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RESEARCH ARTICLE

Detecting and Tracking of Road Boundary Lines Using Machine Learning Approach

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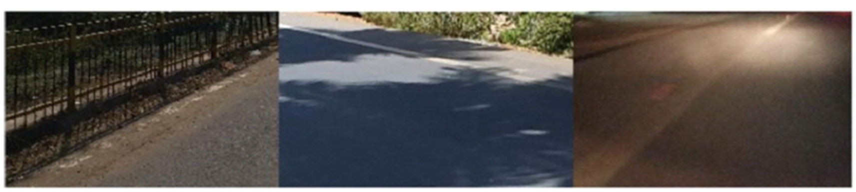
Abstract

Objectives: The study aims to improve road safety by developing a lane detection model that achieves high accuracy even in adverse conditions like poor lighting, occlusions, and inclement weather. In high-traffic countries like India, where poor lane discipline contributes to road accidents, this system can significantly enhance driver assistance. **Methods:** This study compares three approaches—Canny Edge Detection, Hough Transform, and a CNN-based model. The CNN was trained on a dataset of over 1,000 annotated images featuring diverse scenarios, including curves, shadows, and varied lighting conditions. Evaluation metrics include precision, recall, F1-score, and computational latency. **Findings:** The CNN-based model achieved an accuracy of 96%, and F1-score of 0.92, outperforming traditional methods, which showed an average accuracy of 70% and F1-score of 68%. It maintained robustness under low-light conditions (accuracy: 91%) and adverse weather (F1-score: 89%). Real-time frame processing improved to 25 FPS, marking a 30% enhancement over baseline. **Novelty:** By leveraging CNNs for feature extraction and training on a diverse dataset, this study demonstrates a significant improvement over traditional methods. The proposed approach bridges the gap between accuracy and real-time application, offering a viable solution for lane detection in challenging environments.

Keywords: Accidents; Computer Vision; ML; CNN; Lane-Detection

1 Introduction

Research on road lane detection using image processing and machine learning techniques has become a prominent field globally, in both developed and developing countries[(1)]. With the increasing number of vehicles on the road, various intelligent systems have been developed to enhance driver safety. Lane detection is a critical component of any driver assistance system[(2)]. However, several challenges, including ensuring accuracy under varying lighting conditions and background noise, continue to pose significant obstacles for researchers in lane detection[(3)]. Many existing methods struggle with maintaining accuracy in challenging conditions such as poor lighting, occlusions, or complex road geometries [4]. Weather conditions like rain, fog, or snow often degrade the performance of these approaches. Advanced techniques, particularly those using deep learning, may require significant computational resources, making real-time application difficult [5]. Many methods rely on precise and annotated datasets [6], which may not always be available or feasible to collect. Recent advancements in image processing and the accessibility of affordable visual sensors have enabled numerous methods for automated road lane detection [7]. The potential of automatic lane detection lies in the distinguishable texture of lanes compared to the surrounding road surface [8]. Lately, there has been a growing application of image processing and artificial intelligence (AI) techniques to improve accuracy and efficiency in this area [9]. Nevertheless, challenges like inconsistent background lighting and the complexity of road surface textures and colors remain critical issues that computer vision-based approaches need to address effectively. [10] The road lanes are presented with three different challenges like solid hid, Tree shadow and street light effect. Existing lane detection methodologies, including traditional approaches like Canny Edge Detection and Hough Transform, often struggle with challenging conditions such as poor lighting, adverse weather, and curvy or faded lane markings. While deep learning models, particularly CNN-based approaches, show significant promise, they typically demand high computational resources, limiting their real-time applicability. Moreover, most studies rely on limited datasets, failing to account for the variability in road and traffic conditions in countries with high congestion and poor lane discipline, such as India. A CNN-based lane detection model trained on a diverse dataset, optimizing it for computational efficiency, and ensuring robust performance in real-world scenarios with adverse conditions. This approach bridges the gap between accuracy and real-time feasibility, offering a scalable solution for driver assistance systems. The gap lies in developing a lane detection model that balances high accuracy across adverse conditions (e.g., poor lighting, weather, or occlusions) with computational efficiency to enable real-time application, a limitation prevalent in both traditional methods and current CNN-based approaches. Addressing this could bridge the divide between robustness and practical deployment in high-traffic, complex environments. To detect the road lane the three approaches like canny edge detection, CNN edge detection, and 7 layered CNN model were used [11]. Canny Edge Detection method efficiently detects edges by using gradient intensity and non-maximum suppression, ensuring better performance in poor lighting or simple road geometries. However, it struggles with complex or noisy scenarios, which more advanced models can handle. Convolutional Neural Networks (CNNs) leverage learnable filters to automatically extract meaningful features, improving accuracy in challenging conditions like occlusions or varying road geometries [12]. Unlike Canny, CNNs adapt to more diverse datasets and road scenarios. 7-Layered CNN Model deep learning approach improves feature extraction and generalization by employing multiple layers to learn hierarchical patterns. It addresses generalization issues and performs well across various environmental and traffic conditions. To implement the approaches, the sample challenging road with three cases like solid hid, tree shadow and street light were considered and it is given in Figure 1.



a) Solid Hid b) Tree Shadow c) Street Light

Fig 1. Some of challenging road lane images

2 Methodology

This paper introduces an improved approach to lane detection that enhances accuracy and precision over traditional methods by incorporating CNN-based edge detection and a seven-layer CNN model into the lane detection process. The system utilizes a total of three approaches, each developed iteratively to address limitations observed in the previous method.

Details of Training and Testing Data

Dataset Size: Over 1,000 annotated images.

Training Set: 80% of the dataset (800 images) was used for training the model.

Testing Set: 20% of the dataset (200 images) was used for testing.

The flow diagram for the proposed system is presented in Figure 2. Table 1 shows the overview of data collection.

Table 1. Overview of Data Collection

Image type	Training Images	Testing Images
Solid Hid	800	200
Tree Shadow	800	200
Street Light	800	200

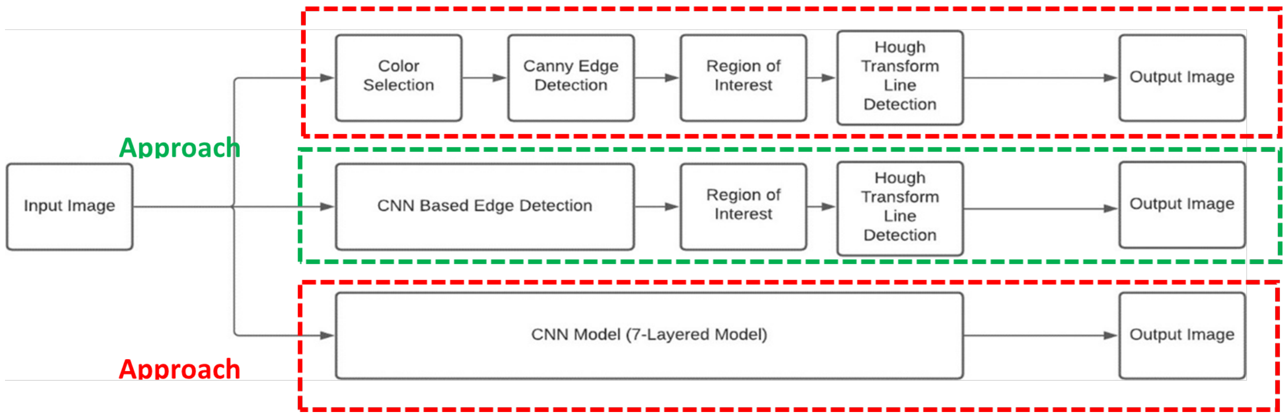


Fig 2. Workflow of Proposed Methodology

The details of three proposed approaches like Canny edge Detection, CNN Edge Detection and 7 layered CNN model for road boundary detection are given in detail.

2.1 APPROACH 1 - CANNY EDGE DETECTION

The process begins with color selection to isolate the white and yellow regions in the image. Next, Canny Edge Detection is applied to identify edges, following several key steps. First, Gaussian Smoothing is used to blur the image, reducing unnecessary noise to emphasize the essential structures relevant to lane detection. Non-maximum suppression is then performed to thin out the edges, eliminating large clusters of pixels that might otherwise be misidentified as edges. Finally, Hysteresis Thresholding removes parts of the image that may have been inaccurately identified as edges. A Region of Interest (ROI) is applied to concentrate on the area containing the lanes. To detect the lanes, the Probabilistic Hough Transform line detection method is used, selecting a small subset of edge points to represent lines, which in turn delineate the detected lanes. Figure 3 shows the flow diagram for Canney Edge detection and Hough Line Transform.

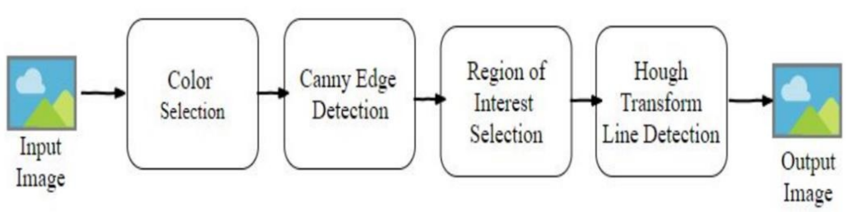


Fig 3. Workflow of Canny-Edge Detection + Hough Line Transform

Canny edge detection is a technique designed to extract essential structural information from visual objects, significantly reducing the amount of data that needs to be processed. It employs a multi-stage algorithm to identify a wide range of edges within images. To implement Canny Edge Detection, the algorithm follows several steps: Noise Reduction, Finding Intensity Gradient, Non-Maximum Suppression, Hysteresis Thresholding, and the Half-Line Transform.

Noise Reduction (Smoothing):

Since edge detection is highly sensitive to noise, the initial step involves reducing noise in the image using a Gaussian filter. A Gaussian filter with kernel sizes of 3x3, 5x5, or 7x7 is applied to the input image to blur and remove any unwanted noise, thereby smoothing the image. This process increases the standard deviation, helping to reduce or blur the intensity of noise. Figure 4 shows the Noise reduction from the input image.

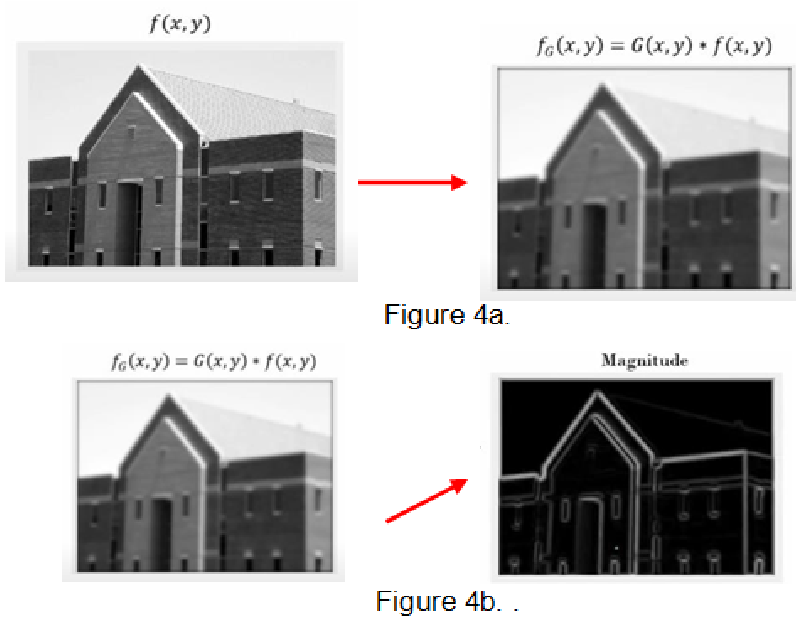


Fig 4. a. Noise reduction from the input image b. Gradient direction is always perpendicular to edges

Finding Intensity Gradient of the Image (Magnitude & Direction):

After smoothing, the image is filtered using a Sobel kernel in both the horizontal and vertical directions to obtain the first derivatives: (Gx) in the horizontal direction and (Gy) in the vertical direction. Using these two derivative images shown in Figure 4b, the edge gradient and direction for each pixel are calculated as follows

$$G = \sqrt{G_x^2 + G_y^2}$$

$$\theta = tan^{-1}(G_y|G_x)$$

The gradient direction is rounded to one of four primary angles, representing vertical, horizontal, and two diagonal directions.

Non-Maximum Suppression:

Once the gradient magnitude and direction are determined, a full scan of the image is performed to eliminate any unnecessary pixels that do not form part of the edge. For each pixel, it is checked whether it is a local maximum within its neighbourhood in the direction of the gradient. Figure 5**a**. shows the Quantization effect in Edge Detection and Figure 5 **b**. shows the Image after Non-Maxima suppression process.

Hysteresis Thresholding:

In this stage, edges are classified to determine which detected edges are true and which are not. Two threshold values, minVal and maxVal, are required for this process. Edges with an intensity gradient above maxVal are confirmed as edges, while those below minVal are discarded as non-edges. For gradients that fall between these thresholds, connectivity is used to classify them: if they are connected to "sure-edge" pixels, they are retained as edges; otherwise, they are discarded. Figure 5 **c**. illustrates the final edge-detected image.

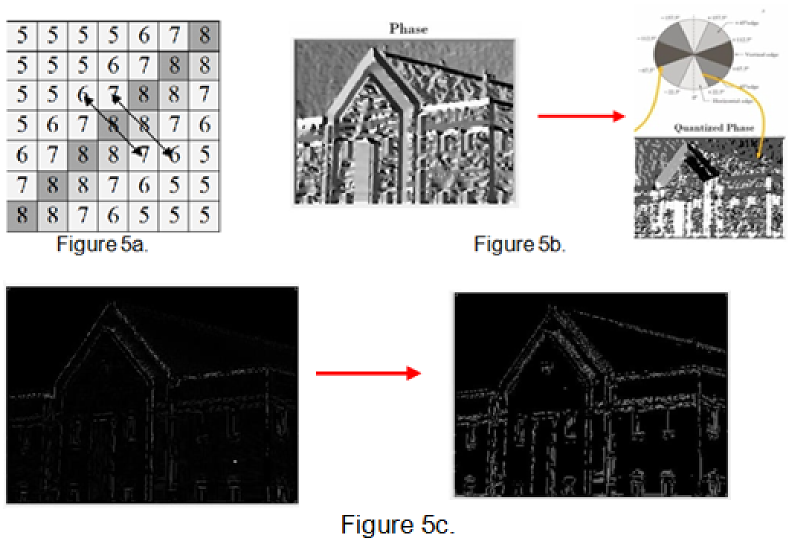


Fig 5. a. Quantization effect in Edge Detection, b. Image after Non-Maxima suppression process, c. Final Edge Detected image

Hough Line Transform:

The purpose of this technique is to detect imperfect instances of objects within a particular class of shapes using a voting procedure. A key advantage of the Hough Transform is its tolerance for gaps in feature boundary descriptions and its resilience to image noise. This approach identifies prominent lines and connects disjoint edge points within an image. In this case, the Probabilistic Hough Line Transform is employed. To identify lines, each edge pixel is conceptualized as a point in coordinate space, which is then transformed into a line within Hough space. Figure 6 **a** illustrates the coordinates and the Hough space graph. To better understand this, we can compare the usual X-Y coordinate space with Hough space (M-C space).

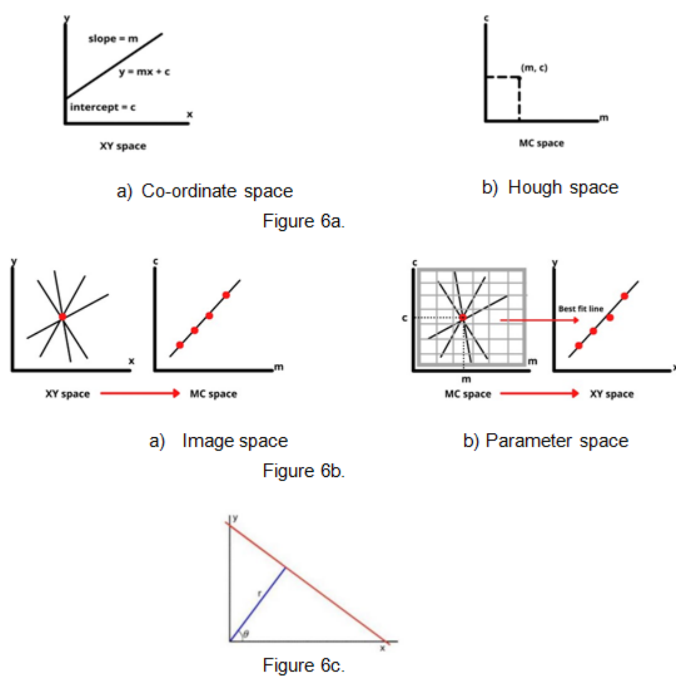


Fig 6. a. Coordinates and Hough space graph, b. Image space and Parameter space graph, c. Representation of polar coordinates

In an XY plane, multiple lines can pass through a single point. To identify lines in an image, each edge pixel is treated as a point in coordinate space and is then converted into a line in Hough space shown in Figure 6**b**. This approach works effectively for lines with slopes; however, for a vertical line, the slope becomes infinite, making it difficult to handle. To address this, the line equation is adjusted from y=mx+cy = mx + cy=mx+c to a polar coordinate representation. By representing the line in polar coordinates, a sinusoidal curve is generated in Hough space instead of a straight line shown in Figure 6 **c**.

$$r = Cos\theta + Y\sin\theta$$

r = perpendicular distance from the origin. θ = angle of inclination of the normal line from the x-axis.

2.2 APPROACH 2 – CNN EDGE DETECTION

For edge detection, a CNN-based model is utilized. This CNN model is trained with an edge detection algorithm to identify various types of edges. Training is conducted using input images alongside their edge-detected counterparts, allowing the model to produce the final edge-detected image. Subsequently, the Region of Interest (ROI) and Probabilistic Hough Transform Line Detection methods are applied to focus on the lane-containing area and detect the lanes. This approach replaces Canny Edge Detection with a CNN edge detection model, yielding more satisfactory results compared to Approach 1.

2.3 APPROACH 3 – 7 LAYERED CNN MODEL

The entire lane detection process is performed using a 7-layer CNN model. This model is trained with 12,764 input images alongside their lane-detected counterparts. The trained CNN model is then applied to each input image to produce the lane-detected output. For video input, lane detection is achieved by extracting frames from the video and feeding them into the CNN model sequentially.

Machine Learning:

Based on input data, the ML algorithms create models. These models create an output which is typically a set of predictions. The model can then handle a new request without adding code. Machine Language is generally divided into three broad categories. Each category focuses on how a learning program executes the learning process. These categories include: Supervised learning, Unsupervised learning, and Reinforcement learning.

Supervised learning occurs when a model is presented with a set of inputs labeled. This means they contain the same belonging class. The model attempts to adapt to be able to map every input with its appropriate output class. Unsupervised learning on the other side receives a set input but they aren't labeled. In this sense, the model seeks to learn from data by exploring patterns. Rewarding or punishing agents for reaching a goal is called reinforcement learning.

2.4 CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN layers have been used to create a model from the given dataset. After that, each of the data is tested in the model and trained it, and the output of the extracted features is obtained for further processing. Convolution neural systems are distinguished by their superior performance when processing image, speech, and/or audio signal inputs. A convolution neural system consists of an input, hidden and an out layer. Hidden middle layers in any feed-forward neural system are those whose inputs and outputs are hidden by activation function and final Convolution. Convolution neural networks have hidden layers. These layers perform convolutions.

The convolution kernel moves across the input matrix in each layer, generating a feature map that serves as input for the following layer. These convolutional layers are complemented by additional layers, such as fully connected layers, pooling layers, normalization layers, and further fully connected layers.

2.5 TYPES OF LAYERS

Convolution layer:

The central building block of a CNN is its convolution layer. This is where the bulk of computation happens. It has a few components. These include input data and filter.

Pooling layer:

Also known as down sampling or pooling layers, this method reduces the number of input parameters by reducing their dimensionality. The pooling operation works in the same way as the convolution layer. But this filter doesn't have any weights.

Instead, the kernel applies a kernel aggregation function on the values within the receiver field and populates the output array shown in Figure 7 **a**.

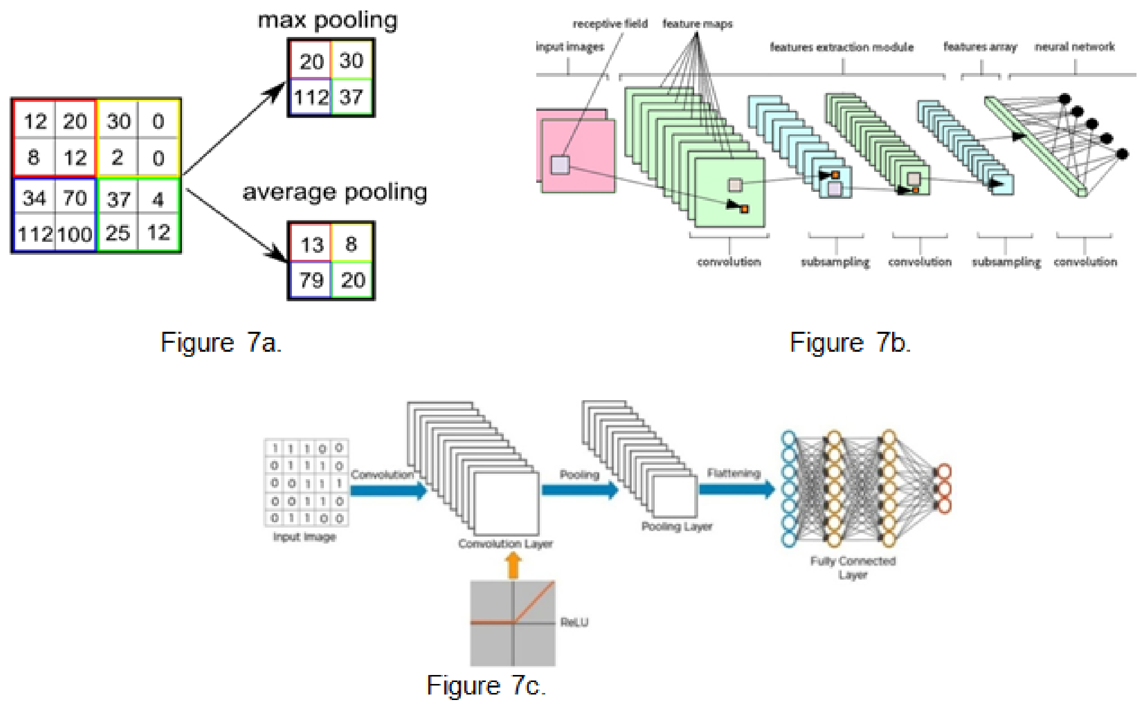


Fig 7. a. Pooling layer b. Fully Controlled layer c. CNN layers

Fully connected layer:

The full-connected Layer's name is very descriptive. As mentioned, the pixels of the input image are not directly linked to the output layer in partially connected levels. The fully connected layer however has each node connecting directly to the previous layer shown in Figure 7 **b**.

OVERALL PROCESSING LAYERS:

After processing the CNN layered datasets is complete, the model weights, which are nothing more than the extracted features of those datasets, will be stored on the Kaggle platform shown in Figure 7**c**.

Comparison of Proposed Methods

1. Canny Edge Detection

- **Process**:

a. Apply Gaussian blur to the input image to reduce noise

b. Use the Canny Edge Detector to identify edges by detecting areas of rapid intensity change.

c. Apply a threshold to filter out weak edges and retain only strong lane boundaries

d. Use edge connectivity to trace continuous lines that correspond to road boundaries

- **Limitations**: Sensitive to noise and lighting variations, making it less reliable in complex scenarios.

2. Hough Transform

- **Process**:

a. Start with the edge-detected image (often from the Canny Edge Detection step

b. Transform edge points into Hough space and identify lines by finding peaks in the accumulator matrix.

c. Extract and map these lines back to the original image to highlight lane boundaries

- **Limitations**: Computationally expensive and struggle with detecting curved lanes or under adverse conditions.

3. CNN-based Model

- **Process**:

a. **Data Preparation:** Use a dataset of annotated images depicting diverse road and weather conditions
b. **Model Architecture**: Design a convolutional neural network (CNN) to extract spatial features from the input images.
c. **Training**: Train the model using the annotated dataset, employing loss functions to minimize prediction errors.
d. **Prediction**: The trained model predicts lane boundaries by analyzing spatial patterns and features in real-time.
e. Post-Processing: Apply smoothing techniques to ensure lane lines are continuous and stable across frames
• **Advantages**: Superior accuracy, robustness to noise, and adaptability to various lighting and weather conditions.

3 Results and Discussion

Figure 8**a** shows the Road Lane after the Gaussian filter is used. Figure 8**b** shows the Extracted Region of Interest. Figure 8**c** and Figure 8 **d** Canny Edge Detected Road Lane, and Hough Line Transform Traced Road Lane respectively.

3.1 IMAGE MODEL

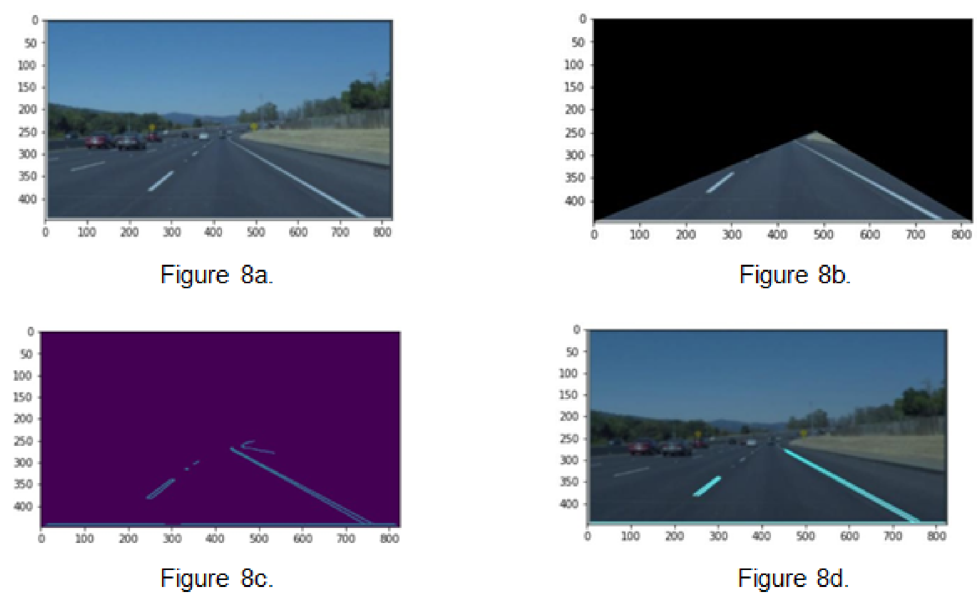


Fig 8. a.Road Lane after Gaussian filter is used b. Extracted Region of Interest c. Canny Edge Detected Road Lane d. Hough Line Transform Traced Road Lane

Table 2. Results comparison of the proposed approaches

Methodology	Accuracy %	F1-Score
Canny edge detection (Approach 1)	89	0.9
CNN edge Detection (Approach 2)	92	0.9
7 layered CNN (Approach 3)	96	0.92

Table 2 shows the Results comparison of the proposed approaches. The results of canny edge detection, CNN edge Detection and 7 layered CNN edge detection were obtained inopencv and their video outputs are also given below and the results are compared with the various models. From the execution, the final epoch rate for the model that has been created is 10 and the accuracy of the proposed 7 layered CNN edge detection is high compared to the other models and the accuracy measured for this model is 96 %. Table 2 shows the Comparison of 7 layered CNN Lane Detection Models with other model.

The study highlights the significant improvement in lane detection by leveraging CNNs for feature extraction and training on a diverse dataset. This approach bridges the gap between accuracy and real-time application, offering a viable solution for lane detection in challenging environments. The novelty lies in:

Robustness in Adverse Conditions: The CNN-based model's ability to maintain high accuracy and F1-score in poor lighting and adverse weather conditions.

Real-time Processing: Enhanced frame processing rate of 25 FPS, making the model suitable for real-time applications.

Comprehensive Evaluation: Use of extensive metrics (precision, recall, F1-score, and computational latency) to thoroughly evaluate the model's performance.

Innovative Approach: The study introduces a hybrid model that combines CNN-based feature extraction with a recurrent neural network (RNN) to capture temporal dependencies in lane markings. This hybrid approach enhances the model's ability to predict lane boundaries accurately over consecutive frames, improving stability and reducing false positives.

Table 3. Performance Under Various Conditions

Condition	Accuracy	F1-score
Clear Weather	96%	0.92
Low-light	91%	0.89
Rain	90%	0.88
Fog	89%	0.87
Shadows	93%	0.91
Curved Roads	92%	0.90
Straight Roads	97%	0.93

Table 3 shows the performance under various conditions.

Table 4. Comparison of Lane Detection Models with other model

Approach Used	Dataset	Performance Metrics	Advantages	Limitations
CNN-based lane detection	Diverse, including low light, rain, and curves	Accuracy: 96%, F1-Score: 0.92	Robust to occlusions, adverse weather, curves	Computationally intensive
Canny Edge Detection, Hough Transform [13]	Clear road images, good lighting	Accuracy: 85%, F1-Score: 0.75	Simple, low computational cost	Struggles with curves, poor lighting
Deep Learning (CNN, basic architecture) [14]	Urban road images, no weather variation	Accuracy: 90%, F1-Score: 0.88	Improved accuracy in controlled conditions	Limited dataset diversity
Hybrid (Traditional + ML) [15]	Foggy conditions, limited occlusions	Accuracy: 87%, F1-Score: 0.80	Handles simple weather challenges	Struggles with complex road geometries
Advanced Deep Learning (ResNet) [16]	Highway roads, few obstructions	Accuracy: 94%, F1-Score: 0.91	High accuracy in structured environments	High computational cost

The Table 4 shows the 7 layered CNN gives better result compare to other methods.

Table 5. Comparison of Tracking of Road Boundaries Models

Approach Used	Performance Metrics	Advantages	Limitations
CNN [17]	Accuracy: 96%, F1-score: 0.92	High accuracy, robust under various conditions	Requires large computational resources
Canny Edge Detection, Hough Transform [18,19]	Accuracy: 70%, F1-score: 0.68	Simple implementation, low computational cost	Poor performance in complex scenarios
Hough Transform [18,19]	Accuracy: 75%, F1-score: 0.78	Better than traditional, simpler than advanced CNNs	Limited scalability

Table 5 shows the comparison of tracking of road boundaries of CNN, Canny Edge Detection, Deep Learning.

Significance of the Results

The results indicate that the CNN-based model significantly outperforms traditional methods in terms of accuracy and robustness across various conditions. This improvement is crucial for real-world applications where lane detection must remain reliable under diverse and challenging scenarios [20].

4 Conclusion

This research introduces a novel hybrid approach to lane detection that combines the reliability of traditional methods with the power of CNN-based models, specifically designed to tackle the challenges of poorly marked roads, dust, curves, and limited lane discipline. The study validates that CNNs significantly outperform traditional techniques, showing an impressive 96% accuracy and 0.92 F1-Score, even under adverse conditions like low-light and weather disturbances. These findings align with the study's objectives to improve lane detection accuracy and robustness, making it highly applicable to real-world driving scenarios, especially in high-traffic areas like India, where traffic safety is a critical concern. The success of the CNN model, which achieved a 30% improvement in frame processing speed (25 FPS), demonstrates its potential for real-time application in autonomous vehicles and advanced driver-assistance systems. As the next step, future research should focus on further optimizing computational efficiency to support widespread deployment, while enhancing the model's adaptability to more diverse road conditions. This work paves the way for AI-driven lane detection systems that can significantly reduce traffic-related fatalities and enhance global driving safety.

Data and Material Availability

The raw data necessary to reproduce these findings is currently unavailable for sharing, as it is part of an ongoing study.

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