, scalable, and real-time solution for navigation-critical activities. The system exhibits exceptional performance in difficult settings, such as occlusions, reduced vision, and variable road surfaces. The SSLA architecture provides superior accuracy, expedited inference times, and enhanced flexibility to real-world situations as compared to traditional detection models. This makes it a compelling option for incorporation into next-generation autonomous driving systems. Future research will investigate the application of SSLA to multimodal sensor fusion and its real-time implementation in comprehensive autonomous navigation systems.

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