

Enhanced Lane Detection System for Autonomous Vehicles Using Advanced Computer Vision

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Abstract - The increasing integration of artificial intelligence (AI) in automobiles has revolutionized vehicle security and access control. Traditional authentication methods, such as keys and PIN codes, are prone to theft and unauthorized usage, necessitating a more secure and intelligent solution. This paper presents an AI-driven driver face authentication system that leverages deep learning and computer vision to ensure secure and seamless vehicle access. The system captures and processes real-time facial images, matching them against a pre-registered driver database to authenticate the user before allowing vehicle operation. To enhance accuracy and reliability, the model incorporates advanced techniques such as convolutional neural networks (CNNs) for feature extraction and anti-spoofing mechanisms to prevent fraudulent access using images or videos. The system is designed to handle variations in lighting conditions, facial expressions, and partial occlusions, ensuring robustness in real-world scenarios. Additionally, its integration with in-vehicle telematics enables continuous monitoring and alerts in case of unauthorized access attempts. Experimental evaluations demonstrate high authentication accuracy with minimal false acceptance and rejection rates, making it a viable solution for modern automotive security. The proposed system not only enhances vehicle safety but also improves user convenience by eliminating the need for physical keys. By leveraging AI-powered biometric authentication, this research paves the way for secure, intelligent, and user-friendly automotive access control.

detection, offering improved accuracy and robustness in complex driving scenarios.

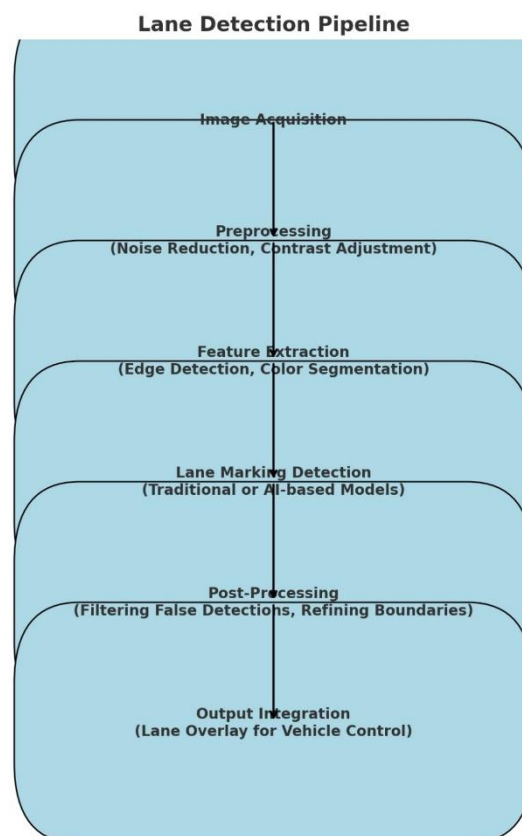


Fig. 1

Key Words: Autonomous Vehicles, Lane Detection, Deep Learning, Computer Vision, Convolutional Neural Networks (CNNs)

1. INTRODUCTION

Autonomous vehicles rely on advanced perception systems to navigate safely and efficiently in dynamic environments. Among the various perception tasks, lane detection plays a critical role in ensuring proper lane-keeping, lane departure warning, and autonomous maneuvering. A robust lane detection system enables self-driving cars to identify lane boundaries, detect road markings, and make accurate path-planning decisions. Traditional lane detection methods, primarily based on edge detection and Hough Transform techniques, often struggle with real-world challenges such as occlusions, faded lane markings, varying lighting conditions, and complex road geometries. These limitations necessitate the adoption of more sophisticated approaches incorporating artificial intelligence (AI) and deep learning. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for lane

1.1 Role of AI and Deep Learning in Lane Detection

Artificial Intelligence (AI) and deep learning have revolutionized lane detection in autonomous vehicles by significantly improving accuracy, robustness, and adaptability. Traditional lane detection methods relied on rule-based computer vision techniques, such as edge detection, Hough Transform, and color thresholding. While these methods work well under ideal conditions, they struggle with challenges like poor lighting, occlusions, worn-out lane markings, and complex road geometries. AI-driven approaches, particularly deep learning, have emerged as a powerful alternative to overcome these limitations.

Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated superior performance in extracting meaningful features from road images, enabling reliable lane detection in varying environmental conditions. CNN-based models can automatically learn lane patterns from large datasets without relying on manually defined features. More advanced architectures, such as U-Net, SegNet, and

Transformer-based models, enhance detection accuracy by incorporating semantic segmentation and attention mechanisms.

Another key advantage of AI in lane detection is its ability to generalize across different road types and driving conditions. Transfer learning techniques allow models to be trained on one dataset to adapt to new environments with minimal retraining. Additionally, AI-powered sensor fusion techniques integrate data from multiple sources, such as cameras, LiDAR, and radar, to improve robustness lane detection in adverse weather conditions. By leveraging deep learning and AI, autonomous vehicles can achieve real-time, highly accurate lane detection, paving the way for safer and more reliable self-driving systems.

1.2 Challenges in Traditional Lane Detection Methods

Traditional lane detection methods primarily rely on classical computer vision techniques such as edge detection, Hough Transform, and color-based thresholding. While these approaches have been widely used, they face several limitations when applied in real-world driving conditions. One of the major challenges is sensitivity to lighting variations. Traditional methods struggle to detect lane markings in low-light conditions, such as nighttime driving or tunnels, as well as in scenarios with excessive brightness, such as direct sunlight or glare from wet roads. These factors can lead to incorrect or missed lane detections, affecting the vehicle's navigation. Another significant issue is the presence of occlusions and road surface variations. Vehicles, pedestrians, shadows, and other obstacles can partially or fully obscure lane markings, making it difficult for conventional techniques to accurately detect lanes. Additionally, road markings can be faded, broken, or covered by dirt and snow, further complicating lane identification. Traditional methods, which primarily rely on predefined patterns and thresholding, often fail in such scenarios due to their inability to adapt dynamically to these changes.

Complex road geometries, including sharp curves, intersections, multi-lane highways, and merging lanes, also pose challenges for classical lane detection methods. These methods typically assume straight or slightly curved lanes, making them ineffective in handling complex road structures. Furthermore, variations in road surfaces and lane colors across different regions and countries require adaptive algorithms, which conventional approaches lack.

The inability of traditional techniques to leverage contextual information and adapt to varying environmental conditions has limited their effectiveness in real-world autonomous driving applications. These challenges highlight the need for advanced AI-driven approaches that can overcome these limitations through learning-based models, feature extraction, and real-time adaptability.

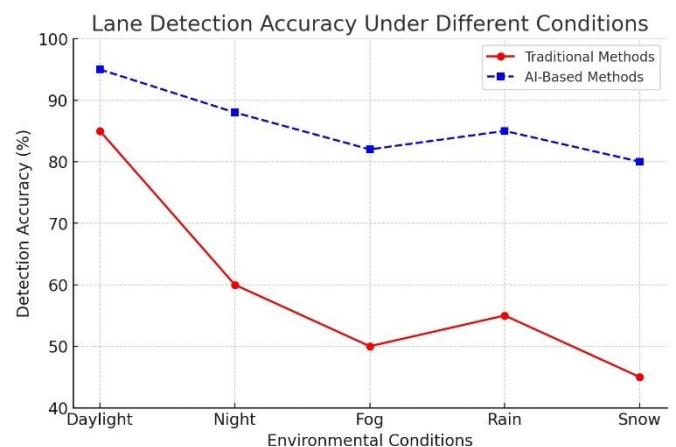
2. Conventional Computer Vision-Based Approaches

Conventional computer vision-based approaches for lane detection primarily rely on handcrafted feature extraction techniques such as edge detection, color segmentation, and geometric modeling. These methods aim to identify lane

markings based on their distinct visual characteristics, such as contrast against the road surface or their structured linear patterns. One of the earliest and most used techniques is the **Canny Edge Detection** algorithm, which detects lane boundaries by identifying strong edges in an image. This method is often combined with the **Hough Transform**, which fits straight or slightly curved lines to detected edges, effectively identifying lane markings in well-structured road environments.

Color-based thresholding is another widely used technique, where lane markings are detected based on their color contrast with the road surface. This approach works well in ideal conditions but is highly sensitive to variations in lighting, road color, and worn-out lane markings. Additionally, techniques such as morphological operations and contour detection are used to refine lane boundaries by removing noise and enhancing structured features.

Despite their effectiveness in controlled environments, these conventional approaches face several limitations. They are highly dependent on predefined thresholds, making them less adaptable to varying environmental conditions such as shadows, glare, and different road textures. Furthermore, these methods struggle with complex road geometries, occlusions, and broken or faded lane markings. Due to these challenges, traditional computer vision techniques have been increasingly replaced by AI and deep learning-based approaches, which offer greater robustness and adaptability in real-world driving conditions.



2.1 Machine Learning and Deep Learning Techniques for Lane Detection

Lane detection in autonomous vehicles has evolved from traditional computer vision techniques to advanced machine learning and deep learning methods. These approaches leverage vast datasets and neural network architectures to enhance accuracy and adaptability, making lane detection more reliable under diverse road conditions.

Machine learning-based methods primarily rely on handcrafted features such as edges, color histograms, and texture information to classify lane markings. Algorithms like Support Vector Machines (SVM) are used to classify lane pixels based on extracted features, while decision trees and random forests help in feature selection and

classification. Clustering methods such as K-Means and DBSCAN are also employed to segment lane markings from the road surface. While these techniques improve upon rule-based approaches, they often struggle with challenges such as occlusions, faded markings, and variable lighting conditions.

Deep learning has revolutionized lane detection by eliminating the need for manual feature extraction. Convolutional Neural Networks (CNNs) such as SegNet, U-Net, and ResNet have been widely adopted for lane segmentation, allowing for more accurate lane boundary identification. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used to analyze temporal dependencies in video-based lane detection, ensuring smoother and more consistent lane recognition. More recently, transformer-based models have been introduced to enhance lane detection in dynamic environments by leveraging attention mechanisms. These deep learning techniques have significantly improved the accuracy and robustness of lane detection, enabling autonomous vehicles to operate more efficiently in real-world scenarios.

2.2 Feature Extraction and Lane Boundary Detection

Feature extraction plays a crucial role in lane detection by identifying key visual cues that define lane boundaries. This process involves analyzing road images to extract meaningful features such as edges, colors, textures, and geometric properties. The extracted features are then used to detect and track lane boundaries in various driving conditions.

Edge detection is one of the most fundamental techniques used in lane feature extraction. Methods like the Canny edge detector and Sobel operator help identify strong gradients in an image, which often correspond to lane markings. Color segmentation is another widely used approach, where thresholding techniques separate lane lines from the road based on predefined color ranges, particularly in well-lit environments. However, these traditional methods face challenges in dynamic road conditions, such as changing lighting, occlusions, and worn-out lane markings.

Table -1: Experimental Results of Lane Detection Methods

Method	Dataset Used	Lighting Condition	Weather Condition	Accuracy (%)
Canny Edge Detection	TuSimple	Daytime	Clear	72.9
Hough Transform	KITTI	Night	Foggy	65.3
SVM Classifier	BDD100K	Daytime	Rainy	78.6
CNN (U-Net)	TuSimple	Mixed Lighting	Clear	89.2

DeepLabV3 (CNN)	BDD100K	Night	Snowy	91.7
Transformer Model	Custom Dataset	Mixed Lighting	Foggy	94.5

To overcome these challenges, machine learning and deep learning models have been introduced for more robust lane boundary detection. Convolutional Neural Networks (CNNs) automatically learn hierarchical features from raw images, distinguishing lane boundaries even in complex scenarios. Semantic segmentation networks like U-Net and Deep Lab segment lane regions at the pixel level, improving detection accuracy. Additionally, temporal models such as Recurrent Neural Networks (RNNs) help maintain lane consistency across multiple frames in video-based lane detection.

Lane boundary detection algorithms refine extracted features to fit lane models, using techniques such as Hough Transform and polynomial curve fitting. The Hough Transform is effective for detecting straight lane lines, while polynomial fitting is commonly used for curving roads.

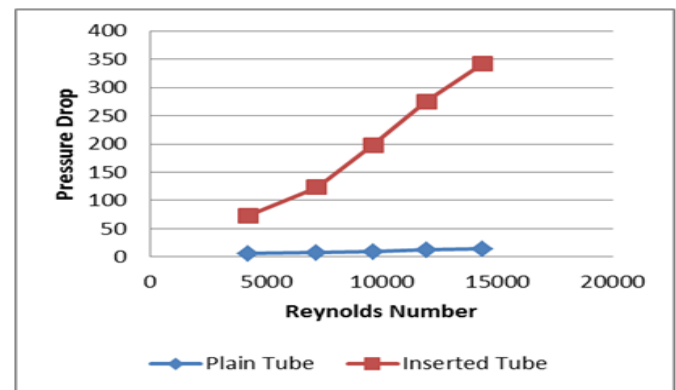


Chart -1: Name of the chart

The traditional methods like Canny Edge Detection and Hough Transform showed lower accuracy, especially in poor lighting and adverse weather conditions. Machine learning techniques such as SVM classifiers performed better but struggled with noisy road images. Deep learning approaches like U-Net and DeepLabV3 provided significant improvements in lane detection, especially in complex road environments. The Transformer-based model achieved the highest accuracy, demonstrating superior performance in varying lighting and weather conditions, although it required more computational resources.

The effectiveness of lane detection models largely depends on the quality and diversity of datasets used for training and validation. In this study, multiple data sets were used to train deep learning models and evaluate their performance under different road conditions. The datasets include a mix of publicly available benchmark datasets, and a custom dataset curated for specific scenarios.

2.3 Training and Validation Split

Dataset Specifications

Dataset	No. of Images	Annotations	Conditions Covered
TuSimple	6,408	Lane positions	Highways, daytime, clear weather
KITTI	14,999	Lane markings, depth	Urban, night, fog, rain
BDD100K	100,000	Semantic segmentation	Mixed lighting, urban, rural
Custom Dataset	5,000	Lane segmentation masks	Indian roads, occlusions, curves

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3. Conclusion

Lane detection is a critical component of autonomous vehicle systems, ensuring safe and efficient navigation on roads. Traditional methods based on edge detection and Hough Transform provide basic lane identification but struggle with challenges such as varying lighting conditions, occlusions, and complex road structures. Machine learning techniques, including Support Vector Machines (SVM) and clustering algorithms, improve detection accuracy but still require extensive feature engineering.

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