

AI-Based Road Lane Detection for Advanced Driver Assistance Systems: A Comparative Review of Traditional and Deep Learning Techniques

Anushka Chaudhari*, Snehal Rathod*, Manasi Shende*, Saniya Ingale*, Dr. Pragati Pawar**

*(Department of Electronics and Telecommunication Engineering, Jawaharlal Darda Institute of Engineering and Technology, Yavatmal

Email: anushkachaudhari369@gmail.com)

**(Department of Electronics and Telecommunication Engineering, Jawaharlal Darda Institute of Engineering and Technology, Yavatmal

Email: pragati_pawar@jdiet.ac.in)

Abstract:

Road lane detection is an important part of Advanced Driver Assistance Systems (ADAS). It helps vehicles identify lane boundaries and maintain their position on the road. Traditional methods use image-processing techniques such as Canny edge detection, Region of Interest (ROI), and the Hough Transform. These methods are simple and fast but may have difficulty with faded lane markings, shadows, curved roads, and changing weather conditions.

Recent AI-based methods use techniques such as CNN, YOLO-based models, image segmentation, and transfer learning to detect lane markings in complex environments, depending on the model architecture and training data. This paper reviews and compares traditional and AI-based lane detection techniques, with a focus on Indian road conditions. The comparison considers detection performance, processing speed, computational requirements, and robustness under different road conditions. Four selected research studies are reviewed to discuss the advantages and limitations of traditional and AI-based lane detection techniques.

Keywords: Lane Detection, ADAS, Image Processing, Artificial Intelligence, Deep Learning, CNN, YOLO.

I. INTRODUCTION

Road safety is an important concern due to increasing traffic and changing road conditions. Advanced Driver Assistance Systems (ADAS) are being developed to improve driving safety by using cameras, sensors, and computer-based techniques. Lane detection is an important part of ADAS because it helps identify road lane boundaries and determine the position of a vehicle on the road. It

can support applications such as Lane Departure Warning and Lane Keeping Assistance.

Traditional lane detection methods use image-processing techniques such as grayscale conversion, Canny edge detection, Region of Interest (ROI), and the Hough Transform. These methods are relatively simple, fast, and computationally efficient. However, their performance may decrease when lane markings are faded, roads are curved, lighting

conditions change, or shadows and other objects obscure the lane markings.

Recent developments in Artificial Intelligence (AI) and Deep Learning have introduced methods such as Convolutional Neural Networks (CNN), YOLO, image segmentation, attention mechanisms, and transfer learning. These methods can learn lane-related features from training data and may perform better under complex road conditions, depending on the model architecture and training data. However, they require suitable datasets, model training, and higher computational resources.

Indian roads present additional challenges such as mixed traffic, motorcycles, auto-rickshaws, pedestrians, faded lane markings, and changing weather conditions. Therefore, selecting a suitable lane detection approach is important for reliable ADAS applications.

This paper reviews and compares traditional image-processing and AI-based lane detection techniques based on accuracy, processing speed, computational requirements, robustness, and suitability for Indian road conditions. Four selected research studies are reviewed to identify current developments and research gaps in AI-based lane detection.



Fig. 1. Real-world road scene showing detected lane boundaries and drivable area.

II. LITERATURE REVIEW

S. Kumari, P. Mamoria, and H. Kumar proposed a lightweight CNN model called Robust-LaneNet for lane detection in difficult visual conditions. The model was designed to work in conditions such as rain, fog, and bright light. It also focuses on reducing the computational requirements, making it suitable for real-time vehicle applications. [1]

C. Pimpalgaonkar, S. Shinde, and R. Sharma studied lane and object detection using YOLO for Indian roads. The study considered problems such as faded lane markings and heavy traffic. YOLO was used because it can perform detection quickly, making it useful for real-time applications. The study explored the use of YOLO for detecting lanes and road objects under Indian road conditions. [2]

K. Kakade, S. Sawant, and P. D. Patil proposed a deep-learning-based road detection system for Indian roads. The researchers created a custom dataset from road videos collected under different environmental and traffic conditions in India. They evaluated YOLOP and HybridNets for multiple perception tasks, including lane detection, object detection, and drivable-area segmentation. The study investigated the performance of these models on Indian road scenes. [3]

A. Mukhopadhyay, L. R. D. Murthy, I. Mukherjee, and P. Biswas proposed a hybrid lane detection model for difficult road conditions. The model combines an encoder-decoder network with dilated convolution networks to detect lane markings. The researchers evaluated the model using the TuSimple dataset and the Indian Lane Dataset (ILD), which includes challenging Indian road environments. Their study focused on improving lane detection in complex and unstructured road conditions. [4]

III. TRADITIONAL LANE DETECTION TECHNIQUES

Traditional lane detection techniques use image processing methods to identify lane markings from road images or video. These methods do not require a large dataset or model training. They mainly depend on the brightness, edges, and shape of lane markings in the image. The basic process consists of input road image, grayscale conversion, Canny edge detection, Region of Interest (ROI) selection, and Hough Transform, as shown in Fig. 2.

A. Input Road Image

The process starts with a road image captured by a camera mounted on the vehicle. The image may contain the road, lane markings, vehicles, trees, buildings, and other objects. The main purpose of the processing is to identify the lane markings from this image. A clear input image helps the system detect the lane boundaries more accurately. However, poor visibility, faded lane markings, or objects covering the road can make the detection more difficult.

B. Grayscale Conversion

The captured color image is first converted into a grayscale image. A color image contains information from different color channels, while a grayscale image contains mainly brightness information. Converting the image to grayscale reduces unnecessary information and makes the image easier and faster to process.

This step is useful because lane markings usually have a different brightness from the road surface. However, changes in lighting, shadows, or very dark road conditions can make the lane markings less visible even after grayscale conversion.

C. Canny Edge Detection

After grayscale conversion, Canny edge detection is used to identify the edges in the image. An edge is a point where there is a significant change in brightness between two areas. Lane markings generally create a noticeable change between the

marking and the road surface, so their boundaries can be detected using this method.

Canny edge detection is widely used because it is simple, fast, and requires less computational power. However, it may also detect unwanted edges caused by vehicles, road cracks, shadows, or other objects. Therefore, further processing is needed to select the edges that belong to the lane markings.

D. Region of Interest

The Region of Interest (ROI) is used to select only the important part of the image where the road and lane markings are present. Usually, the lower and middle portions of the image are selected, while areas such as the sky, buildings, and trees are ignored.

Using ROI reduces the amount of unnecessary information that needs to be processed. This helps improve processing speed and reduces computational requirements. However, a fixed ROI may not work correctly for every road because the camera position, road shape, and driving conditions can change.

E. Hough Transform

The **Hough Transform** is used to detect straight lines from the edges obtained after Canny edge detection and ROI selection. It identifies groups of edge points that form a line. In lane detection, these lines can be used to find the left and right boundaries of the driving lane.

The Hough Transform is simple, fast, and does not require training data. It works well when lane markings are clear and approximately straight. However, it may not give reliable results on strongly curved roads, broken lane markings, or roads where many unwanted edges are present.

F. Detection of Lane Boundaries

After applying the Hough Transform, the detected lines are used to identify the left and right lane boundaries. The region between these boundaries represents the lane in which the vehicle is travelling. This information can help an ADAS system determine the position of the vehicle with respect to the lane.

Traditional lane detection methods are therefore suitable for simple and clear road conditions because they are easy to implement, fast, and require less computational power. They also do not require large training datasets. However, their performance can decrease when lane markings are faded, broken, or covered by vehicles. Shadows, bright sunlight, rain, fog, curved roads, and heavy traffic can also affect the detection results. These limitations have encouraged the development of AI-based lane detection methods that can learn from different road conditions and may provide better performance under complex road conditions.

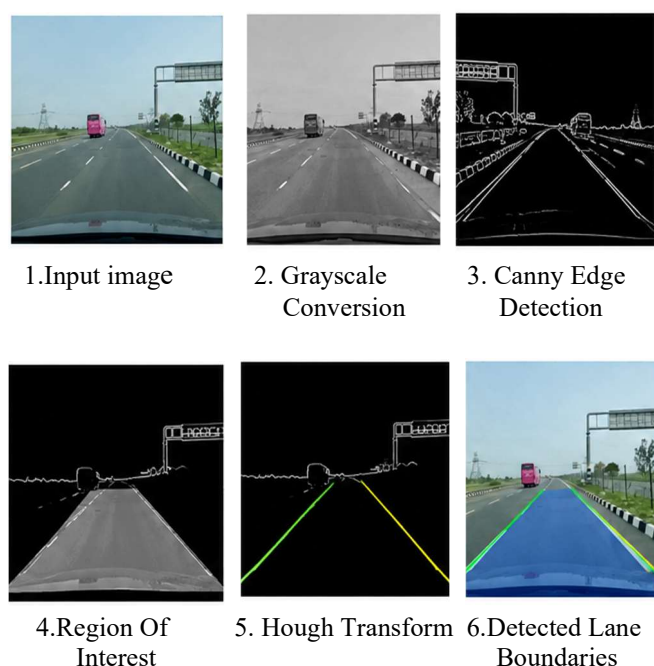


Fig. 2. Steps involved in traditional lane detection using image-processing techniques.

IV. AI-BASED AND DEEP LEARNING LANE DETECTION TECHNIQUES

AI-based lane detection uses Artificial Intelligence (AI) and Deep Learning to detect lane markings from road images or videos. These methods learn useful features from training images and may provide better performance in complex road conditions, depending on the model architecture and training data. Common methods include CNN, YOLO, image segmentation, and transfer learning. The general process is shown in Fig. 3.

A. Input Road Image

The process starts with a road image captured by a camera mounted on the vehicle. The image contains the road, lane markings, vehicles, and other objects. This image is given as input to the AI-based lane detection system.

B. Image Preprocessing

The input image is prepared before it is given to the deep learning model. The image may be resized and normalized so that it can be processed properly by the model. Preprocessing helps the model work with the input image in a consistent way.

C. CNN Feature Extraction

A Convolutional Neural Network (CNN) is used to extract important features from the road image. The CNN learns features such as lane markings, road boundaries, shapes, and patterns from training images. These features are then used for further lane detection.

CNN-based models can learn features automatically, unlike traditional methods that depend on manually selected image-processing operations. CNN-based approaches have been used for lane detection in difficult road conditions. [1], [4]

D. YOLO-Based Detection

YOLO (You Only Look Once) is a fast deep learning method used for detection. In road applications, it can detect vehicles, pedestrians, and other objects. Specialized YOLO-based models, such as YOLOP, can perform lane detection along with other road-perception tasks.

For example, YOLOP can detect lanes, vehicles, and the drivable area of the road. YOLO-based lane and object detection has also been studied for Indian roads with conditions such as faded lane markings and heavy traffic. [2], [3]

E. Lane Segmentation

After feature extraction, image segmentation can be used to separate the lane or road area from other parts of the image. The model identifies the pixels that belong to the lane or road region.

This helps the system understand the shape and position of the lane. Segmentation can represent lane and road regions at the pixel level, making it useful for analyzing complex road scenes. Deep learning-based segmentation has been used for lane and road detection in the reviewed studies [3], [4].

F. Transfer Learning

Transfer learning uses a model that has already learned features from a large dataset and adapts it to a lane detection task. Instead of training the complete model from the beginning, the pre-trained model can be further trained using road and lane images.

This can reduce the training time and the amount of data required. It is useful when a large lane-specific dataset is not available.

G. Detected Lane Output

Finally, the AI model produces the detected lane boundaries or lane region as output. The detected lanes can be shown on the original road image using coloured lines or a highlighted road area. The final output helps the system understand the

position of the vehicle with respect to the lane. This information can be used in ADAS applications such as Lane Departure Warning and Lane Keeping Assistance.

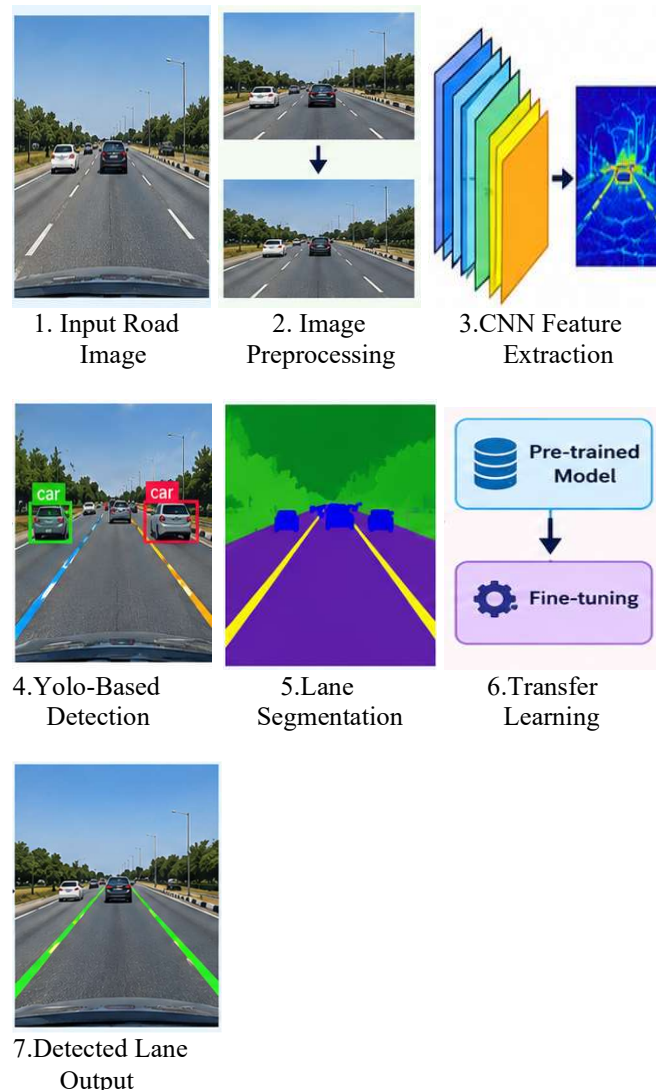


Fig. 3. Steps involved in AI-Based lane detection using deep learning techniques.

V. COMPARATIVE ANALYSIS

Traditional and AI-based lane detection methods have different advantages and limitations. Traditional methods are simple and fast, while AI-based methods can handle more complex road conditions.

Table I presents a qualitative comparison based on the characteristics and findings reported in the reviewed studies; the entries do not represent results from a common experimental evaluation.

Parameter	Traditional Method	AI-Based Method
Accuracy	Generally effective in simple road conditions.	May perform better in complex conditions, depending on the model and data.
Processing Speed	Generally fast	Depends on the model
Computational Power	Low	Usually higher
Training Required	No	Yes
Data Required	Low	Large amount of data
Faded Lane Markings	May struggle to detect faded lane markings.	May detect faded markings better when adequately trained.
Curved Roads	May struggle with complex curves.	Can learn curved lane patterns, depending on the model.
Weather Conditions	Can be affected by rain, fog, shadows, and glare.	May be more robust when trained on diverse weather conditions.
Implementation	Simple	More complex
Real-Time Use	Suitable	Suitable with optimized models

Table I. Comparison of Traditional and AI-Based Lane Detection Methods.

VI. EXPECTED RESULT

The comparative review is expected to show that traditional lane detection methods are simple, fast, and computationally efficient under clear road conditions but may struggle with faded lane markings, curved roads, and poor visibility.

AI-based techniques, such as CNN, YOLO, and image segmentation, may provide better adaptability to complex road conditions, as explored in the reviewed studies [1]–[4]. However, their performance depends on the model architecture, training data, and available computational resources.

Overall, the review is expected to highlight the importance of selecting suitable lane detection techniques for reliable, real-time ADAS applications, particularly under Indian road conditions.

VII. CONCLUSION

This paper reviewed traditional image-processing and AI-based techniques for road lane detection in Advanced Driver Assistance Systems (ADAS). Traditional methods are simple and computationally efficient but may face difficulties under challenging road conditions. AI-based techniques, including CNN, YOLO, and image segmentation, may provide better adaptability to complex road environments, depending on the model and training data. The comparative review highlights the importance of balancing detection performance, processing speed, and computational requirements. Future work should focus on evaluating these techniques using Indian road datasets to improve the reliability of lane detection under diverse traffic and environmental conditions.

REFERENCES

- [1] S. Kumari, P. Mamoria, and H. Kumar, “Robust-LaneNet: A Lightweight CNN Model for Autonomous Vehicle System in Adverse Visual Conditions,” in *2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, 2026.
- [2] C. Pimpalgaonkar, S. Shinde, and R. Sharma, “Lane and Object Detection using YOLO: Indian Roads Scenario,” *Journal of Image Processing and Intelligent Remote Sensing*, vol. 4, no. 4, pp. 23–29, 2024.
- [3] K. Kakade, S. Sawant, and P. D. Patil, “Robust and Real-Time Road Detection on Indian Roads using Deep Learning,” *International Journal of Advance Computational Engineering and Networking*, vol. 10, no. 9, pp. 7–12, 2022.
- [4] A. Mukhopadhyay, L. R. D. Murthy, I. Mukherjee, and P. Biswas, “A Hybrid Lane Detection Model for Wild Road Conditions,” *IEEE Transactions on Artificial Intelligence*, vol. 4, no. 6, pp. 1592–1601, 2023.