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Advanced Road Safety: Object Detection in Autonomous Vehicles Using Deep Learning and IOT

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Abstract

Every year, approximately 1.5 lakh people die on Indian roads, which translates, on average, into 1130 accidents and 422 deaths every day or 47 accidents and 18 deaths every hour [7]. In the face of this alarming reality, there is an increasing call for safety. Recent technological advancements in object detection for self-driving cars and their crucial role in addressing India's road safety crisis. These innovations enable vehicles to enhance object detection, improve autonomous vehicle safety, and establish real-time communication between vehicles and infrastructure. Emerging technologies hold immense promise in revolutionizing road safety. By mitigating human error, delivering real-time data for informed decision-making, and driving economic efficiencies, these innovations can potentially transform accident prevention and enhance road safety. Specifically, advancements in object detection, coupled with deep learning and IoT integration, empower autonomous vehicles to play a pivotal role in reshaping the road safety landscape.

Introduction

India faces a dire road safety crisis, with 1.5 lakh lives lost annually due to accidents. Recent technological advancements, including enhanced object detection, deep learning, and IoT, offer hope in addressing this issue. These innovations enable vehicles to improve safety through better object detection and real-time communication. They also reduce human error, leading to significant economic savings and environmental benefits. The pressing need for these transformative technologies is evident, given the staggering economic impact of road accidents, estimated at 3% of India's GDP. Beyond their environmental advantages, the increased mobility provided by autonomous vehicles underscores the pressing need for their widespread adoption. To drive this transformation, cutting-edge technologies like advanced object detection, deep learning, and the Internet of Things (IoT) play a pivotal role in shaping the future of autonomous vehicle development.

Related Work:

In recent years, the advancement of object detection systems has been paramount in enhancing the safety and efficiency of self-driving cars. Various studies have proposed innovative methodologies leveraging a combination of calibrated cameras and LiDAR sensors to achieve robust detection capabilities.

One notable approach, as outlined by [14], implements a Hybrid PointPillar Method. This method integrates a Pillar Feature Encoder to extract crucial high-level features and a Region Proposal Network (RPN) to identify regions through the generation of anchor boxes and proposals. The inclusion of non-maximum suppression (NMS) further refines the process by selecting top-scoring proposals and eliminating redundant ones based on confidence scores. Remarkably, this system achieves an average precision of 75.8% on the KITTI validation dataset, with a mean average precision of 70.8%, encompassing various classes like Cars, Pedestrians, and Cyclists.

Moreover, the landscape of scene classification in self-driving cars has seen significant advancements. In a study focusing on this aspect ([9]), an Improved Deep Network-Based Scene Classification Method is proposed. This method employs an enhanced Faster RCNN for local feature extraction and an Inception_V1 network for global features, thereby creating a comprehensive scene classification architecture. Impressively, after 19,000 training iterations, the system achieves a high accuracy of 95.04% on the validation set, utilizing a dataset comprising categories such as crosswalks, gas stations, parking lots, highways, and streets.

Additionally, object detection in self-driving cars has seen notable improvements through deep learning solutions. For instance, an Improved Deep Learning Solution presented in [12] utilizes a deep neural network architecture with a pyramid feature structure for feature extraction. The system employs dense bounding box generation and classification scoring, along with non-maximum suppression, resulting in average precision metrics of 58.4% and 63.8% for input sizes of 320x320 and 512x512, respectively.

Furthermore, real-time object detection remains a crucial aspect of self-driving technology. Studies such as the one described in [4] showcase the effectiveness of using MobileNet SSD from the OpenCV library, achieving a mean average precision of up to 72.8% on the PASCAL VOC dataset. Similarly, the utilization of the YOLO algorithm, as discussed in [1], enables real-time detection of traffic participants, demonstrating precision improvements until overfitting at the 120th epoch, with a recorded precision of 0.63.

Moreover, advancements continue with the introduction of hybrid approaches. In [11], a hybrid model combining YOLO and Faster R-CNN architectures showcases improved segmentation and classification accuracy. Trained on a local dataset of 10,000 labeled traffic images, this hybrid model demonstrates a 5-7% accuracy increase over standalone YOLO models, emphasizing its superior performance in providing both high accuracy and practical real-time object detection for autonomous vehicles.

These collective efforts signify a continuous push towards safer and more efficient self-driving technologies, underscoring the importance of robust object detection systems in realizing the full potential of autonomous vehicles.

Proposed System

The project's objective is to seamlessly integrate a camera module with a Raspberry Pi to capture real-time visual data. A robust data communication system is established between the Raspberry Pi and a computer, facilitating the efficient transmission of camera feeds and the reception of control directives. An advanced object detection algorithm is meticulously implemented to accurately identify potential obstacles encountered on the road. Conclusively, a sophisticated control system is engineered to interpret these detections and issue precise navigational commands, ensuring adept maneuvering of the vehicle.

This integration aims to enhance the autonomous capabilities of the car, promoting safer and more reliable navigation.

Architecture

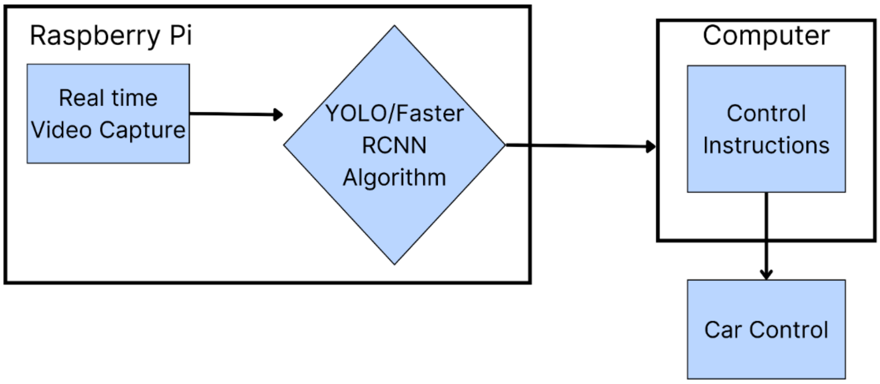


Figure 1: Dataflow diagram of the modules

Implementation

Hardware components:

1. Raspberry Pi 4 Model B 2. MicroSD Card 3. Power Supply 4. HDMI Cable
5. Keyboard and Mouse 6. Monitor 7. Motor Fan 8. USB Camera

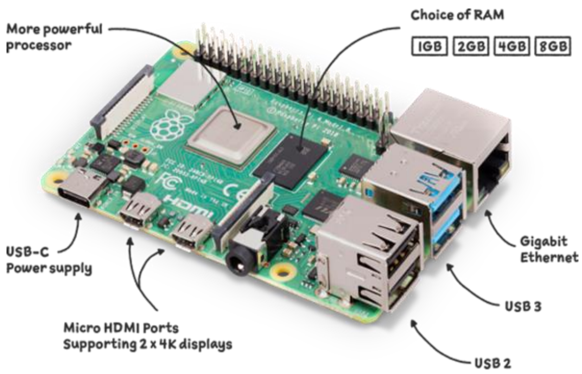


Figure 2: Raspberry Pi board

Setting up a Raspberry Pi with a motor fan starts with downloading the Raspberry Pi Imager from the official source. The next step involves inserting the SD card into the computer's card reader and running the Imager. One must select the Raspberry Pi OS image and the designated SD card for the installation, then proceed by clicking "Write" to begin the installation process. After completion, the SD card should be ejected and then inserted into the Raspberry Pi. For the fan connection, the red wire is attached to a 5V GPIO pin to provide power, and the black wire is connected to a Ground (GND) pin. Additionally, if there is a third wire present, it is connected for speed control. It is essential to check all connections thoroughly to prevent any damage to the components

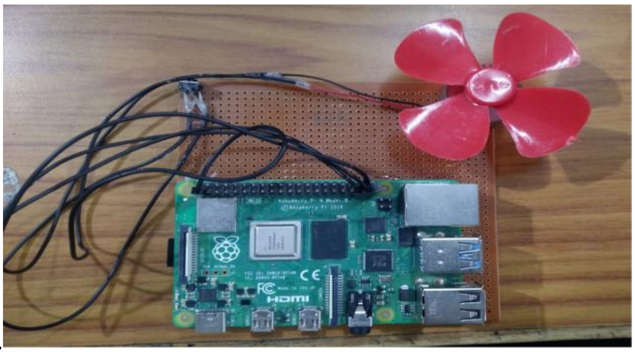
\. 

Figure 3: Raspberry Pi board with connections

The figure above shows the Raspberry Pi board after connecting the motor fan.
Once you've successfully installed the Raspberry Pi OS on the SD card, proceed by inserting the card into the microSD slot on the Raspberry Pi. Power on the Raspberry Pi, and it will initiate the boot process, loading the operating system directly from the SD card.

Wired Data Communication:

A data communication system is established between the Raspberry Pi and a computer to transmit camera data and receive control instructions. The data communication system is wired and involves the following connections:

1. A USB cable connects the Raspberry Pi to the computer.
2. Connect a USB camera to the Raspberry Pi to take real-time video input.
3. Connect a monitor through the micro-HDMI port to Raspberry Pi.
4. Connect a USB port to a mouse, and to a keyboard connected to the Raspberry Pi for navigating through modules and updating code.

Dataset

The COCO dataset is a comprehensive collection of 328,000 images that serve as a visual encyclopedia for a multitude of everyday scenarios and items. This dataset is instrumental in advancing research across a spectrum of computer vision fields, such as object recognition and scene parsing. It encompasses annotations for object detection, including bounding boxes and segmentation masks, across 91 diverse object types. These types range from ubiquitous items like vehicles, bicycles, and fauna to more niche objects like umbrellas, handbags, and athletic gear. Additionally, the dataset is enriched with natural language image descriptions, key points for pose estimation, segmentation for 'stuff' categories, comprehensive panoptic segmentation, and detailed dense pose annotations.

Figure 4: COCO dataset Stuff image annotations

Object Detection using the YOLO algorithm

In the realm of object detection algorithms, non-max suppression plays a pivotal role in refining bounding box predictions. When faced with multiple bounding boxes corresponding to potential objects within an image, non-max suppression selectively retains the most relevant boxes while discarding redundant or overlapping ones. Comparing confidence scores across overlapping boxes, ensures that only the box with the highest confidence survives, streamlining the detection process and yielding more accurate and concise results. Consequently, each object in the image is effectively represented by a single bounding box, enhancing the efficiency and precision of object detection systems.

Object Detection using Faster RCNN Algorithm

Faster R-CNN algorithm, the Region Proposal Network (RPN) assumes a critical role. As the initial stage of Faster R-CNN, the RPN efficiently generates region proposals for potential objects within an input image. Leveraging a convolutional neural network (CNN), the RPN analyses feature maps extracted from the input image. At each point in the feature map, anchors—representing potential object locations across various scales and aspect ratios—are strategically placed. Through subsequent convolutions and layers, the RPN evaluates whether each anchor region contains an object and refines its coordinates via bounding box regression. This meticulous process yields high-quality region proposals, which in turn facilitate accurate object detection and subsequent classification in the subsequent stages of Faster R-CNN.

Results:

1. YOLO

In this module, we have used the YOLOv2 algorithm for object detection the accuracy score is 82%. The mean Average Precision is 37.2%. The object detection algorithm was implemented successfully. It can recognize obstacles on the road accurately and quickly, even under different lighting conditions and with different types of objects.

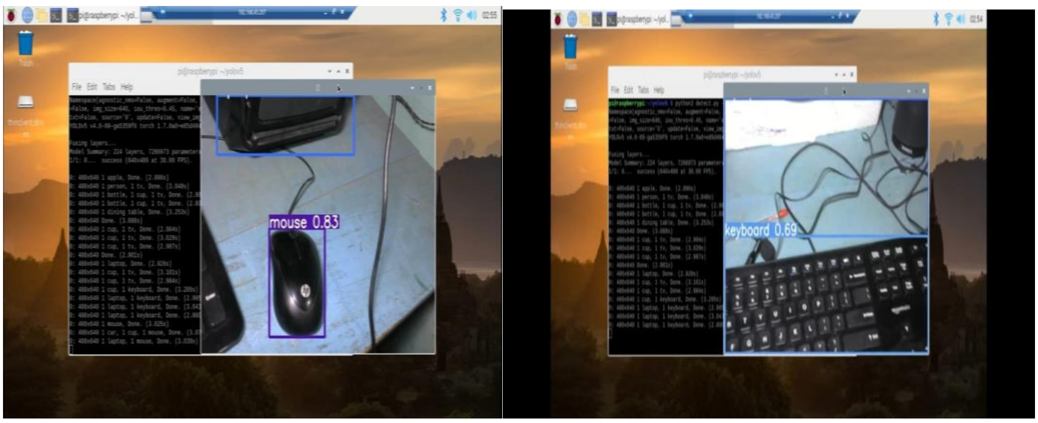


Figure 5: Real-time Object detection of YOLO algorithm

The Figure above shows the output of object detection using the YOLO algorithm

2. Faster RCNN

Faster RCNN has achieved an accuracy of 79%.and the Mean Average Precision is 42.5%. The object detection algorithm was implemented successfully. It can recognize obstacles on the road.

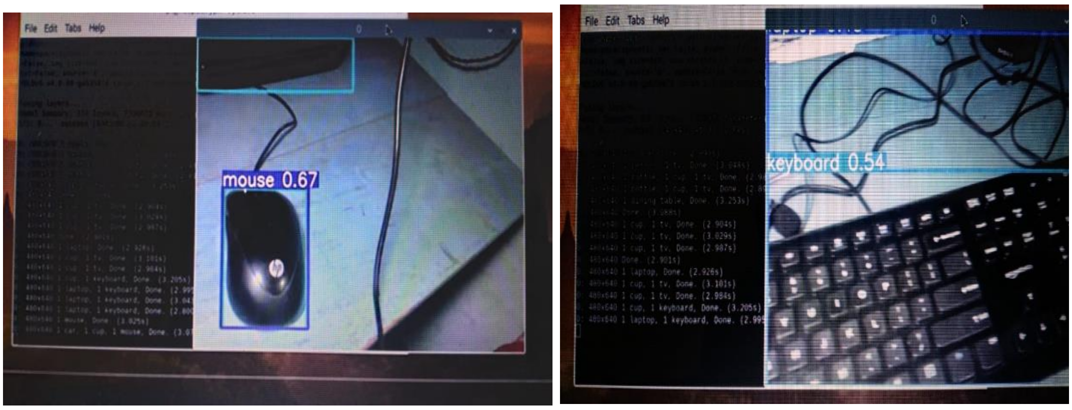


Figure 6: Real-time Object detection of Faster RCNN

The Figure above shows the output of the object detection using the Faster RCNN algorithm.

Conclusion

The integration of a camera module with a Raspberry Pi, augmented by a robust data communication system, has established a versatile foundation for applications in autonomous systems and surveillance domains. The deployment of the YOLOv2 object detection algorithm, with an impressive accuracy rate of 82%, highlights its effectiveness in identifying road obstacles, surpassing the capabilities of Faster RCNN. Notably, YOLOv2 demonstrates superior accuracy and higher frame rates during execution compared to Faster RCNN, particularly in the precise detection of smaller objects. Conversely, Faster RCNN excels in processing high-resolution images with greater accuracy.

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