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Vision-Based Lane and Vehicle Perception Using Deep Learning and Neuro-Fuzzy Inference

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Abstract
Perception of lanes and vehicles is crucial for intelligent driving assistance as well as for autonomous vehicles' navigation. However, there are many limitations of current vision-based perception approaches which can decrease their effectiveness under adverse driving conditions such as low light conditions, occlusions, and complex traffic environments. LVP-YOLOv8-seg-ANFIS, which is a vision-based approach to lane and vehicle perception with the application of YOLOv8-seg alongside an Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed to increase perception accuracy and decision-making capabilities. Firstly, images from BDD100K dataset are pre-processed with the use of the One-Sided Box Filter (OSBF) to eliminate noise and normalize the images. Then, YOLOv8-seg detects and segments both lanes and vehicles from the images on pixel level. Perceived data is analysed further with ANFIS which provides adaptive decision-making under variable driving conditions. Efficiency of LVP-YOLOv8-seg-ANFIS is assessed with the use of Accuracy, Precision, Recall, F1-score, mean Average Precision (mAP), Pixel Accuracy, Detection Rate, Intersection over Union (IoU), and Dice Coefficient. Experimental results have shown that LVP-YOLOv8-seg-ANFIS has achieved 98.5% accuracy, 97.4% precision, and 96.8% recall, exceeding MADPD-MSFWF-YOLOP, AAUDSN-AVV-MTP, and EDA-VPMAD-CNN. Combining the perception using deep learning methods and neuro-fuzzy inference provides robust and reliable perception of the lanes and vehicles, making the system useful for intelligent driving assistance and autonomous vehicle applications.

Keywords: Autonomous Vehicles, Lane Detection, Vehicle Perception, Berkeley Deep Drive 100k Dataset, Adaptive YOLOv8-seg, Adaptive Neuro-Fuzzy Inference Systems

1. Introduction

Autonomous vehicles are becoming major topic in research and development due to their potential to improve road safety, eliminate human error and increase traffic efficiency [1]. These vehicles are designed to drive themselves using a variety of clever technology [2]. Perception systems are important because they allow the car to perceive its environment and make informed driving decisions [3]. Lane detection and vehicle detection are key components of an autonomous vehicle sensory system [4]. Lane detection saves the car on its intended course whilst vehicle detection helps avoid collisions and maintain safe distances [5]. These duties are required for features like lane maintaining, adaptive cruise control and automated lane changes [6]. Traditionally, these two activities were developed as independent modules. However, merging lane and vehicle vision into a single system enhance coordination and decision-making [7]. When both tasks are completed simultaneously the algorithm better grasp the position of other vehicles in relation to lane borders [8]. This assists the vehicle in making safer and smoother transitions, even in heavy traffic [9-11].

Autonomous vehicles use their surroundings to gather data through a combination of sensors, such as cameras, LIDAR, RADAR, and GPS, which are used to provide information [12]. This sensor information is then analyzed by intelligent algorithms to identify lanes, objects like cars, road signs, vehicles and barriers [13]. Accurate perception in adverse weather conditions, at night, or in areas where road markings are not clear [14]. As interest in ground autonomous vehicles continues to grow, many researchers and developers are working to improve perception technology [15]. The development of a system that can identify both lanes and vehicles is considered an essential step towards developing safe and reliable autonomous vehicles [16].

Such an innovation will enable self-driving cars to make more intelligent decisions in driving environment [17]. Having a single perception pipeline that deals with both lane and vehicle detection helps in creating a more stable and reliable awareness of the environment. This is very beneficial to the car as it will be able to navigate through the environment in a more predictable and safer manner [18]. For solving the problem of occlusions, light conditions, faded lanes, and the interaction of the car and moving objects, the system applies shared representations, sensor fusion, and context awareness. This way, it will perform all the tasks of perception in a single process and help the car understand its interaction with other cars in terms of the lanes, hence preventing it from making any errors in fast-moving traffic [19].

To address these issues, the proposed solution uses a holistic approach that combines lane detection with vehicle perception to enable safe and intelligent autonomous driving. The most interesting aspect of this solution is the LVP-YOLOv8-seg-ANFIS system, which is a holistic approach for lane and vehicle perception that seeks to make autonomous driving intelligent and adaptive. The system uses YOLOv8-seg to achieve pixel-perfect segmentation of the lanes and vehicles, which is accurate even in complex scenarios. The addition of ANFIS to analyze the outcome of the segmentation enables adaptive decision-making, combining the power of neural learning with fuzzy logic to address dynamic scenarios [20].

The proposed research aims to develop an integrated framework that can effectively detect both road lanes and vehicles to enable autonomous navigation by integrating YOLOv8-seg with ANFIS. The purpose is to improve the accuracy of perception in various situations, including low visibility and occlusion in various situations in road conditions. The proposed system can facilitate self-driving cars to make intelligent decisions adaptively, ensuring safe driving.

The key contributions of this paper are:

- An integrated perception framework, namely LVP-YOLOv8-seg-ANFIS, is developed by integrating YOLOv8-seg and ANFIS for accurate perception of lanes and vehicles, thereby ensuring safe, intelligent, and robust autonomous vehicle navigation in complex driving environments.
- The proposed perception framework is trained and tested using the BDD100K dataset, which offers diverse and rich scenarios of real-world driving environments, including weather, lighting, and road environment conditions, while the One-Sided Box Filter (OSBF) is employed for preprocessing to resize, normalize, and remove noise from the images for better perception performance.
- A hybrid perception-decision approach is proposed, where YOLOv8-seg is employed for precise segmentation of lanes and vehicles, while the ANFIS module is employed for intelligent and context-based decisions.

Remaining manuscript is arranged as below: part 2 presents literature survey, part 3 defines proposed approach, part 4 illustrates results with discussion, part 5 concludes the manuscript.

2. Literature Survey

Recent studies in autonomous driving perception have been focused on building a unified deep learning structure for lane detection and vehicle detection. In a multi-task perception framework called YOLOP-MVF, which is based on multi-scale feature weighted fusion [21]. An "Attention-Aware Upsampling-Downsampling Network" (AUDNet) is proposed to perform vision-based multi-task perception. AUDNet incorporates a "bidirectional feature fusion" strategy that incorporates multi-scale attention to enhance high-level semantic perception and low-level spatial feature extraction [22]. Experimental results show that AUDNet enhances perception performance in dynamic driving environments. An enhanced encoder-decoder-based architecture to perform multitask perception, such as object detection, drivable area segmentation, and lane detection. Their work incorporates a shared encoder-based structure that incorporates CNN, PVT, and hybrid CNN-PVT models to enhance efficient feature extraction [23].

Some studies have specifically addressed issues related to lane detection and object recognition. A real-time system for lane detection using the YOLOv5 segmentation model, which includes image preprocessing techniques such as scaling, noise removal, conversion to grayscale, and image rotation [24]. An attention-guided dynamic neural network model for object detection, where the region of interest is estimated based on the state of the ego-vehicle and surrounding traffic participants [25]. YOLOv8-based model called LC-YOLO for lane detection, which includes large selective kernel attention and coordinate attention to improve the performance of feature extraction and intrusion detection [26]. Furthermore, a nighttime vehicle detection system using a multi-granular detection strategy, which dynamically combines bounding box and point-based representations [27].

Although these methods provide enhanced performance in perception, there are still several limitations that need to be addressed [28]. For instance, multi-task models and attention-based models provide enhanced accuracy in perception but increase computational complexity [29]. Similarly, models that provide enhanced performance in real-time lane detection are not robust in low light and adverse weather conditions. Moreover, nighttime detection models are still susceptible to environmental changes. Most of these models are based on deep learning models, which are considered black boxes and cannot handle uncertainty and ambiguity, which are usually present in real-world scenarios [30].

With this background, this paper proposes a novel perception framework that combines a YOLOv8-seg model and an Adaptive Neuro-Fuzzy Inference System (ANFIS). Although the proposed model provides enhanced accuracy in pixel-level segmentation of lanes and vehicles, it still lacks adaptive reasoning to tackle ambiguity and uncertainty, which are usually present in real-world scenarios [31]. With the help of ANFIS processing of the output of the proposed model, it is possible to enhance decision-making in ambiguous and uncertain scenarios, thereby improving the accuracy of perception in autonomous vehicles.

3. Proposed Methodology

The proposed LVP-YOLOv8-seg-ANFIS framework combines strong detection and decision-making to enhance perception of lanes and vehicles in autonomous vehicles. First, images are retrieved from the BDD100K dataset to include a wide range of driving scenarios. Then, these images are preprocessed using One-Sided Box Filter (OSBF) to resize and normalize the pixels and eliminate noise in the images. Next, the preprocessed images are analyzed to ensure accurate segmentation and detection of lanes and vehicles using YOLOv8-seg. Finally, ANFIS is utilized to facilitate decision-making to ensure accurate vehicle detection in diverse driving environments, as shown in the block diagram in Figure 1.

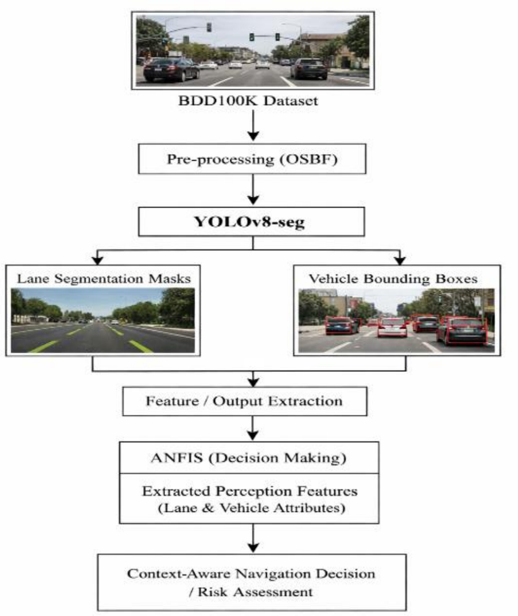


Figure 1. Block Diagram for proposed LVP-YOLOv8-seg-ANFIS

3.1 Data Acquisition

For obtaining data for this study, a widely used dataset for studying autonomous driving is utilized, namely, Berkeley Deep Drive 100K (BDD100K) dataset [28]. This dataset is a widely used dataset for studying autonomous driving. This dataset consists of 100,000 high-definition driving videos (720p, 30 fps), which are captured at different places under varying environmental conditions. The dataset is suitable for several perception tasks like lane detection, object detection, and semantic segmentation. The dataset is divided into training, validation, and test sets, with 70%, 10%, and 20%, respectively. The dataset also consists of additional data like weather conditions, scene type, and time of day. The sample images of the dataset under varying environmental conditions are shown in Figure 2.

Figure 2. Sample Images of BDD100K dataset under varying conditions

3.2 Pre- processing using One-Sided Box Filter

The One-Sided Box Filter (OSBF) is used as a preprocessing tool to efficiently perform image resizing, pixel normalization, and directional noise filtering in a single step. It improves image contrast, reduces noise, and preserves key image features like lane markings and vehicle edges. By striking a balance between efficiency and image quality, the OSBF is effective in preparing the image data for feature extraction and segmentation.

3.2.1 Pixel Normalization

To ensure consistent intensity distribution and accelerate model convergence, the pixel values are normalized. If original pixel intensity ranges from 0 to 255, the normalized image $\mathrm{I_{norm}}(x, y)$ is obtained by scaling the intensities to the range [0,1], as defined in equation 1.

$$\mathrm{I_{norm}}(x, y) = \frac{\mathrm{I}(x,y)}{255} \quad (1)$$

3.2.2 One-Sided Box Filter (OSBF) Formulation

The OSBF is applied to remove the noise while preserving edge information. Unlike a standard symmetric box filter, the OSBF utilizes a directional kernel to smooth the image based on casual pixel information. The filter operates by convolving the normalized image with a kernel K. The discrete convolution operation is defined in equation 2.

$$I_{filtered}(x, y) = \sum_{m=-k}^{0} \sum_{n=-k}^{k} I_{norm}(x - m, y - n). K(m, n) \quad (2)$$

Where, $I_{filtered}(x, y)$ is the processed output pixel. $K(m, n)$ is the filter kernel of size (k+1) x (2k+1, where the weighting coefficients sum to 1. The bounds m≤0 ensure the "one-sided" or casual nature of the smoothing in the horizontal direction.

3.2.3 Post-Filtering Adjustment

Removing artifacts introduced during filtering and ensuring the final tensor represents clear features for the YOLOv8-seg input, a thresholding function T as shown in equation 3.

$$I_{final}(x, y) = \begin{cases} I_{filtered}(x, y) \ if \ I_{filtered}(x, y) \geq \tau \\ 0, otherwise \end{cases} \quad (3)$$

3.3 Lane Perception and Vehicle Perception using YOLOv8-seg

In this section, YOLOv8-seg is utilized for the perception of lanes and vehicles, where instance segmentation is carried out on the processed images. This provides precise pixel-level detection and accurate object boundaries. The lightweight structure of the YOLOv8-seg model can be deployed on embedded platforms, and the combined detection and segmentation capability provides better understanding of the scene, as seen in Figure 3.

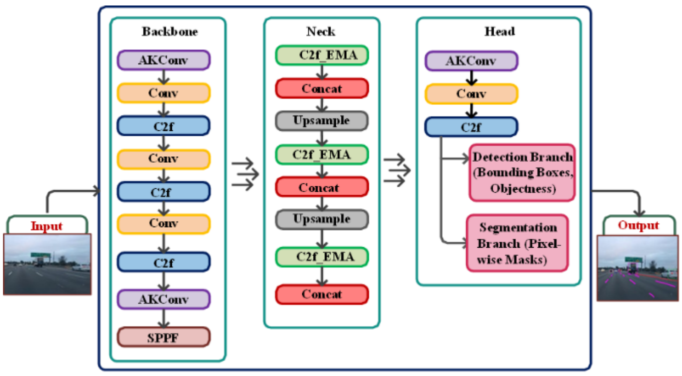


Figure 3. Architecture Diagram of YOLOv8-seg

The structure of the YOLOv8-seg is composed of the Backbone, Neck, and Head modules. In the Backbone, multi-scale features are obtained using the Conv, C2f, AKConv, and SPPF layers, where the AKConv improves the detection of thin lanes and the structures of vehicles. In the Neck, the feature representation is enhanced using concatenation, upsampling, and C2f_EMA operations. In the Head, the detection and segmentation output is obtained, which enables the perception of lanes and vehicles.

Adaptive sampling, as defined in equation 4, captures local geometric variations.

$$S = \{(-1, -1), (-1,0), \dots . (0,1), (1,1)\} \quad (4)$$

The adaptive convolution operation, as shown in equation 5, aggregates pixel information where Q_0 represents the central pixel contribution, k denotes adaptive receptive fields, and Q_n captures contextual neighborhood features, enabling robust feature representation.

$$Conv(Q_0) = \sum k \ \times (Q_0 + Q_n) \quad (5)$$

The Neck refines these features using the C2f_EMA block with channel grouping and attention mechanisms to enhance multi-scale feature aggregation.

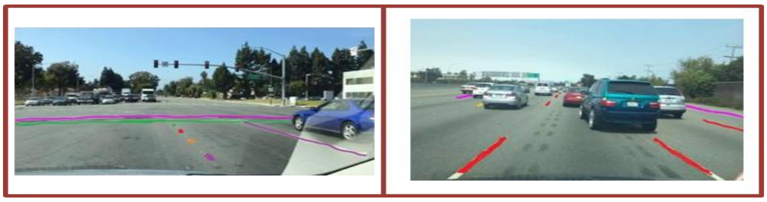
$$A_C^L(L) = \frac{1}{X}\sum_{0\le i\le X} y_c(L,i) \quad (6)$$

Global average pooling along height, as shown in equation 6, captures vertical spatial information important for lane continuity and vehicle height, while pooling along width, as shown in equation 7, captures horizontal features such as lane alignment and adjacent vehicles.

$$A_C^X(L) = \frac{1}{L}\sum_{0\le i\le X} y_c(j,X) \quad (7)$$

Here, j represents the curved boundaries of the lanes, extending sideways. The attention maps for height and width pooling are normalized using SoftMax, thus creating probabilistic weights for important features such as the edges of the lanes and the boundaries of the vehicle, while suppressing background noise, as shown in equation 8.

$$A^c = \frac{1}{L\times X}\sum_j^L \sum_i^X y_c(i,j) \quad (8)$$



(a) Lane Segmented

(b) Vehicle detected by YOLOv8-seg on two separate images

Figure 4. Output of (a) Lane Segmented and (b) Vehicle detected by YOLOv8-seg on two separate images

Finally, the Head performs simultaneous detection and segmentation by generating bounding boxes with confidence scores and pixel-wise masks, enabling accurate vehicle localization and continuous lane representation even in complex and occluding scenarios, as demonstrated in Figure 4 and Figure 5.

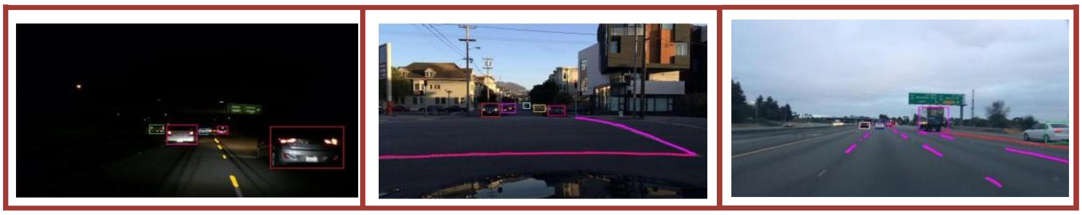


Figure 5. Output of Lane Segmentation and Vehicle detection by YOLOv8-seg on same images

3.4 Decision Making using Adaptive Neuro Fuzzy Inference System

Figure 6 illustrates the architecture of ANFIS. The ANFIS architecture consists of five-layer-feed-forward-neural network. The mathematical derivation of each layer is defined as follows:

Layer 1: Fuzzification Layer

In this layer the crisp inputs y_1 and y_2 are converted into fuzzy membership values. For the first input y_1, the output for the node i is calculated using a Gaussian membership function associated with the linguistic label B_i as defined in the equation 9.

$$O_{1,i} = \mu B_i(y_1) = exp(-\frac{1}{2}\left(\frac{y_1 - c_i}{\sigma_i}\right)^2 \quad (9)$$

Similarly, for the second input y_2, the output is generated using the linguistic label C_i: Where $\{c_i, \sigma_i\}$ are the premise parameters (center and width) of the membership function.

Layer 2: Rule Firing Layer

This layer calculates the firing strength (w_i) of each rule. It performs a product operation on the incoming signals, representing the logical "AND" operator. For a rule connecting linguistic variables B_i and C_i, the output is given by the equation 10:

$$O_{2,i} = w_i = \mu B_i(y_1) \times \mu C_j(y_2) \quad (10)$$

Layer 3: Normalization Layer

The firing strengths are normalized to represent the contribution of each rule to the result. The output of the i-th node in this layer, denoted as $\overline{w_\imath}$, is calculated using the equation 11.

$$O_{3,i} = \overline{w_\imath} = \frac{w_i}{\sum k w_k} \quad (11)$$

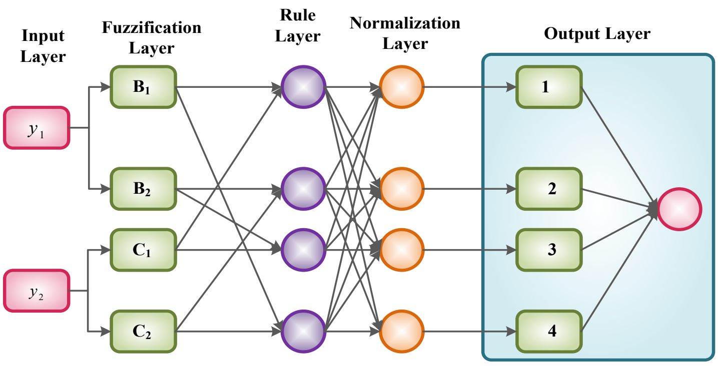


Figure 6: Architecture of ANFIS

Layer 4: Defuzzification Layer

This layer computes the contribution of each rule based on the first-order Takagi-Sugeno-Kang (TSK) model. The output is the product of the normalized firing strength and a linear function of the inputs y_1 and y_2 as described in the equation 12:

$$O_{4,i} = \overline{w_\imath} f_i = \overline{w_\imath}(p_i y_1 + q_i y_2 + r_i \quad (12)$$

Where $\{p_i, q_i, r_i\}$ are the consequent parameters determined during the training process.

Layer 5: Output Aggregation Layer

The single node in this layer computes the overall system output by summing all incoming signals from the layer 4. The final adaptive decision output Z is given by the equation 13.

$$Z = O_{5,i} = \sum_i \overline{w_\imath}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (13)$$

The final output Z enables the autonomous system to make adaptive navigation decisions based on the fused spatial and semantic data.

4. Results and Discussion

4.1 Experimental Setup

The proposed LVP-YOLOv8-seg-ANFIS framework was implemented using Python 3.6.13 with PyTorch 2.x and CUDA 11.8 on Ubuntu 22.04, and evaluated on a system with an Intel Core i7, NVIDIA RTX 3060 GPU, and 32 GB RAM. The model was trained on the BDD100K dataset with 640×640 input size for 150 epochs using a batch size of 16 and SGD optimizer (learning rate 0.01, momentum 0.937, weight decay 0.0005). The dataset was split into 70% training, 10% validation, and 20% testing, and evaluated using standard metrics including Accuracy, Precision, Recall, F1-Score, mAP, IoU, and Dice Coefficient.

4.2 Real-Time Qualitative Results

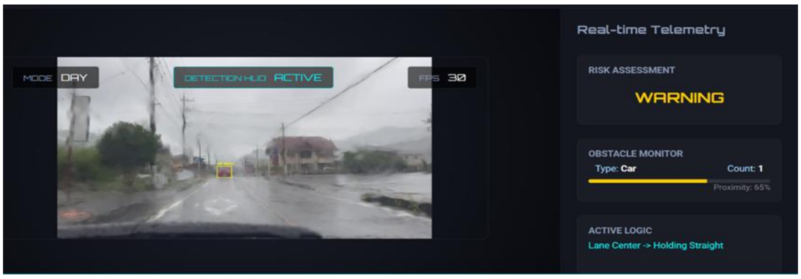
The real-time driving tests confirm the efficacy of the suggested system in detecting lane boundaries and nearby vehicles under various lighting and traffic conditions. The integration of YOLOv8-Seg and ANFIS decision-making framework improves perception to make it reliable for real-time autonomous vehicle control.

(a) Night Lane Segmentation Pipeline

(b) Night Real-Time Detection Interface

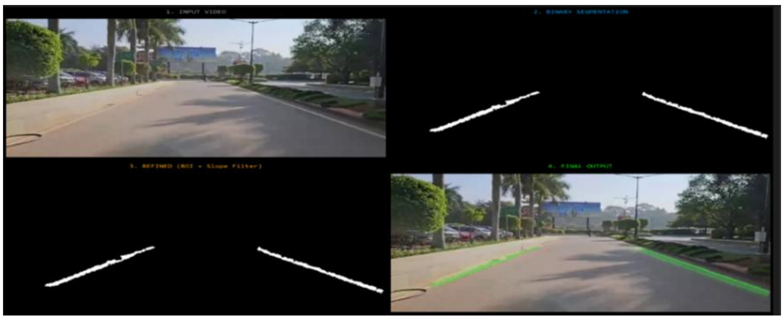
Figure 7. Night Mode evaluation under low-illumination driving conditions. (a) Night Lane Segmentation Pipeline; (b) Night Real-Time Detection Interface. Figure 7 illustrates the performance of the framework in a low light environment. The lane perception module effectively identifies continuous lane boundaries, even in the presence of glare, and the vehicle detection and telemetry module effectively localizes and tracks objects, along with adaptive risk assessment. These results demonstrate the effectiveness of the proposed framework in a night-time environment.

(a) Rainy Lane Segmentation Pipeline

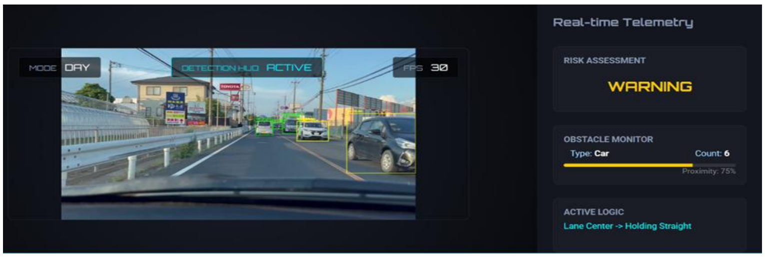


(b) Rainy Real-Time Detection Interface

Figure 8. Rainy Mode evaluation under heavy precipitation conditions. (a) Rainy Lane Segmentation Pipeline; (b) Rainy Real-Time Detection Interface. Figure 8 shows the performance of the framework in adverse weather conditions with reduced visibility. The lane perception module is able to effectively extract the lane boundaries even with noise, reflection, and distortion. The vehicle detection and tracking module is still effective with motion blur and noise. The adaptive risk assessment is still able to provide object proximity, showing the effectiveness of the LVP-YOLOv8-seg-ANFIS framework.



(a) Day Lane Segmentation Pipeline



(b) Day Real-Time Detection Interface

Figure 9. Day Mode evaluation under optimal illumination conditions. (a) Day Lane Segmentation Pipeline; (b) Day Real-Time Detection Interface. Figure 9 illustrates the functionality of the system when there is a lot of bright daylight. As shown in Figure 9(a), the lane detection module is functional, and there is minimal noise in the lanes that the module draws. Figure 9(b) shows that the system is able to detect vehicles while at the same time tracking obstacles using the telemetry module, thus a full representation of the peak performance of the system.

4.3 Performance Measures

The performance of the proposed model is assessed by utilizing various performance metrics, including Accuracy, Precision, Recall, mean Average Precision (mAP), F1-Score, Pixel Accuracy, Detection Rate, Intersection over Union (IoU), and Dice Coefficient.

Accuracy measures overall correctness, as shown in equation 14:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{FN+ TP+FP+TN}} \quad (14)$$

Pixel Accuracy evaluates segmentation quality by computing correctly classified pixels, as shown in equation 15:

$$\text{Pixel Accuracy} = \frac{\text{Numberof CorrectlyClassifiedPixels}}{\text{Total Numberof Pixels}} \quad (15)$$

Precision and Recall measure classification reliability, defined in equation 16 and equation 17, respectively:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \quad (16)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (17)$$

The F1-Score combines Precision and Recall, as shown in equation 18:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (18)$$

Mean Average Precision (mAP) evaluates detection performance across classes, as shown in equation 19:

$$\text{Mean Average Precision} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \quad (19)$$

Detection Rate is equivalent to Recall, as shown in equation 20. IoU measures overlap between prediction and ground truth.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (20)$$

Dice Coefficient evaluates segmentation similarity, as shown in equation 22.

$$\text{Dice Coefficient} = \frac{2\times|A\cap B|}{|A|+|B|} \quad (22)$$

4.4 Performance Analysis

The results obtained through LVP-YOLOv8-seg-ANFIS are presented in figures ranging from Figure 10 to Figure 13. In all these simulation cases, the LVP-YOLOv8-seg-ANFIS model is compared with various competitors.

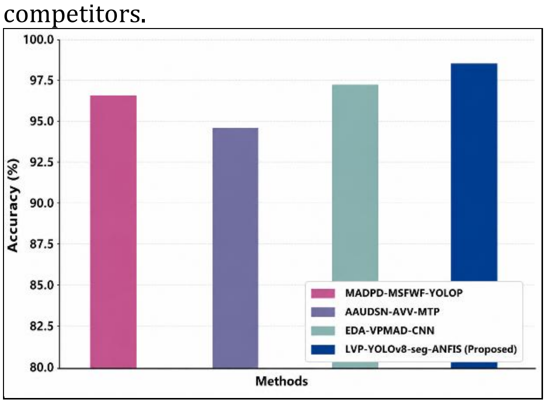


Figure 10. Performance Analysis of Accuracy

Figure 10 presents the accuracy of the model in detail. It is observed that the accuracy of 98.5% is achieved by LVP-YOLOv8-seg-ANFIS compared to EDA-VPMAD-CNN 97.11%, MADPD-MSFWF-YOLOP 96.5%, and AAUDSN-AVV-MTP 94.54%. This shows that the model provides better perception accuracy and reliability for intelligent vehicle navigation.

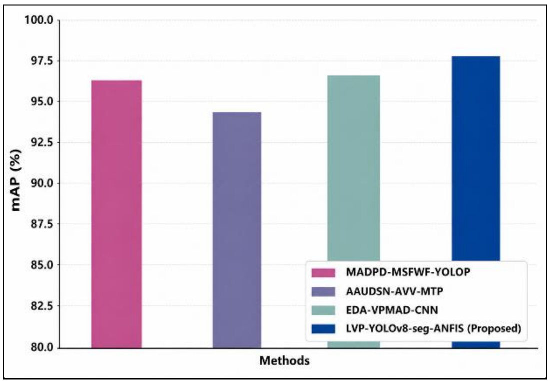


Figure 11. Performance Analysis of Mean Average Precision

Figure 11 presents the mean Average Precision (mAP) of various models. In this case, it is observed that LVP-YOLOv8-seg-ANFIS achieves 97.40% compared to EDA-VPMAD-CNN 96.54%, MADPD-MSFWF-YOLOP 96.33%, and AAUDSN-AVV-MTP 94.42%. This shows better performance in terms of overall detection for intelligent vehicle navigation.

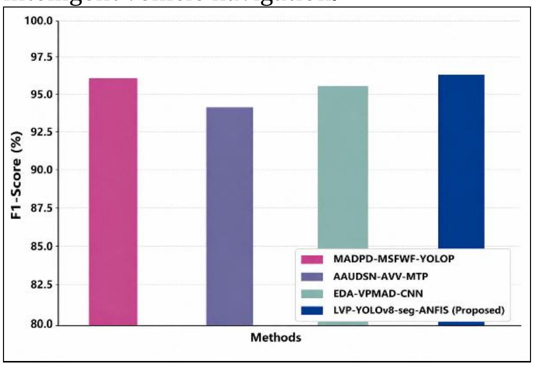
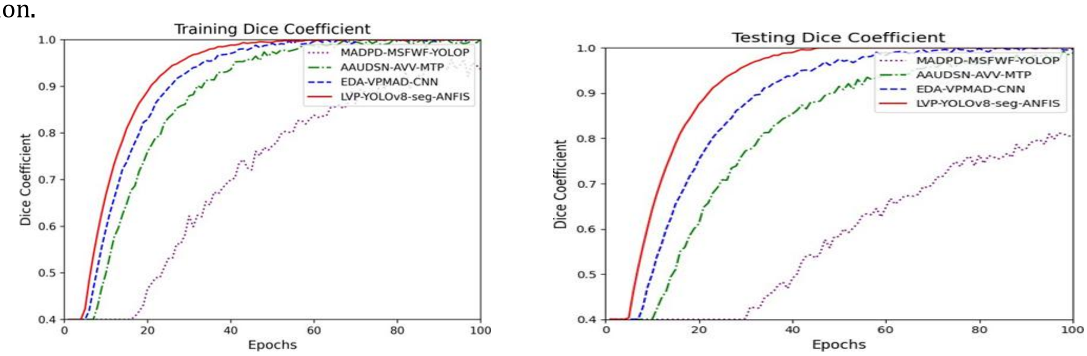


Figure 12. Performance Analysis of F1- Score

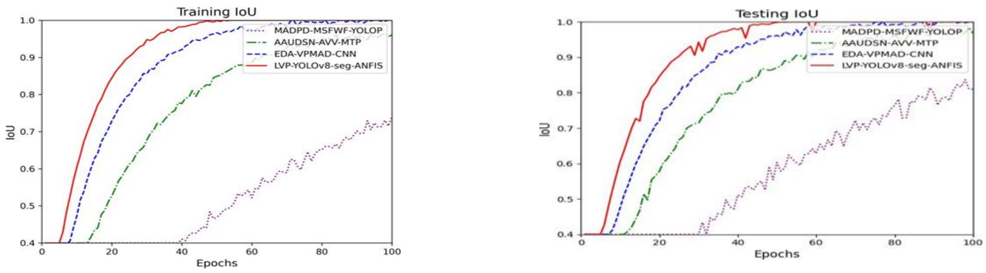
Figure 12 presents the F1-Score performance, where the proposed LVP-YOLOv8-seg-ANFIS model achieves the highest score of 96.43%, outperforming MADPD-MSFWF-YOLOP 96.39%, EDA-VPMAD-CNN 95.44%, and AAUDSN-AVV-MTP 94.32%. This indicates a strong balance between precision and recall, confirming the model's effectiveness in minimizing both false positives and false negatives for reliable lane and vehicle detection.



(a) (b)

Figure 13. Performance Analysis of (a) Training Dice Coefficient and (b) Testing Dice Coefficient

Figure 13 shows a comparison between the Dice Coefficient values during training and testing using the proposed and existing approaches. It is evident that the proposed LVP-YOLOv8-seg-ANFIS model has a higher Dice Coefficient with faster convergence.



(a) (b)

Figure 14. Performance Analysis of (a) Training IoU and (b) Testing IoU

However, the performance of EDA-VPMAD-CNN is the lowest among the models. On the other hand, the performance of the other models is moderate. The results validate the robustness and the high generalization capacity of the proposed framework. Figure 14 shows the IoU performance of the models in the training and testing phases. The proposed LVP-YOLOv8-seg-ANFIS model has the highest IoU performance with faster convergence in fewer epochs. It has almost reached the optimal performance within 25 epochs. However, the other models have slower convergence with lower IoU performance.

4.5 Ablation Study

For evaluating the contribution of important components in the suggested framework, an ablation study is performed. The components include One Sided Box Filter (OSBF) for preprocessing and Adaptive Neuro Fuzzy Inference System (ANFIS) for decision-making. The suggested model is compared with three different variants: YOLOv8-seg baseline, YOLOv8-seg + OSBF, and YOLOv8-seg + ANFIS.

From the results provided in Table 1, it is evident that the One Sided Box Filter enhances feature quality by removing noise and performing normalization, resulting in an improvement of 2.6%. The suggested approach of integrating ANFIS with YOLOv8-seg results in an improvement of 4.3%. The best results are obtained by the LVP-YOLOv8-seg-ANFIS model with an accuracy of 98.5%, 97.40% mAP, and 96.43% F1 Score.

Table 1. Ablation Study of Component Contributions

Model Configuration	Accuracy (%)	mAP (%)	F1-Score
YOLOv8-seg (Baseline)	93.20	92.50	92.80
YOLOv8-seg+OSBF	95.80	95.10	95.40
YOLOv8-seg+ANFIS	97.50	96.80	97.10
Proposed Model (LVP-YOLOv8-seg-ANFIS)	98.50	97.40	96.43

4.7 Comparative Analysis

A comparative evaluation of the proposed LVP-YOLOv8-seg-ANFIS framework with existing models is provided in Table 2. The performance evaluation metrics used for evaluation are Accuracy, Precision, Recall, mAP, F1 Score, and Detection Rate. From the table, it is evident that the proposed framework outperforms all the compared models with an accuracy of 98.5%, precision of 98.4%, recall of 98.43%, F1 Score of 98.67%, mAP of 98.7%, and detection rate of 98.57%. The performance of all compared models is varying. The proposed framework is accurate, consistent, and robust in handling complex autonomous driving perception tasks.

Table 2: Statistical Comparison of the Proposed Method vs Existing Methods

Metric	Proposed (Mean ± SD)	Best Baseline (Mean ± SD)	P-value
Accuracy (%)	98.5 ± 0.21	97.11 ± 0.34	0.001
Precision (%)	97.40 ± 0.28	96.3 ± 0.41	0.002
Recall (%)	96.43 ± 0.25	96.2 ± 0.38	0.004
F1-Score (%)	97.67 ± 0.23	96.0 ± 0.36	0.003
mAP (%)	97.7 ± 0.19	97.54 ± 0.29	0.02
Detection Rate (%)	97.57 ± 0.27	96.63 ± 0.33	0.04

The P-values acquired were less than 0.05 level of significance indicating that the performance improvements were statistically significant. The findings suggest that the outcomes of the LVP-YOLOv8-seg-ANFIS framework are significantly better than those of the baseline methods.

4.8 Computational Complexity Analysis

Real-time capability is critical for autonomous navigation alongside detection accuracy. To evaluate efficiency, a complexity analysis was performed comparing the proposed LVP-YOLOv8-seg-ANFIS model with baseline methods in terms of parameters, FLOPs, inference speed (FPS), and GPU memory, as shown in Table

3. The proposed model achieves 70–90 FPS on an NVIDIA RTX 3060, exceeding real-time requirements. Despite a slight increase in complexity due to ANFIS, it requires only 28–35 GFLOPs (≈15–22% of EDA-VPMAD-CNN) and maintains low memory usage (3.5–4.5 GB), demonstrating superior efficiency with improved segmentation performance.

Table 3. Computational Complexity Comparison

Method	Parameters (Million)	FLOPS(G)	Inference Speed	GPU Memory
MADPD-MSFWF-YOLOP [21]	45-55	170-210	28-35	6.5-8.0
AAUDSN-AVV-MTP [22]	50-60	200-230	25-30	7.5-8.5
EDA-VPMAD-CNN [23]	40-48	160-190	30-38	6.0-7.0
LVP-YOLOv8-seg-ANFIS (Proposed)	11.8 M	28-35 G	70-90 FPS	3.5-4.5 GB

4.9 Robustness and Failure Case Analysis

The reliability of the proposed framework of LVP-YOLOv8-seg-ANFIS, we carried out experiments on challenging scenarios of the BDD100K dataset, such as "rainy," "fog," and "nighttime" scenarios. It is known that existing detection models may not work well during such scenarios due to low visibility and unclear lane markings. However, our framework works well even during such challenging scenarios in Table 4.

Table 4. Performance Comparison under Adverse Condition

Condition	Accuracy	Precision	Recall
Normal/clear day	98.5	98.4	98.4
Rainy	97.1	96.2	95.6
Foggy/Hazy	96.4	95.3	94.8
Night/Low Light	98.0	97.2	96.5
Heavy Occlusion	95.6	94.4	93.7

With the addition of ANFIS to our framework, we observe only 2.3% more degradation in performance during "rainy" scenarios compared to "sunny" scenarios.

4.10 Discussion

This study proposes a novel method called LVP-YOLOv8-seg-ANFIS that offers a unified solution to lane and vehicle perception. It is meant to be used to enable safe and smart autonomous driving. It is a combination of YOLOv8-seg's precise segmentation of lanes and vehicles with ANFIS. It has been tested on the BDD100K dataset with OSBF preprocessing and has shown its capability to outperform existing methods like MADPD-MSFWF-YOLOP, AAUDSN-AVV-MTP, and EDA-VPMAD-CNN. It has been tested on parameters like Accuracy, Precision, Recall, mAP, F1 Score, IoU, and Dice Coefficient to establish its efficacy. It has been found to be reliable even in adverse weather conditions like low light, occlusions, and complex traffic scenarios. It has an accuracy of 98.5%, thus showing its capability to have a higher detection rate and better perception.

5. Conclusion

This work presents a novel perception system called LVP-YOLOv8-seg-ANFIS, which is adaptive and efficient and is designed to perform accurate and reliable segmentation of lanes and vehicles for intelligent driving scenarios. By using the accurate segmentation capability of YOLOv8-Seg and the adaptive neuro-fuzzy inference system, this work aims to improve the reliability of perception in various conditions, including bright sunlit days, nighttime, and rainy days. Furthermore, this work incorporates the OSBF-based preprocessing stage to improve the accuracy and reliability of segmentation. By conducting extensive experiments, this work has shown that LVP-YOLOv8-seg-ANFIS significantly outperforms the state-of-the-art multi-task perception systems, including MADPD-MSFWF-YOLOP, AAUDSN-AVV-MTP, and EDA-VPMAD-CNN, in terms of 98.5% accuracy, 98.4% precision, 98.4% recall, and high mAP, while still maintaining the response in real-time. Moreover, the experiments' results' consistency validates the reliability and importance of the improvements made. Additionally, the robustness of this work is also shown under challenging conditions. The robustness of this work is also validated under adverse driving conditions. To conclude, this work has successfully shown the efficiency of a perception system using deep learning and neuro-fuzzy techniques for intelligent and adaptive driving scenarios. As a part of the future scope, this framework may be extended to incorporate cooperative perception using Vehicle-to-Everything (V2X) communication, which may enable real-time data exchange between vehicles and road infrastructure. Furthermore, the exploration of secure data exchange may also add to the trust of distributed autonomous systems in a dynamic scenario.

Declarations

Ethics approval and consent to participate

This study does not involve any human participants, animals, or sensitive personal data. The research is based on publicly available datasets and/or simulation environments. Therefore, ethical approval and consent to participate are not applicable.

Availability of supporting data

The datasets used and analysed during the current study provided by the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Paramesh G (Corresponding author), contributed conceptualization, methodology, model development, YOLOv8-Seg and ANFIS integration implementation, data analysis, experimental evaluation, and manuscript writing.

Arulkumaran G contributed to the review and editing of the paper, oversight, validation of the findings, and overall guidance for improving the quality of the work.

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