

HYBRID U-NET AND FUZZY LOGIC FRAMEWORK FOR RELIABLE NAVIGATION ON UNMARKED ROADS

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ABSTRACT Autonomous vehicle navigation on roads without lane markings presents a significant challenge, as conventional systems relying solely on GPS often fail to accurately determine the vehicle's lateral position. This study proposes a semantic segmentation approach based on a Convolutional Neural Network (CNN), specifically the U-Net architecture, to recognize road elements using a single camera as the visual sensor. The objective is to develop a real-time navigation system capable of identifying lane positions by classifying images into road and road-edge categories. The segmentation results are then processed using a fuzzy logic controller to determine appropriate steering decisions. Experimental evaluation shows that U-Net with a MobileNetV2 encoder achieves the highest Mean Intersection over Union (MIoU) of 96.9%. The navigation system performed effectively, achieving a 100% non-fallback navigation rate in straight-road conditions without shadows, while performance decreased to 48% in branching road scenarios wider than 4.5 meters. Speed testing further indicates that the system maintains consistent computational latency, with distance delay increasing linearly with vehicle speed, suggesting an optimal operating range of 5–20 km/h. These results demonstrate the feasibility of combining U-Net segmentation and fuzzy logic for autonomous navigation on unmarked roads.

KEY WORDS : U-Net segmentation, Fuzzy logic decision-making, Navigation, Unmarked roads, Hybrid

1. INTRODUCTION

Autonomous driving technologies continue to advance and are increasingly adopted in transportation, logistics, and last-mile delivery systems due to their potential to reduce operational costs and improve safety (Bagloee et al., 2016; Srivastava, 2020). Despite significant progress, reliable navigation remains a major challenge in environments where lane markings are absent, faded, or inconsistent. Many rural, suburban, and campus-area roads lack clear boundary cues and exhibit irregular surface textures, creating difficulties for conventional lane-based navigation systems that rely on structured visual features or satellite positioning (Schoettle and Sivak, 2015; Jo et al., 2015).

Earlier studies explored texture cues, handcrafted features, and global positioning fusion for navigation on unmarked roads. However, these approaches often degrade under shadows, irregular road edges, or abrupt geometric changes (Guan et al., 2021; Fagnant and Kockelman, 2015). Deep semantic segmentation emerged as a promising solution because of its ability to classify road regions at pixel-level precision, but most

existing segmentation approaches are optimized for well-marked highways or structured urban environments, with limited evaluation on narrow and unmarked roads (Al-Jubouri and Jin, 2020; Alam and Dempster, 2013). Recent works also indicate that lightweight encoder-decoder architectures can achieve real-time performance on resource-limited hardware, though robustness under shadows and branching roads remains an open issue (Qureshi, 2019; Velaga et al., 2012).

In addition to perception challenges, steering control must remain stable despite uncertainties in visual detection. Fuzzy logic-based controllers have shown effectiveness in handling uncertainty and nonlinear behaviors in autonomous steering tasks (Katrakazas et al., 2015; Zhao and Thorpe, 2000). However, few studies integrate deep segmentation with fuzzy decision-making specifically for unmarked road navigation, where boundary cues are weak and fluctuations in visual input can lead to unstable steering.

To address these limitations, this research proposes a hybrid navigation framework that integrates deep semantic segmentation with a fuzzy logic controller to enable reliable navigation on unmarked roads using a single monocular camera. The contributions of this study are threefold. First, a lightweight encoder-decoder segmentation model is developed to detect road and road-

edge regions under varied lighting and environmental conditions. Second, a fuzzy logic controller interprets the segmentation output and provides robust steering control in the presence of uncertainty. Third, the system is evaluated in real-world road scenarios, including shadows, curves, and intersections, to demonstrate practical feasibility for low-speed autonomous navigation.

2. METHOD

This research was conducted at Universitas Padjadjaran's Jatinangor campus, which features unmarked roads—an ideal environment for testing autonomous vehicle navigation systems designed to maintain a left-lane position. The system employs a camera as the sole visual sensor and utilizes semantic segmentation based on a CNN with a U-Net architecture to recognize road elements from captured images. Because the vehicle prototype was not yet fully autonomous, image acquisition was performed manually while maintaining the camera's height and angle to simulate a real vehicle's perspective.

Experiments were conducted on various track types, including straight roads, curved roads, and straight roads with intersections, under two main lighting conditions: sunny and shaded. These variations were used to evaluate the system's robustness against environmental changes. The collected image data were labeled into two main classes—road and road edge—and were used to train the U-Net model with data augmentation techniques. The segmentation results were processed according to the active navigation mode, either straight or turn, using first-order or second-order polynomial modeling to determine the path. The system then calculated the lateral distance to the road edge and its rate of change to determine vehicle direction through a fuzzy logic-based control system.

All inference processes were executed on a CPU-based laptop to simulate system performance on devices with limited computational resources. This setup aims to develop a vision-based navigation system adaptable to unmarked road conditions. The autonomous vehicle developed in this study integrates several subsystems, namely segmentation, object detection, navigation, and control. The main focus of this research is the segmentation subsystem, which utilizes a camera and the U-Net model to identify road surfaces and boundaries. The object detection subsystem combines a camera and ultrasonic sensors to detect obstacles, while the navigation subsystem processes data from GPS and a digital compass to determine the vehicle's heading direction. All sensor data, including inputs from the Inertial Measurement Unit (IMU), are analyzed by the control subsystem to make real-time movement decisions.

Figure 1. illustrates the overall research scope and system architecture of the proposed autonomous vehicle navigation system designed for unmarked roads. The system consists of two main components: the

segmentation system and the controller. The segmentation system receives visual input from a front-mounted camera and processes the image data using a U-Net-based Artificial Intelligence (AI) model to perform two-class semantic segmentation—distinguishing between road and road edge areas. The output of the segmentation stage is used to calculate the distance between the vehicle and the left road edge, which represents the vehicle's lateral position.

A fuzzy logic decision-making module then estimates the left-edge distance and determines the appropriate navigation action required to maintain the vehicle's position within the lane. The resulting control signal is sent to the Arduino Mega 2560 controller, which operates the actuator to adjust the vehicle's direction. This closed-loop process enables the autonomous vehicle to navigate unmarked roads effectively using only visual input and intelligent decision-making.

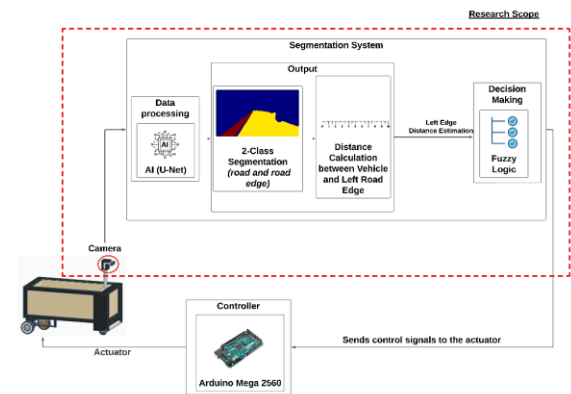


Figure 1. Research scope of the autonomous vehicle navigation system based on semantic segmentation and fuzzy logic.

The experimental scenarios in this study were designed to evaluate the reliability of the autonomous vehicle navigation system on unmarked roads, with a particular focus on semantic segmentation using the U-Net architecture. The U-Net model was trained to classify images into two main classes: road and road edge. Real-time images captured by the vehicle's camera were processed to generate pixel-level segmentation maps, which were then used to calculate the Edge Distance (JT) and its frame-to-frame rate of change (dJT). These JT and dJT values served as inputs to the fuzzy logic-based control system to determine the appropriate steering angle for navigation. The resulting steering angle was transmitted to an Arduino Mega 2560 microcontroller, which controlled the vehicle's actuators.

The U-Net is a CNN architecture consisting of two main components: an encoder, which extracts hierarchical image features, and a decoder, which reconstructs the segmentation map through upsampling and feature concatenation processes. This structure allows the network to preserve the spatial details of the original image while maintaining high segmentation accuracy (Sun et al., 2023). The segmentation process using U-Net can be mathematically represented as a mapping function between the input image and the corresponding segmented output.

$$Y = f(X; \theta) \quad (1)$$

Where $f\theta$ denotes the function represented by the U-Net network, X denotes input image and (θ) refers to the set of parameters optimized during the training process. The U-Net architecture maps input images to class probability distributions through its characteristic U-shaped encoder-decoder structure, which has demonstrated strong performance even with limited training data. Its capability to produce highly precise segmentation results makes it particularly suitable for autonomous vehicle navigation in unmarked road environments, with a primary focus on accurately identifying the road edge class.

To enhance segmentation performance, this study further investigates the effect of different encoder backbones integrated within the U-Net framework, namely EffnetB0, MobileNetV3-Large, and MobileNetV2. Each encoder offers distinct advantages in computational efficiency and feature extraction capability, thereby contributing to improved segmentation robustness under varying environmental and lighting conditions.

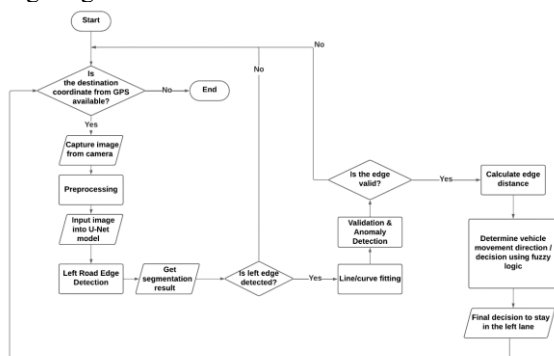


Figure 2. Flowchart of the proposed hybrid navigation system for unmarked roads

Figure 2. illustrates the workflow of the proposed hybrid navigation system that integrates U-Net-based semantic segmentation with fuzzy logic decision-making for autonomous vehicle navigation on unmarked roads. The process starts by verifying the availability of destination coordinates from the GPS. If available, the system captures real-time images using the onboard camera, followed by preprocessing and segmentation using the U-Net model to detect the left road edge. When the left edge is detected, the system performs line or curve fitting and validation or anomaly detection to ensure reliable edge information. The valid edge data are then used to calculate the edge distance between the vehicle and the road boundary. These distance parameters are processed by the fuzzy logic controller, which determines the steering angle required to maintain the vehicle's position within the left lane. If the left edge

is not detected or the data are invalid, the process loops back to recapture and reprocess new image frames, ensuring adaptive and continuous navigation performance even in unstructured or unmarked road environments. The vehicle's directional decision is made using a fuzzy logic system, which handles data uncertainty through degrees of membership (values between 0 and 1) in a fuzzy set. The Fuzzy Logic Controller (FLC) consists of three stages: fuzzification (converting numerical input into fuzzy values), rule evaluation (using rules to determine the system's response), and defuzzification (converting the fuzzy output into a numerical value for vehicle control) (Febrian et al., 2023).

The fuzzy logic approach enables more flexible and safer navigation, especially when road boundaries are unclear or change dynamically. In this study, the fuzzy logic system serves as the decision-maker based on image segmentation data estimating the vehicle's distance to the left road edge, ensuring the vehicle remains on a safe path. The system design involves several key stages, starting with defining the input and output variables—namely, distance to the left edge and its change as inputs, and vehicle direction (θ) as the output. The next stage is fuzzification, where each variable is converted into fuzzy values using membership functions. Then, fuzzy rules are structured in a matrix based on combinations of left edge and its changes values to determine the movement direction. The inference process uses the Mamdani method with Min-Max operators to generate a fuzzy output set. Finally, the result is converted back into a concrete value through defuzzification using the centroid method, which is chosen for its ability to produce smooth and stable directional control. With this workflow, the fuzzy logic system can adaptively steer the vehicle based on image segmentation results, even in the absence of explicit road markings (Febrian et al., 2023; Akmal Arista et al., 2024).

3. RESULTS AND DISCUSSION

The dataset was collected in the environment of Universitas Padjadjaran by selecting routes with varying road shapes, elevations, and lighting conditions to generate data that is representative of real-world unmarked road scenarios. Videos were recorded using a camera and converted into image frames, then manually annotated using Roboflow into two classes: road and road edge. The labeling process took into account visual disturbances such as shadows, other vehicles, and surface variations to ensure the model can perform robustly under various conditions. The initial dataset consisted of 746 images, which were proportionally and randomly

split into training (522), validation (149), and testing (75) sets. All images underwent preprocessing, including resizing to 384×224 pixels using a "fit with reflect edges" method to maintain aspect ratio and improve computational efficiency. Data augmentation was then applied to increase dataset diversity, resulting in a total of 1,790 images. Augmentation techniques included horizontal flipping, zooming, rotation, shearing, grayscale conversion, lighting variation, blurring, and noise addition, to simulate diverse visual conditions and improve the model's robustness against suboptimal inputs.

3.1. Model Development

The semantic segmentation model used in this study is U-Net, which features an encoder-decoder structure to extract features and reconstruct the segmentation map. In addition to the basic U-Net version, variants with pretrained encoders such as EfficientNetB0, MobileNetV2, and MobileNetV3-Large were also tested.

Table 1. Model Parameters

Epoch	100
Batch Size	8
Optimizer	Adam
Learning Rate	0.0001
Early Stop Patience	10

Table 1 presents the training parameters used for developing the U-Net-based semantic segmentation model. The model was trained for 100 epochs with a batch size of 8, using the Adam optimizer and a learning rate of 0.0001, which helps ensure stable convergence during training. An early stopping mechanism with a patience value of 10 epochs was applied to prevent overfitting by stopping the training process when the model's performance no longer improved. These parameters were selected to balance training efficiency and segmentation accuracy.

Parameter		Value				
Metode	Final Epoch	Precision	Recall	F1-score	Val Akurasi	Loss
Basic	57	0.9806	0.9809	0.9807	0.9809	0.0963
EffnetB0	79	0.9394	0.9445	0.9396	0.9445	0.1542
MobileNetV2	56	0.9837	0.9837	0.9837	0.9837	0.0853
MobileNetV3-large	69	0.9804	0.9808	0.9804	0.9808	0.0940

Table 2. Evaluation Metrics

Table 2 summarizes the performance evaluation of the four U-Net encoder variants based on key segmentation metrics. The metrics include Precision, Recall, F1-score, Validation Accuracy, and Loss, with each model evaluated at its final training epoch before early stopping. The results show that MobileNetV2 achieved the best overall performance, with the highest Precision, Recall, F1-score, and Validation Accuracy, alongside the lowest Loss value, indicating strong generalization and stability. The Basic U-Net and MobileNetV3-Large models also performed well with similar accuracy levels, while EffnetB0 showed comparatively lower results across most metrics. These findings indicate that lightweight encoders such as MobileNetV2 offer an effective balance between segmentation accuracy and computational efficiency for unmarked-road navigation tasks.

3.2. Real-Time Performance Evaluation

Testing was conducted using 50 frames from five videos captured under different real-world conditions (straight road, curved road, shadows, bright and cloudy weather). Each frame was manually annotated and evaluated using three segmentation classes: background, road, and road edge. Predictions were compared to the ground truth both quantitatively (using metrics) and qualitatively (through color visualizations). Evaluation was performed in a semi-real-time manner to test the

model's generalization capability under various environmental conditions.

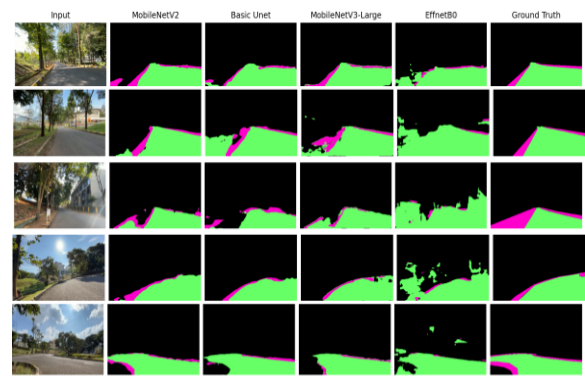


Figure 3. Semantic Segmentation Result Visualizations of Each Model on Selected Test Frames Compared to Ground Truth

The visualizations in Figure 3 and the evaluation results in Table 3 indicate that MobileNetV2-U-Net provided the best performance in semantic segmentation of unmarked roads, producing predictions closest to the ground truth and consistent segmentation results. This model achieved an average accuracy of 96.81%, F1-score of 96.49%, and the lowest loss value. In contrast,

EffnetB0 demonstrated the poorest performance with lower accuracy and F1-score, as well as higher loss.

Table 3. Real-Time Performance Evaluation

Metode	Precision	Recall	F1-score	Akurasi	Loss
Basic	0.9389	0.9403	0.9353	0.9403	0.3655
EffnetB0	0.8989	0.8692	0.8680	0.8692	0.3340
MobileNetV2	0.9678	0.9681	0.9649	0.9681	0.2056
MobileNetV3-large	0.9529	0.9464	0.9416	0.9464	0.3068

Both qualitative and quantitative evaluations confirm that MobileNetV2 is the most optimal model for this task.

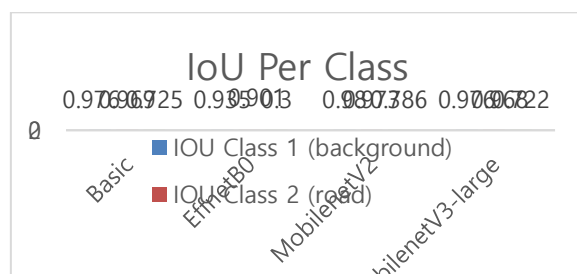


Figure 4. IoU per Class

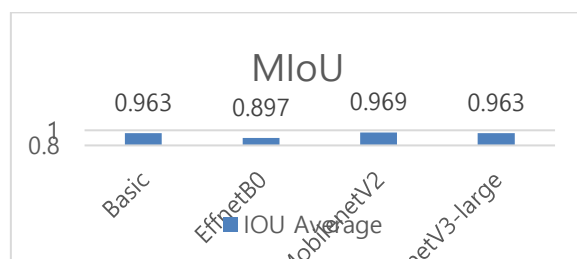


Figure 5. Mean Intersection over Union (MIoU)

Figure 4 illustrates the IoU performance for each class: Background, Road, and Roadside/Road edge. For the background and road classes, all models achieve high IoU values (>0.93), with MobileNetV2 performing the best (0.980 for background; 0.973 for road). The roadside (road edge) class shows the lowest IoU across all models because road edges vary significantly in texture, shape, and visibility in unmarked environments. MobileNetV2 again performs best with a roadside IoU of 0.786, indicating its robustness for boundary detection. EffnetB0 performs the worst for the roadside class (0.300), confirming its challenge in identifying subtle edge features. This comparison highlights that MobileNetV2-U-Net consistently outperforms other models, especially in detecting the road edge, which is the most critical feature for this study's left-lane navigation system.

Figure 5 presents the Mean Intersection over Union (MIoU) performance of four U-Net-based segmentation

models: Basic U-Net, EffnetB0-U-Net, MobileNetV2-U-Net, and MobileNetV3-Large-U-Net. MIoU measures the average overlap between the predicted segmentation and ground truth across all classes. MobileNetV2 achieves the highest MIoU with a score of 0.969, indicating superior overall segmentation accuracy. Basic U-Net and MobileNetV3-Large achieve similar MIoU values (0.963), showing strong consistency despite differences in encoder complexity. EffnetB0 performs the lowest with 0.897, suggesting limitations in capturing boundary features for unmarked road segmentation. These results show that lightweight MobileNet encoders (especially MobileNetV2) provide the best balance between accuracy and computational efficiency for real-time autonomous navigation tasks.

A high MIoU does not by itself guarantee reliable vehicle control, particularly under shadows, intersections and changing road width.

3.3. Testing

After the training process, the best-performing segmentation model, MobileNetV2, was implemented and tested in real-world conditions. This model was used to identify road and roadside areas from camera images, and its segmentation results served as input to the fuzzy logic-based decision-making system. Evaluation was conducted under three main scenarios: straight roads, curved roads, and straight roads with intersections. Each scenario was tested five times to assess the system's steering accuracy. The tests also included analysis of decision types (primary or fallback), frames per second (FPS), time delay, and distance delay. Additionally, performance was tested across various vehicle speeds, from 5 to 40 km/h, to determine the system's accuracy and responsiveness under dynamic conditions. These tests were crucial to ensure the system's reliability across different road types and speeds. The system's robustness was also evaluated for visual reference loss, particularly when approaching intersections.

The semantic segmentation system is equipped with fallback mechanisms to ensure stable navigation even during detection failures. Four types of fallbacks are implemented: validation error, triggered when detected edge lines are illogical, edge anomaly, triggered by

sudden shifts in roadside position, missing edge, activated when the system fails to detect the edge due to visual disturbances, active GPS navigation serves as a final backup when segmentation becomes unreliable.

These strategies allow the system to continue navigating safely and adaptively in various environmental conditions..

Table 4. Testing on Straight Roads (Day and Afternoon Conditions)

No.	Test Condition	Trial No -	FPS		Inference Time (ms)		Navigation Decision (%)	
			Per Trial	Average	Per Trial	Average	Without Fallback	Fallback Mode
1	Daytime	1	7,19	6,436	123,97	135,446	93,3	6,7
		2	6,32		135,82		100	0
		3	6,18		139,92		95,83	4,17
		4	6,27		139,57		100	0
		5	6,22		137,95		100	0
2	Afternoon	1	6,54	6,774	129,99	130,82	93,99	6,01
		2	6,13		144,37		96,67	3,33
		3	7,09		125,12		100	0
		4	6,9		127,96		100	0
		5	7,21		126,66		100	0

Table 4 presents the performance evaluation of the autonomous vehicle's navigation system when tested on straight-road scenarios under two lighting conditions: daytime and afternoon. The table summarizes results across five trials for each condition, reporting FPS, inference time, and navigation decision accuracy, including the percentage of decisions made without fallback and with fallback mode.

The results showed stable navigation performance during both day and afternoon, with an average accuracy

above 97%. FPS remained consistent, ranging from 6.4 to 7.2, indicating real-time processing capability. Lighting intensity did not significantly affect performance; however, further analysis revealed that shadows were the main cause of navigation errors. Shadows from trees, vehicles, or buildings were sometimes misclassified as roadside, triggering fallback mode. Thus, further tests focused specifically on visual conditions with and without shadows, rather than just time of day.

Table 5. Testing on Straight Roads (With and Without Shadows)

No.	Test Condition	Trial No -	FPS		Inference Time (ms)		Navigation Decision (%)	
			Per Trial	Average	Per Trial	Average	Without Fallback	Fallback Mode
1	Shadows	1	7,19	6,472	123,97	135,446	93,3	6,7
		2	6,32		135,82		100	0
		3	6,18		139,92		95,83	4,17
		4	6,54		139,57		93,99	6,01
		5	6,13		137,95		96,67	3,33
2	Without Shadows	1	6,27	6,738	129,99	130,82	100	0
		2	6,22		144,37		100	0
		3	7,09		125,12		100	0
		4	6,9		127,96		100	0
		5	7,21		126,66		100	0

Table 5 presents the performance of the autonomous vehicle navigation system on straight-road scenarios under two different lighting conditions: with shadows and without shadows. This evaluation highlights how environmental lighting, specifically the presence of shadows, affects the system's perception, inference speed, and navigation accuracy. In shadowed conditions, the system still performed stably, with an average FPS of 6.47 and a 95.96% navigation success rate without

fallback. However, shadows caused edge anomalies that triggered fallback, especially during trials 1 and 4. No other fallbacks such as missing edges or GPS switching were observed. Under shadow-free conditions, the system performed perfectly, with an FPS of 6.73 and 100% navigation success without fallback. The segmentation was cleaner and more accurate, unaffected by visual disturbances, making this the most ideal condition.

Table 6. Testing on Curved Roads

No.	Test Condition	Trial No -	FPS		Inference Time (ms)		Navigation Decision (%)	
			Per Trial	Average	Per Trial	Average	Without Fallback	Fallback Mode
1	Shadows	1	7,06	6,98	127,99	130,24	88	12
		2	7,61		121,16		64	36
		3	6,99		129,08		74	26
		4	6,34		142,07		88	12
		5	6,89		130,89		96	4

2	Without Shadows	1	6,99	7,19	130,01	126,39	82	18
		2	7,01		127,17		80	20
		3	6,83		130,96		88	12
		4	8,27		113,06		90	10
		5	6,85		130,74		98	2

Table 6 presents the performance of the autonomous navigation system when operating on curved roads, evaluated under two lighting conditions: with shadows and without shadows. Curved roads are more challenging than straight segments because the vehicle must continuously adjust its steering based on the detected left road edge. Therefore, this test assesses both perception stability and the effectiveness of the fuzzy logic

controller when handling directional changes. This test assessed the system's ability to maintain direction in geometrically complex paths. Only edge anomalies triggered fallback, and no other fallback types were observed. Visual results supported these findings, showing more accurate segmentation and maintained vehicle direction, although curved shapes still introduced minor errors.

Table 7. Testing on Straight Roads with Intersections

No.	Intersection width	Trial No -	FPS		Inference Time (ms)		Navigation Decision (%)	
			Per Trial	Average	Per Trial	Average	Without Fallback	Fallback Mode
1	0-4,5m	1	7,48	7,53	119,9	120,38	100	0
		2	8,15		114,05		84	16
		3	7,43		120,88		100	0
		4	7,23		123,23		82	18
		5	7,36		123,85		84	16
2	>4.5 meters	1	5,9	6,578	153,82	139,59	64	36
		2	6,08		150,02		48	32
		3	6,94		130,24		66	44
		4	7,13		131,46		34	66
		5	6,84		132,4		48	52

Table 7 presents system performance when navigating straight roads that include intersections of varying widths, which is one of the most challenging scenarios for road-edge-based autonomous navigation. Intersections introduce sudden changes in road geometry, making the left-edge segmentation less consistent and forcing the navigation system to rely more on fuzzy decision-making. This test evaluated the system's ability to maintain a straight path when passing intersections on unmarked roads. The key challenge was distinguishing the main road from a left-branching side road without clear markings. Intersections were divided by width: ≤ 4.5

meters and >4.5 meters, corresponding to the system's detection threshold. For narrow intersections (≤ 4.5 m), the system performed well with a 90% success rate without fallback. Most fallbacks were due to edge anomalies but were not critical. The narrow side road was still recognized as a roadside, helping the system stay on the main path. In contrast, at wide intersections (>4.5 m), performance dropped significantly to only 52% success without fallback. The system failed to detect the roadside as the wide side street was too large to be considered an edge, leading to decision failures in fuzzy logic and activation of fallback modes such as GPS.

Table 8. Testing with Varying Speeds

No	Speed		FPS	Time Delay (ms)	Distance Delay (m)
	Km/jam	m/s			
1	5	1,39	6,94	144	0,2
2	10	2,78	6,8	147	0,41
3	20	5,56	6,85	146	0,81
4	30	8,33	6,96	143	1,19
5	40	11,11	6,93	144	1,59

Table 8 presents the system's real-time performance when the vehicle operates at different speeds ranging

from 5 km/h to 40 km/h. This test aims to evaluate how increased vehicle speed affects processing latency and

the distance delay, which represents how far the vehicle moves during the perception–decision cycle. These measurements are critical for determining the safe and effective operating speed of the autonomous navigation system. Testing across five different speeds showed consistent FPS and latency across all speeds approximately 6.8–6.9 FPS and 143–147 ms latency. While segmentation and steering decisions remained accurate, system latency led to increased distance delays as speed increased. At 40 km/h, delay reached 1.59 meters, meaning steering decisions were based on outdated visual information, reducing responsiveness. Therefore, a safe operational speed is recommended to be under 30 km/h to keep the blind distance below 1 meter, ensuring consistent navigation accuracy and safety.

4. LIMITATIONS

This study has several limitations. First, evaluation was confined to a single campus environment at low speed, with image acquisition performed manually because the vehicle prototype was not fully autonomous, so end-to-end closed-loop autonomous driving was not demonstrated. Second, wide branching intersections (>4.5 m) remain unsolved, with roughly half of trials falling back to GPS, and shadows still trigger edge anomalies. Third, no ablation isolates the contribution of the segmentation model from that of the fuzzy controller, so the benefit of the hybrid design over segmentation alone or a simpler controller is not quantified. Fourth, segmentation is compared only across U-Net encoder variants, not against recent external lightweight segmentation models. Fifth, navigation is reported as a success/fallback rate; lateral-position error, trajectory deviation and steering error are not measured, and results are given as averages without trial-to-trial variance. Sixth, the perception stack uses a single monocular camera and is not evaluated in rain, at night, or in unstructured non-campus environments. The system should therefore be regarded as a low-speed feasibility demonstration for structured unmarked-road environments.

5. CONCLUSION

This study successfully developed an autonomous vehicle navigation system for unmarked roads using semantic segmentation based on the U-Net architecture with a MobileNetV2 encoder and a single forward-facing camera as the visual sensor. The system performs road and road-edge identification and determines vehicle steering direction using a fuzzy logic controller. The MobileNetV2-based U-Net model achieved high segmentation accuracy, with an overall accuracy of 96.81% and a mean Intersection over Union (mIoU) of 0.9689, demonstrating strong capability in recognizing road surfaces and boundaries. Experimental testing across various road scenarios shows that the system navigates straight roads reliably, achieving navigation accuracy greater than 95% in both daytime and afternoon

conditions. Testing on straight roads with and without shadows indicated that shadows introduce moderate challenges, lowering navigation accuracy in some trials but still maintaining safe operation due to fuzzy logic fallback behavior. On curved roads, performance declines due to increased geometric complexity and the difficulty of detecting curved left edges, especially in shadowed conditions. Navigation performance on curves ranged between 64% and 98%, with shadows significantly increasing fallback activation. Tests on straight roads with intersections revealed that the system performs well on narrow intersections (0–4.5 m), achieving navigation accuracy up to 100%. In contrast, wide intersections (>4.5 m) significantly reduce segmentation stability, with accuracy dropping to 34–66% due to the left road edge disappearing or becoming distant in the camera view. Speed testing demonstrated that the system maintains stable real-time performance, with FPS consistently above 6 and latency around 143–147 ms across all speeds. Since the inference time remains constant, the distance delay increases linearly with speed—from 0.20 m at 5 km/h to 1.59 m at 40 km/h. Based on these results, the system operates most effectively at 5–20 km/h, ensuring a distance delay below 1 meter, which is essential for safety in unmarked and narrow campus or village road environments. Overall, the proposed system demonstrates strong potential for low-speed autonomous navigation in unmarked-road conditions, particularly in structured environments such as university campuses. Future work should add an ablation comparing the segmentation model alone, the fuzzy controller alone and the complete framework; benchmark the segmentation stage against recent lightweight models; report navigation using lateral-position error, trajectory deviation and steering error with mean and standard deviation over repeated runs; and validate the system in true closed-loop operation and in more diverse environments, including shadows, wide intersections and higher speeds.

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REFERENCES

- Akmal Arista, A., Paradifta, K. A., Nugraha, Z. and Priambodo, A. S. (2024). Implementasi fuzzy logic pada kendali robot E-Puck wall following. *JEECAE: Journal of Electrical, Electronic, Control and Automotive Engineering*, 9(1), 16-21.
- Al-Jubouri, A. and Jin, Y. (2020). Challenges of GPS-based navigation for autonomous vehicles. *Sensors*.
- Alam, N. and Dempster, A. (2013). Lane-level navigation using low-cost GPS. *IEEE Transactions on Intelligent Transportation Systems*.

- Badrinarayanan, V., Kendall, A. and Cipolla, R. (2017). SegNet. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- Bagloee, S. M., Tavana, M., Asadi, M. and Oliver, T. (2016). Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation*.
- Chen, Z. et al. (2015). End-to-end learning for steering control. *Conference on Neural Information Processing Systems (NeurIPS)*.
- Chen, X. et al. (2019). Deep segmentation for unmarked road boundaries. *IEEE Intelligent Vehicles Symposium (IV)*.
- Fagnant, R. and Kockelman, K. (2015). The travel and environmental implications of automated vehicles. *Transportation Research Part C: Emerging Technologies*.
- Febrian, Y., Yahya, R. A., Dzaluli, M. I., Priambodo, A. S. and Eng, M. (2023). Implementasi fuzzy logic dengan sistem visual camera pada robot Jetbot sebagai line follower.
- Grigorescu, S. et al. (2020). Survey of deep learning for autonomous driving. *IEEE Transactions on Intelligent Transportation Systems*.
- Guan, Y. et al. (2021). Route optimization for autonomous delivery vehicles. *IEEE Access*.
- Hasirci, S. and Hasirci, A. (2017). Fuzzy steering control for autonomous vehicles. *Journal of Intelligent & Robotic Systems*.
- Jo, K., Kim, J., Kim, D., Jang, C. and Sunwoo, M. (2015). Lane detection using GPS and vision. *IEEE Transactions on Intelligent Transportation Systems*.
- Katrakazas, C. et al. (2015). Real-time motion planning for autonomous on-road driving. *Transportation Research Part C: Emerging Technologies*.
- Kim, H. et al. (2020). Autonomous driving in campus environments. *IEEE Access*.
- Long, J., Shelhamer, E. and Darrell, T. (2015). Fully convolutional networks for semantic segmentation. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Moussa, A. et al. (2021). Lane boundary detection using deep learning. *Sensors*.
- Proença, P. F. and Simões, M. (2020). U-Net for road segmentation. *IEEE Access*.
- Qureshi, M. R. J. (2019). Road infrastructure issues in rural areas. *Rural Engineering Journal*.
- Ronneberger, O., Fischer, P. and Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI)*.
- Schoettle, B. and Sivak, M. (2015). Potential impact of autonomous and connected vehicles on emissions and energy consumption. *University of Michigan*.
- Srivastava, S. (2020). Autonomous delivery robots in e-commerce logistics. *IEEE Transactions on Automation Science and Engineering*.
- Sun, C., Zhao, H., Mu, L., Xu, F. and Lu, L. (2023). Image semantic segmentation for autonomous driving based on improved U-Net. *CMES-Computer Modeling in Engineering & Sciences*, 136(1), 787-801. doi: 10.32604/cmes.2023.025119.
- Velaga, N. R. et al. (2012). Challenges in rural road navigation. *Transportation Planning and Technology*.
- Yazici, A. and Unel, M. (2019). Vision-based lane detection without road markings. *Robotics and Autonomous Systems*.
- Zadeh, L. A. (1965). Fuzzy logic. *Information and Control*.
- Zhao, L. and Thorpe, C. (2000). Unmarked road detection using texture. *IEEE Intelligent Vehicles Symposium (IV)*.
- Zhao, R. et al. (2022). Real-time fuzzy control for low-speed autonomous navigation. *IEEE Access*.