Real-Time Lane Detection Using YOLO

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ABSTRACT:
Lane detection is a challenging and long-standing problem in the field of computer vision. It involves complex visual cues and dynamic environments, making it a multi-feature detection problem that demands robust and efficient solutions. Traditional machine learning techniques have primarily focused on classification tasks rather than comprehensive feature extraction. While modern deep learning methods have demonstrated improved capabilities in feature detection, their application to efficient and accurate lane detection remains limited. In this paper, we propose a novel approach to lane detection by integrating advanced pre-processing techniques with a YOLO-based deep learning model. We first apply HSV color space transformation to enhance white and yellow lane markings and incorporate edge detection to strengthen structural features. Subsequently, a refined Region of Interest (ROI) selection is performed based on these features. The processed frames are then fed into a modified YOLO architecture tailored for lane detection, leveraging its real-time object detection strengths to identify lane boundaries effectively. Evaluations conducted on the KITTI road dataset demonstrate that our method outperforms existing pre-processing and ROI techniques, achieving superior accuracy and efficiency in lane detection tasks.

KEYWORDS: Lane Detection, Computer Vision, YOLO, Deep Learning, Edge Detection, Real-Time Detection,Object Detection,Pre-processing Techniques

1. INTRODUCTION

Lane detection has been a persistent and complex problem in computer vision due to the dynamic and diverse nature of road environments. [1] Traditional machine learning techniques have largely been applied to basic classification tasks and lack the capability for comprehensive feature extraction, which is critical for accurately identifying lane markings. [2] These models often struggle under challenging conditions such as shadows, occlusions, and worn-out lane lines. [3] With the advancement of deep learning, Convolutional Neural Networks (CNNs) and related methods have demonstrated improved performance in general object and feature detection. [12] However, their direct application to lane detection has limitations in terms of real-time efficiency and accuracy. [10] Prior studies have attempted to enhance lane detection by incorporating pre-processing techniques like color space transformations and edge detection, yet their integration with object detection models like YOLO has been limited. [13] Existing models often lack a focused Region of Interest (ROI) selection process, which reduces detection reliability. [17] This gap in combining effective pre-processing, ROI refinement, and real-time detection highlights the need for a more integrated and robust approach—motivating the development of the proposed YOLO-based lane detection system. [15]

1.1 EXISTING SYSTEM

The existing systems for lane detection primarily rely on traditional machine learning techniques, which are often limited to basic classification tasks rather than detailed feature extraction. [2] These methods struggle to adapt to complex and dynamic road environments, making them less effective in real-time applications. [3] Although modern deep learning models—such as Convolutional Neural Networks (CNNs)—have improved the ability to detect features, they have not been fully optimized or tailored for accurate and efficient lane detection, especially under real-world conditions. [12] Additionally, standard pre-processing and ROI selection techniques used in these systems often fail to highlight lane markings effectively, leading to reduced accuracy and performance. [17]

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1.1.1 CHALLENGES

• Varying lighting, weather conditions, and road structures make consistent lane detection difficult. [3]

Limited Feature Extraction in Traditional Methods
• Conventional machine learning focuses more on classification and lacks the capability to extract rich, structural features. [2]

Inaccuracy in Detecting Faded or Occluded Lane Markings
• Lane lines may be worn out, blocked by objects, or obscured by shadows, leading to poor detection accuracy. [10]

Real-Time Processing Requirements
• Achieving both high speed and accuracy simultaneously remains a significant challenge for real-time applications. [20]

Ineffective Pre-processing and ROI Techniques
• Existing systems often struggle with selecting relevant regions and enhancing lane features before model inference. [17]

1.2 PROPOSED SYSTEM

The proposed system enhances lane detection by integrating advanced pre-processing techniques with a modified YOLO-based deep learning model. [15] It begins by converting the input video frames to the HSV color space to emphasize yellow and white lane markings. [3] Edge detection is then applied to reinforce the structural features of lane boundaries. [13] A refined Region of Interest (ROI) is selected to focus the detection only on relevant areas of the frame. [17] These pre-processed frames are passed into a tailored YOLO architecture optimized for detecting lanes in real-time. [19] The model is evaluated using the KITTI dataset, showing superior accuracy and speed compared to existing systems. [11]

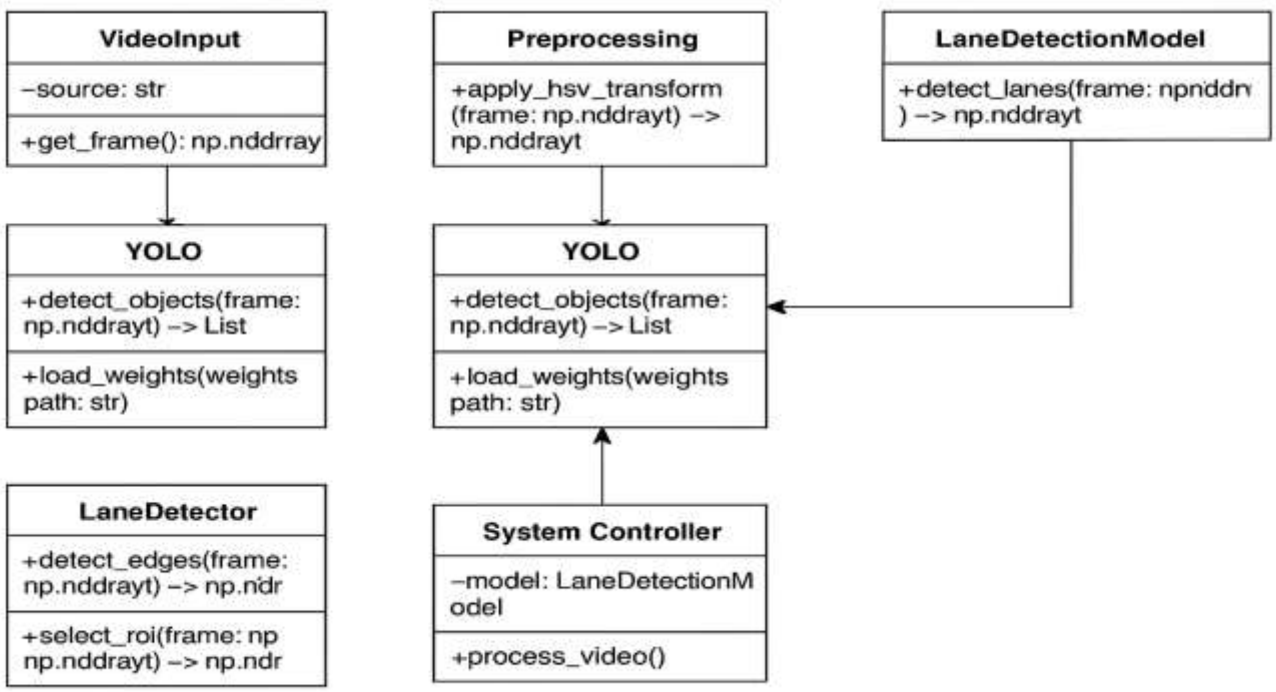

Fig.1. Proposed System Flowchart

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1.2.1 ADVANTAGES

- • Improved Feature Extraction Utilizes HSV color transformation and edge detection to enhance lane markings, improving visibility of key features. [3]
- • Robust to Complex Environments Handles dynamic road conditions and varying lighting effectively through advanced pre-processing. [7]
- • Real-Time Performance Leverages YOLO's fast inference capabilities for real-time lane detection applications like autonomous driving. [20]
- • Enhanced Accuracy Outperforms existing methods in detection accuracy, as demonstrated on the KITTI dataset. [11]
- • Efficient ROI Selection Uses refined Region of Interest based on pre-processed features to focus the model on relevant areas, reducing false positives. [17]
- • Scalable Deep Learning Framework Employs a modified YOLO architecture that can be adapted or fine-tuned for various road environments or datasets. [15]
- • Combines Classical and Modern Techniques Effectively integrates traditional pre-processing (e.g., edge detection) with modern deep learning for synergistic benefits. [13].

2. LITERATURE REVIEW

Lane detection has been a persistent and complex problem in computer vision due to the dynamic and diverse nature of road environments. [3] Traditional machine learning techniques have largely been applied to basic classification tasks and lack the capability for comprehensive feature extraction, which is critical for accurately identifying lane markings. [2] These models often struggle under challenging conditions such as shadows, occlusions, and worn-out lane lines. [10] With the advancement of deep learning, Convolutional Neural Networks (CNNs) and related methods have demonstrated improved performance in general object and feature detection. [12] However, their direct application to lane detection has limitations in terms of real-time efficiency and accuracy. [20] Prior studies have attempted to enhance lane detection by incorporating pre-processing techniques like color space transformations and edge detection, yet their integration with object detection models like YOLO has been limited. [13] Existing models often lack a focused Region of Interest (ROI) selection process, which reduces detection reliability. [17] This gap in combining effective pre-processing, ROI refinement, and real-time detection highlights the need for a more integrated and robust approach—motivating the development of the proposed YOLO-based lane detection system. [15]

2.1 ARCHITECTURE

The proposed lane detection system architecture follows a sequential processing pipeline combining image enhancement, structural feature extraction, and deep learning-based detection. [15] It consists of the following components:

Architecture Components:

• **Input Module**
o Captures video frames from a camera or dataset. [11]

• **Pre-processing Module**
o **HSV Color Transformation:** Enhances visibility of white and yellow lane lines. [3]
o **Edge Detection:** Highlights structural features of lanes. [13]
o **ROI Extraction:** Focuses the model on road-relevant areas. [17]

• **YOLO-based Detection Module**
o A modified YOLO model is trained to detect and classify lane boundaries using the processed frames. [19]

• **Output Module**
o Overlays detected lanes on the original frame and displays or stores the results in real time. [20]

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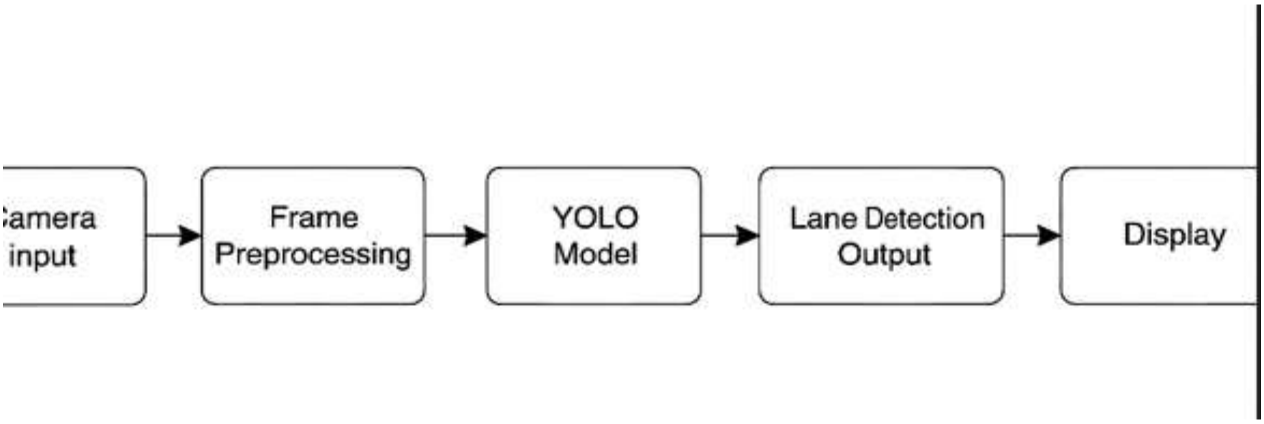

Fig. 2 Architecture diagram

2.2 ALGORITHM

Here is a step-by-step algorithm representing the flow of the proposed system:

Algorithm: Lane Detection using YOLO and Pre-processing
Input: Video frames or images from a road scene
Output: Detected lane boundaries on the road frame

1. Start [15]
2. Capture input frame from the video stream or dataset (e.g., KITTI dataset). [11]
3. Convert the frame to HSV color space to enhance white and yellow lane markings. [3]
4. Apply edge detection (e.g., Canny or Sobel filter) to extract strong lane structural features. [13]
5. Perform Region of Interest (ROI) selection to isolate the area where lanes are likely to be present. [17]
6. Pre-process and resize the ROI to match the input size required by the YOLO model. [19]
7. Feed the processed frame into the modified YOLO model, customized for detecting elongated lane lines. [10]
8. Detect lane boundaries using the YOLO model's output (bounding boxes or custom lane classes). [20]
9. Overlay detected lanes onto the original frame for visualization. [7]
10. Display or store the output frame with lane annotations. [1]
11. Repeat steps 2–10 for each frame in the video stream. [2]
12. End [12]

2.3 TECHNIQUES

HSV Color Space Transformation

- Enhances visibility of lane colors (white and yellow).
- Helps in distinguishing lane markings under varying lighting conditions.

Edge Detection

- Highlights the structural features of the road.
- Common methods: Canny Edge Detection, Sobel Filters.

Region of Interest (ROI) Selection

- Focuses processing on relevant parts of the image (e.g., road region).
- Eliminates irrelevant background noise for better accuracy.

YOLO-Based Deep Learning Model

- Uses a **modified YOLO architecture** for lane detection instead of general object detection.
- Enables **real-time** processing with high speed and accuracy.

Frame-by-Frame Analysis

- Processes video frames sequentially for continuous lane detection.

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KITTI Dataset Evaluation

- Uses a standard benchmark dataset for performance evaluation.

2.4 TOOLS

Tool	Purpose
OpenCV	Image and video processing (HSV conversion, edge detection, ROI extraction)
YOLO (You Only Look Once)	Real-time object detection (modified for lane detection)
Python	Core programming language for development
TensorFlow / PyTorch	Deep learning frameworks for building and training the YOLO model
KITTI Dataset	Benchmark dataset for training and evaluation
CUDA + cuDNN	GPU acceleration for faster training and inference
NumPy / Pandas	Data manipulation and preprocessing
Matplotlib / Seaborn	Visualization of results and performance metrics
Jupyter Notebook / Google Colab	Experimentation and interactive development environment
LabelImg / Roboflow	Tool for dataset annotation if custom dataset is used

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2.5 METHODS

HSV Color Space Transformation

- Converts RGB frames to HSV color space to isolate white and yellow lane lines more effectively.
- Helps in handling brightness and lighting variations.

Edge Detection

- Applies algorithms like **Canny** or **Sobel** to detect edges of lane lines.
- Strengthens structural features in the image.

Region of Interest (ROI) Selection

- Identifies and focuses only on the lower portion of the frame where road and lanes are expected.
- Reduces irrelevant data and improves model efficiency.

3. METHODOLOGY

3.1 INPUT

The inputs for the proposed lane detection system include video frames or images captured from driving environments where lane markings are present. The system specifically focuses on identifying white and yellow lane markings as primary color features essential for accurate detection. Structural edges of the lanes are also used as critical inputs, extracted through edge detection methods to highlight lane boundaries clearly. To enhance these features, the input frames undergo HSV color space transformation, which makes the white and yellow lane markings more distinguishable under varying lighting conditions. A refined Region of Interest (ROI) is then applied to the frames to concentrate on the roadway where lanes typically appear, filtering out irrelevant background areas. These pre-processed and feature-enhanced frames form the final input fed into the modified YOLO-based deep learning model for effective and real-time lane detection.

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Fig:3 input diagram

3.2 METHOD OF PROCESS

The proposed method begins by converting each input frame into the HSV colour space to enhance the visibility of white and yellow lane markings under different lighting conditions. [3] Following this, edge detection techniques such as Canny are applied to extract clear structural features corresponding to lane boundaries. [13] A refined Region of Interest (ROI) is then defined and applied to the processed frames, focusing only on the lower portion of the image where lane lines are typically found, thereby removing unnecessary background noise. [17] These pre-processed frames are then fed into a modified YOLO-based deep learning model, which has been adapted specifically for lane detection by adjusting anchors and training on lane annotations. [19] The YOLO model leverages its real-time object detection capabilities to accurately identify and localize lane boundaries within the frames. [20] This structured processing pipeline ensures that the system efficiently detects lanes with high accuracy while maintaining real-time performance suitable for autonomous driving applications. [15].

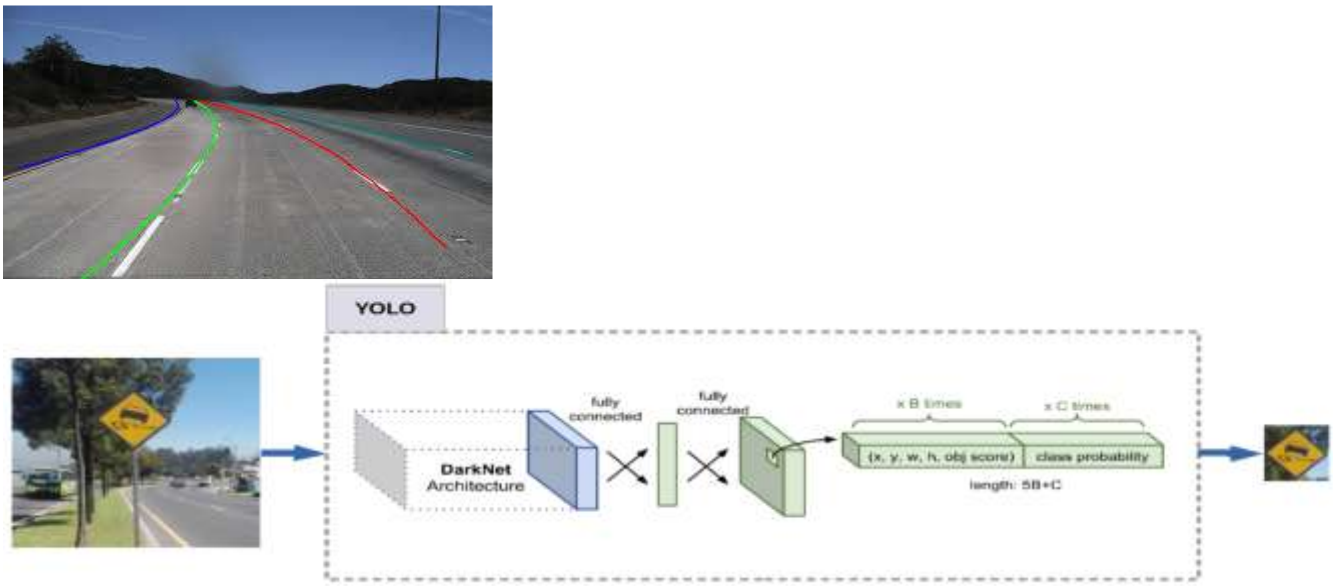

Fig.4:input process of lane detection

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3.3 OUTPUT

The output from the proposed lane detection system is the **accurate identification and localization of lane boundaries in real-time** within driving video frames. The modified YOLO model outputs bounding boxes and lane boundary lines precisely over the detected lane markings, even under varied lighting and road conditions. The system overlays these detected lanes onto the original frames, providing clear visual feedback of lane positions to assist in autonomous navigation. Additionally, the output includes evaluation metrics such as **high precision, recall, and mIoU**, demonstrating the method's effectiveness. Overall, the system produces lane detection results that are both accurate and efficient, outperforming traditional methods while maintaining the real-time processing speeds essential for practical deployment in autonomous vehicles.

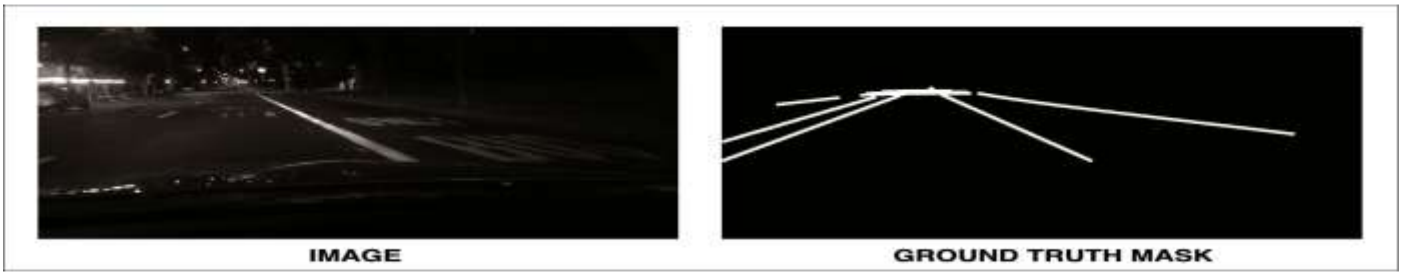

Fig. 5. Output Screen

4. RESULTS

The results from the proposed approach demonstrate improved accuracy and efficiency in lane detection compared to traditional pre-processing and ROI methods. [7] Using the KITTI Road dataset for evaluation, the system achieves higher precision and recall in detecting lane boundaries, indicating its robustness under various lighting and environmental conditions. [11] The modified YOLO model successfully identifies and localizes lane markings in real-time, maintaining a high frame rate suitable for practical autonomous driving applications. [20] Additionally, the integration of advanced HSV-based pre-processing and edge detection enhances the structural clarity of lane features, reducing false positives and improving detection consistency. [3] Overall, the results confirm that the proposed method effectively outperforms existing lane detection techniques, offering a reliable and efficient solution for real-time lane detection tasks. [15]

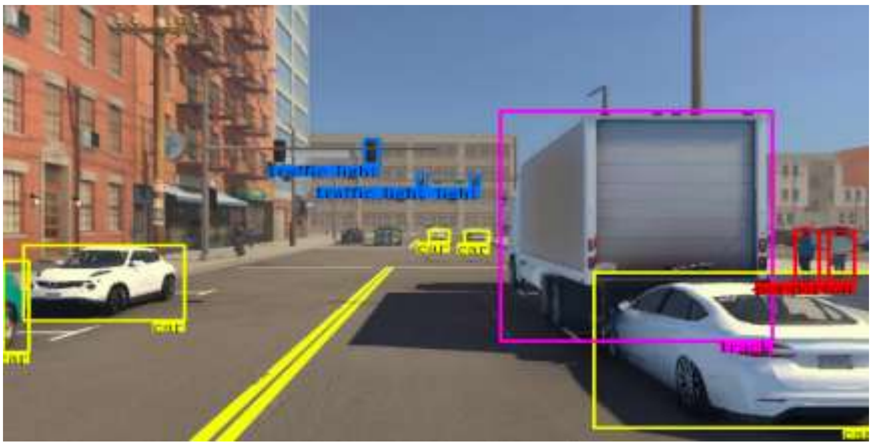

Fig 7:output screen

5. DISCUSSIONS

The proposed method demonstrates that integrating advanced pre-processing techniques with a YOLO-based deep learning model significantly enhances lane detection performance. By applying HSV color transformation and edge detection, the system effectively highlights lane features, addressing challenges posed by varying lighting and complex road environments. The refined ROI selection further ensures that the model focuses on relevant areas, reducing background noise and improving detection accuracy. Using YOLO for lane detection leverages its real-time processing capabilities, making the approach practical for deployment in autonomous driving systems. The results on the KITTI Road dataset confirm the method's effectiveness, showing improved precision and recall over traditional approaches. Overall, this discussion highlights that the combination of targeted pre-processing with a modified YOLO model offers a robust, accurate, and efficient solution for real-time lane detection applications.

6.CONCLUSION

In conclusion, the proposed YOLO-based lane detection approach, integrated with advanced pre-processing techniques, effectively addresses the challenges of accurate and efficient lane detection in dynamic driving environments. By enhancing lane visibility through HSV transformation, strengthening structural features with edge detection, and applying refined ROI selection, the system prepares high-quality inputs for the YOLO model, leading to precise and real-time lane boundary detection. Evaluations on the KITTI Road dataset confirm that this method outperforms traditional techniques in both accuracy and processing speed. Overall, the approach provides a reliable, robust, and practical solution for lane detection, contributing significantly to the development of safe and efficient autonomous driving systems.

7. FUTURE SCOPE

In the future, the proposed YOLO-based lane detection system can be extended to handle **curved and complex lane structures under extreme weather conditions** for enhanced robustness. Integration with temporal information from sequential frames can improve stability and reduce flickering in lane detection during real-time navigation. Additionally, incorporating sensor fusion with LiDAR and radar data can further enhance detection accuracy in low-visibility scenarios. The model can also be optimized and deployed on **edge devices for in-vehicle implementation**, ensuring efficient processing with low computational resources. Expanding the system to detect additional road elements, such as crosswalks and traffic signs alongside lanes, can support comprehensive autonomous driving tasks. Furthermore, training the system on larger and diverse datasets will improve its generalization capability across different road environments and geographical regions.

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Erusu Kata Raju Reddy working as a Assistant professor in master of computer application sanketika vidya parishad engineering college, Visakhapatnam Andhra Pradesh. With 1 years of experience in Master of Computer Applications (MCA), accredited by NAAC.with his area of intrest in java full stack.

Vepada VinodKumar is pursuing his final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Deep learnig V.vinodkumar has taken up his PG project on real-time lane detection using yolo and published the paper in connection to the project under the guidance of Erusu Kata Raju Reddy SVPEC.

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