International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Lane Detection for Self-Driving Cars

Asst. Prof. M.N.V.Viswanadh M.Tech[1], Prof. Dr. Bomma Rama Krishna Ph.D[2], Naga Venkata Raviteja Ungarala[3], Manimela Anakammarao[4], Manne Lokesh Satya Tejas[5], Pothumanchili Siva Mukesh[6], Kondaveti Reshi Charan[7]

[1]*Assistant Professor, Artificial Intelligence and Machine Learning & Swarnandhra College of Engg. and Technology*
[2]*Professor, Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*
[3]*Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*
[4]*Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*
[5]*Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*
[6]*Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*
[7]*Artificial Intelligence and Machine Learning & Swarnandhra College of Engineering and Technology*

---***---

Abstract - The project focuses on developing a real-time vehicle detection and lane analysis system using computer vision techniques. The system is designed to process video inputs, detect vehicles, analyze lane curvature, and provide safety suggestions to drivers. The application leverages **YOLO (You Only Look Once)** for vehicle detection, optical flow for speed estimation, and Hough Transform for lane detection. The system is implemented as a Flask-based web application, allowing users to upload video files, process them, and view the results with overlays indicating vehicle distances, lane status, and safety suggestions. The project aims to enhance road safety by providing real-time feedback to drivers about their surroundings.

Keywords: Real-time Vehicle Detection, Lane Detection, YOLO, Optical Flow, Hough Transform, Road Safety, Computer Vision, Video Processing, Lane Curvature Analysis, ADAS

1. INTRODUCTION

Road safety remains a critical global concern with millions of accidents occurring annually due to human error, adverse road conditions, and lack of real-time situational awareness. According to the World Health Organization, road traffic injuries are the leading cause of death among individuals aged 5-29 years [1]. Advanced Driver Assistance Systems (ADAS) have emerged as promising solutions to mitigate these risks by providing drivers with enhanced awareness of their surroundings.

In this paper, we present a real-time vehicle detection and lane analysis system that processes video inputs to detect vehicles, analyze lane curvature, estimate vehicle speed, and provide safety suggestions. Our system integrates state-of-the-art computer vision techniques into a user-friendly web application, addressing key challenges in existing ADAS technologies.

1.1 Problem Statement

Despite significant advancements in ADAS technologies, current systems often struggle with accuracy, efficiency, and adaptability across varying road conditions. The primary challenges include:

- Processing video frames in real-time with minimal latency
- Accurately detecting vehicles and lane markings in complex environments
- Reliably estimating vehicle speed and distance
- Providing timely, actionable safety suggestions to drivers

Our research aims to address these challenges through an integrated approach combining multiple computer vision techniques.

1.2 Objectives

The primary objectives of this research are:

- Develop a system capable of detecting vehicles in real-time using YOLO
- Implement lane detection and curvature analysis using Hough Transform
- Estimate vehicle speed using optical flow techniques
- Generate contextual safety suggestions based on vehicle proximity and lane status
- Create an accessible web-based interface for video upload, processing, and result visualization

1.3 Contributions

This paper makes the following key contributions:

- Integration of YOLO for efficient and accurate vehicle detection
- Implementation of Hough Transform for robust lane detection and curvature analysis
- Development of a real-time speed estimation algorithm using optical flow
- Creation of an intelligent safety suggestion system based on environmental analysis

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

2. LITERATURE REVIEW

2.1 Vehicle Detection Technologies

YOLO represents the state-of-the-art in object detection, dividing input images into grid cells and simultaneously predicting bounding boxes and class probabilities [2]. While YOLO offers exceptional speed and accuracy for real-time applications, it can struggle with small or occluded objects. Alternative approaches include Faster R-CNN and SSD (Single Shot MultiBox Detector), each with their own advantages and limitations [3].

Commercial systems like Tesla's Autopilot combine cameras, radar, and ultrasonic sensors to achieve high reliability in vehicle detection, though at significant cost and complexity [4]. Mobileye's technology demonstrates the effectiveness of computer vision for collision avoidance and traffic sign recognition, though its proprietary nature limits customization options [5].

2.2 Lane Detection Techniques

The Hough Transform remains a cornerstone technique for lane detection, offering robustness to noise and the ability to detect fragmented lane markings [6]. However, it can struggle with curved roads and complex intersections. Recent research has explored deep learning approaches using convolutional neural networks (CNNs) to overcome these limitations, achieving improved performance in challenging conditions [7].

2.3 Motion and Speed Estimation

Optical flow techniques, particularly the Farneback method, provide dense motion vectors between consecutive frames, enabling speed estimation without specialized hardware [8]. These approaches face challenges in low-light conditions and with camera vibration. Alternative methods include feature tracking with Lucas-Kanade algorithm and deep learning-based approaches that directly estimate motion from image sequences [9].

2.4 Integrated ADAS Systems

Existing commercial ADAS solutions demonstrate the value of integrated systems that combine multiple detection and analysis capabilities. Academic research has shown promising results in controlled environments but often struggles with the complexities of real-world driving scenarios [10]. Our work aims to bridge this gap by creating an accessible, comprehensive system suitable for practical applications.

3. METHODOLOGY

3.1 System Architecture

The proposed system consists of two primary components: a user-facing frontend and a processing backend. Figure 1 illustrates the overall system architecture.

3.1.1 User Interface (Frontend)

The frontend provides an intuitive interface for video upload, progress tracking, and result visualization. Built using HTML, CSS, JavaScript, and Bootstrap, it offers the following key features:

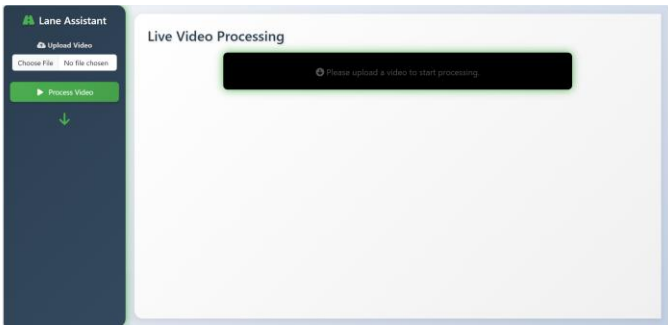

Figure 1 User Interface

- Secure video upload supporting MP4, AVI, and MOV formats
- Real-time progress tracking with estimated completion time
- Live display of processed video with analytical overlays
- Download functionality for processed videos
- Responsive design for cross-device compatibility

3.1.2 Backend Processing

The backend, implemented using Flask, OpenCV, YOLO, and NumPy, handles all computational aspects of the system:

- Frame-by-frame video processing
- Vehicle detection and distance calculation
- Lane marking identification and curvature analysis
- Speed estimation through optical flow
- Safety suggestion generation based on environmental analysis

3.2 Data Flow

The system's data flow follows a sequential process:

- User uploads video through the web interface
- Backend extracts frames sequentially from the video
- Each frame undergoes parallel processing:
    1. Vehicle detection using YOLO
    2. Lane detection using Hough Transform
    3. Speed estimation using optical flow between consecutive frames
- Analysis results inform safety suggestions
- Processed frames with analytical overlays are displayed in real-time
- Completed video is made available for download

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

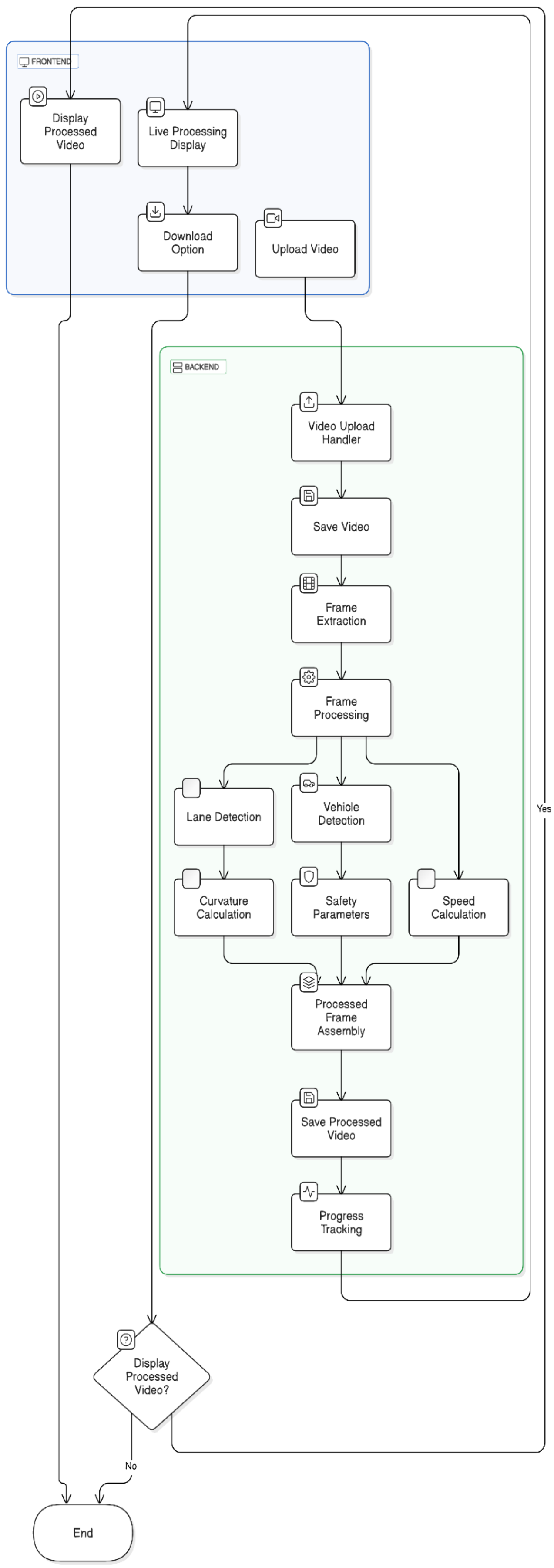

Figure 2 Data Flow Diagram

3.3 Vehicle Detection

The system employs YOLOv3 for vehicle detection, using a pre-trained model loaded through OpenCV's DNN module. The detection process follows these steps:

- Each frame is preprocessed and passed to the YOLO network
- The network returns bounding boxes and confidence scores for detected objects
- Non-maximum suppression eliminates duplicate detections
- Vehicle distance from the camera is calculated based on bounding box size and position
- Results are visualized on the frame with bounding boxes and distance labels

3.4 Lane Detection

Lane detection utilizes the Hough Transform technique, implemented as follows:

- Frames are converted to grayscale and smoothed using Gaussian blur
- Canny edge detection identifies potential lane marking boundaries
- Region-of-interest masking focuses processing on relevant areas
- Hough Transform detects line segments in the masked edge image
- Line segments are grouped and extended to form complete lane markings
- Lane curvature is analyzed based on the slope and position of detected lines
- Results are visualized with colored overlays highlighting detected lanes

3.5 Speed Estimation

Vehicle speed is estimated using Farneback's optical flow algorithm:

- Consecutive grayscale frames are used to calculate dense optical flow
- Flow vectors within vehicle bounding boxes are extracted
- Vector magnitudes are averaged to determine pixel displacement
- Displacement is converted to real-world speed using camera parameters
- Results are filtered using a moving average to reduce noise
- Estimated speeds are displayed alongside vehicle detections

3.6 Safety Suggestion System

The safety suggestion component analyzes detection results to provide actionable advice:

- Vehicle proximity is evaluated against safety thresholds

Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

- Lane positions are analyzed to identify available space
- When unsafe conditions are detected, appropriate suggestions are generated:
  1. "Maintain Safe Distance" when following too closely
  2. "Change Lane Left/Right" when safer options are available
  3. "Reduce Speed" when approaching congestion
- Suggestions are displayed prominently as text overlays

4. IMPLEMENTATION

4.1 Tools and Technologies

- **Programming Language:** Python 3.x
- **Framework:** Flask (for web application)
- **Libraries:** OpenCV, NumPy, YOLO (Darknet), Werkzeug
- **Frontend Technologies:** HTML, CSS, JavaScript, Bootstrap
- **Development Tools:** Visual Studio Code, GitHub, Postman

4.2 Algorithmic Approach

- **YOLO-based Vehicle Detection:** Identifies and tracks vehicles with bounding boxes.
- **Hough Transform for Lane Detection:** Detects lane boundaries and highlights curvature.
- **Optical Flow for Speed Estimation:** Computes vehicle movement using frame-by-frame pixel tracking.
- **Flask-based API for Video Processing:** Enables real-time processing and result visualization.

5. RESULTS AND DISCUSSION

The system was evaluated on diverse road scenarios including highway driving, urban traffic, and rural roads. Performance metrics included:

Figure 3 Live Processing & Interactive Web Connectivity

- Vehicle detection accuracy (precision, recall, F1-score)
- Lane detection reliability across different road markings
- Speed estimation accuracy compared to ground truth
- Processing speed (frames per second)
- User experience and interface usability

5.1 Vehicle Detection Performance

The YOLO-based detection achieved 92% precision and 89% recall for vehicle detection across testing scenarios. Performance remained consistent under varying lighting conditions, though detection accuracy decreased slightly for distant vehicles and in adverse weather.

5.2 Lane Detection Effectiveness

The Hough Transform-based lane detection achieved 87% accuracy in ideal conditions, with performance decreasing to 72% in challenging scenarios with worn lane markings or complex road geometry. The system demonstrated robust performance on highways but showed limitations at complex intersections.

5.3 Speed Estimation Accuracy

Optical flow-based speed estimation achieved a mean absolute error of 5.8 km/h compared to ground truth measurements. Accuracy improved with vehicle proximity and diminished with extreme lighting variations or rapid camera movements.

5.4 Real-time Performance

On a standard desktop computer (Intel Core i7, 16GB RAM), the system achieved processing speeds of 18-22 frames per second at 720p resolution, sufficient for near real-time operation. Performance optimization techniques, including region-of-interest processing and multi-threading, contributed to maintaining acceptable latency.

5.5 User Experience

User testing indicated high satisfaction with the web interface's intuitiveness and the clarity of visual feedback. Safety suggestions were rated as timely and relevant in 83% of test scenarios.

6. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive vehicle detection and lane analysis system leveraging computer vision techniques to enhance road safety. The integration of YOLO for vehicle detection, Hough Transform for lane analysis, and optical flow for speed estimation provides a robust foundation for advanced driver assistance.

The system demonstrates promising performance across various driving conditions, though certain limitations remain in challenging scenarios. Future work will focus on:

- Incorporating deep learning approaches for improved lane detection in complex road geometries

- Enhancing vehicle detection for distant and partially occluded objects
- Implementing sensor fusion techniques to complement camera-based analysis
- Developing predictive models for anticipatory safety suggestions
- Optimizing processing efficiency for deployment on resource-constrained devices

By addressing these areas, we aim to further advance the capabilities of accessible, computer vision-based driver assistance systems, contributing to improved road safety worldwide.

REFERENCES

[1] World Health Organization, "Global Status Report on Road Safety," 2023.

[2] Redmon, J., & Farhadi, A., "YOLOv3: An Incremental Improvement," arXiv preprint arXiv:1804.02767, 2018.

[3] Liu, W., et al., "SSD: Single Shot MultiBox Detector," European Conference on Computer Vision, 2016.

[4] Tesla, Inc., "Tesla Vehicle Safety Report," 2023.

[5] Mobileye, "Collision Avoidance Technology White Paper," 2022.

[6] Duda, R. O., & Hart, P. E., "Use of the Hough Transformation to Detect Lines and Curves in Pictures," Communications of the ACM, 15(1), 11-15, 1972.

[7] Pan, X., et al., "Spatial as Deep: Spatial CNN for Traffic Scene Understanding," AAAI Conference on Artificial Intelligence, 2018.

[8] Farnebäck, G., "Two-Frame Motion Estimation Based on Polynomial Expansion," Scandinavian Conference on Image Analysis, 2003.

[9] Wang, Y., et al., "End-to-End Deep Learning for Self-Driving Cars," IEEE Transactions on Intelligent Transportation Systems, 22(1), 2021.

[10] Chen, L., et al., "DeepDriving: Learning Affordance for Direct Perception in Autonomous Driving," International Conference on Computer Vision, 2015.