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Advanced Self-Driving Vehicle Model for Complex Road Navigation using Integrated Image Processing and Sensor Fusion

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Abstract: *This paper presents a self-driving vehicle (SDV) model designed to navigate complex road environments that contain heavy traffic, changing road conditions, road signs, potholes, pedestrians, and domestic animals. The approach combines image processing, object detection, ultrasonic sensing, sensor fusion, lane detection, and a decision-making algorithm. A camera connected to a Raspberry Pi captures road frames, while object-detection models identify vehicles, people, animals, potholes, signs, and traffic signals. Ultrasonic sensors measure obstacle distances and help construct a two-dimensional view of the surroundings, including areas that may not be visible to the camera. The processed information is transferred to Arduino controllers, which generate motor-control signals. The source study reports a mean average precision of 0.729 for obstacle detection, an average recall of 0.758, and processing at approximately 24 frames per second in its prototype tests. Experiments in a custom artificial road environment considered lane following, U-turns, traffic signals, stationary obstacles, heavy traffic, potholes, and animals. The approach demonstrates how combining visual information with sensor measurements can support more informed navigation. However, the reported testing was conducted in an artificial environment, and hardware limitations remain important considerations.*

Keywords: Self-driving vehicles; image processing; object detection; EfficientDet; Haar Cascade; sensor fusion; Raspberry Pi; Arduino; lane detection.

I. INTRODUCTION

Self-driving vehicle technology aims to improve mobility by allowing a vehicle to perceive its environment and make driving decisions with limited or no direct human control. Potential benefits include reducing accidents caused by human error, improving access to transportation, and supporting more efficient traffic movement. Despite these possibilities, autonomous navigation remains difficult on complex roads. Such roads may include mixed vehicle types, pedestrians, domestic animals, potholes, unclear lane markings, unexpected obstacles, and changing traffic conditions. An autonomous system must identify these elements quickly and choose a safe response.

A vehicle that relies only on a camera may fail to detect objects in blind spots or objects that are difficult to recognize visually. Sensors can provide additional distance information, but individual sensors also have limitations. Combining camera-based perception with ultrasonic distance measurements can therefore improve the system's awareness of its surroundings. This approach is known as sensor fusion.

The system described in the source study uses a Raspberry Pi for image processing and object detection, and Arduino boards for sensor communication and motor control. Lane detection estimates the vehicle's position relative to road boundaries. Object-detection models identify obstacles and traffic-related objects. Ultrasonic sensors provide distance measurements that help form a two-dimensional map. A decision-making module combines these outputs to determine movement, speed, stopping, or obstacle avoidance.

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A. Problem Statement

Complex road environments contain varied and unpredictable objects and conditions. A practical self-driving prototype must detect lanes, recognize relevant objects, estimate obstacle distances, and respond without excessive processing delay. High-computation models may provide accurate detections but can be difficult to run at a suitable frame rate on low-cost hardware. The design problem is to combine visual detection, sensor data, and control logic in a way that balances detection performance, processing speed, and hardware cost.

B. Objectives

The main objectives are to detect road lanes and objects, combine camera and ultrasonic sensor information, create a two-dimensional representation of nearby obstacles, support decisions such as stopping and changing direction, and evaluate the prototype in multiple artificial road scenarios.

II. EXISTING SYSTEM

Existing self-driving vehicle prototypes commonly use camera-based image processing to identify lanes, vehicles, pedestrians, road signs, and other objects. Some systems rely mainly on visual information, while others use separate distance sensors to detect nearby obstacles. A camera-only design can be affected by poor lighting, occlusion, unclear road markings, or objects outside the camera's view. A system that uses only distance sensors may not provide enough information to classify what an obstacle is. The source study combines a camera, ultrasonic sensors, Raspberry Pi processing, and Arduino-based control to address these limitations in a low-cost prototype.

III. PURPOSE OF THE SYSTEM

The purpose of the proposed system is to demonstrate how image processing and sensor fusion can support navigation on complex roads. Camera images are processed to detect lanes and recognize road objects. Ultrasonic sensors provide distance information about nearby obstacles. The system combines these inputs to form a more useful representation of the surrounding road and then selects an action such as moving forward, slowing down, stopping, or turning. The design is intended as a prototype for research and learning; it is not presented as a road-certified autonomous driving system.

IV. SYSTEM DIAGRAM AND WORKING

Figure 1 presents the high-level architecture. The camera and ultrasonic sensors collect complementary information. Image-processing and sensor-fusion modules interpret the inputs, after which the decision-making stage sends commands through the Arduino controller to the vehicle motors. Feedback from the vehicle's movement allows the sensing and decision cycle to continue.

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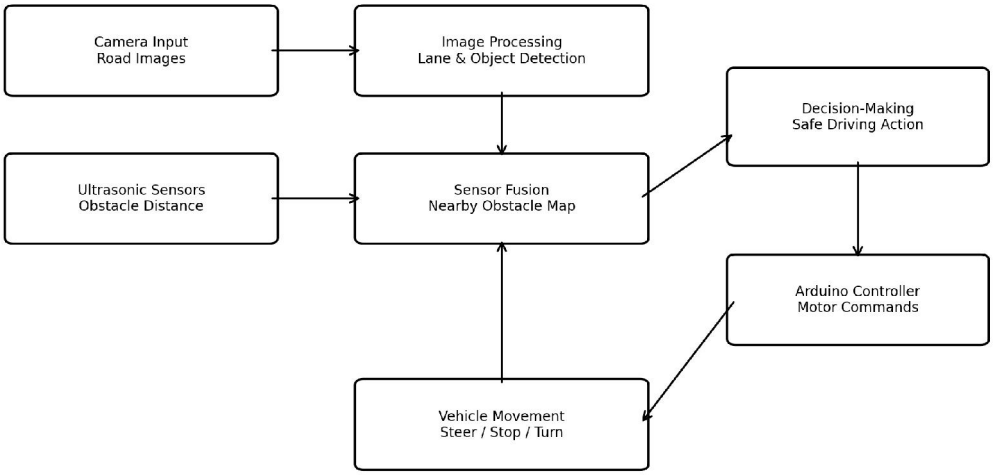


Fig. 1. System architecture of the self-driving vehicle prototype.

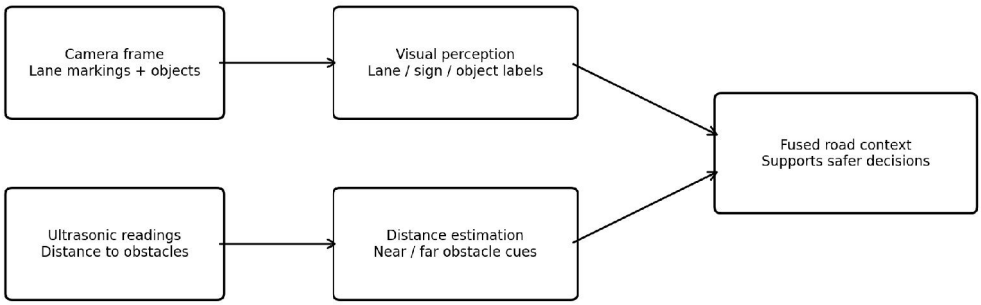


Fig. 2. Conceptual relationship between image processing and sensor fusion.

V. RELATED WORK

Earlier research on autonomous vehicles has investigated object detection, lane identification, trajectory planning, sensor fusion, vehicle communication, and decision-making. Deep-learning methods such as convolutional neural networks have been used to recognize road scenes and predict vehicle movement. EfficientDet is designed to provide object-detection performance with comparatively modest computational requirements. Other approaches, including YOLO-based models and support-vector-machine methods, have also been studied for recognizing road users and hazards.

Research on sensor fusion indicates that combining information from multiple sensors can reduce the weaknesses of a single sensing method. Cameras provide rich visual information, while ultrasonic sensors measure the distance to nearby obstacles. Radar and LiDAR can offer detailed distance measurements, but they may increase system cost, power use, and processing requirements. The prototype in the source paper uses a camera and an array of ultrasonic sensors as a lower-resource alternative.

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A. Research Gap

Many individual methods focus on a single function, such as pedestrian detection, lane detection, or trajectory planning. Complex roads require these functions to work together. The described approach integrates object detection, lane detection, ultrasonic sensing, two-dimensional mapping, and a decision-making process in one prototype. This integrated design is intended to help the vehicle respond to obstacles and traffic conditions in a coordinated manner.

B. Main Contributions

The source study reports five main contributions: integration of modern object-detection methods into a self-driving prototype; use of multiple object-detection models for different categories; fusion of camera and ultrasonic data for obstacle awareness; a methodology covering prototype design, dataset preparation, evaluation, hardware implementation, and experiments; and integration of object locations with lane information to support navigation decisions.

VI. PROPOSED SYSTEM ARCHITECTURE

The prototype uses a camera, Raspberry Pi, Arduino UNO controllers, ultrasonic sensors, a motor driver, and DC motors. When the system starts, the camera captures video frames and sends them to the Raspberry Pi through a camera serial interface. The frames are resized and processed to reduce computational load. Lane-detection and object-detection modules process the images. Object information and lane-position information are organized into data packets and transferred to the primary Arduino. Ultrasonic sensors, connected through a secondary Arduino, measure distances to obstacles. The sensor data is transferred to the primary controller using I2C communication. The controller combines the information and sends pulse-width-modulation signals through a motor driver to control the motors.

A. Image Processing

The source model resizes camera frames to 400 × 240 pixels to reduce processing requirements. The camera frames are converted from BGR to RGB before the detection process. The image-processing block supports lane detection and object detection. Lower-resolution frames help the system process images more quickly on limited hardware.

B. Lane Detection

Lane detection begins by selecting a region of interest from the camera frame. A perspective transformation changes the view to make the road area easier to analyze. Thresholding and Canny edge detection are then used to distinguish lane markings from the road and surroundings. A histogram of image intensity is used to estimate the left and right lane positions. The average of the two positions gives the lane centre. Comparing the lane centre with the frame centre provides an error value, which can be used to correct the vehicle's direction.

Lane-centre error can be represented as: Lane Centre = $(x_1 + x_2) / 2$; Frame Centre = $(a - 1) / 2$; Error = Lane Centre − Frame Centre. Here, x_1 and x_2 represent estimated lane positions, and a represents the frame width. The controller uses this error to guide the vehicle toward the centre of its lane.

VII. OBJECT DETECTION AND SENSOR FUSION

Object detection is used to recognize obstacles and road-related objects that affect driving decisions. The source study describes EfficientDet D0 and custom-trained detection models. The custom models are divided by purpose: an obstacle detector for vehicles, pedestrians, and domestic animals; a traffic-sign and signal detector; and a pothole detector. This division is intended to reduce the computational requirements of the system.

A. EfficientDet and Haar Cascade

EfficientDet D0 uses convolutional neural networks and a bidirectional feature network to detect and classify objects. It offers a balance between accuracy and computation, but its frame rate can be limited on the Raspberry Pi used in the prototype. For artificial-environment hardware testing, the source study also uses Haar Cascade classifiers based on the Viola–Jones method. Haar Cascade requires less processing power and can produce higher frame rates, although its generalization to varied objects and environments is more limited.

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B. Dataset Preparation

The source study reports combining publicly available images, including the COCO dataset, with custom images. The obstacle dataset contained approximately 12,000 labelled images covering 12 object classes. The traffic-sign and signal dataset contained around 1,500 labelled images representing 21 commonly encountered signs and signals. A separate dataset of about 900 labelled images was prepared for potholes of different sizes and types. The data was divided into 80% for training and 20% for testing.

C. Sensor Fusion and 2D Mapping

Ultrasonic sensors are positioned at important points around the vehicle to measure distances in different directions. The camera provides object labels and image locations, while ultrasonic readings provide distance information. Combining these sources supports a two-dimensional representation of the surrounding obstacles. This map can help address cases in which an object is outside the camera's view or is difficult to identify visually. The source study notes that LiDAR or radar may produce more precise maps, but they require additional resources.

D. Decision-Making and Control

The decision-making algorithm considers lane error, detected object type and position, obstacle distance, traffic signs, traffic signals, and navigation information. It selects actions such as maintaining the lane, reducing speed, stopping, waiting, or maneuvering around an obstacle. A PID controller is used to help regulate direction and speed. The controller sends PWM signals to the motor driver, which operates the motors.

VIII. EXPERIMENTS AND RESULTS

The prototype was evaluated on a custom artificial road track approximately 4.5 metres long and 20 inches wide. The track included curves, two lanes, obstacles, potholes, road signs, and traffic signals. Experiments were compared with simulations prepared using MATLAB's driving-scenario tools. The tests focused on whether the integrated system could identify road features and follow programmed responses.

A. Object-Detection Performance

The source paper reports a mean average precision (mAP) of 0.729 for the obstacle detector and an average recall of 0.758. The prototype processed approximately 24 frames per second during the reported lane-following test. These values indicate the measured performance of the source study's implementation and should not be interpreted as results independently reproduced for this reformatted paper.

B. Scenario Testing

In an empty-road test, lane markings were detected and the calculated lane error was used to keep the prototype within the lanes. In the U-turn test, the vehicle received an artificial navigation signal, checked for obstacles, and followed a sequence of control steps to complete the turn. In the traffic-sign test, the prototype detected a stop sign and stopped when it reached the configured distance. It also responded to a red traffic light by stopping and continued when the signal changed to green.

In a stationary-obstacle test, the prototype detected an object in its path, stopped, waited, and then maneuvered around it according to the programmed sequence. In the heavy-traffic test, the system handled a scenario involving vehicles in both directions and pedestrians crossing the road. In the pothole test, the detector identified potholes and the control algorithm reduced speed or moved around them. In the domestic-animal test, the system detected a cow, slowed down or stopped, and waited before proceeding or moving around it.

Table I. Summary of Reported Results

Metric	Reported result
Obstacle detector mean average precision	0.729
Average recall	0.758
Processing rate in prototype lane test	Approximately 24 frames per second
Obstacle dataset	Approximately 12,000 labelled images

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Traffic signs and signals dataset	Approximately 1,500 labelled images
Pothole dataset	Approximately 900 labelled images
Training/testing split	80% / 20%

IX. DISCUSSION AND LIMITATIONS

The prototype demonstrates the value of combining visual perception, lane detection, distance sensing, and decision-making. Each component contributes different information: lane detection supports lane keeping, object detection identifies relevant road users and hazards, and ultrasonic sensing estimates distances. The controller uses these outputs to select movement and stopping actions. The use of a Raspberry Pi and Arduino boards also shows how the system can be implemented using relatively accessible hardware.

The reported performance must be considered in the context of the testing environment. The prototype was evaluated on an artificial track rather than through comprehensive public-road trials. Therefore, the results do not establish reliable performance in every real-world situation. Weather changes, poor lighting, unusual obstacles, damaged lane markings, sensor noise, and crowded road scenes may affect detection and control.

A. Limitations

The source study identifies hardware constraints that restrict the use of computationally demanding detection models. Haar Cascade classifiers have limited generalization compared with more flexible detection approaches. The accuracy of two-dimensional mapping based on ultrasonic sensors is lower than that available from LiDAR or radar systems. In addition, artificial testing cannot fully represent the diversity and unpredictability of real traffic.

B. Future Scope

Future work may improve the decision-making algorithm, incorporate stronger safety mechanisms, and investigate more capable sensors where resources allow. Broader tests under different lighting, road layouts, traffic densities, and weather conditions would be needed to evaluate generalization. Additional work could also optimize the detection models for embedded hardware and study how the system handles uncertainty or conflicting sensor readings.

X. CONCLUSION

This paper describes an integrated self-driving vehicle model for complex road navigation. It combines image processing, lane detection, object detection, ultrasonic sensing, sensor fusion, two-dimensional mapping, and a decision-making controller. The source study reports a mean average precision of 0.729, an average recall of 0.758, and processing at approximately 24 frames per second in its prototype tests. Artificial scenarios covered lane following, U-turns, traffic signs and signals, stationary obstacles, heavy traffic, potholes, and domestic animals. The integrated approach supports the design of low-resource autonomous-driving prototypes, while further real-world evaluation and improved sensing remain necessary.

ACKNOWLEDGMENT

The author acknowledges the researchers of the source study for the reported system design, evaluation approach, and findings summarized in this paper. This document is a reformatted and paraphrased academic summary based on the supplied research article; the reported measurements belong to that original study.

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