International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2024.0338
e ISSN: 2584-2854
Volume: 02
Issue: 07 July 2024
Page No: 2341-2347

Detection of Lane and Speed Breaker Warning System for Vehicles Using Machine Learning

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Abstract

With the rapid advancement of vehicle technologies, ensuring the safety of these vehicles on roads has become a paramount concern. One of the critical aspects of safe driving is the accurate detection of lanes and potential road hazards, such as speed breakers. In this study, we propose a Lane and Speed Breaker Warning System (LSBWS) that employs machine learning algorithms to enhance the perception capabilities of vehicles. The LSBWS utilizes a combination of computer vision and machine learning techniques to detect and analyze road lanes, speed breakers in real-time and also a real time object detection on road. The system utilizes a camera sensor to capture the road scene ahead and then employs image processing algorithms to identify lane markings and speed breakers, objects on road. Random Sample Consensus Algorithm is used for the lane detection and tracking for speed breaker detection YOLOv4 is employed to accurately detect and classify these features within the captured images and for the object detection YOLOv5 is used for detecting the real time objects and classify them.

Keywords: *Lane Detection, Speed Breaker Detection, Vehicles, Machine Learning Algorithms, Random Sample Consensus, YOLOv4, YOLOv5, Road Safety.*

1. Introduction

Vehicles represent a revolutionary advancement in the field of transportation, offering the promise of increased road safety, reduced traffic congestion, and enhanced mobility. Lane detection is crucial for maintaining proper vehicle positioning within lanes and preventing unintentional lane departures. Accurate detection of lane markings is essential for ensuring safe lane changes, turns, and overall trajectory planning. On the other hand, identifying speed breakers in advance is crucial to ensure the vehicle's smooth and controlled navigation, minimizing discomfort to passengers and reducing the risk of damage to the vehicle's suspension system. The study seeks to demonstrate that a well-trained machine learning model can effectively learn to differentiate between various lane markings and speed breaker types, adapting to different environmental and road conditions. By integrating the LSBWS into the perception framework of autonomous vehicles, it is expected to provide timely warnings and alerts to the vehicle's control unit, enabling the vehicle to make informed decisions and maneuvers to ensure the safety of passengers, pedestrians, and other road users. The Lane and Speed Breaker Warning System for vehicles, focusing on enhancing safety and awareness during driving consisting of three modules: Lane Detection, Speed Breaker Warning, and Object Detection on Roads. The system comprises two main components: Lane Detection and Speed Breaker Warning. The Lane Detection component utilizes the Random Consensus Method to analyze video input and accurately identify lane markings. By continuously tracking lane boundaries, the system provides real-time alerts to the driver, indicating lane changes or deviations. This feature assists in preventing lane departure accidents and aids in maintaining a steady and safe trajectory on the road. The Speed Breaker Warning system utilizes YOLOv4, a powerful object detection model, to identify speed breakers in the vehicle's path. When a speed breaker is detected, the system issues an alert to the driver, prompting them to slow down or take necessary precautions. This proactive warning mechanism helps to reduce the risk of vehicle damage and ensures a smoother driving experience. Furthermore, the Object Detection module, utilizing YOLOv5, identifies various objects on the road. It detects and classifies objects such as vehicles, pedestrians, and obstacles, contributing to better road awareness and accident prevention. By integrating these modules, the Lane and Speed Breaker Warning System enhances the safety and efficiency of vehicle operations, offering real-time alerts and aiding drivers in navigating through complex road environments. [1]

2. Proposed Methodology

A system architecture for a lane and speed breaker warning system for vehicles using video input typically involves several components and stages:

2.1. Preprocessing & Data Cleaning

Prepare the raw video data for further processing by enhancing image quality and removing irrelevant information. Video Frame Extraction: Convert the continuous video feed into individual frames for analysis. Image Enhancement: Techniques like histogram equalization improve contrast, noise reduction removes unwanted noise, and edge enhancement highlights important features. Data Cleaning: Remove frames that are not useful (e.g., frames with too much blur or obstruction) to ensure the quality and reliability of the data being processed.

2.2. Feature Extraction

Identify and extract specific features from the preprocessed images that are relevant for lane detection, speed breaker detection, and general object detection. Edge Detection: Use algorithms like Canny Edge Detection to identify edges in the image, which helps in finding lane boundaries. ROI (Region of Interest) Selection: Focus on specific areas of the image where lanes, speed breakers, and other objects are likely to be found. ROI (Region of Interest) Selection: Focus on specific areas of the image where lanes, speed breakers, and other objects are likely to be found, as shown in Figure 1.

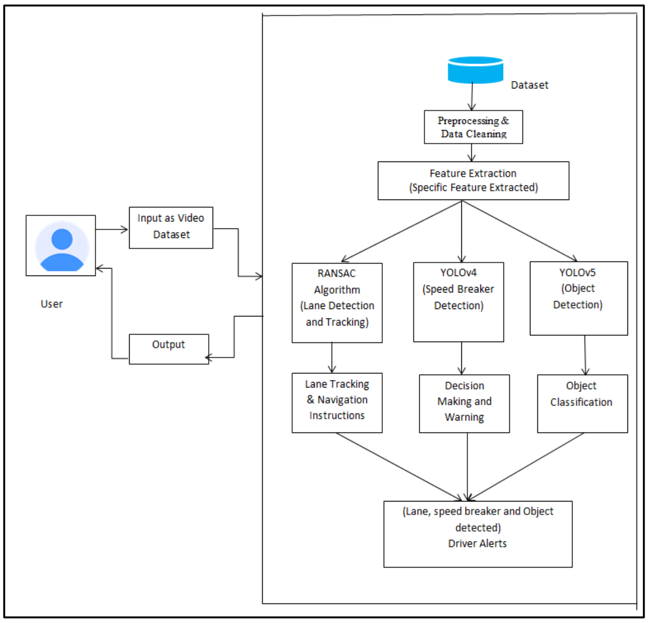

Figure 1 **Feature Extraction**

2.3. Ransac Algorithm (Lane Detection and Tracking)

Robustly detect and track lane lines in the presence of noise and outliers using the RANSAC algorithm. Line Detection: Use the Hough Transform to detect line segments in the ROI.RANSAC: Fit lines to the detected points while handling outliers, ensuring that the lane lines are accurately identified.

Lane Tracking: Use a Kalman filter or similar method to track the position of the lanes across successive frames, providing continuous lane information

2.4. YOLOv4 (Speed Breaker Detection)

Detect and localize speed breakers in the video frames using the YOLOv4 object detection model. Input: Video frames are fed into the YOLOv4 model. Detection: The model outputs bounding boxes around detected speed breakers along with confidence scores. Warning System: When a speed breaker is detected within a certain distance, generate a warning for the driver.

2.5. YOLOv5 (Object Detection)

Detect and classify various objects on the road, such as vehicles, pedestrians, and animals, using the YOLOv5 model. Input: Video frames are fed into the YOLOv5 model.Detection and Classification: The model outputs bounding boxes and class labels for detected objects. Tracking: Use an object tracking algorithm like SORT (Simple Online and Realtime Tracking) to follow the movement of detected objects across frames.

2.6. Decision Making and Warning System

Integrate data from lane detection, speed breaker detection, and general object detection to make driving decisions and generate warnings. Data Fusion: Combine the outputs from the RANSAC lane detection, YOLOv4 speed breaker detection, and YOLOv5 object detection modules. Decision Making: Analyze the fused data to determine the best course of action (e.g., maintain lane, slow down for a speed breaker, avoid obstacles).Warning Generation: Generate real-time alerts for the driver about detected lanes, speed breakers, and other objects.

2.7. Driver Alerts

Provide real-time information and warnings to the driver to enhance safety and aid in navigation. Lane Keeping: Alerts for lane departures and guidance to stay within the lane. Speed Breaker Warnings: Alerts when approaching a speed breaker.

3. Implementation

3.1. Lane Detection and Tracking

Lane detection and tracking, coupled with instructions for navigating turns, is a crucial aspect of autonomous driving systems. Employing the random sample method, this report delineates the methodology and implementation for achieving this task, utilizing video input. The process begins with the input of video data captured by the vehicle's onboard cameras. These videos typically consist of frames depicting the road ahead, with lanes and other relevant features visible. Firstly, the lane detection algorithm is applied to each frame. This involves techniques such as color thresholding, edge detection, and morphological operations to identify lane markings accurately. Once detected, the lanes are represented as mathematical models, often lines or polynomials, to facilitate tracking. Tracking of lanes across consecutive frames is then carried out to estimate their positions and trajectories. This involves employing methods like Kalman filters or particle filters to predict the probable location of lanes in the current frame based on their positions in previous frames. To provide instructions for turning, the system evaluates the relative positions of the detected lanes vis-à-vis the vehicle's current position. For instance, if the right lane is detected to be closer to the vehicle's right side, a right turn instruction is generated. Conversely, if the left lane is closer to the vehicle's left side, a left turn instruction is produced. The random sample method enhances the robustness of lane detection and tracking by incorporating randomness into the process. This involves randomly selecting a subset of points or regions from the image to perform lane detection, thus reducing the risk of the algorithm getting stuck in local minima or being misled by outliers.

3.2. Speed Breaker

Detecting speed breakers and issuing timely audio warnings is crucial for enhancing road safety, particularly in autonomous driving systems. This report delineates the methodology and implementation for achieving this task, utilizing YOLOv4, a state-of-the-art object detection algorithm, with video input. The process commences with the input of video data captured by the vehicle's cameras, providing a continuous stream of visual information depicting the road ahead. The YOLOv4 algorithm is then applied to each frame to detect objects of interest, specifically speed breakers. YOLOv4, renowned for its accuracy and efficiency, employs a deep neural network architecture to detect and classify objects in real-time. Through a series of convolutional layers and advanced techniques such as anchor boxes and feature pyramid networks, YOLOv4 excels at detecting objects of various sizes and shapes, making it ideal for speed breaker detection. Once a speed breaker is detected in the frame, the system triggers an audio warning to alert the vehicle's occupants. This warning serves as a proactive measure to prepare passengers for an upcoming

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speed breaker, enabling them to brace for impact and mitigate discomfort or potential injury. The integration of YOLOv4 for speed breaker detection ensures high precision and reliability, crucial for real-world applications where the accuracy of object detection directly impacts safety. Additionally, the use of audio warnings enhances user experience by providing clear and intuitive cues, thereby fostering a safer driving environment for both passengers and pedestrians. [2]

3.3. Object Detection

Implementing object detection on roads using YOLOv5, a powerful and efficient deep learning algorithm, presents a robust solution for enhancing road safety and facilitating various applications such as autonomous driving and traffic monitoring. This report provides a detailed overview of the methodology and implementation of object detection on road scenes utilizing YOLOv5, with video input. The process begins with the acquisition of video data captured by cameras mounted on vehicles or roadside infrastructure, providing a continuous feed of real-time road scenes. YOLOv5, renowned for its speed and accuracy, is then deployed to analyze each frame of the video stream and identify objects of interest, including vehicles, pedestrians, cyclists, traffic signs, and obstacles. YOLOv5 achieves superior object detection performance through a streamlined architecture that combines advanced convolutional neural network (CNN) techniques with efficient inference strategies. The model is trained on large-scale datasets, enabling it to generalize well to various road environments and object classes. During inference, YOLOv5 processes each frame with remarkable speed, accurately detecting objects and their corresponding bounding boxes in real-time. The model's ability to handle complex scenes with multiple objects of different sizes and orientations makes it well-suited for diverse road scenarios. The detected objects are then classified and tracked across consecutive frames to provide valuable insights into traffic flow, road conditions, and potential hazards. This information can be leveraged for various applications, such as adaptive cruise control, collision avoidance systems, and traffic management.

3.4. Algorithm Details

3.4.1. Random Sample Consensus Algorithm

Random Sample Consensus (RANSAC) is a robust iterative algorithm used in computer vision and machine learning for fitting models to data sets that contain outliers. It works by repeatedly selecting random subsets of the data, estimating model parameters from these subsets, and then determining the number of inliers, which are data points that fit the estimated model within a certain tolerance. The process involves the following steps: a random sample of the minimum required points is chosen, a model is fitted to this sample, and the consensus set (inliers) is identified based on a predefined threshold. This process is repeated for a fixed number of iterations or until a model with a satisfactory number of inliers is found. The model with the highest consensus set is selected as the final solution. RANSAC is particularly effective in scenarios where a significant portion of the data is contaminated with outliers, as it focuses on the most consistent subset of the data to produce accurate model estimations.[3]

3.4.2. YoloV4 Algorithm

YOLOv4 (You Only Look Once version 4) is an advanced object detection algorithm that balances high speed and accuracy, making it suitable for real-time applications. It utilizes CSPDarknet53 as the backbone for feature extraction, which improves gradient flow and reduces computation. The algorithm incorporates several techniques to enhance performance, such as Mosaic and Self-Adversarial Training for data augmentation, Mish activation function for better learning, and Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PANet) for multi-scale feature aggregation. [4] YOLOv4 operates by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell through a single pass of the neural network. During training, it uses techniques like auto-anchor tuning and CIoU (Complete Intersection over Union) loss to optimize predictions. At inference, non-maximum suppression (NMS) is applied to eliminate redundant boxes, ensuring only the best detections are kept, thus making YOLOv4 highly efficient for tasks requiring both accuracy and speed. YOLOv4 is designed for fast and accurate object detection in images and videos. It achieves this by combining several innovative techniques and improvements over previous versions, making it suitable for deployment on both powerful GPUs and less powerful devices.[5]

3.4.3. YoloV5 Algorithm

YOLOv5 is a state-of-the-art real-time object detection algorithm developed as an improvement over the previous YOLO models, specifically engineered for high speed and accuracy. Unlike its predecessors, YOLOv5 is implemented in PyTorch, which simplifies deployment and integration. It introduces enhancements such as auto-learning bounding box anchors, improved loss functions, and better data augmentation techniques like Mosaic and MixUp. YOLOv5 is highly efficient, boasting faster training times and lower latency, making it ideal for applications ranging from autonomous driving to surveillance, while maintaining robust performance across various computational environments, from powerful GPUs to edge devices. YOLOv5 operates by dividing the input image into a grid and predicting bounding boxes and class probabilities for each grid cell. It uses a single neural network that processes the entire image, allowing for real-time performance. The network consists of three main parts: a backbone, a neck, and a head. The backbone (e.g., CSPDarknet) extracts essential features from the input image, the neck (e.g., PANet) aggregates feature maps at different scales, and the head predicts the final bounding boxes and class scores. During training, YOLOv5 employs techniques such as auto-anchor tuning, which optimizes the anchor boxes to better fit the dataset, and advanced augmentation strategies like Mosaic and MixUp to improve generalization. The model's architecture is designed to balance speed and accuracy, enabling efficient computation and real-time inference. In practice, [7] YOLOv5 processes an image by forwarding it through the network to generate predictions for object locations and classes. These predictions are then filtered using non-maximum suppression (NMS) to eliminate redundant boxes and retain the most accurate detections.

4. Results

4.1. Lane Detection and Tracking with Navigation Instructions (Using Yolov4)

Accurate Lane Detection: The system successfully detects and tracks lanes on the road, providing real-time updates on lane positions and trajectories. Robust Navigation Instructions: Based on the detected lane positions relative to the vehicle, the system generates precise navigation instructions, such as "take slight left" or "Take right," to assist the driver in making safe and timely turns. Enhanced Driving Experience: By providing proactive guidance on lane navigation, the system improves the overall driving experience, reducing the likelihood of lane departure and enhancing road safety [8], as shown in Figure 2.

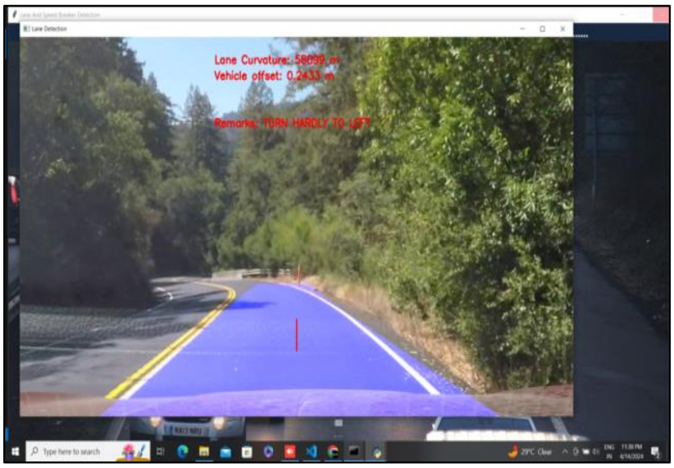

Figure 2 Lane Detection

4.2. Speed Breaker Detection and Audio Warning System (Using Yolov4)

Effective Speed Breaker Detection: The system accurately identifies speed breakers on the road, allowing for timely detection of potential hazards. Timely Audio Warnings: Upon detecting a speed breaker, the system triggers audio warnings to alert the driver, enabling them to slow down and navigate the obstacle safely.[6] Improved Road Safety: The integration of audio warnings enhances driver awareness and responsiveness to speed breakers, ultimately reducing the risk of accidents and ensuring safer driving conditions, as shown in Figure 3.

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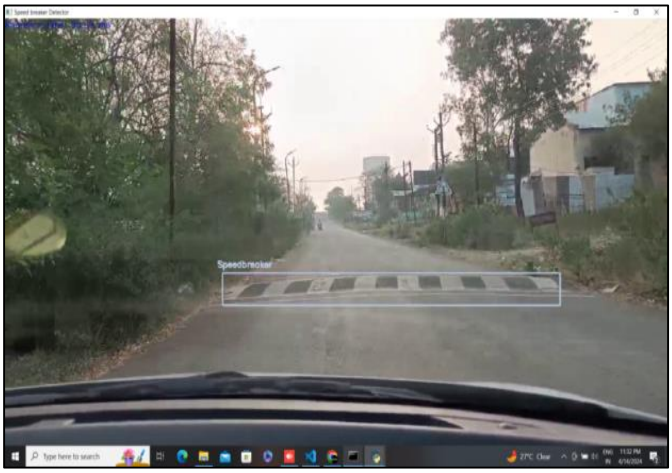

Figure 3 **Speed Breaker Detection**

4.3. Object Detection on Road (Using Yolov5)

Comprehensive Object Detection: The system successfully detects various objects on the road, including vehicles, pedestrians, cyclists, and traffic signs, with high accuracy and efficiency. Real-Time Performance: Leveraging the capabilities of YOLOv5, [9] the system achieves real-time object detection, providing instantaneous feedback on the presence and positions of objects in the road scene. Versatile Applications: The object detection system has diverse applications, ranging from traffic monitoring and surveillance to autonomous driving and intelligent transportation systems, contributing to enhanced road safety and efficiency, as shown in Figure 4.

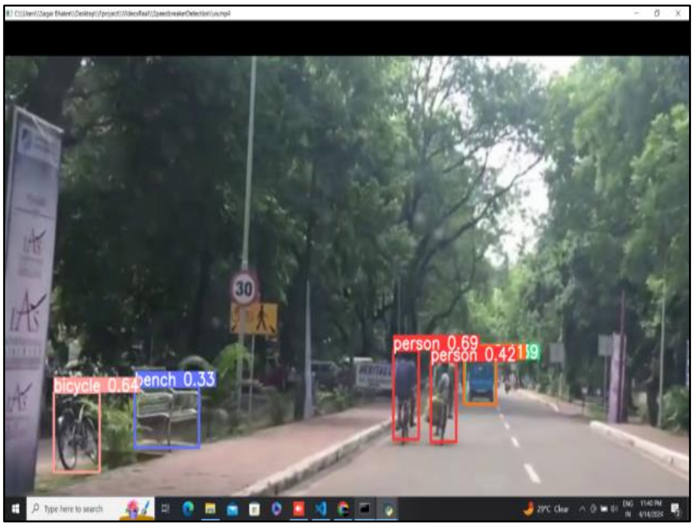

Figure 4 **Object Detection**

Conclusion

The "Lane and Speed Breaker Warning System for Vehicles" research presents a comprehensive approach to enhancing the safety and reliability of vehicles through accurate lane and speed breaker detection. By leveraging machine learning algorithms, The proposed system addresses critical challenges in autonomous driving, contributing to the realization of safer and more efficient transportation systems. By effectively combining machine learning algorithms with real-world road scenarios, the system contributes to the broader goal of reshaping transportation, enhancing road safety, and establishing vehicles as a safer and more viable mode of transportation. As the field of vehicles progresses, the research's insights will undoubtedly serve as a foundation for further advancements in perception systems and vehicle technology as a whole.

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