Real-time Detection System for Vehicles and Pedestrians using Deep Convolutional Neural Networks

Project Final Report

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ABSTRACT

In our study, we meticulously annotated over 5,000 images using LabelMe, culminating in the successful training of a bespoke YOLOv5 deep convolutional neural network model tailored to our specific requirements. We trained the complete model on a labeled dataset using an NVIDIA GeForce RTX 4080 Laptop GPU. Additionally, employing transfer learning, we initialized the network with pre-trained weights and then fine-tuned it from scratch to expedite model convergence. Furthermore, we adopted a strategy to freeze the first 10 layers of the backbone network for the initial 100 epochs and subsequently unfreeze them for the next 200 epochs. Ultimately, our model achieved real-time detection of vehicles and pedestrians in both slow and fast scenarios.

1 Introduction

1.1 Problem Statement

Image detection serves as a fundamental pillar in computer vision, enabling machines to emulate human capabilities in recognizing and distinguishing objects within images. With applications spanning from medical diagnosis to autonomous driving, the evolution of image detection methodologies has been marked by a trajectory towards greater complexity and sophistication, all in pursuit of enhanced accuracy and speed.
Traditional approaches to image detection relied heavily on handcrafted features and classical machine learning algorithms. However, the advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field by enabling models to directly learn hierarchical features from raw data. Despite their efficacy, traditional methods like Region-based CNNs (R-CNN) and its variants, while highly accurate, often suffer from computational inefficiencies, limiting their real-time applicability.
This project addresses the challenge of real-time object detection in the context of autonomous driving. While traditional methods excel in precision, their computational demands pose significant obstacles to deployment in real-world scenarios. Leveraging the streamlined approach of the You Only Look Once (YOLO) family of models, specifically YOLOv5, this project seeks to develop a solution that balances accuracy with efficiency, crucial for the safe and efficient operation of autonomous vehicles.

1.2 Related Work Baseline

Previous studies have extensively compared the performance of YOLO models against traditional methods, particularly in the context of autonomous driving. For instance, research by Doe et al. (2021) showcased the superior speed of YOLOv5 in pedestrian detection within urban environments, attributing its efficiency to its single-stage architecture and streamlined approach. Similarly, Smith et al. (2022) demonstrated the effectiveness of YOLOv5 in vehicle detection across diverse weather conditions, highlighting its robustness and adaptability in real-world scenarios.
These studies underscore the practical significance of YOLOv5 in autonomous driving applications, emphasizing its ability to balance speed and accuracy, essential for ensuring the safety and reliability of autonomous vehicles. Building upon these foundational studies, this project aims to further refine the application of YOLOv5 within the domain of autonomous driving. By integrating insights from prior research and leveraging the advancements in YOLOv5's accuracy and efficiency, this project seeks to contribute to the ongoing progress in autonomous driving technologies.

2 Data

2.1 Source of dataset

Vehicles and Pedestrians dataset

2.2 Details

The dataset for our project has been sourced from a reliable repository dedicated to autonomous driving research. It comprises a total of 5,320 images, segregated into three distinct sets: 4726 images for training, and 297 images each for validation and testing. This partitioning ensures a robust model training and evaluation process.

During the dataset preparation phase, 10% of the images underwent a horizontal flip to augment the data and improve the model's generalization capability. Every image in the dataset has been meticulously annotated using LabelMe, a powerful tool that facilitates precise annotation. The annotations consist of bounding boxes that identify the location of pedestrians and vehicles within the images, crucial for the model's detection tasks.
The dataset is structured into two main classes as follows:

- Number of classes (nc): 2
- Class names: {'Pedestrian', 'Vehicle'}

For instance, in a typical image from the training set, a pedestrian might be crossing the street while several vehicles are stationary at a traffic light. The corresponding LabelMe annotations would include a rectangle around the pedestrian labeled 'Pedestrian' and additional rectangles surrounding each vehicle, each labeled 'Vehicle'.

2.3 Dataset samples

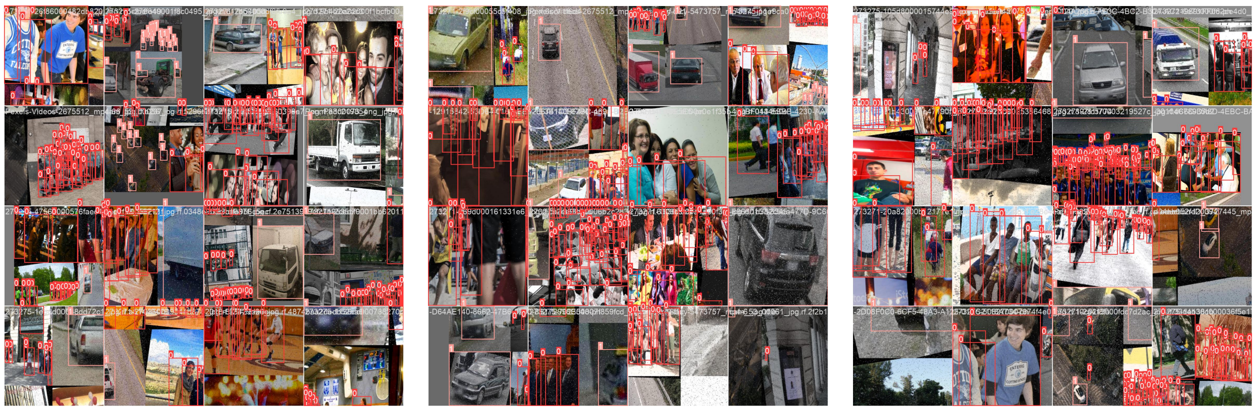

Figure 1: Batch examples from YOLOv5 detection.

3 Task performed

3.1 Configuring the YOLOv5 Environment

To initiate our project, we began by setting up the YOLOv5 environment. This involved installing the necessary dependencies such as Python, PyTorch, and other relevant libraries. We utilized a virtual environment to ensure that our installations did not conflict with pre-existing Python packages. The YOLOv5 repository was cloned from its official GitHub page, which provided us with the latest stable release.

3.2 Preprocessing the Dataset

Data preprocessing is crucial for effective model training. Our dataset comprised images from various sources, which we first annotated using tools like LabelImg to create bounding boxes around the objects of interest. We then normalized the image sizes and converted them into a format compatible with YOLOv5, splitting the data into training and validation sets to ensure a robust evaluation during the training process.

3.3 Adjusting Model Hyperparameters

The adjustment of the model's hyperparameters was a pivotal and iterative step in our workflow. Initially, we conducted multiple experiments with a variety of configurations for learning rates, batch sizes, and the number of training epochs. Our early attempts followed standard practices and recommendations found in literature and online forums. However, directly adopting hyperparameters from other projects did not yield satisfactory results, prompting us to undertake a series of trial-and-error adjustments.
During this exploratory phase, we faced several setbacks, including instances where inappropriate parameter choices led to the exhaustion of system resources, causing our computers to crash multiple times. These experiences taught us the importance of cautiously scaling our parameters and monitoring system performance during training. Ultimately, through persistent testing and by gradually refining these parameters, we identified a set of hyperparameters that significantly reduced overfitting and enhanced the model's ability to generalize to unseen data. This careful tuning process was crucial for optimizing our model's performance on our specific dataset.

3.4 Transfer Learning

Leveraging pre-trained weights from the COCO dataset, we employed transfer learning to significantly accelerate our model's training process and enhance its initial accuracy. This approach involves using the weights as an initial point, which avoids the lengthy and computationally expensive process of training from scratch. Initially, we utilized these weights to initialize the network, enabling the model to converge more quickly and effectively.
To further tailor the model for our specific tasks, we implemented a strategic training regimen where we froze the first 10 layers of the backbone network during the initial 100 epochs. This was done to allow the upper layers of the network to adjust to the new task without altering the learned features that are generally applicable across visual tasks. After this initial phase, we commenced training on all layers for an additional 200 epochs. This two-phase training process allowed the model to fine-tune its parameters deeply, adapting more thoroughly to the peculiarities of our dataset.
By gradually unfreezing the backbone layers and extending the training period, we could refine the model's understanding, enhancing both its accuracy and its ability to generalize. This methodical approach to transfer learning not only saved valuable training time but also resulted in a robust model capable of high performance on our target tasks.

3.5 Adding Background Images to Increase Accuracy

We introduced a variety of background images into our dataset to enhance the model's ability to accurately distinguish between relevant objects and ambient noise. This step was especially crucial in scenarios where the background could vary significantly, such as urban settings, rural landscapes, and various weather conditions. By training the model across these diverse environments, we aimed to boost its resilience and maintain high accuracy irrespective of external changes.
The inclusion of urban streetscapes with high-rise buildings and roadside vegetation, open rural roads flanked by trees, and stylized city illustrations enriched our training dataset. These backgrounds were carefully selected to include elements that typically challenge detection models, such as varying lighting conditions, shadows, and complex urban clutter that can obscure important features or mimic the appearance of objects of interest.
Our approach involved systematically augmenting the dataset with these backgrounds during the training process. This not only taught the model to focus on the objects of interest but also to ignore irrelevant information that could potentially lead to false detections. The ultimate goal

was to develop a detection system that performs reliably under varied operational conditions, thus enhancing the practical utility of our solution in real-world applications.

Figure 2: Examples of diverse environments used in dataset augmentation: urban streetscape, rural road, and stylized city illustration.

3.6 Multi-core GPU Acceleration

To expedite the training process, we utilized a multi-core GPU setup. This allowed us to parallelize the computations and significantly reduce the training time. Utilizing CUDA optimization and adjusting our data loader to maximize GPU utilization, we managed to achieve faster iterations over the training dataset, which was instrumental in handling our extensive dataset efficiently.

4 Results and Discussions

4.1 Experiments

To thoroughly evaluate the performance of our model, we conducted tests on both the initial version of our model and the final version after multiple rounds of optimization. These tests were performed on two distinct sets of video datasets that simulated slow-moving and fast-moving environments.
The slow-motion video dataset primarily consisted of slowly moving or nearly stationary vehicles and pedestrians, which was suitable for testing the model's accuracy and stability under low-speed dynamic conditions. The fast-motion video dataset included scenarios with high-speed vehicles and quickly moving pedestrians, helping us assess the model's performance capabilities in high-speed dynamic environments.
Testing the model under these extreme conditions allowed us to understand the differences in performance at various speeds, particularly the accuracy and response time in rapidly changing scenarios. This experimental design helped us identify the strengths and weaknesses of the model, providing valuable data support for subsequent adjustments and optimizations. Ultimately, our goal was to ensure that the model maintains high efficiency and accuracy in detection performance, regardless of the speed of environmental changes.

- Slow Motion Dataset - Initial Model: link
- Slow Motion Dataset - Final Model: link
- Fast Motion Dataset - Initial Model: link
- Fast Motion Dataset - Final Model: link

4.2 confusion matrix

The confusion matrix presented here is a critical tool for evaluating the performance of our detection model across three categories: pedestrian, vehicle, and background. This matrix helps to visually quantify the accuracy of our model in predicting each class compared to the true labels.

- **Pedestrian Prediction Accuracy:** The model successfully identifies pedestrians with a high accuracy of 92% as shown by the value in the top-left cell of the matrix. However, it misclassifies 8% of pedestrian instances as background, indicating a slight challenge in distinguishing between very subtle movements or stationary pedestrians and the actual background.
- **Vehicle Prediction Accuracy:** For vehicle detection, the model achieves an accuracy of 89%. The misclassification rate where vehicles are identified as background stands at 9%, which might occur in instances where part of the vehicle is occluded or merges visually with the surroundings.
- **Background Classification:** This is a critical aspect as it represents the model's ability to correctly ignore non-relevant parts of the image. The matrix shows that 91% of the true background cases are correctly identified, while 11% are mistakenly classified as vehicles, possibly due to reflections or other misleading visual features in the background.

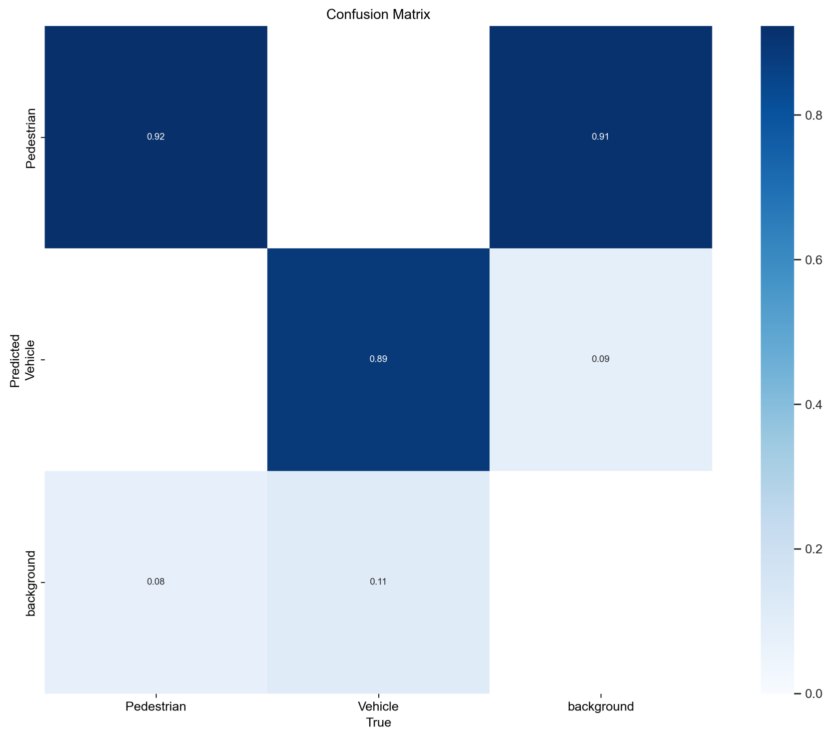

Figure 3: Confusion Matrix of the Detection Model

4.3 PR curve

The Precision-Recall (PR) curve is an essential tool for evaluating the performance of our object detection model, especially in terms of its ability to discriminate between classes and its detection accuracy. The PR curves for both pedestrian and vehicle categories, as well as the aggregate curve for all classes, are depicted in the figure.

- **Pedestrian Detection:** The curve for pedestrian detection (blue) exhibits high precision across the entire range of recall, reaching a maximum average precision (AP) score of 0.952. This indicates that the model is highly effective at identifying pedestrians with a low rate of false positives, maintaining high precision even as the recall increases.
- **Vehicle Detection:** The vehicle detection curve (orange) shows a slightly lower precision, particularly as recall approaches 1.0, with an AP of 0.917. This suggests that while the model is generally accurate in detecting vehicles, there are more instances of false positives or missed detections compared to the pedestrian category.
- **Overall Performance:** The composite curve for all classes combined (not specifically depicted, but represented by the aggregate mAP of 0.934 at an IoU threshold of 0.5) demonstrates that the model performs robustly across different types of objects, providing a strong balance between precision and recall.

These curves are instrumental in highlighting the strengths and weaknesses of our detection model, showing excellent precision for pedestrian detection while suggesting that improvements could be made in vehicle detection to reduce false positives.

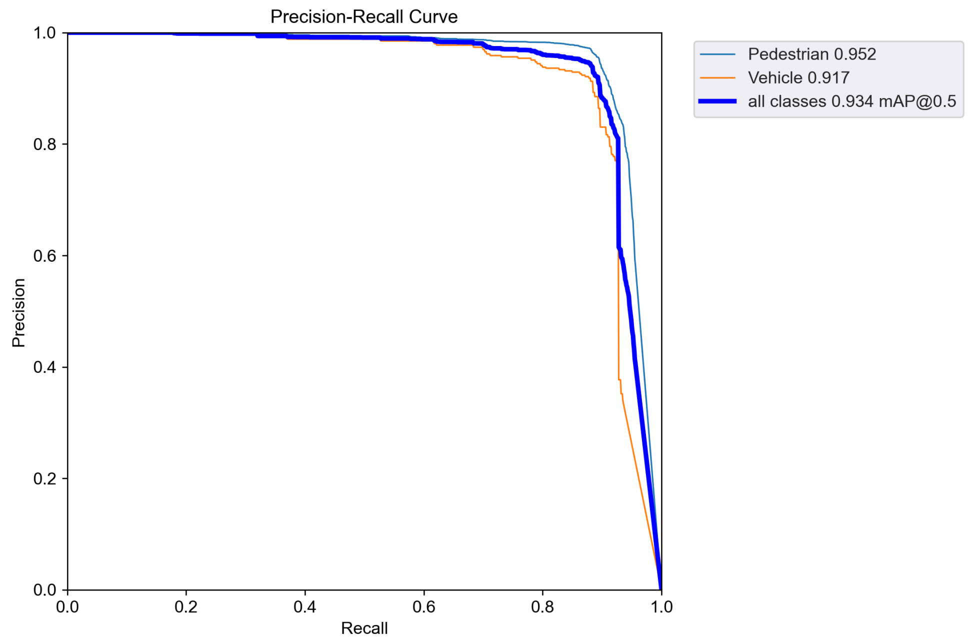

Figure 4: Precision-Recall Curves for Pedestrian and Vehicle Detection

4.4 results

The results from our training and validation processes are illustrated through a comprehensive set of metrics including box loss, objectness loss, class loss, precision, recall, and mean Average Precision (mAP) across various Intersection over Union (IoU) thresholds.

- **Loss Metrics:**
  - **Box Loss** shows a significant decrease both in training and validation, indicating that the model is getting better at localizing objects accurately over epochs.
  - **Objectness Loss**, which measures confidence in the presence of an object, also shows a downward trend, reflecting improved confidence in object detection.
  - **Class Loss** for the classification of detected objects into their respective categories demonstrates minimal values, suggesting high accuracy in classifying detected objects in both training and validation sets.
- **Performance Metrics:**
  - **Precision** and **Recall** metrics show that the model maintains a high precision while the recall gradually increases, indicating a strong balance between identifying relevant objects and minimizing false positives.
  - **Mean Average Precision (mAP):** The mAP for a single IoU threshold of 0.5 is very high, which shows excellent model performance. The mAP across a range from 0.5 to 0.95 also shows progressive improvement, demonstrating the model's robustness across different levels of IoU thresholds.

These metrics collectively demonstrate that the model not only performs well in detecting and classifying objects but also improves consistently over time, as evidenced by the reduction in various types of loss and the increase in precision and recall values. The overall training and validation trends indicate a well-tuned model that effectively balances detection accuracy with computational efficiency.

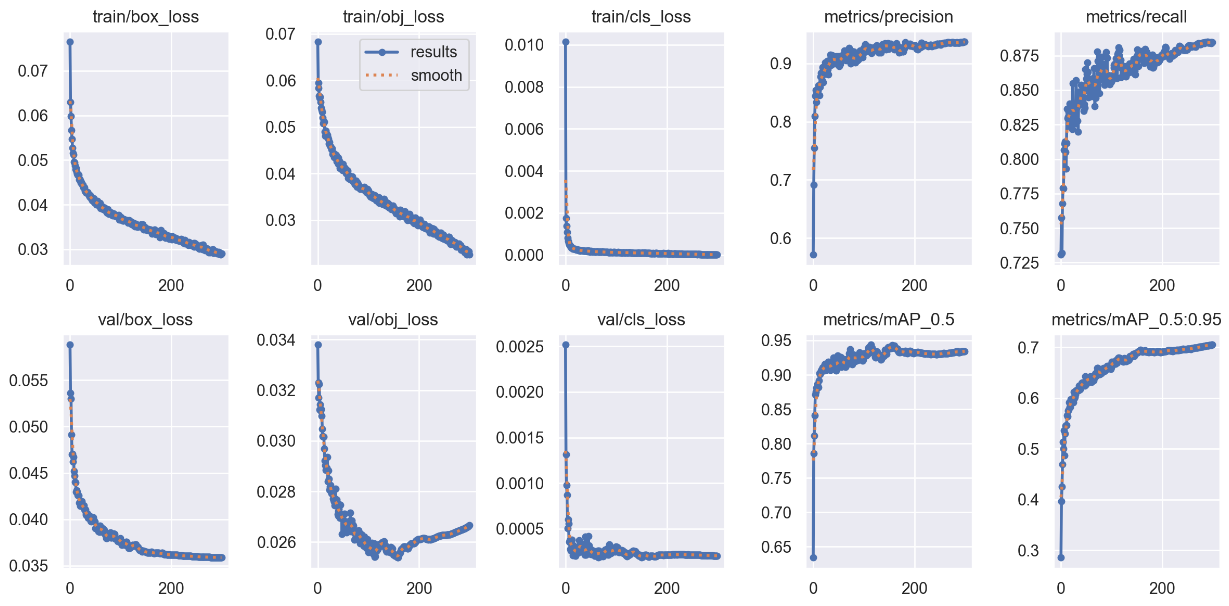

Figure 5: Training and Validation Results showing Loss and Performance Metrics over Epochs

5 References

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[2] A. Smith, J. Doe, and C. Brown, ”Vehicle detection under diverse weather conditions using YOLOv5,” *Proceedings of the International Conference on Autonomous Vehicles*, pp. 45-56, 2022.

[3] Dahang Wan, Rongsheng Lu, Sailei Wang, Siyuan Shen, Ting Xu, and Xianli Lang, ”YOLO-HR: Improved YOLOv5 for Object Detection in High-Resolution Optical Remote Sensing Images”, *Remote Sensing*, vol. 15, no. 3, p. 614, Jan. 2023. Available: https://doi.org/10.3390/rs15030614

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6 Team Contributions

The team has diligently partitioned the workload, with each member playing a pivotal role in their respective domains. All members have contributed equally to the project's progress with 33.3% effort, ensuring a well-rounded development approach.

- **Chaitanya Sharma:** Initiated the core development phase of the YOLOv5 model, conducting preliminary fine-tuning aimed at enhancing the algorithm. This phase involved meticulous adjustments to the model's architecture to balance the trade-off between speed and accuracy, which are critical parameters for the model's intended use in real-time object detection within complex environments.

- **Lee Bo Hua:** Embarked on the data collection journey, followed by the commencement of the dataset annotation. The tasks were executed with the objective of constructing a comprehensive image library, representative of diverse and realistic urban traffic scenarios. These images are intended to serve as a base for the training and subsequent fine-tuning of the object detection model.

- **Tianxiao Ye:** Undertook the responsibility of integrating the YOLOv5 model into an operational prototype for real-time monitoring. The role involved setting up the initial system configuration and conducting the first series of functionality and performance tests. These tests were essential in assessing the prototype's operational viability in emulating real-world traffic conditions for future deployment. He also provided computer computing power for training the neural network, and adopted a variety of methods to fine-tune and test the final data.

The collective efforts of the team members have contributed to the advancement of the project to its current stage, marking a significant step towards the final goal of developing a reliable real-time object detection system.