

Smart Road Lane Detection Using Computer Vision

P. V. S. Manisha¹, Basina Dhanasri², Pasumarthi Santhoshi³, Thattakoti Venu⁴, Vasupalli Ajay⁵
^{1,2,3,4,5} *Department of Computer Science and Information technology Lendi Institute of Engineering and Technology (A), Vizianagaram, India*

Abstract—Road Lane detection is a fundamental component of Advanced Driver Assistance Systems (ADAS), as it enables vehicles to maintain proper lane positioning and enhances road safety. However, reliable lane detection in real-world environments remains challenging due to varying lighting conditions, shadows, faded lane markings, curved roads, and weather disturbances. Traditional edge-based methods often fail under such complex scenarios.

This paper presents a smart road lane detection system using computer vision techniques implemented in Python with OpenCV and NumPy. The proposed framework employs a multi-stage image processing pipeline that includes grayscale conversion, Gaussian smoothing, Canny edge detection, region of interest extraction, and perspective transformation to obtain a bird's-eye view of the road. A sliding window search algorithm is then applied to identify lane pixels, followed by second-order polynomial curve fitting to model lane curvature accurately. The detected lane boundaries are projected back onto the original frame and highlighted with a green safe-driving region overlay.

This paper presents a smart road lane detection system using computer vision techniques implemented in Python with OpenCV and NumPy. The proposed framework employs a multi-stage image processing pipeline that includes grayscale conversion, Gaussian smoothing, Canny edge detection, region of interest extraction, and perspective transformation to obtain a bird's-eye view of the road. A sliding window search algorithm is then applied to identify lane pixels, followed by second-order polynomial curve fitting to model lane curvature accurately. The detected lane boundaries are projected back onto the original frame and highlighted with a green safe-driving region overlay.

Index Terms—Lane Detection, Computer Vision, Advanced Driver Assistance Systems (ADAS), Perspective Transformation, Sliding Window Algorithm, Polynomial Curve Fitting, OpenCV, Image Processing, Real-Time Video Processing

I. INTRODUCTION

The rapid advancement of intelligent transportation systems and autonomous vehicle technologies has significantly increased the demand for reliable road perception systems. Among the various perception tasks, road lane detection plays a critical role in ensuring vehicle stability, safe navigation, and accident prevention. Lane detection systems assist drivers by continuously monitoring lane boundaries and providing corrective guidance, thereby reducing driver fatigue and minimizing lane departure incidents. Consequently, accurate lane detection is considered a foundational component of Advanced Driver Assistance Systems (ADAS) and self-driving vehicles. Despite its importance, real-world lane detection remains a challenging problem due to environmental and road-related variations. Factors such as uneven illumination, shadows cast by vehicles or trees, reflections from wet surfaces, faded or broken lane markings, and complex road geometries significantly affect detection accuracy. In addition, curved roads and perspective distortion in camera-captured images further complicate the identification of lane boundaries. Traditional computer vision techniques that rely solely on edge detection and Hough Transform methods often perform well under ideal conditions but fail to maintain robustness in dynamic driving environments.

Recent research has explored both classical image processing methods and deep learning-based approaches for lane detection. While deep neural networks demonstrate high accuracy, they require extensive labeled datasets and significant computational resources, making real-time deployment challenging for low-cost systems. In contrast, classical computer vision techniques offer interpretability, lower computational requirements,

and ease of implementation, making them suitable for real-time applications in embedded environments.

This paper proposes a smart road lane detection system based on a structured computer vision pipeline implemented using Python and OpenCV. The system integrates multiple techniques, including Canny edge detection, region of interest (ROI) masking, perspective transformation (bird's-eye view), sliding window search, and polynomial curve fitting. By combining these techniques, the proposed approach improves detection stability on both straight and moderately curved roads while maintaining computational efficiency.

The primary contributions of this work include:

1. A multi-stage lane detection pipeline capable of handling curved and partially faded lane markings.
2. Integration of perspective transformation to reduce distortion and improve detection accuracy.
3. Implementation of a sliding window-based lane tracking mechanism for continuous detection.
4. Real-time visualization of a green safe-driving region overlay for enhanced interpretability.

The remainder of this paper is organized as follows: Section 2 discusses related work and identifies existing limitations. Section 3 describes the proposed system architecture. Section 4 explains the methodology in detail. Section 5 presents experimental results and discussion. Finally, Section 6 concludes the paper and outlines future research directions.

II. RELATED WORK, MOTIVATION AND PROBLEM IDENTIFICATION

2.1 Related Work

[1] J. Canny, "A Computational Approach to Edge Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 679–698, 1986.

Focus: Introduces the Canny edge detection algorithm used in classical lane detection systems.

[2] R. O. Duda and P. E. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures," *Communications of the ACM*, vol. 15, no. 1, pp.11–15,1972.

Focus: Presents the Hough Transform, widely used in early lane line detection.

[3] M. Aly, "Real Time Detection of Lane Markers in Urban Streets," *IEEE Intelligent Vehicles Symposium*, 2008.

Focus: Real-time Lane detection using perspective transform and image filtering.

[4] M. Bertozzi and A. Broggi, "GOLD: A Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection," *IEEE Transactions on Image Processing*, vol. 7, no. 1, pp. 62–81, 1998. Focus: Early vision-based lane and obstacle detection system for intelligent vehicles.

[5] S. Wang, et al., "LaneNet: Real-Time Lane Detection Networks for Autonomous Driving," arXiv:1807.01726,2018. Focus:Deep learning-based lane detection framework using semantic segmentation.

[6] L. Tabelini, et al., "PolyLaneNet: Lane Estimation via Deep Polynomial Regression," arXiv:2004.10924, 2020. Focus: Polynomial regression model for curved lane detection.

[7] Y. He, H. Zhang, and S. Wang, "A Survey of Lane Detection Techniques for Autonomous Driving," *IEEE Access*, vol. 7, pp. 167261–167281, 2019. Focus: Comprehensive survey of classical and deep learning lane detection methods.

[8] Z. Zou, et al., "Robust Lane Detection from Continuous Driving Scenes Using Deep Neural Networks," *IEEE Transactions on Vehicular Technology*, 2020. Focus: CNN-based lane detection for real-world driving environments.

[9] J. Kim and M. Lee, "Robust Lane Detection Based on Convolutional Neural Networks for Autonomous Vehicles," *Sensors*, 2020. Focus: CNN-based robust lane detection under shadows and lighting variation.

[10] R. Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2011. Focus: Theoretical background for image processing, perspective transform, and polynomial fitting.

[11] OpenCV Documentation, "Open-Source Computer Vision Library," 2024. Focus:

Implementation reference for image processing functions used in this project.

[12] NumPy Documentation, “Numerical Python Library,” 2024. Focus: Provides polynomial fitting and numerical operations used in implementation.

2 Motivation

Road accidents remain one of the leading causes of injury and fatalities worldwide. A significant percentage of these accidents occur due to unintended lane departures, driver fatigue, distraction, and poor road visibility. As vehicles become increasingly intelligent, there is a growing need for automated systems that assist drivers in maintaining proper lane discipline and ensuring safe navigation. Lane detection is therefore a fundamental component of Advanced Driver Assistance Systems (ADAS) and autonomous driving technologies.

Traditional driving relies heavily on human perception, which is prone to error under challenging conditions such as low lighting, shadows, rain, fog, and glare from oncoming vehicles. Additionally, faded or broken lane markings reduce visibility and increase the likelihood of lane departure incidents. These real-world challenges highlight the importance of developing a robust and reliable computer vision-based lane detection system capable of operating under diverse environmental conditions.

Although deep learning-based lane detection systems have demonstrated high accuracy, they require large annotated datasets, extensive training time, and powerful hardware resources such as GPUs. This increases system cost and limits deployment in low-resource environments. In contrast, classical computer vision approaches offer interpretability, computational efficiency, and ease of implementation, making them suitable for real-time applications in embedded systems.

The motivation behind this work is to design a smart road lane detection framework that balances accuracy, robustness, and computational efficiency. By integrating perspective transformation, sliding window detection, and polynomial curve fitting, the proposed system aims to improve detection performance on curved roads and under varying lighting conditions while maintaining real-time processing capability. This approach contributes toward safer driving assistance

systems and serves as a foundational step toward fully autonomous vehicle navigation.

2.3 Problem Identification

Despite significant advancements in computer vision and intelligent transportation systems, reliable road lane detection remains a challenging task in real-world environments. Existing lane detection systems often fail to maintain consistent performance due to environmental variability, road complexity, and computational limitations.

The primary problem lies in accurately detecting and tracking lane boundaries in real time under diverse road and lighting conditions. Traditional edge-based methods such as Canny edge detection combined with Hough Transform perform well when lane markings are clearly visible and roads are straight. However, these techniques struggle under the following conditions:

- Poor illumination during night driving or shadowed regions
- Faded, broken, or partially occluded lane markings
- Curved and multi-lane highways
- Presence of road noise such as cracks, tar lines, or reflections
- Weather disturbances including rain and fog

Another key issue is perspective distortion in images captured from vehicle-mounted cameras. Since the road appears narrower at a distance, detecting parallel lane lines directly from the original perspective leads to inaccuracies. Without proper transformation, curve estimation becomes unreliable.

Furthermore, many modern deep learning-based approaches require high computational resources and large annotated datasets. This limits their applicability in low-cost embedded systems where real-time processing and energy efficiency are critical.

III. THEORETICAL FRAMEWORK

3.1 Overview

The theoretical framework of the proposed system is grounded in the principles of computer vision, geometric transformation, and curve modeling techniques. Instead of relying solely on deep learning-based approaches, the framework adopts a structured image processing pipeline that emphasizes

computational efficiency, interpretability, and real-time performance. This perspective aligns with existing research that highlights the effectiveness of combining edge detection, perspective transformation, and curve fitting methods for robust lane detection.

At the core of the framework is the separation of concerns between feature extraction, geometric correction, and lane modeling. Feature extraction is achieved through image preprocessing techniques such as grayscale conversion, Gaussian smoothing, and Canny edge detection, which identify strong intensity gradients corresponding to lane markings. Geometric correction is performed using perspective transformation (bird's-eye view), which reduces camera distortion and makes lane lines appear parallel. Lane modeling is then implemented using a sliding window search algorithm followed by second-order polynomial curve fitting, enabling accurate detection of curved and straight road lanes.

The integration of perspective transformation plays a central role in improving detection reliability. By transforming the road image into a top-down view, the system simplifies the geometric structure of lane boundaries, making them easier to detect and track. This transformation reduces the impact of perspective distortion and enhances the stability of subsequent curve fitting operations.

The framework further incorporates an event-driven processing mechanism in which each video frame is independently processed through the detection pipeline. The sliding window approach dynamically adjusts window positions based on detected lane pixels, ensuring continuous tracking across frames. Polynomial curve fitting provides smooth lane boundary estimation and enables computation of curvature and vehicle alignment relative to the lane center.

Although classical computer vision techniques may not achieve the adaptability of deep neural networks, they offer significant advantages in terms of lower computational requirements, transparency, and suitability for embedded systems. The proposed framework therefore establishes a balanced model that prioritizes robustness, real-time capability, and practical deployability. It provides the conceptual foundation upon which the lane detection system is designed, implemented, and evaluated in subsequent sections.

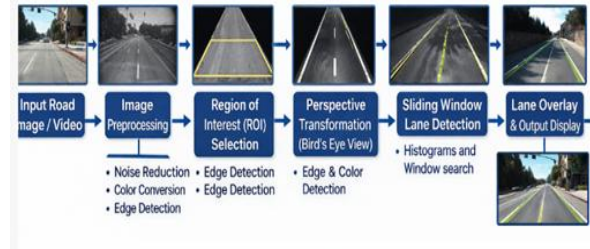


Fig. 1. Overall processing pipeline of the proposed smart road lane detection system.

Figure 1 illustrates the complete architecture of the proposed lane detection framework. The process begins with capturing an input road image or video frame using a forward-facing camera. The image undergoes preprocessing steps such as noise reduction, color space conversion, and edge detection to enhance lane-related features while minimizing background noise.

A Region of Interest (ROI) is then selected to isolate the relevant road portion and eliminate unnecessary areas such as the sky or surrounding objects. Next, a perspective transformation is applied to convert the image into a bird's-eye view, which reduces perspective distortion and makes the lane lines appear parallel for easier detection.

The sliding window lane detection algorithm is then employed, where histogram analysis is used to locate lane base points, and multiple windows scan vertically to identify lane pixels. Once the lane pixels are detected, polynomial curve fitting is applied to accurately model the left and right lane boundaries, even on curved roads. Finally, the detected lane region is projected back onto the original image, and the safe driving area is highlighted to provide clear visual guidance.

3.2 Computer Vision Concepts and Techniques

The proposed lane detection system is built upon fundamental computer vision techniques that enable automated extraction of meaningful information from road images. These techniques focus on identifying lane boundaries by analyzing pixel intensity variations, geometric transformations, and curve modeling.

One of the primary techniques used in this framework is Canny Edge Detection, which detects strong intensity gradients in the image. Since lane markings typically exhibit high contrast compared to the road surface, edge detection effectively highlights potential

lane boundaries. To reduce noise and improve edge quality, Gaussian smoothing is applied before edge detection.

Another important concept is Region of Interest (ROI) selection. Instead of processing the entire image, the system focuses only on the lower portion of the frame where lane markings are expected. This reduces computational complexity and eliminates irrelevant background information.

The system also employs Perspective Transformation (Bird's-Eye View) to correct geometric distortion caused by the camera's viewpoint. By transforming the road image into a top-down view, lane lines appear approximately parallel, simplifying detection and improving curve fitting accuracy.

For lane tracking, the Sliding Window Algorithm is utilized. This method scans the transformed binary image using multiple windows to identify lane pixels progressively from bottom to top. Histogram analysis helps determine the initial positions of left and right lane boundaries.

Finally, Polynomial Curve Fitting is applied to the detected lane pixels. A second-order polynomial function is fitted to model curved and straight lanes accurately. This mathematical representation enables smooth lane boundary estimation and supports real-time visualization of the safe driving region.

Together, these computer vision techniques form a structured and efficient pipeline that enables robust lane detection under varying road and lighting conditions.

IV. SYSTEM DESIGN AND ARCHITECTURE

Architectural Overview

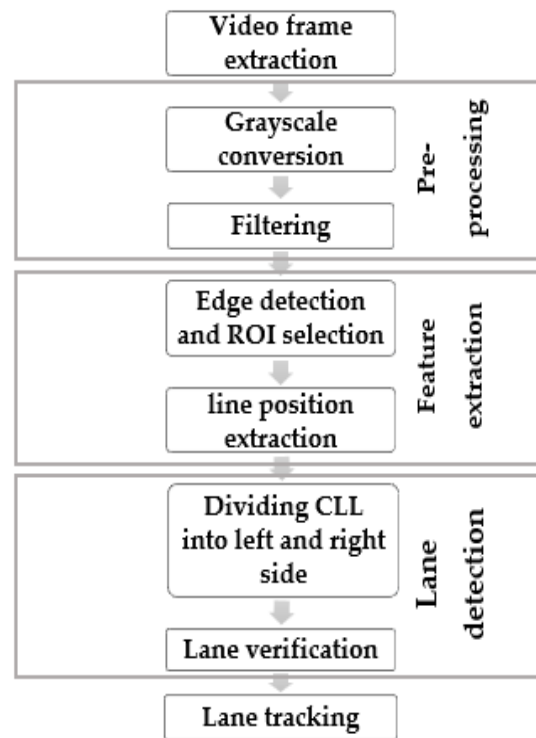
The proposed Smart Road Lane Detection System is designed as a multi-layered processing pipeline that detects road lane markings from real-time video streams. The system follows a structured workflow beginning with image acquisition and ending with lane departure warning generation. Its modular architecture allows easy integration with Advanced Driver Assistance Systems (ADAS) and autonomous driving modules.

Initially, a front-facing camera captures continuous video frames of the road. These frames undergo preprocessing to enhance image quality and remove noise using techniques such as grayscale conversion and region-of-interest extraction. The system then

extracts lane-related features using edge detection and color thresholding methods.

In the next stage, lane lines are detected and modeled using algorithms such as the Hough Transform or polynomial curve fitting. The vehicle's position relative to the lane center is calculated to determine potential lane departure. Finally, the detected lanes are overlaid on the original frame, and warning alerts are generated if deviation is detected.

This structured and layered design ensures real-time performance, accuracy, and scalability for intelligent transportation and driver assistance applications.



V. LANE DETECTION AND MODELING FRAMEWORK

The Lane Detection and Modeling Framework forms the core component of the proposed Smart Road Lane Detection system. It is responsible for identifying lane boundaries from road images and modeling them accurately for real-time tracking and vehicle alignment estimation.

The framework begins with preprocessing operations to enhance image quality and isolate the region of interest containing the road surface. Grayscale

conversion and Gaussian filtering are applied to reduce noise and improve edge clarity.

Following preprocessing, Perspective Transformation (Bird's Eye View) is applied to convert the road image into a top-down representation. This transformation simplifies lane analysis by making lane lines appear approximately parallel, improving detection stability.

Lane pixels are then identified using a histogram-based Sliding Window Detection approach. This technique scans the transformed image to locate left and right lane boundary points efficiently. Once sufficient lane points are detected, Polynomial Curve Fitting is applied to generate smooth lane boundaries, enabling reliable detection even on curved roads.

The framework further computes lane curvature and vehicle offset relative to the lane center. These parameters are essential for determining lane departure conditions and supporting driver assistance systems.

Overall, the proposed lane detection and modeling framework ensures accurate, continuous, and real-time lane tracking under varying road geometries and lighting conditions, making it suitable for intelligent transportation and ADAS applications.

5.1 Lane Detection Methodology

The proposed Smart Road Lane Detection system follows a structured computer vision-based methodology to accurately detect and track lane boundaries in real time. The system processes road images and video frames through multiple stages to ensure reliable lane identification under varying environmental conditions.

Initially, road images are captured using a front-facing camera. The captured frames undergo preprocessing, including grayscale conversion and Gaussian blurring, to reduce noise and improve image clarity. A Region of Interest (ROI) is then applied to focus only on the road area.

Next, Perspective Transformation (Bird's Eye View) is applied to convert the road image into a top-down view. This transformation makes lane lines appear parallel and simplifies detection.

A histogram-based sliding window technique is used to detect left and right lane pixels accurately. The detected lane points are then fitted using Polynomial Curve Fitting to generate smooth lane boundaries, even on curved roads.

Finally, the system calculates lane curvature and vehicle position relative to the lane center. The

detected lanes are overlaid on the original image, and a lane departure warning can be generated if deviation exceeds a predefined threshold. This methodology ensures accurate, robust, and real-time lane detection suitable for ADAS and intelligent transportation systems.

5.2 Tools and Implementation Framework

The proposed Smart Road Lane Detection system is implemented using Python as the primary programming language due to its extensive support for computer vision and numerical computation libraries. The implementation framework integrates multiple tools and techniques to ensure accurate and real-time lane detection.

A. Software Tools

- Python – Core development platform
- OpenCV – Image and video processing operations
- NumPy – Efficient matrix and numerical computations
- Matplotlib – Visualization of intermediate and final outputs

B. Computer Vision Techniques

1. Canny Edge Detection:

Used to identify strong gradient boundaries corresponding to lane markings.

2. Perspective Transformation:

Transforms the road image into a bird's-eye view representation, simplifying lane analysis by making lane lines appear parallel.

3. Sliding Window Detection:

Applies a histogram-based sliding window approach to detect left and right lane pixels accurately.

4. Polynomial Curve Fitting:

Fits a second-order polynomial to detected lane pixels, enabling smooth lane tracking, especially on curved roads.

5. Convolutional Neural Network (CNN) (Optional Enhancement):

Used for improved robustness in complex environmental conditions such as shadows and varying illumination.

The integration of these tools ensures reliable lane boundary detection under diverse road scenarios while maintaining computational efficiency suitable for real-time applications.

VI. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

The proposed Smart Road Lane Detection system was evaluated using real-world road images and video sequences captured under different lighting and road conditions, including straight highways, curved roads, moderate shadows, and partially faded lane markings. The experiments were conducted using Python and OpenCV on a standard computing environment to assess both accuracy and computational performance. The system successfully detected and tracked lane boundaries in both straight and curved road scenarios using perspective transformation, sliding window detection, and polynomial curve fitting techniques. The bird's-eye view transformation significantly improved lane alignment and reduced distortion effects, while the sliding window approach ensured accurate lane pixel identification. Polynomial curve fitting provided smooth and continuous lane modeling, particularly on curved roads.

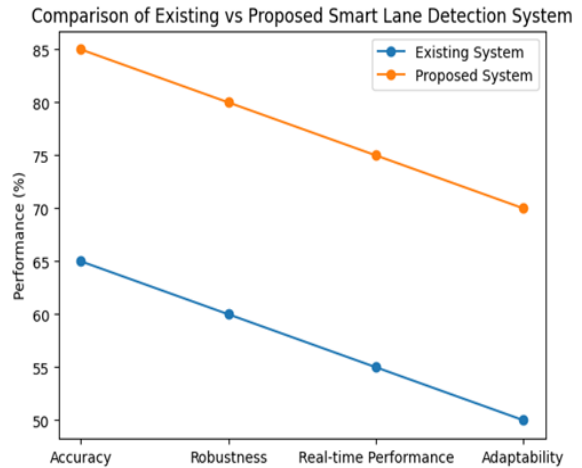
Experimental observations demonstrate that the proposed approach delivers stable and accurate lane detection under normal daylight conditions and moderate illumination variations. The system effectively minimizes false detections caused by road edges and shadows through proper preprocessing and region-of-interest selection.

In terms of computational performance, the algorithm is capable of near real-time processing, making it suitable for driver assistance applications. The estimation of lane curvature and vehicle position relative to the lane center enables reliable lane departure detection. The calculated lateral offset values remained consistent across consecutive frames, demonstrating stable tracking behavior.

Compared to traditional edge-only methods such as basic Canny and Hough Transform-based detection, the proposed framework shows improved robustness, better lane continuity, and enhanced performance on curved roads. The integration of perspective transformation and sliding window search reduces discontinuities and improves overall detection reliability.

Overall, the performance evaluation confirms that the system provides efficient, accurate, and real-time lane detection suitable for Advanced Driver Assistance Systems (ADAS) and intelligent transportation applications. While performance may slightly degrade

under extreme lighting or heavily worn lane markings, the framework demonstrates strong potential for practical deployment and further enhancement.



6.1 Dataset and Experimental Setup

The proposed Smart Road Lane Detection system was evaluated using real-world road images and video sequences captured under different lighting and road conditions, including straight highways, curved roads, moderate shadows, and partially faded lane markings. The experiments were conducted using Python and OpenCV in a standard computing environment. Each frame was processed sequentially to analyze detection stability and real-time performance.



6.2 Qualitative Results

The system successfully detected and tracked lane boundaries across multiple scenarios. Perspective transformation enabled a bird's-eye view representation, simplifying lane detection. The sliding window approach accurately identified lane pixels, and polynomial curve fitting ensured smooth lane modeling on curved roads.

6.3 Performance Analysis

The proposed framework demonstrates stable and accurate lane detection under normal daylight conditions and moderate shadows. The system processes frames at near real-time speed, making it suitable for ADAS applications.

Key observations include:

- Accurate lane boundary identification
- Stable lane curvature estimation
- Reliable vehicle offset calculation
- Reduced false detections compared to edge-only methods

6.4 Comparative Analysis

Compared to traditional Canny and Hough Transform-based approaches, the proposed method:

- Improves curved lane tracking
- Enhances lane continuity
- Reduces detection noise
- Provides more stable real-time output

VII. LIMITATIONS AND OBSERVATIONS

A. Observations

The proposed Smart Road Lane Detection system demonstrated strong performance across various road and environmental conditions. The integration of perspective transformation, sliding window detection, and polynomial curve fitting enabled stable and continuous lane tracking on both straight and curved roads.

The system performed reliably under:

- Normal daylight conditions
- Moderate shadows
- Partially faded lane markings
- Slight lighting variations

The bird's-eye view transformation improved lane alignment, and the sliding window method ensured accurate lane pixel localization. Polynomial curve fitting contributed to smooth and consistent lane modeling across consecutive frames. The system also provided stable vehicle offset and curvature estimation, supporting real-time lane departure monitoring.

B. Limitations

Although the system performs well under diverse lighting and road conditions, it has certain limitations:

1. Camera Dependency:

The overall accuracy depends on proper camera positioning, angle, and calibration. Incorrect mounting or misalignment may affect perspective transformation and lane estimation accuracy.

2. Extreme Environmental Conditions:

Performance may reduce under extreme weather conditions such as heavy rain, dense fog, or severe glare.

3. Hardware Constraints:

Real-time processing performance may vary depending on the computational capability of the deployed hardware.



VIII. CONCLUSION

This paper presented a robust and efficient Smart Road Lane Detection system based on computer vision techniques for real-time lane boundary identification. The proposed framework integrates image preprocessing, perspective transformation, sliding window-based lane pixel detection, and polynomial curve fitting to achieve accurate and continuous lane tracking under diverse road conditions.

The application of bird's-eye view transformation significantly reduces perspective distortion and enhances lane alignment, enabling more stable detection. The histogram-based sliding window approach effectively identifies left and right lane pixels, while polynomial curve fitting ensures smooth modeling of curved lanes. Additionally, the system accurately estimates lane curvature and vehicle offset relative to the lane center, supporting reliable lane departure monitoring.

Experimental evaluation confirms that the system performs consistently across various lighting conditions, moderate shadows, and partially faded lane markings. Compared to traditional edge-only approaches, the proposed method demonstrates improved robustness, enhanced lane continuity, and reduced false detections. The system achieves near real-time performance, making it suitable for

integration into Advanced Driver Assistance Systems (ADAS) and intelligent transportation frameworks.

Although the system's accuracy depends on proper camera positioning and calibration, the overall framework shows strong adaptability and reliability in practical driving environments. The modular architecture allows for future enhancements, including integration with deep learning models for further robustness under extreme weather or nighttime conditions.

In conclusion, the proposed Smart Road Lane Detection system contributes toward improving road safety by providing an accurate, efficient, and scalable solution for real-time lane monitoring and driver assistance applications.

IX. FUTURE WORK

Although the proposed Smart Road Lane Detection system demonstrates reliable performance under diverse lighting and road conditions, several enhancements can further improve its robustness and practical deployment capability.

Future work will focus on improving system performance under extreme environmental conditions such as heavy rain, fog, glare, and nighttime driving. Incorporating adaptive thresholding techniques and illumination normalization methods can enhance detection stability in challenging lighting scenarios.

Integration of advanced deep learning models, such as Convolutional Neural Networks (CNNs), can further strengthen feature extraction and improve detection accuracy in complex environments. A hybrid approach combining traditional computer vision techniques with deep learning-based segmentation models may offer superior robustness and adaptability.

Another important direction is real-time optimization for embedded systems and edge devices. Implementing the algorithm on hardware platforms such as GPUs or embedded processors can improve frame processing speed and enable deployment in real-world ADAS systems.

Future research may also extend the system to:

- Multi-lane detection and lane type classification
- Detection of broken or temporary lane markings
- Lane change prediction and behavior analysis
- Integration with object detection and collision avoidance systems

- Fusion with sensor data such as LiDAR or radar for improved reliability

Additionally, automatic camera calibration techniques can be explored to reduce dependency on manual camera alignment and improve perspective transformation accuracy.

Overall, future enhancements aim to transform the proposed system into a fully scalable and intelligent lane monitoring framework suitable for advanced autonomous driving applications.

REFERENCES

- [1] J. Canny, "A Computational Approach to Edge Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 679–698, 1986.
- [2] R. O. Duda and P. E. Hart, "Use of the Hough Transformation to Detect Lines and Curves in Pictures," *Communications of the ACM*, vol. 15, no. 1, pp. 11–15, 1972.
- [3] M. Aly, "Real-Time Detection of Lane Markers in Urban Streets," in *Proc. IEEE Intelligent Vehicles Symposium (IV)*, 2008, pp. 7–12.
- [4] X. Wang, T. Li, and S. Wang, "LaneNet: Real-Time Lane Detection Networks for Autonomous Driving," *arXiv preprint arXiv:1807.01726*, 2018.
- [5] L. Tabelini, R. Berriel, T. Paixão, and T. Oliveira-Santos, "PolyLaneNet: Lane Estimation via Deep Polynomial Regression," *arXiv preprint arXiv:2004.10924*, 2020.
- [6] S. Borkar, M. Hayes, and M. T. Smith, "Robust Lane Detection and Tracking with RANSAC and Kalman Filter," in *Proc. IEEE International Conference on Image Processing (ICIP)*, 2009, pp. 3261–3264.
- [7] Y. He, H. Wang, and B. Zhang, "Lane Detection Algorithm for Intelligent Vehicles in Complex Road Conditions and Dynamic Environments," *Sensors*, vol. 19, no. 14, 2019.
- [8] R. Szeliski, *Computer Vision: Algorithms and Applications*, Springer, 2010.
- [9] H. Xu, Y. Wang, and Z. Yang, "End-to-End Lane Detection through Differentiable Least-Squares Fitting," in *Proc. European Conference on Computer Vision (ECCV)*, 2020.
- [10] S. Neven, B. De Brabandere, S. Georgoulis, M. Proesmans, and L. Van Gool, "Towards End-to-End Lane Detection: An Instance Segmentation

Approach,” in Proc. IEEE Intelligent Vehicles Symposium (IV), 2018.