2024 CSE 40685/60685 Final Project Report

Prepared by

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1. Objectives and Expected Significance

Objective:
The main goal of this project is to develop a machine learning based car sensor system that uses a camera to enhance road safety by detecting potential hazards on the road.This system aims to provide timely and accurate alerts to drivers by utilizing advanced object detection algorithms. By detecting potential hazards on the road, such as vehicles, pedestrians, and road signs, the system can alert drivers to imminent dangers, allowing for proactive rather than reactive driving.

Expected Significance

The expectation of the system is to contribute to overall safety when operating a vehicle, these include:

- **Reduction in Collision rate** – By providing real-time alerts to drivers about potential hazards, the system can aid in avoiding collisions.

- **Keep Driver attention** – By continuously monitoring the road, an alert can pop for a driver that is not paying attention. If a person is looking at their phone while driving, they are not focused on their immediate surroundings.

- This can also be integrated into Autonomous driving vehicles potentially in a future project

Potential Applications:
- **Personal Vehicles:** Owners of personal vehicles can install this system to enhance their safety on the road. The system can help in preventing accidents by alerting drivers to unseen obstacles or abrupt changes in traffic conditions.
- **Commercial Fleets:** Companies operating delivery trucks, buses, and other commercial vehicles can use this technology to improve the safety of their operations. It can potentially reduce the incidence of accidents, lower insurance costs, and ensure the well-being of drivers and goods.
- **Ride-Sharing Services:** Ride-sharing companies can integrate this system into their fleets to enhance passenger safety and maintain high safety standards. This can serve as a competitive advantage by increasing the trust and satisfaction of passengers.
- **Driver Training Programs:** Driving schools can utilize this technology as a teaching tool, providing real-time feedback to learners about potential hazards. It can help new drivers develop the skills needed to notice and react to hazards before they become second nature.
- **Insurance Companies**:Insurance providers can offer this device as part of an incentive program for safer driving. Policyholders with the device installed could potentially benefit from lower premiums due to reduced risk profiles.
- **Smart City Initiatives:** As part of smart city infrastructure, this technology can be used to monitor traffic conditions and enhance public safety on roads. It can provide valuable data for city planners and traffic management systems.

2. Related Background

Dataset Used:
For the training and fine-tuning of our machine learning model, we utilized two primary datasets:

Berkeley DeepDrive (BDD-100K) Dataset: After the initial training on the ImageNet dataset, we fine-tuned our model using the Berkeley DeepDrive (BDD-100K) dataset. This dataset is specifically designed for automotive environments, containing over 100,000 videos that include diverse driving scenarios across different times of the day and weather conditions. The BDD-100K dataset is critical for adapting our model to the specific challenges and requirements of road safety and hazard detection, such as identifying vehicles, pedestrians, and road signs under various lighting and weather conditions.
The combination of these datasets ensures that our model is not only trained with a broad base of general image recognition but is also finely attuned to the specific nuances of road environments.
Class list:

- traffic sign
- traffic light
- car
- rider
- motor
- person
- bus
- truck
- bike
- train

BDD100K (vis.xyz)

The model architecture is inspired by the Quantized MobileNet V2, known for its efficiency on mobile devices. The implementation leverages adaptations from similar projects found on GitHub, which demonstrate the application of MobileNet V2 in object detection tasks. Specific functions and methodologies were adapted and optimized to suit the project's hardware constraints and objectives. Training of the model was done as instructed by the following: Train_TFLite2_Object_Detction_Model.ipynb - Colab (google.com), this was used in order to fully train and quantize the model for implementation with the Raspberry PI.

The project was also heavily inspired by this project Autonomous Driving Object Detection on the Raspberry Pi 4 (ecd1012/rpi_road_object_detection: Repository to run object detection on a model trained on an autonomous driving dataset. (github.com)) where the usage of MobileNetV2 and Quantization of model was taken from. The main difference between the two projects is the addition of all the real-time feedback devices.

3. Approach

Our final approach to developing the machine learning-powered dashboard camera system was systematic and focused on achieving high-performance, real-time object detection tailored for automotive safety. Here's an overview of the systematic approach we employed:

The approach for the system involved several key components:

- Hardware Integration: Configuring the Raspberry Pi to interface with a high-definition dash camera and peripheral alert systems (LEDs and speakers).
- Software Development: Developing Python scripts to handle real-time video processing, object detection using TensorFlow Lite, and trigger mechanisms for alerts.
- Model Deployment: The TensorFlow Lite model of Quantized MobileNet V2 was deployed after being fine-tuned on the BDD-100K dataset to recognize and predict objects with high accuracy and speed, it was trained on 40k steps.

Hardware components

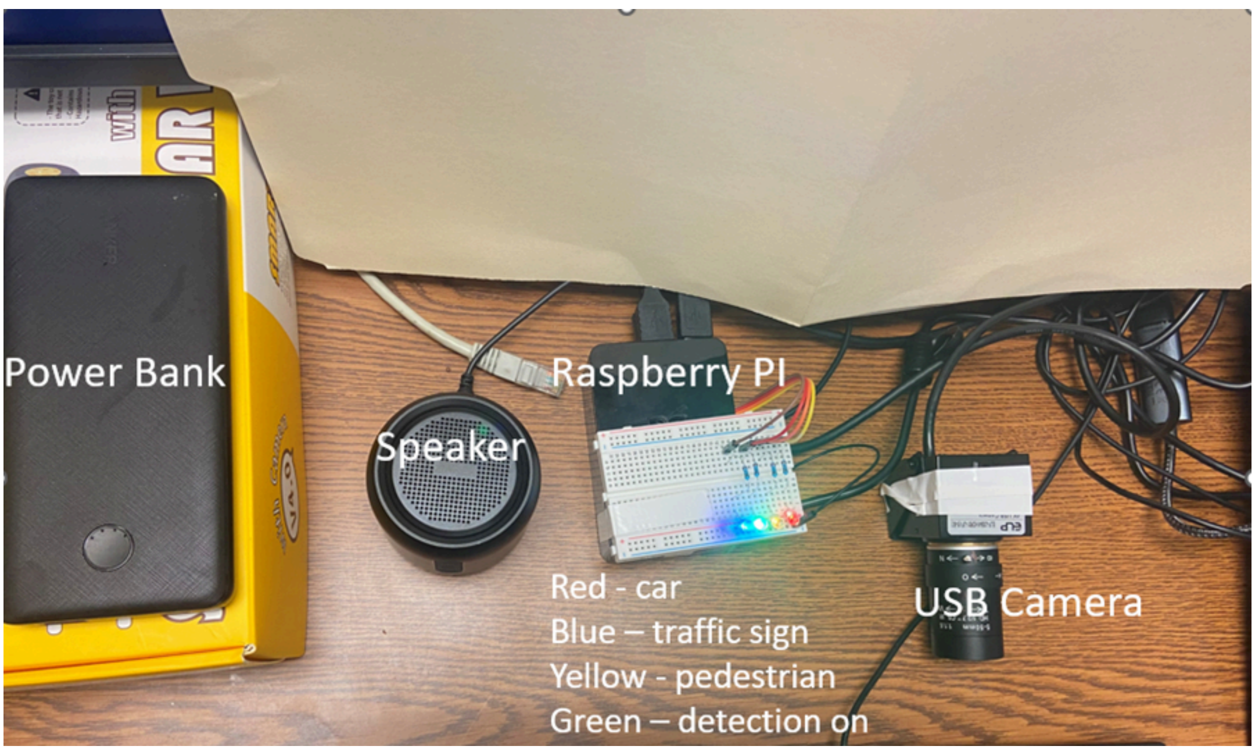

Figure 1. Hardware required for completion of project

- Raspberry PI: Responsible for processing the input from the USB camera, running the object detection algorithm, and controlling the output signals to the speaker and LEDs.

- USB Camera: Attached to the Raspberry Pi, this camera captures live video footage of the road. The video feed is then processed by the Raspberry PI to detect objects such as cars, traffic signs, traffic lights and pedestrians.

- Speaker: This component is used to alert the user audibly when an object is detected. Depending on the object type, different sounds are played.

- LEDs on Breadboard:
  - Red LED: Lights up when a car is detected.
  - Blue LED: Indicates the detection of a traffic sign or traffic light.
  - Yellow LED: Activated when a pedestrian is detected.
  - Green LED: Shows that the detection system is actively running and monitoring the road.

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- Power Bank: Provides power to the Raspberry PI. This makes the system portable and not dependent on a fixed power source, allowing for flexibility in testing and deployment.

Application pipeline

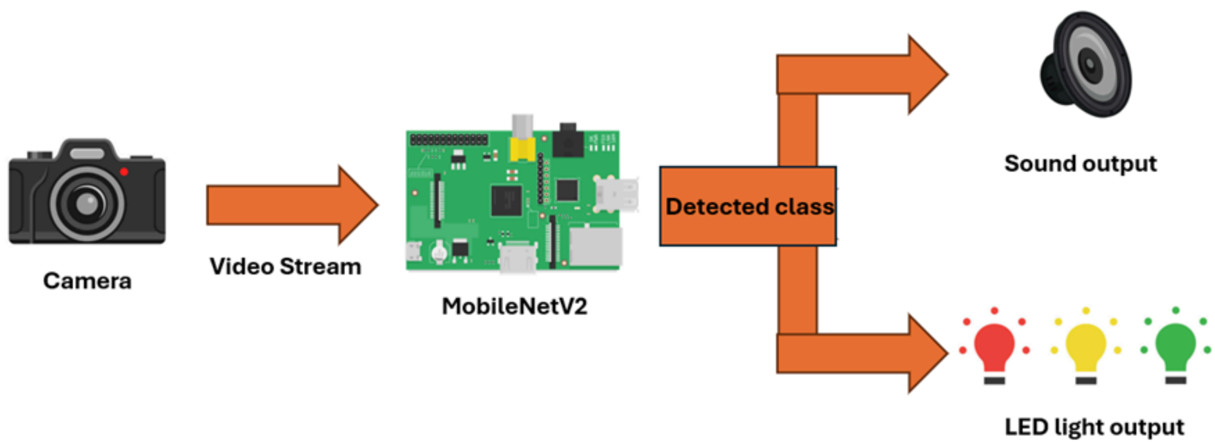


Figure 2. Application pipeline from input to output device

Input is taken from the USB camera as a VideoStream, then it is processed by the MobileNetV2 model and given a proper class distinction, this happens each frame. If a class is detected the designated sound and light for said class gets activated.

4. Project Outcome

Our project successfully resulted in the development of a fully functional machine learning-powered dashboard camera system designed to enhance road safety. Our system utilizes a streamlined Quantized MobileNet V2 model, trained on the COCO dataset and fine-tuned on the BDD-100K dataset, to detect objects within a 120-meter range. It provides timely alerts to drivers using audio (warning sounds) and visual (LED indicators) cues.

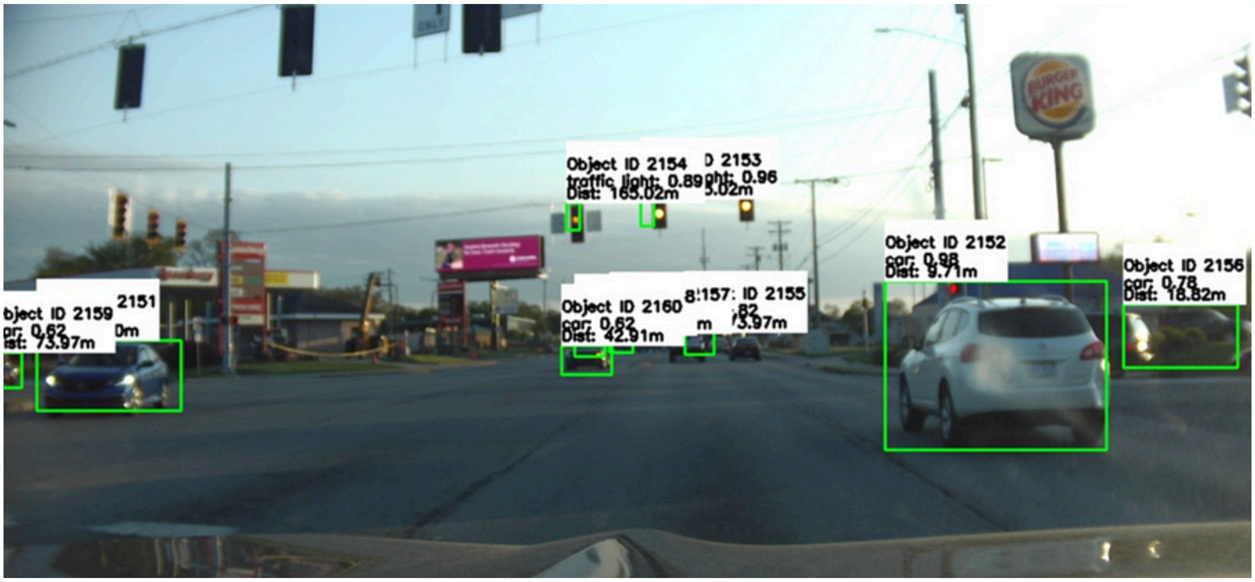
Project can be found on Github: Windtwist/Embedded_Systems_Scope: AI Driver Assistance System - final project - Notre Dame (github.com)

Key Features and Outputs:

- Real-Time Object Detection: The dashboard camera processes video input at a consistent 30 FPS, ensuring smooth performance in dynamic road environments. It can detect vehicles, pedestrians, and road signs with a mean average precision (mAP) of 70-75%.
- Visual and Audio Alerts: The system is equipped with audio speakers that emit warning sounds and LED indicators that provide visual signals when potential hazards are detected. These alerts are designed to be intuitive and easily noticeable, ensuring that drivers can react promptly to avoid accidents.
- Audio Alerts: Equipped with a speaker to emit warning sounds when potential hazards are detected.
- Low Latency and High Detection Range: With an end-to-end latency of less than 200 milliseconds, the system quickly processes images and delivers alerts, giving drivers adequate time to respond. The detection range extends up to 120 meters, offering advanced warning of potential hazards ahead.
- High Detection Range: Capable of detecting objects up to 120 meters away.

Visual Representations

To demonstrate the effectiveness and functionality of our dashboard camera system, we have compiled a series of photos and video clips that showcase the system in action. These visuals depict how the camera detects various objects and issues alerts in different driving scenarios, such as during day, night, and in adverse weather conditions.



5. Unexpected Events (optional)

Challenges and Resolutions

High System Latency: Initial tests revealed higher than expected latency. The issue was addressed by optimizing the TensorFlow Lite model and enhancing the video processing pipeline.

Hardware Limitations: The Raspberry Pi showed limitations in handling simultaneous input/output operations. This was mitigated by optimizing memory usage and streamlining the code. Another limitation was the original Raspberry Pi camera, because of OpenCV reliability on legacy camera, the model was not able to function with the Raspberry Pi camera. To fix the issue the project switched to a USB-connected camera, which functioned perfectly.

Environmental Impact: Performance can be affected by environmental conditions such as lighting and glare.

Model Bias: There is an inherent bias towards the 'person' class in the training set causing unequal representation as compared to other classes

6. Lessons Learned

Importance of Hardware Capability: Understanding and adapting to the hardware's capabilities were crucial in ensuring the system's effectiveness and efficiency.

Value of Real-World Testing: Field tests provided invaluable insights that significantly influenced the final design and functionality, especially when we were calibrating our camera. During our prototyping phase we were pointing the camera into a screen and getting decent results, however when testing our model outside in real-world scenarios the distance estimation function had to be re-evaluated.

Future work
Improve Traffic Sign Recognition:

- Expand training datasets to include diverse conditions.
- Explore advanced neural architectures like EfficientNet or Vision Transformers.
- Utilize data augmentation and transfer learning from extensive datasets.

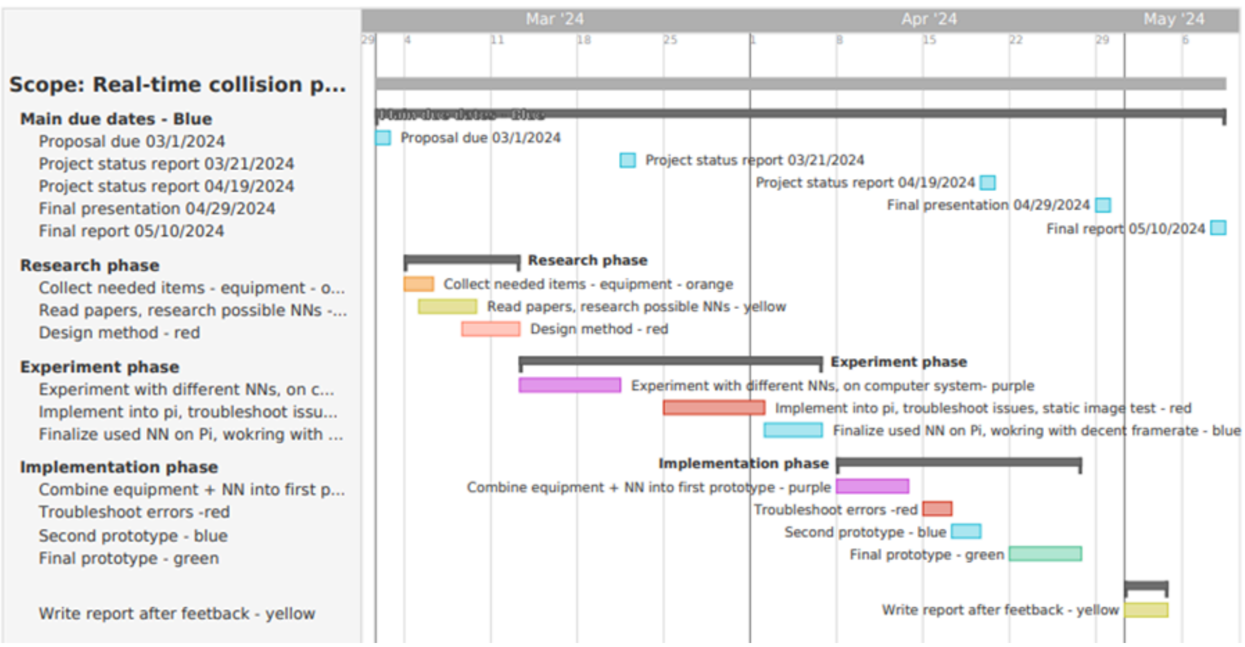
Refine Distance Estimation:
- Implement camera calibration for user setups – current approach very rigid and only works accurately for specific cameras.
- Develop regression models for distance estimation from single-camera inputs.

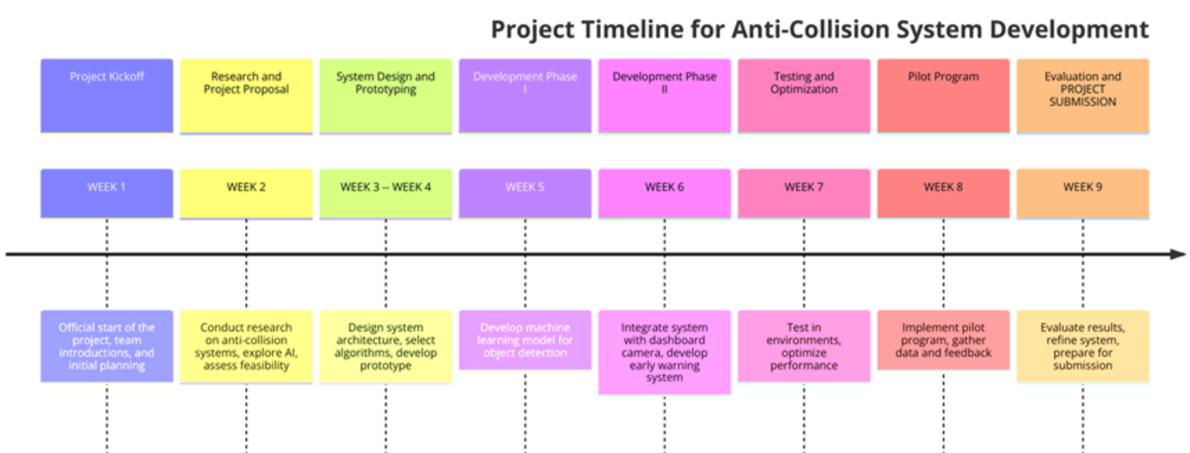
Enhance Alert Systems:
- Develop a more enhanced alert system – more sounds
- GPS integration – pop-up on screen

7. Project Performance

On-time

The project aimed to develop an AI-powered anti-collision system. Several milestones were set during the planning phase. These are the achieved milestones and how they compare to planned milestones.





Research phase – research phase, completed on time – during the first 3 weeks while waiting for hardware parts.

Experiment phase:

- Development of Object Detection Algorithms:
  - Planned to be completed by early April, completed mid-April
  - Encountered difficulties in algorithm optimization and required additional training data to enhance detection accuracy

Implementation phase:

- Integration of Dashboard Camera:
  - Planned for mid-April, completed mid-April, camera change needed.

- System Integration and Preliminary Testing:
  - Targeted for late April, achieved start of May

Final Testing and Project Demonstration: Set for early May, completed on time.

8. Individual Contributions

Nnamdi Chikere – implemented all the hardware aspects of the PI, connected all the components, made the lights and sound react with the final model output.

Luka Cvetko – responsible for training of models and implementing the object detection script and connecting the hardware and software aspect of the project.

Nathan Gandawa – in charge of documentation, meetings, organized meetings, made sure to keep everyone on track with due dates, wrote necessary documentation.