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Rear Collision Avoidance System Using Machine Learning

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Abstract

Rear-end collisions pose a significant threat on our roads, often stemming from driver negligence, distractions like texting or eating, and the perilous practice of tailgating. Rear-end collisions accounted for 37.6% of all road accidents in Malaysia in 2020, according to statistics from the Malaysian Institute of Road Safety Research (MIROS). Despite existing safety features in modern vehicles, such as ABS and rear collision systems, these crashes persist, leading to traffic delays, congestion, and potential harm. This initiative addresses this urgent issue through the development of a cost-effective Rear Collision Avoidance System (RCAS). The absence of such a system jeopardizes road user safety and contributes to the financial and environmental consequences of accidents. The proposed RCAS employs a Raspberry Pi 4B, a camera, and the YOLOv8 algorithm for real-time image processing, relying on machine learning algorithms (Object Detection with CNN) trained on real-world scenarios to identify potential collisions. Customized for the specific challenges of Malaysian roads, the system ensures cost-effectiveness and accessibility, utilizing readily available components like the Raspberry Pi 4 and a Raspberry Pi camera. The core strength lies in providing drivers with real-time alerts upon detecting a potential crash, enabling swift and conscious responses through the immediate activation of an audible alarm. This proactive approach aims to prevent or mitigate the impacts of imminent collisions. This project advances intelligent traffic systems by offering a practical and resource-efficient solution to rear-end collision prevention, ultimately promoting road safety for all drivers. The primary objective centers on developing a cost-effective system to enhance road safety by successfully designing a machine-learning model for early collision detection. The achieved average precision of 80.9% and correct classification of models at 85.5% underscores the system's high accuracy and reliability. Further enhancing real-time responsiveness, the integration of an ultrasonic sensor triggers alerts, such as a buzzer, when objects approach within 50cm. Combining machine learning and sensor technology, this comprehensive approach positions the project as a promising solution for improving overall road safety. The successful synergy of these components highlights the project's potential to revolutionize road safety measures and minimize the impact of rear-end collisions on our streets.

1. Introduction

More and more modern vehicles can now automatically apply the brakes when they sense danger in front of them but what about behind them? Providing emergency auto-braking and rear-end collision avoidance systems for reversing cars claims to enhance this protection. If the car backs up and hits an oncoming vehicle or other obstacles, a mechanism called "rear collision intervention" immediately applies the brakes. To date, most research studies that have identified risk factors associated with the likelihood of injury from a rear-end collision combine and analyze several years of data (usually 2-4 years) into a single data set [1]. Traffic accidents have become a pressing problem resulting in significant loss of life and property damage. Rear-end collisions in particular account for a significant portion of these accidents. To address this critical issue and improve road safety, advanced driver assistance systems (ADAS) have been developed to help drivers avoid and mitigate collisions. A key component of an effective ADAS is a rear collision avoidance system that uses machine learning techniques to detect potential rear collisions and warn drivers promptly. The main goal of this project is to create and implement a powerful collision avoidance system using the Python programming language and advanced object detection algorithm YOLOv8. You Only Look Once version 8 (YOLOv8) is a state-of-the-art deep learning-based architecture known for its outstanding accuracy and real-time object detection capabilities. The goal is to create a reliable and effective system for the accurate detection of ion vehicles and evaluate potential collision risks in real time by utilizing the capabilities of YOLOv8.

Meanwhile, the car-following relationship between leading and following vehicles is primarily studied by the vehicle rear-end collision avoidance model and the safety distance to be maintained to the following vehicle is provided [2]. The rear collision avoidance system being proposed incorporates computer vision and machine learning algorithms for the processing of video streams from a vehicle-mounted rear-facing camera. Acting as input data for the YOLOv8 model, these video streams undergo training using a substantial dataset of annotated images. Different types of vehicles and other essential objects on the road can be learned and recognized by the model through this training process.

Additionally, to assess the likelihood of a rear-end collision, the vehicle in the video stream is first identified, followed by an analysis of its position, distance, and trajectory. Real-time calculations and predictions are performed by the system, which continuously observes the dynamic changes of nearby vehicles. In the event of a suspected collision hazard, prompt warnings or alerts are issued, enabling immediate evasive action by the driver to prevent a collision. Thorough evaluations of the performance and effectiveness of rear collision avoidance systems are carried out through extensive testing involving various scenarios and traffic conditions. Key performance indicators such as detection accuracy, response time, and collision avoidance or mitigation capabilities are assessed, offering insightful information about the system's efficiency and serving as a roadmap for future enhancements.

Furthermore, a rear-end collision is typically triggered by the sudden deceleration of the lead vehicle during a car-following process [3]. The developed model can calculate an effective collision distance by taking into account the distance, weight, angle, and offset of the vehicle [4]. The successful implementation of this rear collision avoidance system holds the potential to significantly enhance road safety, providing drivers with an additional layer of protection. By leveraging the power of machine learning and harnessing the advanced capabilities of YOLOv8, the system aims to minimize the occurrence of rear-end collisions, thereby reducing the loss of lives and property damage. Valuable insights into improving road safety in the context of rear collision avoidance are contributed by this project to the advancement of ADAS technology.

2. Methodology

Fig. 1 displays the block diagram of the rear collision avoidance system. The rear collision avoidance warning system block diagram is made up of numerous critical components. The Raspberry Pi is the primary processor unit that runs the whole system. The Raspberry Pi Camera takes rear-view pictures, which are subsequently processed by the Image Acquisition and Preprocessing step. The preprocessed image is passed into the YOLOv8 Object Detection algorithm, which recognizes things in the back view, mainly cars, pets, and other obstacles on the road. The Collision Detection and Warning System Algorithm analyses identified objects to identify possible collision hazards and provide warning signals. These warning signals are subsequently relayed to the driver through a warning display or alarm, giving real-time notifications concerning the danger of a rear crash. This block diagram depicts the information flow and the interaction between the various components of the rear collision avoidance warning system.

Fig. 2 displays the software design of this project. The Proteus software-created circuit design for the rear collision avoidance warning system includes critical components such as the Raspberry Pi board, the Raspberry Pi Camera, the ultrasonic distance sensor with 50cm distance, and the Buzzer 2 pin. The Raspberry Pi board acts as the system's core processing unit, providing computing power and communication. It serves as the circuit's brain, executing the essential algorithms for object identification and collision warning. The Camera, which is built into the circuit, takes real-time rear-view photos, which the Raspberry Pi processes to detect possible impediments. The output interface is the Buzzer, the audible alarm alerts the driver when something is detected through the camera, and the ultrasonic distance sensor about to collide with the car provides audio feedback to the driver in the form of alerts.

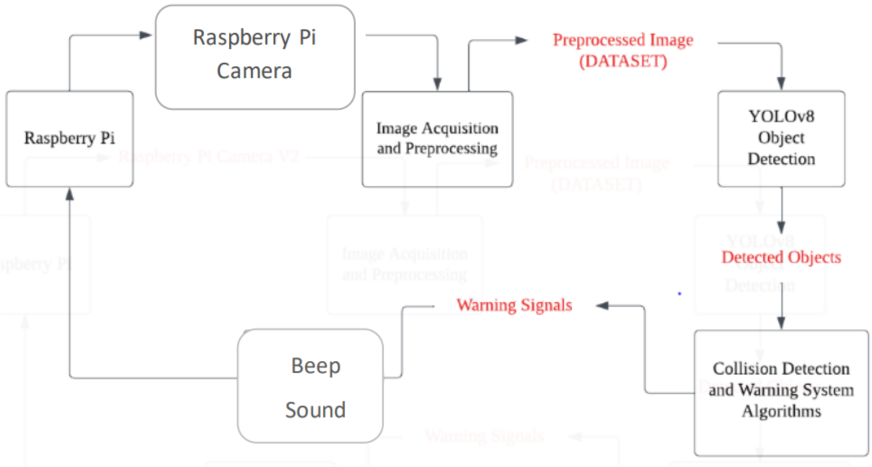


Fig. 1 *Block diagram of rear collision avoidance system using machine learning*

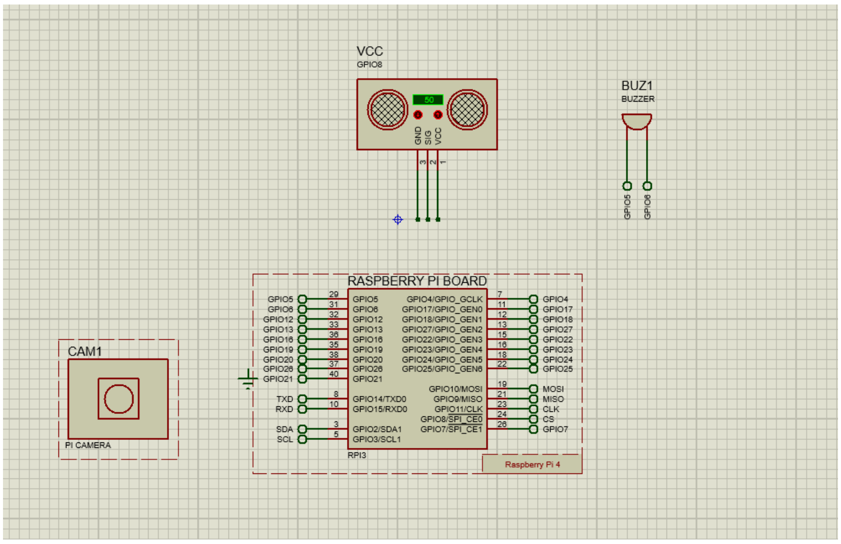


Fig. 2 *Circuit for the system*

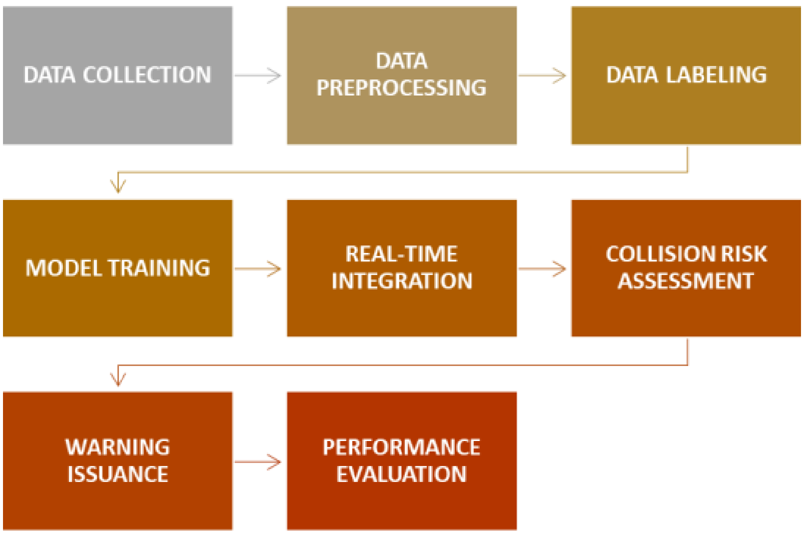


Fig. 3 *Research process flowchart*

Fig. 3 displays the project process flowchart. The workflow begins with collecting data from Roboflow Universe datasets, emphasizing vehicles, people, animals, and barriers. Data preprocessing involves auto-orientation and resizing for standardized input. Over 5800 datasets are manually labeled using Roboflow, with precise annotations. Model training is executed on Google Colab using YOLOv8, reaching convergence in around 5 hours. Real-time integration on Raspberry Pi includes sensor integration and necessary dependencies. Collision risk assessment evaluates challenges while warning issuance integrates audible and visual alerts based on predictions. Continuous performance evaluation involves metrics like accuracy and user feedback, ensuring a robust rear collision avoidance system.

2.1. Data Collection

Table 1 shows the types of classes and number of data collected for training the rear collision system model. This total number of data was trained 3 times to get the accuracy of prediction which was 14974 data with 4 types of classes. The first objective of the project is to develop a vehicle rear-end collision detection and warning system, additionally, animals, barriers, and persons are added to the datasets of the system to improve road safety. The first step in the project is to collect data on vehicle crashes. This dataset is used for training and evaluating collision detection and warning systems. To collect the necessary data, the Camera is set up to record video footage of the rear environment in different scenarios, taking into account factors such as lighting conditions, weather conditions, and traffic density.

Table 1 *Collected Datasets*

Classes		No. of data
Vehicle		2686
Person		1935
Animal		763
Barrier		317

Penerbit UTHM

2.2 Data Preprocessing

Fig. 4 displays the flowchart of data preprocessing for this project. The project used auto-orientation to guarantee uniform orientation across the dataset. This is especially important for keeping a standard format that makes it easy to integrate into machine learning models. Second, resized the images so that they are 800 x 600 pixels in size. This resizing not only normalizes the information size for the models but also finds some kind of harmony between computational proficiency and holding adequate data for successful model preparation. The normalization, which is a common method for scaling pixel values to a standard range, helps the machine-learning models become more convergent. The system is well-equipped to effectively learn and generalize from the provided dataset because these preprocessing steps lay the groundwork for robust model training. The second objective of this project is to develop a vision-based recognition system with machine learning prediction. Data preprocessing is performed to prepare the collected video images for machine learning algorithms. Augmentation techniques such as rotation, mirroring, and noise addition are applied to increase dataset diversity and improve model robustness. Collected data is correctly labeled with Roboflow by sketching a bounding box around the datasets in each photo and giving a class label that indicates the presence of the classes. The YOLOv8 object detection algorithm, implemented using Python and a deep learning framework such as Google Colab, is used to train and tune a model specifically designed to detect vehicles. The tagged dataset is split into a training set and a validation set. A YOLOv8 model is trained using the labeled data from the training set and its performance is evaluated against the validation set.

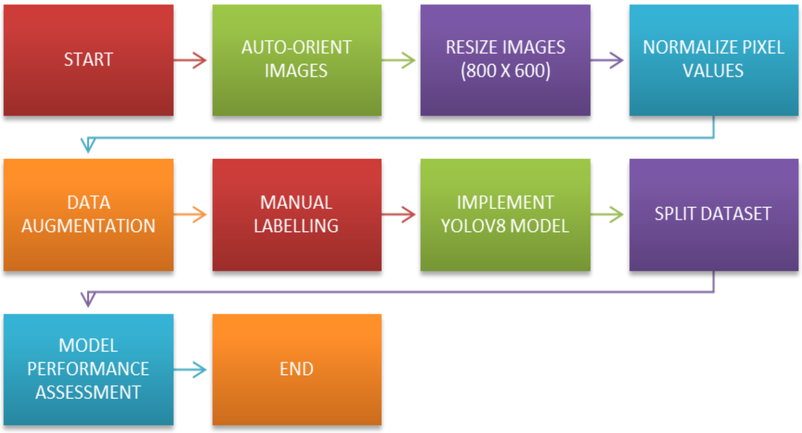
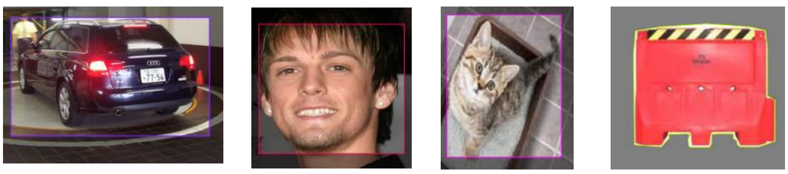


Fig. 4 *Flowchart of Data Preprocessing*

2.3 Data Labeling

Table 2 shows the labeled datasets for this project. This project relies heavily on data labeling, which involves the careful annotation of more than 5800 datasets to train the rear collision avoidance warning system. There are four distinct classes in the labeled dataset: people, cars, animals, and barriers. Each picture in the dataset has gone through exhaustive comments utilizing Roboflow, a powerful stage that works with proficient and precise naming. Comments give critical data about the area and degree of items inside a picture, filling in as ground truth for preparing AI models. For example, explanations indicate the limits of a vehicle or the presence of an individual, empowering the model to learn and perceive these items during the preparation cycle. The utilization of Roboflow smoothes out the marking system, guaranteeing consistency and accuracy across a broad dataset. The machine learning models learned to identify and classify objects based on this labeled dataset, enhancing the efficiency and dependability of the rear collision avoidance system.

Table 2 *Labeled Datasets*



2.4 Model Training

Fig. 5 displays the training of the rear collision avoidance system involved in leveraging the collaborative capabilities of Google Colab and the Roboflow Scratchpad. By utilizing the Roboflow-preprocessed dataset and Google Colab's collaborative environment, the model was trained over 60 epochs, allowing it to learn nuanced patterns in images and converge to a robust state. The combination of YOLOv8, with its advanced object detection algorithms, and the tools provided by the command line interface (CLI) facilitated the integration and configuration of the model. The Roboflow Universe streamlined the workflow for managing datasets, annotations, and model training. The iterative process included meticulous data labeling, fine-tuning model parameters, and rigorous validation to achieve a model meeting high standards of accuracy and recall. The culmination was the deployment of a custom model, capable of accurately predicting real-world rear collision scenarios. The entire process, from YOLOv8 installation to model inference, was a meticulous and iterative journey toward creating an effective rear collision avoidance warning system.

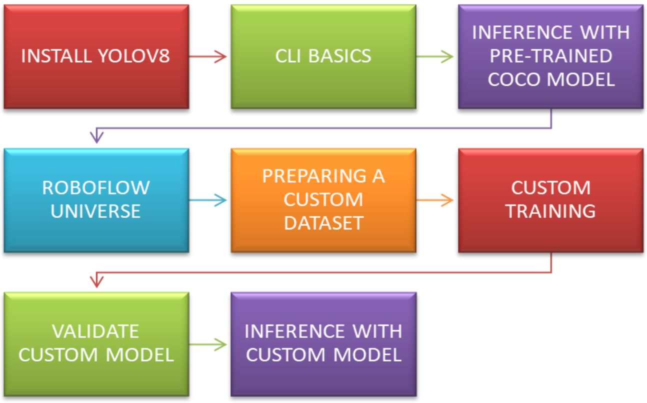


Fig. 5 *Flowchart of Model Training*

2.5 Real-time Integration

The consolidation of the rear collision system advance notice framework into constant situations addresses the last step in the undertaking's execution. After carefully training a custom model with YOLOv8, the attention now turns to the model's seamless integration into real-world applications. It guarantees that the model operates effectively and precisely in dynamic, real-time environments by utilizing the optimized algorithms of YOLOv8. As a result of this deployment strategy, drivers can receive timely alerts and warnings in response to potential dangers from collisions because the model's predictions unfold in real time. All through the combination stage, thorough testing and approval become the dominant focal point, permitting us to calibrate the model's boundaries for ideal execution in the erratic scene of live situations. The model's ability to quickly and reliably issue driver warnings is also a measure of its success in detecting and classifying objects accurately. The blend of cutting-edge AI capacities with continuous responsiveness denotes the peak of the task, yielding a back crash evasion framework that settles on split-subsequent options, contributing essentially to street security.

2.6 Collision Risk Assessment

The collision risk assessment for the rear collision avoidance system involves evaluating potential challenges and hazards. The object detection model's dependability in a variety of situations, like adverse weather and complicated traffic scenarios, is an important factor to take into account. Unpredictability is introduced by driver behavior variation. It is essential to strike a balance between providing unnecessary alerts and providing early warnings. Responsiveness and framework inactivity are evaluated for continuous adequacy. To deal with new dangers and ensure that the vehicle can adapt to changing road conditions, regular updates and maintenance are necessary. The evaluation guides continuous refinements to improve the framework's exhibition in true driving conditions. The evaluation method, real-world testing has been done in the rear collision avoidance system in diverse driving conditions to assess its adaptability, reliability, and overall performance in actual on-road scenarios.

2.7 Warning Issuance

Appropriate warnings are issued to the driver based on the collision risk assessment. Audible alerts such as beeps are implemented, and an ultrasonic sensor is also implemented in this project to improve accuracy. Alerts are clear, attention-grabbing, and customizable for different risk levels. Each incoming image from the camera is processed and the vehicle is detected using the built-in model. A detected vehicle is tracked over successive frames to determine its trajectory.

2.8 Performance Evaluation

The performance of the collision avoidance warning system is evaluated using another dataset containing annotated video footage of known crash scenarios. Metrics such as accuracy and precision are calculated to measure the detection and alerting effectiveness of the system. The results are analyzed and the system is fine-tuned if necessary to improve performance. The detected vehicle trajectory is analyzed to assess the likelihood of a collision.

3. Results and Discussion

After all the sensors are completely installed in the prototype of the rear collision avoidance system, results and data analysis that have been collected are presented here. Fig. 6(a) shows the real vehicle's prototype and Fig. 6(b) shows the project's prototype. Each figure shows the model from a different perspective, providing a complete comprehension of its design and structure.

(a) **(b)**

Fig. 6 *(a) Real vehicle's prototype; (b) The prototype*

3.1 Model Testing Analysis

Fig. 7 displays the model testing analysis of the system. From the figure can conclude all the classes such as vehicles, persons, animals, and barriers have been predicted by the model correctly without any problem. Including 4 different classes which are vehicles, persons, animals and barriers into datasets in the models is crucial for the rear collision avoidance system as it ensures the capability to recognize and respond to different types of obstacles on the road.

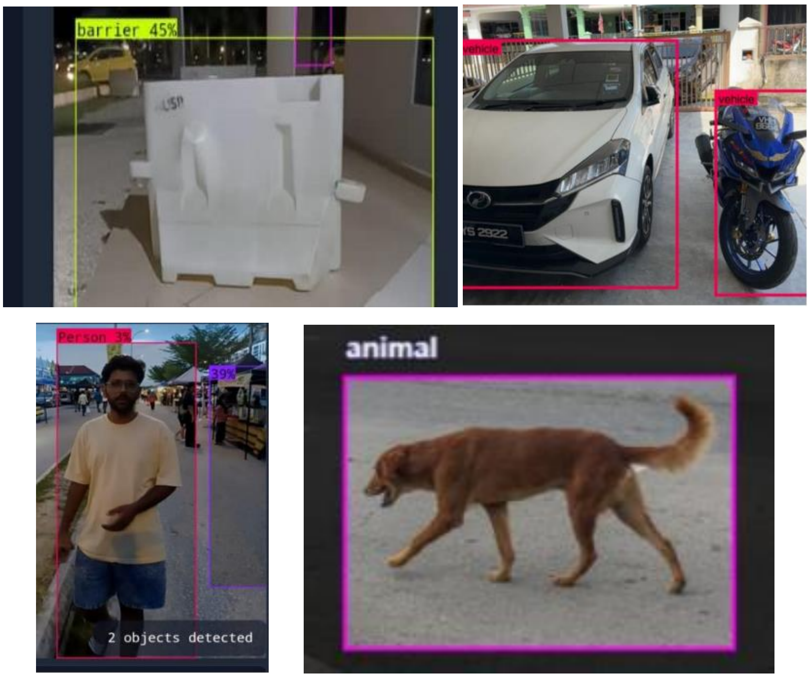


Fig. 7 *Model Testing Analysis*

3.2 Average Precision Metric Analysis

Fig. 8 displays the results of the Average precision metric analysis. It shows a mean average precision graph of 80.9%, The Project's training model predicts a positive instance (potential collision), which is correct about 80.9%

of the time. The x-axis refers to the number of epochs over 5800 datasets with 195. The y-axis refers to several class losses per dataset.

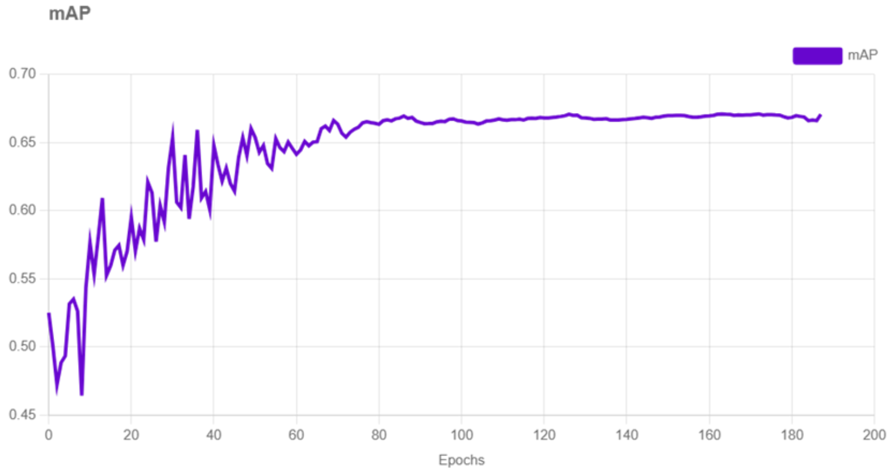


Fig. 8 *Average Precision Metric Analysis*

3.3 Training Model Graphs

Fig. 9 displays the training model graphs of the whole system on how well the model reduces its loss function over 195 epochs. It shows the model's accuracy on the training set, indicating the proportion of correctly classified instances. It also represents the model's performance on a separate validation set, which aids in identifying overfitting. The graphs are a strong tool for detecting and distinguishing between distinct types of objects, allowing the rear collision avoidance warning system to identify probable collisions and trigger appropriate warning alerts.

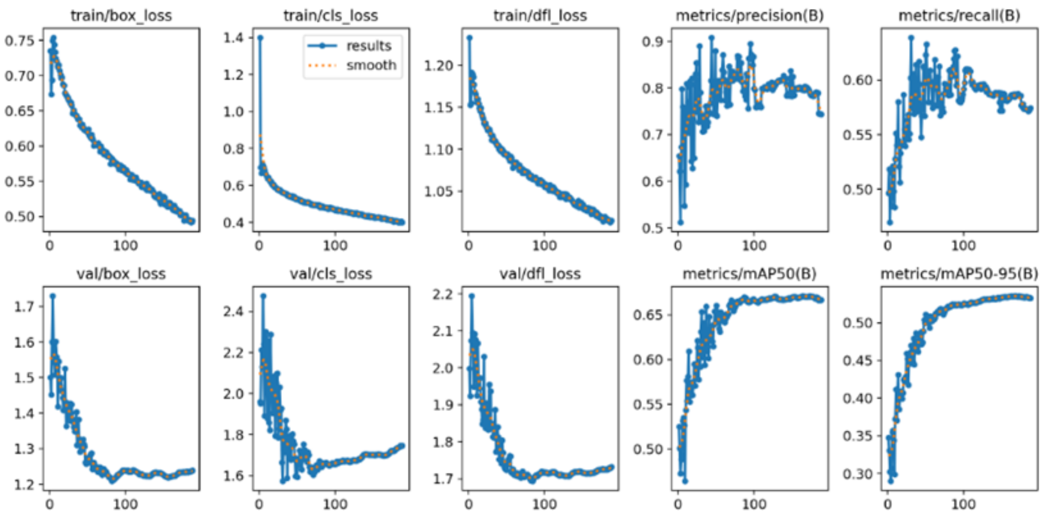


Fig. 9 *Training Model Graphs*

3.4 Confusion Matrix

Fig. 10 shows the confusion matrix of the system. The confusion matrix of the trained models includes different types of class categories, which are vehicles, animals, persons, and road barriers. It also includes the true positives which means the number of detections where the model correctly predicted a specific class. The background class is predicted to capture instances where none of the specified classes are present.

Fig. 10 *Confusion Matrix*

3.5 Pie Chart of Classes

Fig. 11 illustrates the pie chart of the rear collision avoidance system's class balance. The Pie Chart refers class balance of the rear collision system of 5800 images. Dividing the images into different categories in the dataset, as shown in the accompanying pie chart, highlights the importance of key categories in this project to avoid collisions. The majority of the material, 64.62%, is dedicated to 2686 images containing vehicles, indicating the importance of focusing on vehicle detection and recognition. Persons make up the second largest category at 54.5 percent 1935 images underscoring the importance of recognizing and responding to vehicular obstacles. In addition, the dataset includes considerations for scenarios involving animals 763 images (37.81%), suggesting a holistic approach to potential animal-related barriers. Finally, the barriers make up the least with 8.52% with 317 images. A pie chart visually captures a balanced representation of the different classes in the dataset and provides valuable information about the model and training data.

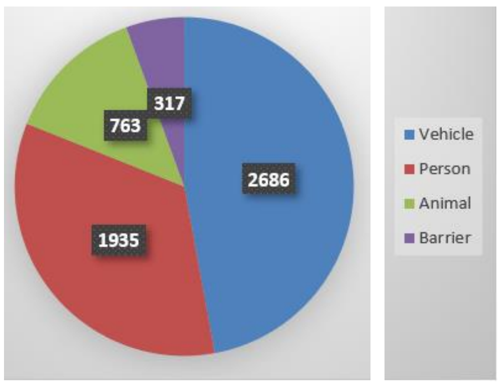


Fig. 11 *Rear Collision Avoidance System Class Balance*

3.6 Dimension Insights

Fig. 12 refers to dimension insights of the rear collision system. The dimension insights refer to the size distribution of the datasets, which is 4 types of sizes. Firstly, tiny size which is 1, for small size 512 images. Then, for the medium size 2166 images, and for the large size the number of images is 3087. Finally, the jumbo size includes 35 images of datasets. This means the Raspberry pi Camera can identify the classes with several types of sizes when it detects the objects.

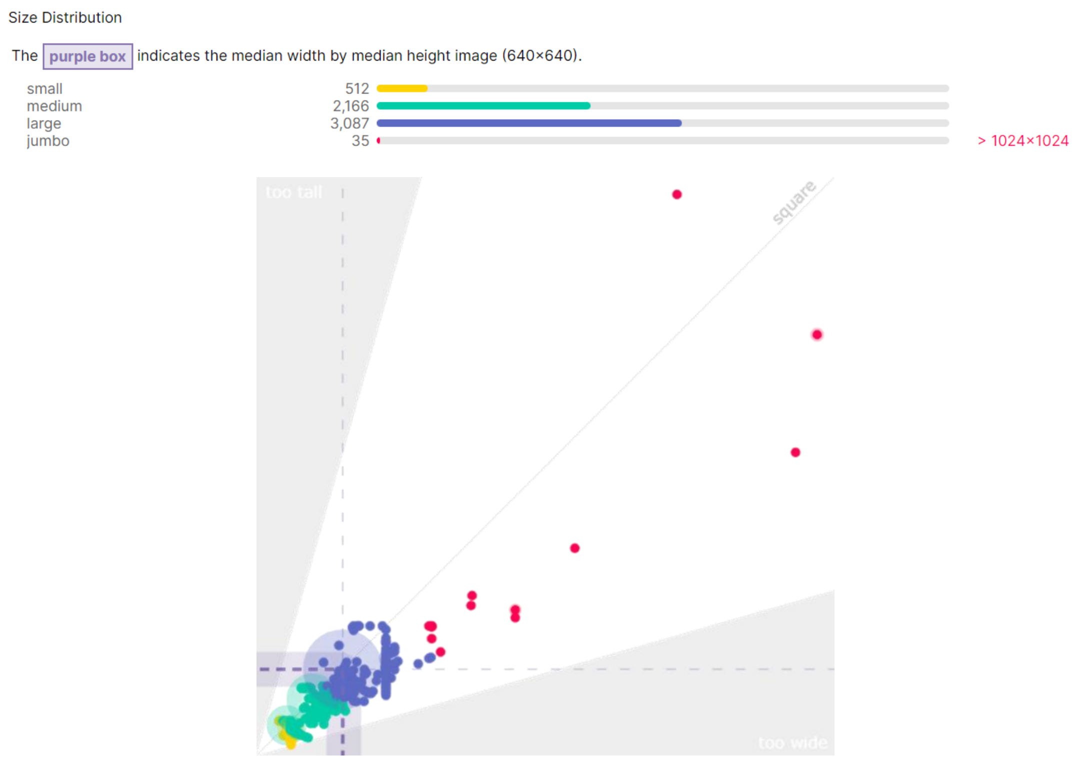


Fig. 12 *Dimension Insights*

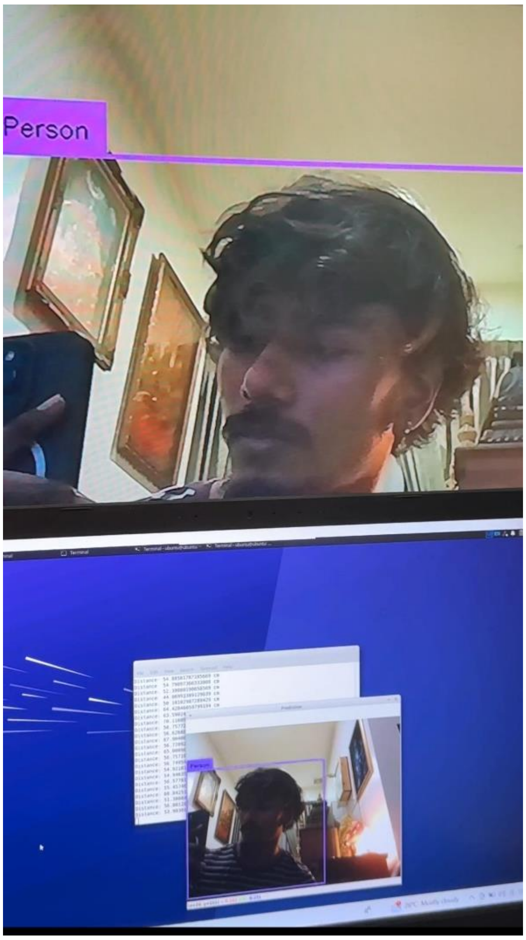


Fig. 13 *Deployment on Raspberry Pi*

3.7 Deployment on Raspberry Pi

Fig. 13 shows the deployment of the system into Raspberry Pi and it can classify the image as a person. The deployment of the model in Raspberry Pi was done in Ubuntu Server. The first step is to create a path for the application on the desktop and then to install all the required dependencies such as:

- OpenCV
- Roboflow
- Inference Server
- Enabling the webcam on the server
- Integrating the ultrasonic sensor and buzzer
- Export the Roboflow api key
- Run the Main.py

The combination of OpenCV for image processing, Roboflow for managing datasets, and the integration of sensors like ultrasonic sensor and buzzer showcase a comprehensive approach to rear collision detection. Moreover, the incorporation of an ultrasonic sensor and buzzer emphasizes the multimodal nature of the system, utilizing both visual and distance-based inputs to enhance collision prediction accuracy. The decision to deploy on the Ubuntu Server underscores the integration process and allows for the utilization of system resources on the Raspberry Pi.

4. Conclusion

In summary, the project has successfully achieved its objectives by developing a rear collision avoidance system. The meticulous AI model training for visual recognition has resulted in a robust system that effectively warns drivers of potential rear collisions. The implementation of Raspberry Pi and seamless integration with the advance notice mechanism demonstrate substantial progress from conceptualization to a practical solution. Ongoing testing and data collection have played a vital role in assessing the system's efficiency, considering metrics such as accuracy, precision, recall, and user feedback. Emphasizing the importance of an iterative improvement process based on real-world insights, this conclusion highlights the project's contribution to enhancing road safety through an adaptable and effective rear collision detection and warning system. The successful culmination of the project marks a significant advancement in intelligent collision prevention systems for vehicular safety technology.

According to this project's rear collision avoidance system, I recommend three suggestions for future improvements to increase the performance and adaptability of the rear collision detection and warning system. First, diversify real-world test scenarios to ensure system reliability under all driving conditions, aiding generalizability. Second, integrate user-centered design principles and actively seek user feedback to refine the warning mechanism to meet driver preferences and usability expectations. Finally, the project must be established for continuous improvement and updating of the model based on continuous evaluation and collection of new data to ensure system efficiency and adaptability to changing circumstances. Implementation of these recommendations contributes to the continued success and satisfaction of users of the collision detection system.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Livenesh;* ***data collection:*** *Livenesh;* ***analysis and interpretation of results:*** *Livenesh;* ***draft manuscript preparation:*** *Livenesh, Nan. All authors reviewed the results and approved the final version of the manuscript.*

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