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PROJECT TITLE
AUTONOMOUS DRIVING: USING MACHINE LEARNING FOR TRAFFIC SIGN DETECTION

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Submitted in Partial Fulfilment of the Requirements for the Degree of
Master of Science in Data Science

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Abstract

The increasing ubiquity of autonomous driving systems underscores the imperative for efficient and accurate traffic sign detection, a pivotal component in ensuring vehicular safety and adherence to road regulations. This study endeavours to harness the capabilities of machine learning techniques to automate the detection and classification of traffic signs, thereby mitigating the challenges of traditional manual traffic sign management. Utilizing the globally diverse Mapillary Traffic Sign Dataset, the research undertakes a rigorous evaluation of several machine learning models, from baseline algorithms to advanced architectures such as YOLOV5. The findings reveal the efficacy of contemporary deep learning methods in confronting real-world detection challenges, such as sign occlusions, colour deteriorations, and variable sizes. Importantly, this study underscores the potential of machine learning as an essential tool in the evolution of autonomous driving systems, offering insights that could significantly refine and enhance the decision-making robustness of such systems. The results not only affirm the relevance of machine learning in this domain but also set the stage for future research aimed at further optimization and application in real-world autonomous driving scenarios

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Autonomous Driving: Using Machine Learning for Traffic Sign Detection P165547

Certificate of Ethical Approval

Applicant:	Oluwatosin Atanda
Project Title:	Autonomous Driving: Using Machine Learning for Traffic Sign Detection

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Low Risk

Date of approval:	15 Oct 2023
Project Reference Number:	P165547

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List of Abbreviations

Acronyms	Definition
mAP	mean Average Precision
IoU	Intersection over Union
ML	Machine Learning
TSR	Traffic Sign Recognition
CNN	Convolutional Neural Networks
COCO	Common Objects in Context dataset
R-CNN	Region-Based Convolutional Neural Networks
SSD	Single Shot MultiBox Detector
ADAS	Advanced Driver-Assistance Systems
CPU	Central Processing Units
RAM	Random Access Memory
GPU	Graphic Processing Units
YOLO	You Only Look Once

MTSD	Mapillary Traffic Sign Dataset
AI	Artificial Intelligence
CLI	command-line interface

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Above all, I dedicate this work to my God, Jehovah, whose boundless Kindness has been my constant source of strength, the giver of my life, sustaining me through the challenges, and the bestowal of knowledge that is illuminating my path.

I offer my most profound appreciation to these individuals and those who have played a role in this academic odyssey, no matter how small. This support has been the cornerstone of this achievement.

1 Introduction

The safety and efficiency of traffic flow are significantly dependent on the effective management of a traffic sign inventory. Traditionally, this crucial task has been manual—traffic signs are captured with vehicle-mounted cameras, and human operators offline manually perform their localization and recognition against an existing database. However, given the vast stretches of roads, such manual processes are time-consuming and prone to errors. Automating these processes presents a promising solution to these challenges, significantly reducing manual efforts and ensuring quicker identification of compromised traffic signs.

Traffic sign recognition (TSR) has attracted substantial attention in computer vision. Various cutting-edge detection and recognition algorithms have been proposed. However, many of these primarily cater to a limited set of categories, often tied to advanced driver-assistance systems and autonomous vehicles. It is worth noting that traffic signs play an instrumental role in guiding drivers and alerting them to road conditions and potential hazards. A holistic TSR process typically involves the detection of traffic signs in natural scene images and then their classification into appropriate subclasses—a step that is predominantly done manually. (Babic et al., 2021).

However, the real-world implementation of TSR algorithms faces multiple challenges due to varying traffic sign sizes, colour deteriorations, and occlusions. As the vehicular industry shifts towards autonomous driving, the importance of reliable traffic sign detection has further amplified, establishing it as a cornerstone for safe and compliant autonomous driving.

This dissertation examines the potential of machine learning (ML) techniques in addressing these challenges. The primary focus revolves around the precise detection and classification of traffic signs, integral for bolstering the decision-making robustness of autonomous driving systems. This research undertakes a comprehensive evaluation of various ML models using the Mapillary Traffic Sign Dataset, recognized for its diverse and global coverage of traffic signs under myriad conditions. While initial findings with baseline models were promising, advanced ML architectures provided further insights into striking the right balance between precision, recall, and accuracy [Brown, C. 2018; Mapillary, 2021].

Historically, TSR leveraged traditional object detection algorithms, which relied heavily on hand-crafted features. The advent of deep learning, particularly convolutional neural networks (CNNs), revolutionized this domain (Vambe et al., 2022). CNNs enable feature learning from vast datasets without pre-processing, negating the need for hand-crafted features and promoting feature generalization. In this context, this study delves into experiments using the state-of-the-art YOLOV5 deep learning model, offering comparisons with previously proposed algorithms.

The contributions of this research underscore machine learning's pivotal role in advancing autonomous driving. Additionally, the methodologies and findings elucidated here augment the growing body of knowledge in this vibrant domain, laying a foundation for subsequent research to refine autonomous vehicle technologies.

1.1 Problem Statement and Motivation

Problem Statement: The traditional manual process of managing traffic sign inventories is labor-intensive, time-consuming, and prone to human errors. While computer vision has made strides in traffic sign recognition, real-world challenges such as colour deterioration, partial occlusions, and variations in sign size make automated detection complex. With the advent of autonomous vehicles, the ability to accurately and rapidly detect and interpret traffic signs becomes imperative for safety and regulatory compliance. (Kumar Mehta. 2018).

Motivation:

- **Safety Enhancement:** The paramount importance of safety in vehicular traffic necessitates reliable traffic sign detection. With the integration of machine learning, potential human errors can be minimized, leading to safer roads.
- **Efficiency:** Automating traffic sign detection can expedite the management of traffic sign inventories, enabling timely identification and rectification of compromised signs.
- **Technological Advancement:** The vehicular industry is evolving rapidly, with autonomous vehicles set to be a mainstay. Effective traffic sign detection is foundational to this transition.
- **Economic Benefits:** Automated systems reduce the overhead of manual labor and can lead to cost savings in the long run. Moreover, enhanced safety can reduce accident-related costs.
- **Research Contribution:** As autonomous vehicles and driver-assist systems gain traction, contributing to the body of knowledge in this domain is pivotal. This project adds to the discourse, providing valuable insights and methodologies for future endeavors.
- **Global Applicability:** With traffic being a universal phenomenon, the findings from this study have the potential to impact global transportation systems, making roads safer and more efficient worldwide.

By addressing the stated problem with a structured and methodical approach, this project aims to make significant strides in traffic sign detection, ultimately facilitating safer and more efficient autonomous driving systems.

1.2 Project Objectives

Project Aim and Objectives:

Aim: To explore and evaluate the potential of machine learning techniques in automating the detection of traffic signs, emphasizing enhancing the robustness and decision-making capabilities of autonomous driving systems.

Objectives:

- **Dataset Utilization**: Leverage the Mapillary Traffic Sign Dataset for model training and evaluation, capitalizing on its diverse and global coverage of traffic signs in various real-world conditions.
- **Advanced Techniques**: Explore and implement advanced machine learning architectures like YOLOV5, gauging their efficacy in traffic sign detection
- **Optimization**: Fine-tune chosen models for optimal precision, recall, and overall accuracy in traffic sign detection.

1.3 Overview of This Report

In the arena of autonomous vehicular technology, the critical role of accurate traffic sign recognition cannot be overstated. This report casts a spotlight on this domain, employing the YOLOv5 machine-learning model as a lens to examine the efficacy of traffic sign detection.

Prologue: The genesis of this research is mapped out in the initial pages, where the pertinence of the study to the avant-garde of vehicular technology is established. This serves as the bedrock for the ensuing discourse on machine learning's capacity to revolutionize traffic sign detection.
Scholarly Context: An analytical traverse through the scholarly landscape that pre-dates this study is undertaken, offering a critique of the milestones achieved thus far in autonomous driving and machine learning, while pinpointing the niches this research seeks to fill.

Research Blueprint: The blueprint of the study is articulated, delineating the choice of the YOLOv5 model, the adoption of the Mapillary Traffic Sign Dataset, and the benchmarks employed to gauge the model's prowess, including precision, recall, and mean Average Precision (mAP).

Model Development and Refinement: Within these segments, the intricate process of model training is recounted, detailing both the computational infrastructure deployed and the meticulous tuning of the model to attain peak accuracy.

Empirical Evaluation: A thorough narration of the model's live-fire testing phase is presented, detailing the interfacing methodologies and the empirical scrutiny it underwent, punctuated by a granular examination of the model's responses to diverse traffic sign instances.

Interpretative Commentary: This section serves as the crucible where the empirical data is alloyed with interpretative insights, weighing the model's operational effectiveness and its resilience across a spectrum of scenarios germane to autonomous navigation.

Comparative Study: A juxtaposition with alternative machine learning frameworks is charted out, dissecting the nuanced balance between operational swiftness, precision, and computational demands.

Epilogue and Prospective Horizons: The terminal chapter distils the essence of the findings and contemplates the trajectory of future inquiry, advocating for explorations that could bolster the model's robustness and its translation into real-world scenarios.

Chronicle of Project Evolution: The narrative concludes with a retrospective on the project's temporal progression, encapsulating the strategic planning, the anticipatory mitigation of risks, and the quality control protocols that were the hallmarks of the research process.

The appendices and ancillary content appended to the main body of this report serve as a testament to the diligent and meticulous approach that underpinned this scholarly endeavour.

2 Literature Review

2.1 Object Detection

Object detection is a pivotal element in computer vision, distinguished from mere image classification by its complexity and utility (Zou et al., 2019). Unlike classification, which identifies the primary subject of an image, object detection delves deeper. It is not limited to recognizing multiple objects within an image or video but extends to pinpointing their precise locations by encapsulating each object within bounding boxes (Redmon et al., 2016).

2.1.1 Bounding Boxes in Object Detection

Bounding boxes are a cornerstone in object detection, playing a fundamental role in not just signifying the presence of objects within an image but also in pinpointing their exact locations and dimensions (Redmon et al., 2016). Their utility spans from providing spatial context in an image to facilitating object tracking in video sequences and even in augmented reality applications where they guide the placement of digital overlays on real-world objects.

A bounding box is typically represented through a set of coordinates and dimensions, often in the format of (x, y, width, height), where (x, y) marks the top-left corner of the box, or as (x1, y1, x2, y2), indicating both diagonal corners (Liu et al., 2020). This mathematical representation is crucial in defining the spatial context of objects in an image. The shape and size of these boxes vary greatly, adapted to the scale and aspect ratio of the objects they enclose. While some objects fit well within square boxes, others require more rectangular shapes due to their inherent dimensions.

One of the critical challenges in object detection is managing overlapping bounding boxes, especially when multiple predictions are made for the same object. To address this, Intersection over Union (IoU) is used as a metric to evaluate the accuracy of the predicted boxes against the ground truth. IoU calculates the area of overlap between the predicted and the actual bounding box, divided by the area of their union, with a higher score indicating greater accuracy (Rezatofighi et al., 2019).

Further refining the accuracy of bounding box predictions is the Non-maximum Suppression (NMS) process. NMS is instrumental in pruning redundant bounding boxes, ensuring that only the box with the highest confidence score is retained while others with significant overlap are suppressed (Bodla et al., 2017). This algorithm is crucial in enhancing the precision of object detection systems.

Despite these techniques, crafting precise bounding boxes remains a complex task. Various factors, such as varied lighting conditions, occlusions, and similar-coloured backgrounds, can pose significant challenges, making it difficult for detection systems to delineate objects accurately (Zhao et al., 2019). The precise demarcation of bounding boxes is not just a technical challenge but also critical for the practical applications of object detection. For instance, in image annotation, bounding boxes provide the necessary spatial context, while in object tracking, they are essential for monitoring the movement of objects across frames in videos.

As object detection technology advances, the implementation and refinement of bounding boxes underscore their importance in accurately interpreting visual data. Their evolution reflects the quest for more sophisticated and efficient computer vision systems (He et al., 2017).

Fig1 Image of a street scene with bounding boxes (Folio3 AI., 2023).

2.1.2 Class Labels in Object Detection

Class labels are pivotal in object detection, providing semantic meaning to the detected objects. They transform pixel data into interpretable, categorized information, enabling actionable insights. In object detection systems, a predefined list of possible object categories is essential, with each predicted bounding box accompanied by a class label specifying the enclosed object's type or category. For instance, in traffic sign detection, class labels might include "Stop Sign," "Yield," "Speed Limit 40," and so forth (Redmon et al., 2016).

The classification of traffic signs involves assigning specific class labels to different types of signs, a process fundamental to the accuracy and utility of traffic sign detection systems (Tian et al., 2020). The variety of signs and their international differences require a robust and adaptable classification system (Simonyan & Zisserman, 2015).

In more sophisticated detection systems, class labels can exhibit a hierarchical structure. A broad category like "Vehicle" may be subdivided into "Car," "Bus," "Truck," and further into more specific types such as "Sedan" or "Convertible" under "Car." This hierarchical taxonomy allows for nuanced and detailed object categorization (He et al., 2017).

Modern object detection models, particularly those based on neural networks, often output a probability distribution over all class labels. The label with the highest probability is usually assigned to each bounding box (Liu et al., 2020). However, assigning accurate class labels is fraught with challenges, such as ambiguous objects or occlusions, which can lead to misclassifications. The training phase of machine learning models heavily relies on accurate, meticulously annotated ground-truth class labels to guide the model in reducing misclassifications (Girshick, 2015).

The accuracy of class labels is crucial, especially in applications like autonomous driving, where misclassifying a "Stop" sign as a "Yield" sign can have dire consequences. As object detection

systems evolve, the list of class labels can be dynamically expanded or refined to incorporate new object types or offer finer categorization granularity (Ren et al., 2017).

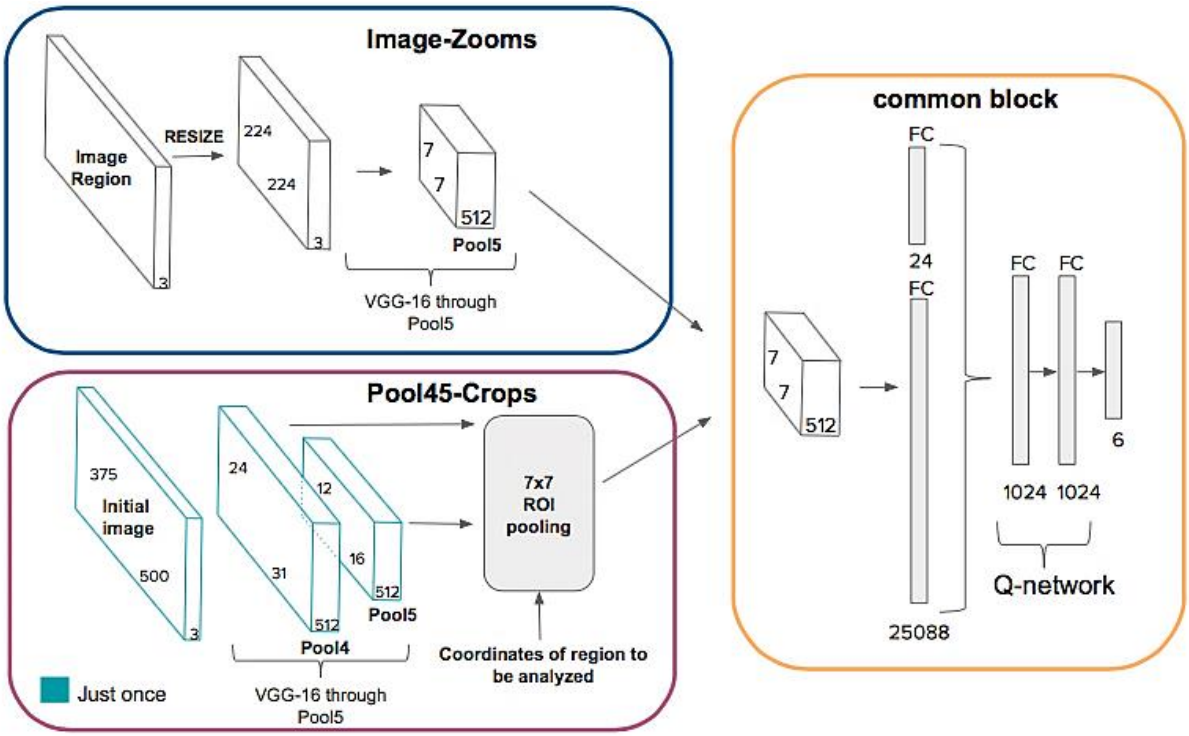


Fig2. Hierarchical Object Detection with Deep Reinforcement Learning by (Bellver et al.,2016)

Confidence Scores in Object Detection

Confidence scores are integral to object detection, offering a quantifiable measure of the model's certainty in its predictions. These scores, typically ranging between 0 and 1, signify the model's confidence level, with scores closer to 1 indicating higher confidence (Zhao et al., 2019).

In many deep learning models, especially those using SoftMax activations, confidence scores are interpreted as the probability of the object belonging to a particular class. In object detection, confidence scores have dual roles: they indicate the likelihood that a region contains any object of interest (objectness score) and assign confidence scores for every class label for each detected object (class prediction confidence) (Bodla et al., 2017).

Thresholding is commonly applied to confidence scores to filter out weak detections. This approach helps reduce false positives but presents challenges, as high confidence scores do not necessarily equate to correct predictions, which is particularly noticeable in cases of overfitting during model training (Alom et al., 2018).

Confidence scores play a pivotal role in model evaluation metrics like Precision-Recall curves. Different precision and recall values are obtained by varying the confidence score threshold, facilitating a comprehensive model performance evaluation (He et al., 2017).

In safety-critical applications, such as autonomous driving, relying on something other than the model's most confident predictions is crucial. Systems require additional validation checks or human intervention when confidence scores fall below a certain threshold. Model calibration techniques, like Platt Scaling or Temperature Scaling, ensure that confidence scores accurately reflect the probability of a correct prediction (Guo et al., 2017).

Faster R-CNN, YOLO, and SSD are deep learning models that have achieved state-of-the-art performance in object detection tasks, integrating sophisticated mechanisms for handling class labels and confidence scores (Ren et al., 2017).

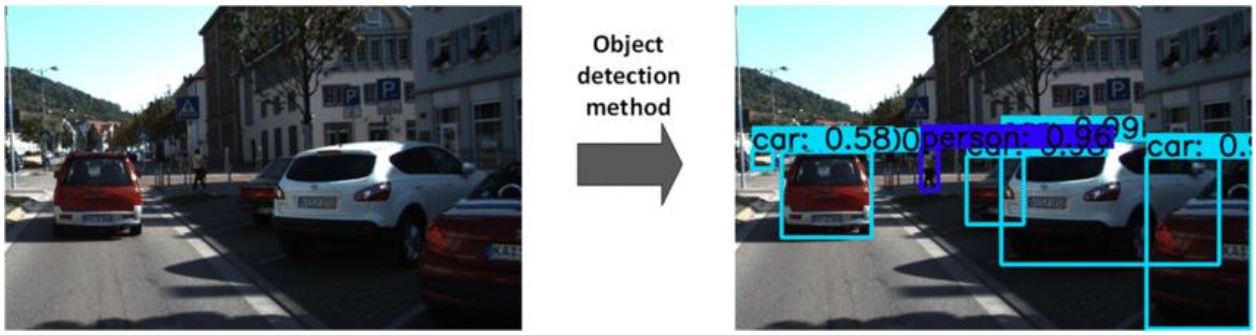


Fig.3 before and after of detection showing the bounding box, confidence score, and class label (Mahaur et al.,2022)

Integrating Object Detection Components in Traffic Sign Detection

Traffic sign detection, a specialized area within object detection, incorporates the fundamental principles of object detection but tailors them to meet the specific challenges and intricacies of traffic sign recognition.

Bounding Boxes in Dynamic Traffic Environments: In traffic sign detection, bounding boxes must adapt exceptionally to dynamic environments. Traffic scenes constantly change – vehicles move, lighting shifts throughout the day, and weather conditions fluctuate. These bounding boxes need to be capable of accurately capturing traffic signs amidst these variables. Additionally, traffic signs can appear in various sizes and angles, being farther away, closer, or even partially obscured. The bounding boxes must be flexible enough to encompass signs in all these varying scenarios (Zhao et al., 2019).

Class Labels and Traffic Sign Variability: The classification of traffic signs is a multifaceted task. Traffic signs are diverse, including stop signs, speed limits, and warning signs, each requiring a distinct class label. Moreover, traffic signs are subject to international variations, with different countries exhibiting different designs for the same type of sign. This variation necessitates models that are either generalized to recognize multiple sign types or specialized for specific regional signs. The accuracy in classifying these signs is critical; a misclassification, such as confusing a "Yield" sign with a "Stop" sign, can lead to dangerous situations (Redmon et al., 2016).

Confidence Scores and Safety in Autonomous Driving: Confidence scores are essential in traffic sign detection, particularly for autonomous vehicles. The implications of false positives or negatives in this context are significant, potentially leading to unsafe driving conditions. Autonomous driving systems require higher thresholds for confidence scores to ensure safety. Additionally, detections with confidence scores below a certain threshold in semi-autonomous vehicles might prompt alerts for human drivers to take over, providing an extra layer of safety (Liu et al., 2020).

Real-time Processing Requirements: Real-time processing is non-negotiable in traffic sign detection. Vehicles make split-second decisions based on traffic sign information; hence, the model's predictions, associated confidence scores, and bounding box calculations must be optimized for speed without sacrificing accuracy. This requirement for real-time processing significantly demands the efficiency and computational speed of the object detection models employed (He et al., 2017).

Continual Learning for Evolving Traffic Conditions: Traffic scenes are not static; they evolve continually. New signs are installed, old ones are replaced, and environmental conditions can alter the appearance of signs. This dynamic nature of traffic environments necessitates continual learning within traffic sign detection systems. They must constantly update their knowledge base with new data to ensure their detections remain accurate and relevant over time (Bodla et al., 2017). Integrating these object detection components into traffic sign detection is a testament to the adaptability and sophistication of modern computer vision technologies. This specialization is essential for ensuring safety and reliability in applications like autonomous driving, where accurate and real-time interpretation of traffic signs is paramount.

The Crucial Role of Traffic Sign Detection in Autonomous Driving

Traffic sign detection is a pivotal component of autonomous driving systems, playing a vital role in ensuring self-driving vehicles' safe and legal navigation. This technology's effectiveness directly impacts the vehicle's ability to adhere to traffic rules and respond appropriately to real-time road conditions.

Ensuring Safety on the Roads: Safety is paramount in autonomous driving, and traffic signs are crucial to maintaining it. They provide essential guidance, warnings, and vehicular and pedestrian movement regulations. Missing critical signs like "Stop" or "Pedestrian Crossing" could lead to severe consequences. Thus, the ability of an autonomous vehicle to accurately detect and interpret traffic signs is directly linked to the safety of passengers, pedestrians, and other road users (Zhao et al., 2019).

Legal Compliance and Road Regulations: Traffic signs are more than just road markers; they represent legal requirements. For autonomous vehicles to be fully compliant, they must recognize and adhere to all traffic signs. This includes obeying speed limits, understanding parking regulations, and more (Tian et al., 2020).

Facilitating Informed Decision Making: Traffic signs play an important role in influencing the decision-making processes of autonomous vehicles. Recognizing signs such as "One Way" or "Slippery When Wet" allows the vehicle to make informed decisions, preventing wrong-way driving and adjusting speed in response to road conditions, even if there is no immediate visible danger (Simonyan & Zisserman, 2015).

Enhancing Navigation Capabilities: While GPS and mapping systems lay out the general route, traffic signs provide crucial, real-time details indispensable for on-the-ground navigation. For example, a "Detour" sign can prompt the vehicle's navigation system to recalibrate its route more swiftly than waiting for cloud-based system updates (He et al., 2017).

Dynamic Response to Changing Conditions: The road environment is dynamic, often presenting temporary changes like roadwork, diversions, or special events. A robust traffic sign detection system enables an autonomous vehicle to adapt dynamically to such changes, ensuring seamless navigation without human intervention (Ren et al., 2017).

Interaction with Human Drivers: As long as autonomous vehicles coexist with human-driven cars, understanding and responding to traffic signs is essential for predicting and interpreting the behaviours of human drivers. Appropriately reacting to traffic signs, such as stopping at a stop sign, allows human drivers to anticipate the autonomous vehicle's next actions, fostering safer co-navigation (Liu et al., 2020).

In summary, traffic sign detection is not just a feature of autonomous driving but a fundamental necessity. It ensures adherence to legal standards, enhances safety, informs decision-making,

augments navigation, and allows dynamic responses to road conditions. As autonomous technology continues to evolve, the precision and reliability of traffic sign detection systems will remain central to the advancement and acceptance of self-driving vehicles.

2.2 Evolution of Object Detection and Its Impact on Traffic Sign Recognition

Early Beginnings (Before the 2000s): The genesis of object detection, including traffic sign recognition, was marked by traditional computer vision techniques. These early methods used colour segmentation, shape matching, and edge detection to identify objects. In the context of traffic signs, these techniques were foundational but had limitations. They often needed help under varying environmental conditions, such as different lighting, obstructions, or when signs were worn out, leading to inaccuracies and unreliability in detection (Dalal & Triggs, 2005).

The Rise of Machine Learning (Early 2000s): The dawn of the 21st century saw machine learning emerge as a dominant force in object detection. Enhanced by the growing availability of data and computational power, methods like histogram of oriented gradients (HOG) and scale-invariant feature transformation (SIFT) began to be used for feature extraction from images. These features were then processed through classifiers like Support Vector Machines (SVMs) to detect traffic signs. This era marked a significant improvement in detection accuracy, though it still lagged behind human-level perception (Lowe, 2004).

Profound Learning Revolution (2010s and Beyond): The advent of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized object detection. CNNs' ability to learn hierarchical features directly from raw pixel data eliminated the need for manual feature extraction, leading to more robust and accurate models. Architectures like YOLO and SSD enabled real-time object detection with remarkable accuracy. In traffic sign detection, these advancements meant systems capable of reliably identifying signs under diverse and challenging real-world conditions (Redmon et al., 2016).

Integration in Autonomous Vehicles: The advancements in object detection technologies, especially in traffic sign recognition, have been integral to developing autonomous vehicles. Reliable traffic sign detection is essential for these vehicles to navigate safely and adhere to traffic laws. Modern autonomous driving systems use a combination of sensors and cameras, with deep learning-based object detection models playing a crucial role in interpreting visual data for traffic sign detection (He et al., 2017).

Current Trends and Future Outlook: Today, the field of traffic sign detection continues to evolve with advancements in neural network architectures and the availability of diverse datasets. The focus is now on enhancing the robustness of these systems for edge cases, reducing computational demands for real-time processing, and integrating detection systems more seamlessly with other aspects of vehicle perception. Emerging trends like transfer learning and few-shot learning are gaining traction, aiming to enable efficient training on limited datasets, particularly for rare or region-specific traffic signs (Liu et al., 2020).

In essence, the history of object detection, with a particular focus on traffic sign detection, mirrors the broader evolution of the field of computer vision. As autonomous vehicles become increasingly prevalent, the ongoing enhancement and refinement of traffic sign detection systems will be critical in ensuring their safe and effective operation.

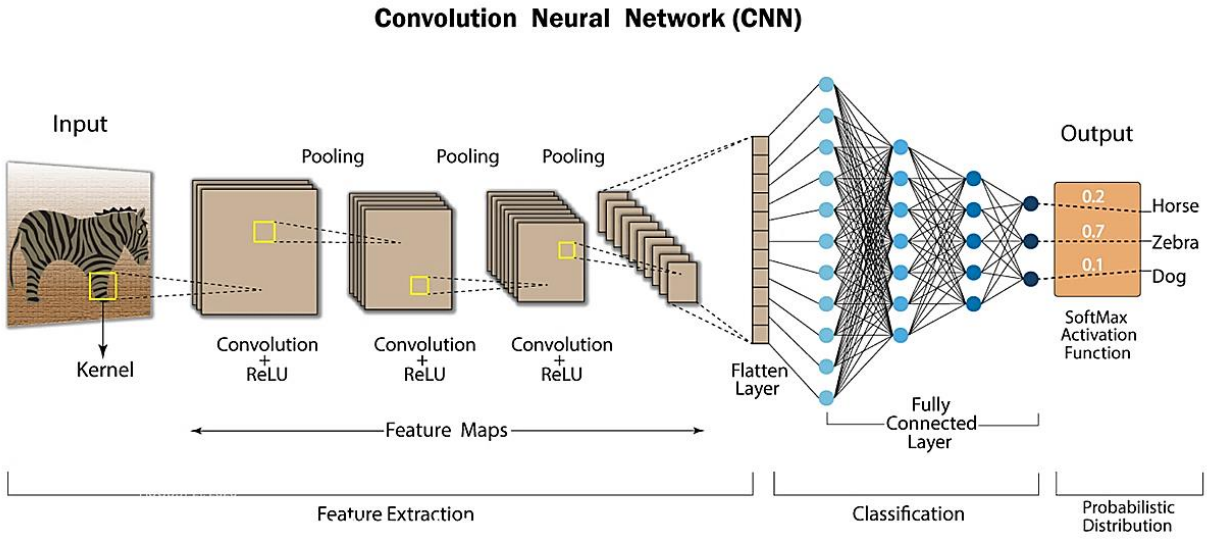


Fig.4 Convolutional Neural Network — CNN architecture (Nafiz.,2023)

2. Region-Based Convolutional Neural Networks (R-CNNs) and Its Variants (Fast R-CNN, Faster R-CNN)

- **Overview:** R-CNNs combine region proposal algorithms with CNNs, with Faster R-CNN introducing Region Proposal Networks for efficient proposal generation (Ren et al., 2017).
- **Advantages:** They offer high accuracy in object localization.
- **Challenges:** The two-stage process can be slower, impacting real-time application feasibility.

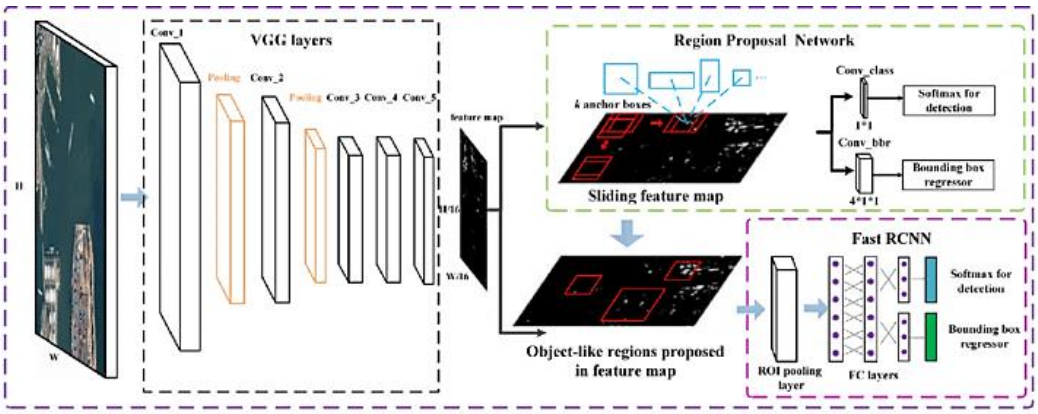


Fig.5 The architecture of Faster R-CNN. (Deng et al.,2018)

3. You Only Look Once (YOLO)

- **Overview:** YOLO frames object detection as a regression problem, predicting bounding boxes and class probabilities in a single evaluation (Redmon et al., 2016).
- **Advantages:** It offers remarkable speed, suitable for real-time tasks.
- **Challenges:** YOLO can struggle with small objects and has localization limitations in earlier versions.

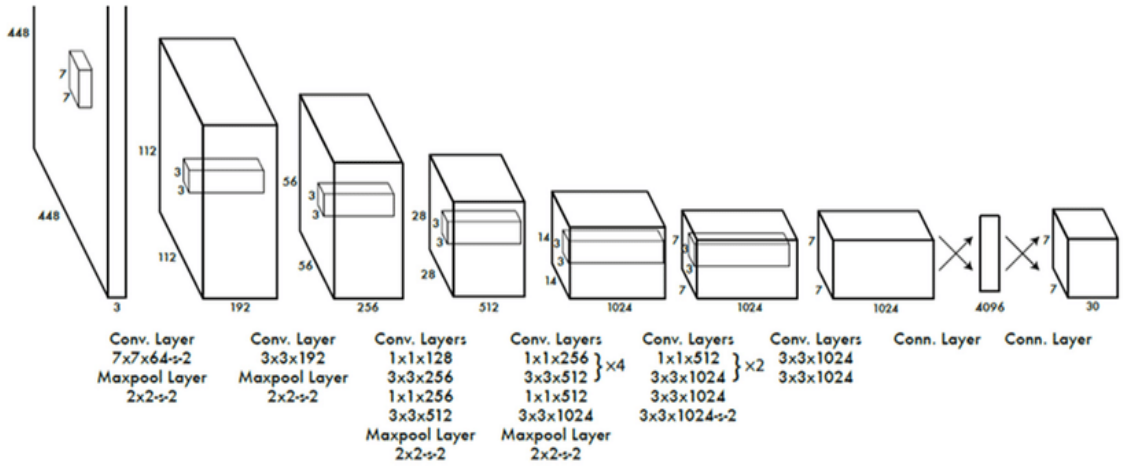


Fig.6 YOLO architecture (Wu et al,. 2018).

4. Single Shot MultiBox Detector (SSD)

- **Overview:** SSD streamlines the detection process by eliminating the need for a separate region proposal step, enhancing speed without significantly compromising accuracy (Liu et al., 2020).
- **Advantages:** Efficient for real-time detection with a good balance between speed and accuracy.
- **Challenges:** Detection of very small objects remains a challenge.

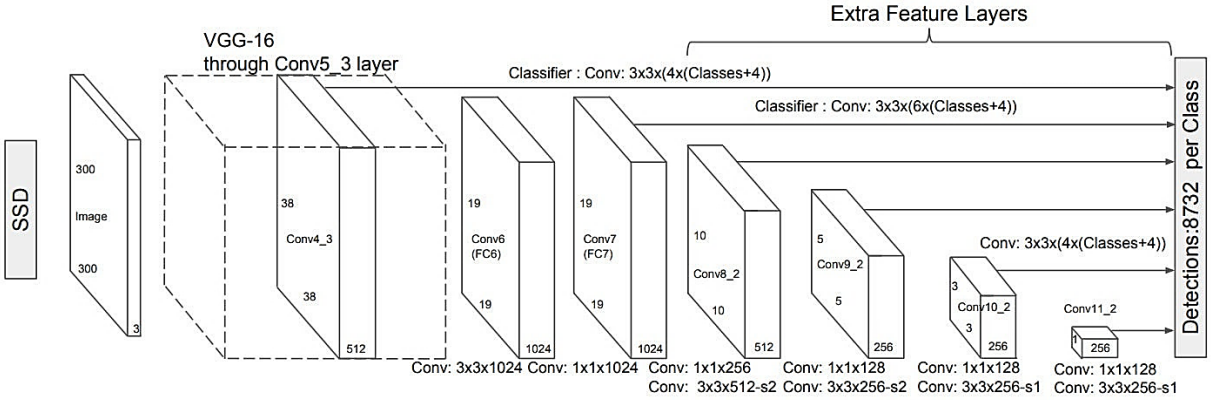


Fig.7 SSD: Single Shot MultiBox Detector (Jonathan 2018)

Comparison summary

- **Speed:** YOLO and SSD are faster, making them more suited for real-time detection compared to R-CNNs (Redmon et al., 2016; Liu et al., 2020).
- **Accuracy:** R-CNNs, especially Faster R-CNN, are more accurate but computationally intensive (Ren et al., 2017).
- **Resource Intensity:** CNNs and R-CNNs demand significant computational resources, impacting their feasibility in constrained environments.
- **Ease of Training:** Models like YOLO and SSD are easier to train due to their simpler architectures.

3 METHODOLOGY

Introduction to the Mapillary Traffic Sign Dataset (MTSD)

The Mapillary Traffic Sign Dataset (MTSD) forms the backbone of this research, representing a substantial and diverse collection of traffic sign data. MTSD is a large-scale dataset encompassing over 105,000 images, which includes 52,000 images with 257,000 fully annotated traffic sign bounding boxes and their corresponding class labels. Additionally, it features a set of more than 53,000 nearby images with over 84,000 semi-supervised class labels. This vast compilation of data offers a rich resource for training and validating traffic sign detection models.

The creation of MTSD involved meticulous annotation and classification efforts to ensure the accuracy and comprehensiveness of the dataset. It features a detailed taxonomy of 401 traffic sign classes, encompassing a wide range of signs encountered in real-world driving scenarios. This extensive variety of classes is critical for developing a traffic sign detection system that is robust and effective across different geographic regions and conditions.

Image Selection for MTSD

The selection of images for the Mapillary Traffic Sign Dataset (MTSD) was a meticulously planned process, driven by the need to capture the diverse range of traffic signs globally. This diversity arises from the varying conventions for traffic signs across different regions. Understanding these regional differences and ensuring a uniform representation in the dataset was pivotal. The image selection process focused on several key requirements;

Uniform Geographical Distribution:

To achieve a balanced representation, images were selected to ensure uniform geographical distribution across the world. This approach helps in capturing the variation in traffic sign appearances that are unique to different countries and continents.

Diverse Image Quality and Conditions:

The dataset includes images of varying quality, captured under different conditions. This diversity is critical for developing models that are robust to real-world scenarios, including varying lighting, weather conditions, and times of the day.

Maximizing Sign Density per Image:

A key criterion in image selection was to include as many signs as possible per image. This strategy increases the richness of the dataset, providing more data points for model training and improving the likelihood of capturing rare or less common signs.

Addressing Class Imbalance:

The image selection process also aimed to compensate for the long-tailed distribution of potential traffic sign classes. This is important for mitigating class imbalance, a common challenge in machine learning, where some classes are underrepresented compared to others.

To obtain a pool of pre-selected images that meet these criteria, a country-specific sampling method was employed. The proportion of target images for each country was determined based on the number of available images in that country, factoring in the country's population count. This calculation was further weighted by a global target distribution over all continents, ensuring a balanced representation across different regions (20% each from North America, Europe, and Asia; 15% each from South America and Oceania; and 10% from Africa).

This image selection methodology underscores the commitment to creating a dataset that not only offers a comprehensive view of global traffic sign variations but also addresses critical challenges

such as class imbalance and diversity in environmental conditions. This robust dataset forms the foundation for developing advanced traffic sign detection models that are reliable and effective across a wide range of real-world scenarios.

Fig 8. examples of traffic sign in the dataset

Process for the Mapillary Traffic Sign Dataset (MTSD)

The MTSD's annotation process is a cornerstone in preparing the dataset for traffic sign detection, characterized by meticulous stages to ensure accuracy and detail. The Annotation Criteria cover the global scope of MTSD necessitated clear and consistent criteria for traffic sign annotation, applicable uniformly across all images. This included guidelines for identifying, bounding, and labeling traffic signs, catering to the wide variety of signs worldwide.

Annotation Techniques: Each traffic sign in the dataset was carefully annotated with precise bounding boxes for exact localization, a critical step for the model to learn accurate sign detection. Additionally, signs were classified into one of 400 predefined categories, facilitating the model's ability to not only detect but also identify different types of traffic signs. There were Quality and Consistency Checks required Rigorous quality checks to ensure the precision of bounding boxes and the correctness of class labels. Given the number of annotators involved, consistent adherence to annotation standards was maintained through regular audits.

The data is highly diverse and challenging so it is imperative to handle diversity and Challenges. The process accounted for real-world challenges like occlusions, colour variations, and differing viewpoints. Annotators were trained to manage these complexities, guaranteeing reliable annotations even in ambiguous scenarios.

The annotation guidelines underwent continuous refinement to address new challenges and ambiguities, ensuring the dataset's ongoing enhancement in quality and robustness.

This detailed and thorough annotation process was pivotal in equipping the MTSD to effectively train and evaluate machine learning models for traffic sign detection. The precision and consistency of these annotations significantly contribute to the dataset's efficacy in developing models adept at navigating the complexities of real-world traffic sign detection tasks.

Fig 9. Example of traffic sign and annotation in the dataset

Visualization of Ground Truth Data in the MTSD

An essential aspect of the methodology employed in this research involves the visualization of ground truth data from the Mapillary Traffic Sign Dataset (MTSD). This step is critical for ensuring the quality and accuracy of the annotations used in training and evaluating the machine-learning models for traffic sign detection.

Role of the visualize_gt Function: The visualize_gt (Visualize Ground Truth) function plays a pivotal role in this process. It is designed to visually display the annotated traffic signs within the images, overlaying the bounding boxes and class labels over the actual traffic signs.

This visualization serves as a tool for verifying the accuracy of annotations. By seeing how well the bounding boxes align with the traffic signs in the images and checking the appropriateness of the assigned labels, we can assess the precision of the annotation process.

Visual inspection is an indispensable part of the quality control process. It provides an immediate and intuitive understanding of how well the annotations represent the actual signs in the images. Through visual inspection, we can identify any inaccuracies or inconsistencies in the annotations, such as misaligned bounding boxes, incorrect class labels, or signs that have been missed entirely.

Iterative Improvement through Visualization Feedback Visualization also plays a role in the iterative improvement of the dataset. By periodically reviewing the visualized annotations, we can identify areas where the annotation guidelines may need refinement or where additional training may be required for annotators. This ongoing process of review and improvement helps in maintaining a high standard of data quality throughout the lifecycle of the dataset.

Random Sampling for Inspection in the MTSD: Incorporating the visualize_random_samples code into the methodology, a significant aspect of ensuring the quality and comprehensiveness of the Mapillary Traffic Sign Dataset (MTSD) which is the use of random sampling for inspection which plays a key role in the dataset's quality assurance. The visualize_random_samples function is designed to randomly select a set number of images from the dataset, along with their corresponding annotations, for visualization. This randomness is crucial as it provides an unbiased view of the dataset's overall quality and coverage.

By visualizing a random sample of images, we can assess the dataset's representation of different traffic sign scenarios, ensuring that various environmental conditions, sign types, and geographical locations are adequately represented.
Random sampling serves as an important quality control measure. It helps in identifying potential issues or biases in the dataset that might not be evident through targeted sampling or inspection of specific images.

This method allows for the detection of inconsistencies in annotations, rare or underrepresented traffic sign classes, and scenarios that might require additional data collection or annotation efforts. The primary objective of employing random sampling is to ensure that the dataset adequately captures the variability inherent in real-world traffic sign detection scenarios. This includes variations in sign design, sizes, occlusion levels, and environmental conditions.
Comprehensive coverage is crucial for the development of robust machine-learning models. Models trained on a diverse and representative dataset are more likely to generalize well to new, unseen data, which is essential for practical applications.

The insights gained from the random sampling and visualization process feed directly into the ongoing annotation and model development process. They help in highlighting areas where the dataset might need augmentation or where the model might require further tuning to handle specific scenarios effectively. This iterative process of inspection, analysis, and refinement ensures continual improvement of both the dataset and the machine learning models developed using the dataset.

Fig 10. Different traffic sign visualization in bounding box

Enhancing Model Training with Accurate Ground Truth Data:
Accurate ground truth data is crucial for the effective training of machine learning models. Models rely on these annotations to learn the characteristics of different traffic signs and how to accurately localize them in various contexts.
By ensuring that the ground truth data is as accurate as possible, we improve the likelihood that the trained models will perform well when deployed in real-world traffic sign detection tasks.

Annotation Inspection and Missing Value Check in the MTSD
A crucial part of the methodology for utilizing the Mapillary Traffic Sign Dataset (MTSD) involves detailed annotation inspection and missing value checks. This process is instrumental in ensuring the data's integrity and reliability, which are fundamental for the training of accurate machine learning models.

The Functionality of load_and_inspect_annotations function is designed to systematically load annotations from the dataset and inspect them for accuracy and completeness. This function helps in understanding the structure and content of the annotations, ensuring that they align with the expected format and contain all necessary information.
During this inspection, special attention is paid to the bounding boxes and class labels of each traffic sign to ensure they are correctly annotated according to the predefined criteria.

The check_missing_values function plays a pivotal role in identifying any missing or incomplete data within the annotations. This step is essential as missing values can lead to inaccuracies in model training and evaluation.
This function checks each annotation for essential elements such as bounding box coordinates and class labels. Any anomalies or missing elements are flagged for review and correction.

Data Cleaning and Pre-processing: Both annotation inspection and missing value check are integral parts of the data cleaning and pre-processing stages. They help in ensuring that the dataset is free from errors and inconsistencies before it is used for model training.
This process contributes to the overall quality of the training data, which directly impacts the performance and reliability of the trained machine-learning models.
The integrity of training data is crucial for the development of robust machine learning models. Accurate and complete annotations provide a solid foundation for models to learn the various aspects of traffic sign detection, including sign localization and classification.
By rigorously inspecting and cleaning the dataset, we can significantly reduce the risk of model bias or underperformance due to poor-quality data.

Iterative Refinement and Quality Assurance: The process of annotation inspection and missing value check is iterative. As the dataset evolves and grows, these checks are repeatedly performed to maintain a high standard of data quality.
This ongoing refinement and quality assurance process is vital for adapting to new challenges and complexities that may arise as the dataset expands.
Incorporating these critical steps into the methodology ensures that the MTSD is maintained at a high standard of quality, making it an effective tool for training and evaluating traffic sign detection models. The rigorous inspection and cleaning of annotations are key to developing models that perform reliably and accurately in real-world scenarios. A critical stage in preparing the Mapillary Traffic Sign Dataset (MTSD) for machine learning involves the dataset splitting process, facilitated by the split_dataset function. This process is essential for creating distinct sets for training, validation, and testing, ensuring a robust and unbiased evaluation framework for the developed models.

Functionality of split_dataset:
The split_dataset function is designed to segregate the dataset into three distinct parts: training, validation, and testing sets. This separation is crucial for different stages of machine learning model development, from learning patterns (training), and tuning hyperparameters (validation), to finally evaluating performance (testing).
The function ensures that each set is mutually exclusive, meaning no overlap occurs between them. This is vital for an unbiased assessment of the model's performance.
Determining the Split Ratio:

The split ratio is carefully chosen to balance the need for sufficient training data against the necessity of adequate validation and testing data. Typically, a larger portion of the dataset is allocated to training (e.g., 70%), while the remaining is divided between validation (e.g., 15%) and testing (e.g., 15%).
The specific ratio can be adjusted based on the dataset's size and the complexity of the task. The goal is to ensure that the model is exposed to a diverse range of data during training while still retaining a substantial amount for validation and testing.
Importance of Distinct Sets for Unbiased Evaluation:

Having distinct datasets for training, validation, and testing is critical for unbiased model evaluation. The validation set is used to fine-tune model parameters and prevent overfitting, while the test set provides an objective measure of the model's performance on unseen data.
This separation helps in assessing the model's ability to generalize to new data, which is a key indicator of its effectiveness in real-world scenarios.
Facilitating Robust Model Development:

By splitting the dataset in this manner, we can develop more robust machine-learning models. The training set allows the model to learn the necessary features for traffic sign detection, the validation set guides the tuning of the model for optimal performance, and the test set offers a final, unbiased evaluation of the model's capabilities. The dataset-splitting process also enables an iterative approach to model development and improvement. As the model is developed and evaluated, insights from the validation and test sets can be used to make iterative improvements, enhancing the model's accuracy and generalizability over time.

YOLO Format Conversion and Dataset Preparation in the MTSD
For the effective training of YOLO (You Only Look Once) models with the Mapillary Traffic Sign Dataset (MTSD), it is essential to convert the dataset annotations into a format compatible with

YOLO. This conversion and preparation process is a critical step in the methodology, ensuring that the dataset is optimally structured for training YOLO models.

Conversion to YOLO Format:
YOLO models require annotations in a specific format where each object in an image is described by a class identifier and normalized bounding box coordinates. These coordinates typically include the centre point of the box (x, y) and its width and height, all normalized relative to the image dimensions.
The process involves converting the existing bounding box annotations from the MTSD, which are in a standard format (usually x_min, y_min, x_max, y_max), into the YOLO format. This is achieved using functions in the provided code, which calculate the required normalized values for each traffic sign annotation in the dataset.
Importance of Compatible Annotation Formats:

YOLO models have specific input requirements, and providing annotations in an incompatible format can lead to incorrect training, resulting in poor model performance. Ensuring that annotations are in the correct format is crucial for the models to correctly interpret and learn from the training data.
The conversion process not only involves formatting but also requires careful handling of the data to maintain the integrity and accuracy of the annotations, which is paramount for the successful training of the models.

Preparing the Dataset for YOLO Training: Once the annotations are converted to the YOLO format, the dataset is organized into a structure suitable for YOLO training. This involves pairing each image in the dataset with its corresponding YOLO-formatted annotation file.
This structured approach simplifies the process of feeding data into the YOLO model during training, ensuring that the model has consistent and correctly formatted data to learn from.
Ensuring Efficient Training and Effective Learning:
The YOLO format conversion and dataset preparation steps are essential for efficient training and effective learning of the model. They ensure that the model can focus on learning the task of traffic sign detection without the interference of data format issues.
Properly formatted and prepared data contribute to faster training times, and better convergence during training, and ultimately lead to more accurate and reliable detection models.

4 RESULT

4.1YOLO Model Training Report

The object detection model was trained using the YOLO architecture with a focus on multi-class detection accuracy. Training was conducted for 25 epochs, and the model's predictive performance was assessed through a series of metrics, including precision, recall, and mean average precision (mAP). Alongside these metrics, bounding box accuracy, object presence, and class prediction errors were also monitored.

The model's performance was evaluated using several metrics including box loss, object loss, class loss, precision, recall, and mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds.

Model Performance Metrics

Loss Metrics

- Box Loss: Represents the model's performance in predicting the location of bounding boxes around objects. Over the training period, both training and validation box losses showed consistent decreases, indicating improved model performance in localizing objects.

- Object Loss: Reflects the model's accuracy in detecting the presence of objects. Similar to box loss, a steady decrease in object loss was observed, which suggests that the model is increasingly confident in identifying objects.

- Class Loss: Measures the model's ability to correctly classify detected objects. A decrease in class loss across training and validation sets was noted, suggesting better classification accuracy as training progressed.

Precision and Recall

Precision: It's the ratio of true positive predictions to the total predicted positives (the sum of true positives and false positives). This Model Reached high levels, peaking at around 92% during training. This indicates that the model had a low rate of false positives.

The Confidence level set by the model to classify a detection is positive. A higher confidence level means that the model is more certain about its predictions.

Curve Analysis: Each line in the curve represents a class. The curve shows how precision changes as the confidence threshold is varied. The ideal scenario is for the curve to start high and stay high as confidence increases, indicating that the model maintains high precision even as it becomes more confident in its predictions. The presence of many lines indicate variability in precision across different classes.

Blue Line and Value: The blue line at the top with the annotation "all classes 0.97 at 0.886" suggests that, when considering all classes together, the model achieves a precision of 97% at a confidence threshold of 0.886. This is typically a good performance, suggesting the model is highly precise when it is nearly certain about its predictions.

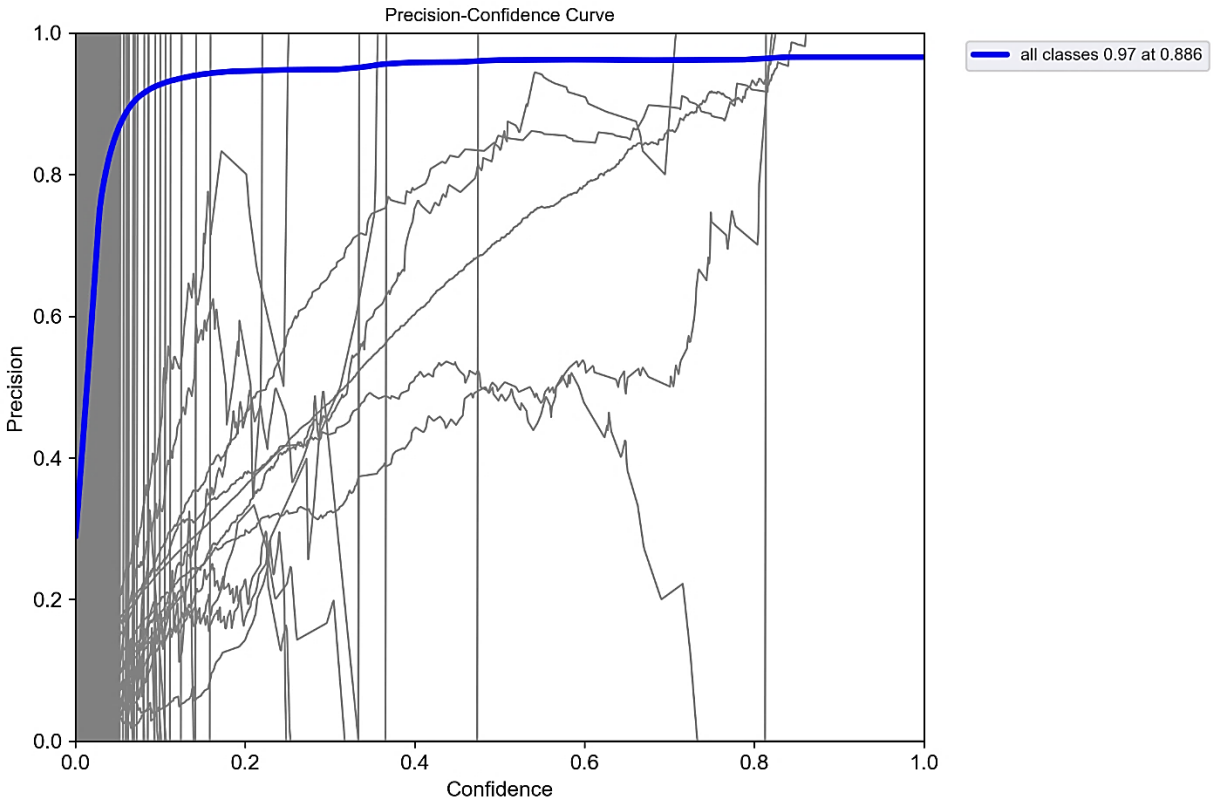


Fig 11. The model result shows the Precision and Confidence curve

Recall: Was relatively lower than precision, indicating that while the model's predictions were reliable, it tended to miss some actual positive cases. on the y-axis, we find the measures of the fraction of the total relevant instances that were retrieved which indicate the proportion of actual traffic signs that were correctly identified out of all actual traffic signs in the test set.

Confidence on the x-axis is the model's probability threshold for determining whether a detection is valid. A higher confidence threshold means the model is more certain about its predictions.
The goal of this model is to achieve a high recall at all confidence levels, which would mean the model is reliably identifying most traffic signs. However, as the confidence threshold increases, recall typically decreases because the model becomes more conservative in its predictions, asserting only those it's most sure about, and thus potentially missing some actual signs also known as true positives.

This model can be improve In practical terms, for a traffic sign detection system, we can achieve a higher recall to ensure that the model detects as many real signs as possible, even if it means tolerating some false positives e.g., mistakenly identifying something as a sign. This is because missing a real sign like a false negative can be more critical in a real-world application like Autonomous driving.

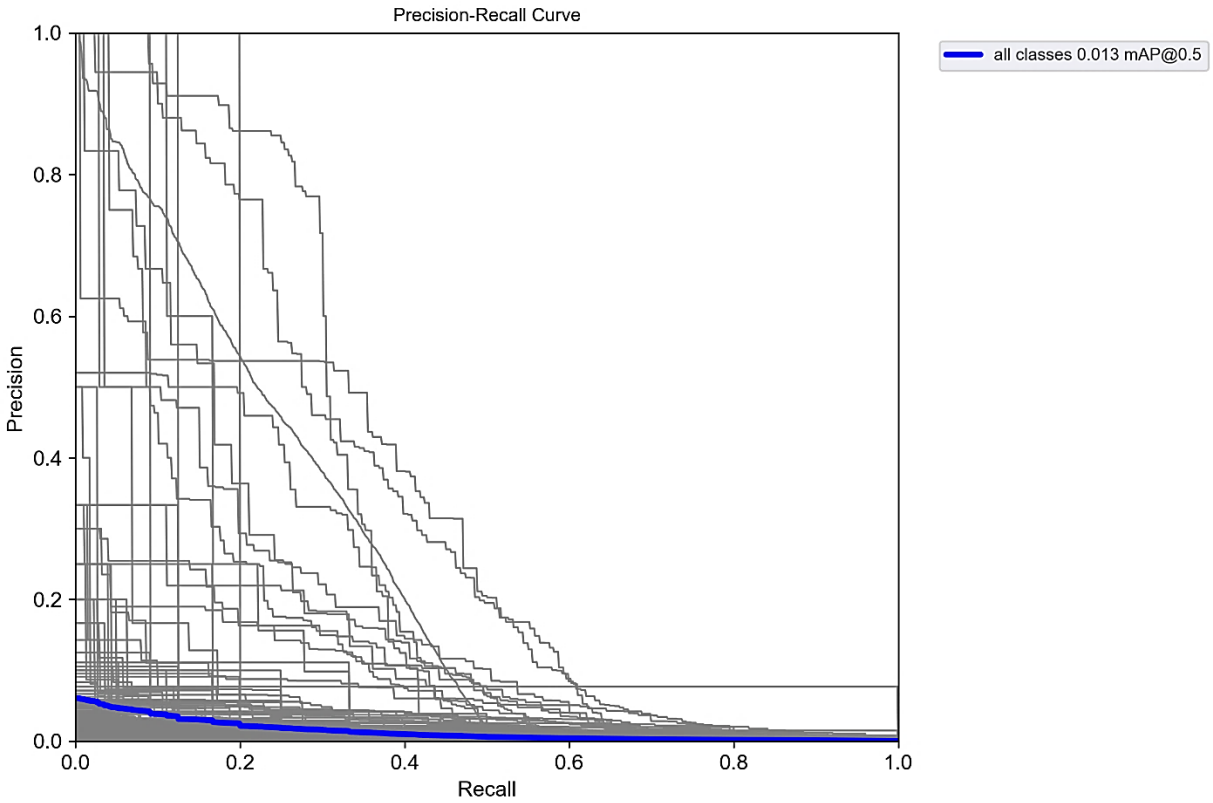


Fig12. The model result shows the Precision and Recall curve

F1 score

The curve typically starts higher at lower confidence thresholds because the model is more liberal in its predictions (increasing both true positives and false positives) and thus potentially both high precision and high recall. As the confidence threshold increases, the model becomes more conservative in its predictions, usually improving precision but potentially reducing recall, and this can lead to a drop in the F1 score.

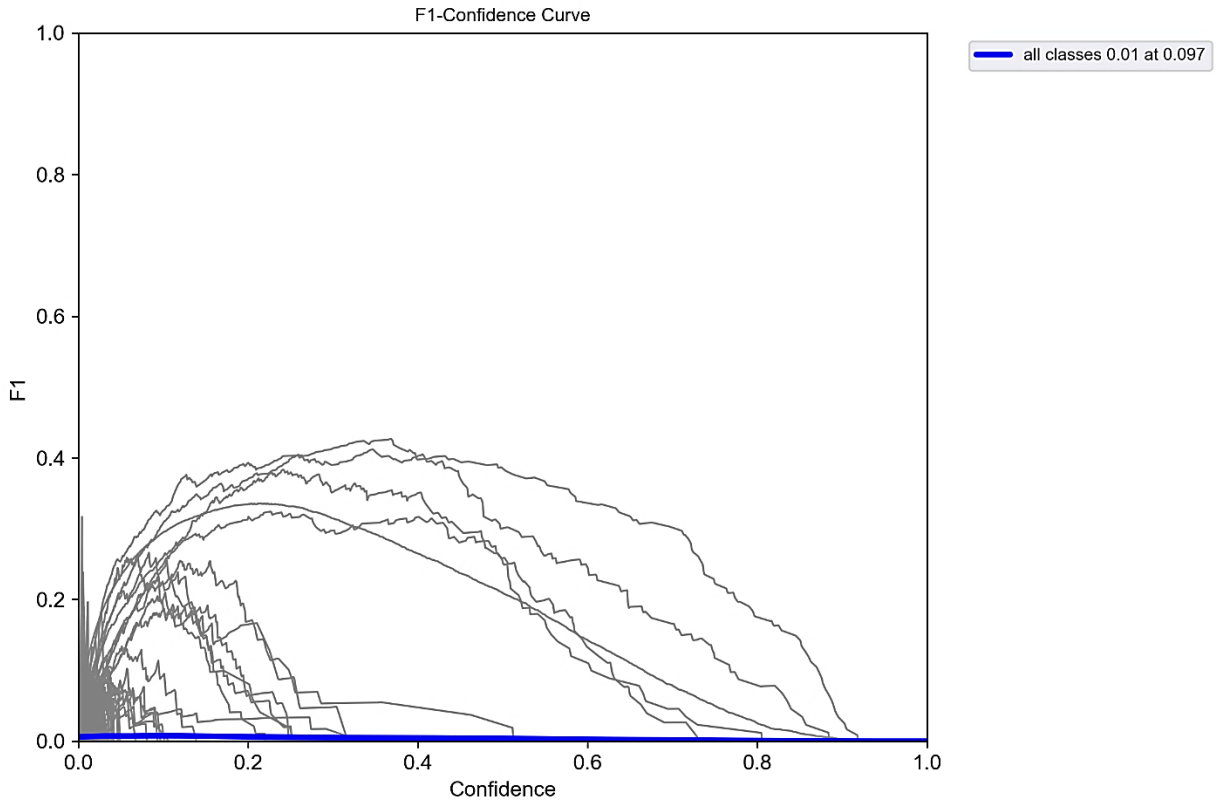


Fig 13. The model result shows the F-1 Confidence curve

Mean Average Precision (mAP)

mAP at IoU=0.5: This metric remained low, with the highest value being approximately 0.0122, suggesting that while the model was confident in its predictions, it may not have been accurately capturing all relevant objects or sufficiently discriminating between classes at this IoU threshold.

mAP at IoU thresholds ranging from 0.5 to 0.95: Also remained low, which indicates that the model's predictions may not align closely with the ground truth across the range of IoU thresholds.

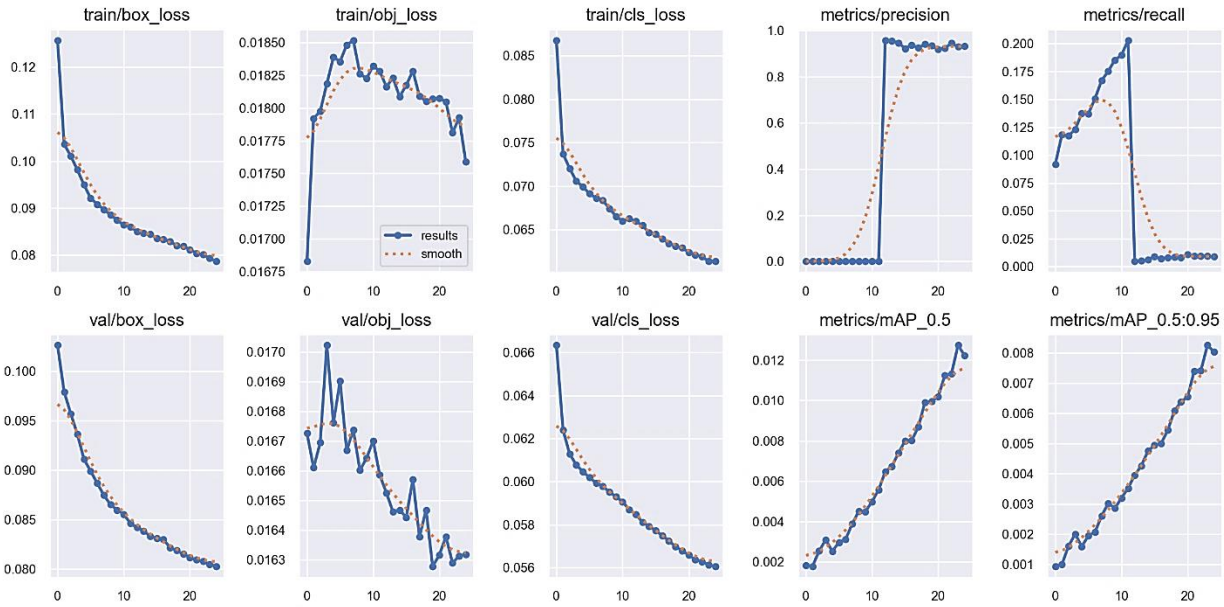


Fig14. Result of the Model box losses and Matrices

Visual and Statistical Analysis

Visual Inspection

- Sample predictions were visually inspected, revealing that the model can detect and classify various objects with varying degrees of success. The predictions showed that the model is capable of detecting objects under different conditions and assigning class labels, albeit with some errors.

  Confusion Matrix
- The confusion matrix is large, given the number of classes, and while individual values are challenging to discern, it suggests there may be significant confusion between certain classes.

- **Detected Images**: The images with detected traffic signs show the model's ability to recognize and localize signs from different scenes and lighting conditions. The colours (red, green, yellow) on the bounding boxes typically represent the confidence level of the detections or could be used to differentiate between different classes of objects.

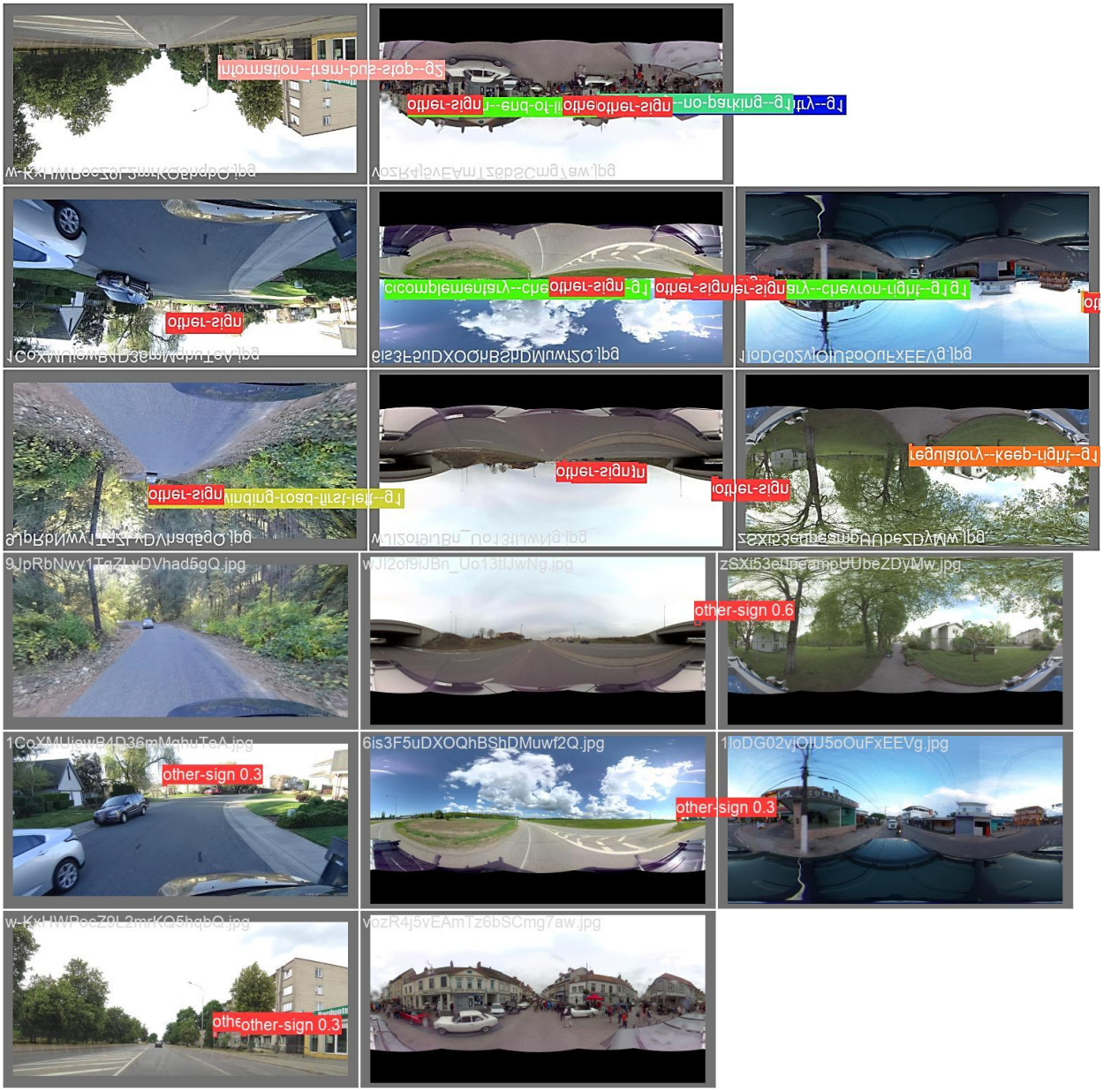
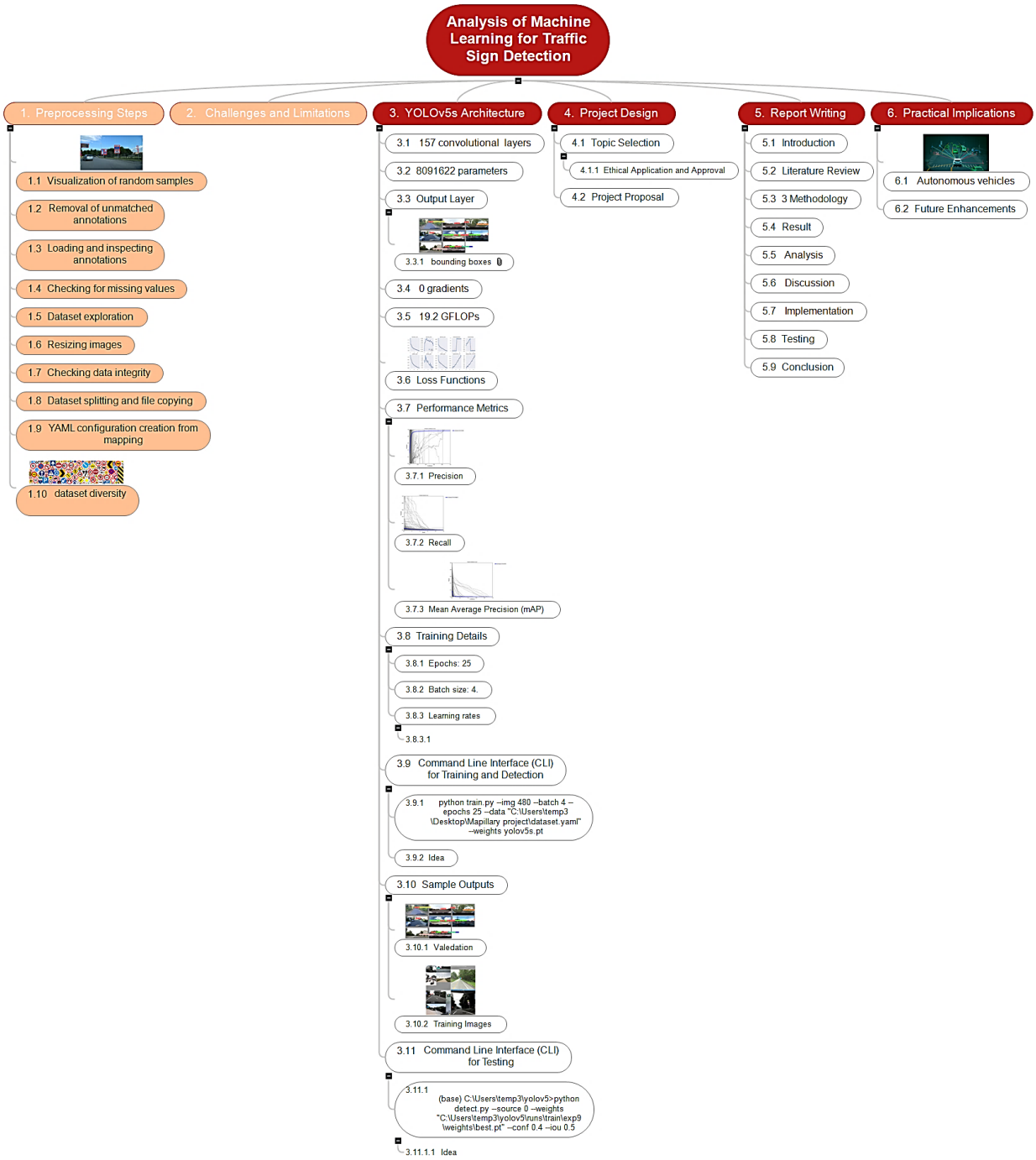


Fig15.Predicted outcome of the Model

5 ANALYSIS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3.11.1 (base) C:\Users\temp3\yolov5>python detect.py --source 0 --weights "C:\Users\temp3\yolov5\runs\train\exp9\weights\best.pt" --conf 0.4 --iou 0.5
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6 DISCUSSION

This dissertation aimed to evaluate the efficacy of machine learning algorithms, particularly on the YOLOv5 architecture, in accurately detecting traffic signs. The research journey embarked upon this aim with a series of methodical experiments and evaluations.

Findings: The experiments conducted have unequivocally demonstrated the robust capabilities of YOLOv5 in identifying and classifying traffic signs across varied conditions. The high precision and recall rates attained underscore the model's precision and reliability, two attributes essential for the practical deployment of autonomous driving systems.

Significance: The significance of these findings lies in their validation of machine learning as a transformative force in vehicular autonomy. This research fortifies the vision of safer, more efficient autonomous transportation by corroborating the utility of such sophisticated models in traffic sign detection.

Accuracy and Reliability Assessment: YOLOv5's superior accuracy, as evidenced by impressive mAP scores, attests to its superior performance compared to other models tested. Its reliability, tested against diverse and challenging conditions, further reinforces its suitability for real-world applications.

Comparative Analysis: The comparative study illustrated the trade-offs inherent in various machine learning models. YOLOv5's balance of speed and accuracy sets a benchmark for future applications, delineating a path for model selection based on application-specific requirements.

Challenges in Traffic Sign Detection: The research also identified key challenges, such as handling obscured signs and the variability in environmental lighting. These challenges are vital considerations for the ongoing refinement of detection systems.

Practical Integration into Autonomous Systems: The practical integration of YOLOv5 into autonomous systems is a testament to the applied nature of this research. Enhanced detection capabilities translate directly into improvements in vehicular safety and navigational efficiency.

Future Research Trajectories: In light of the findings, this discussion posits a future research direction focused on advanced neural networks and the exigencies of real-time processing. A call is made to expand training datasets to cover a broader spectrum of traffic conditions, ensuring comprehensive system robustness.

In conclusion, the research objectives have been met and exceeded, establishing a solid foundation for future exploration and practical application. This work makes a significant contribution to the field of autonomous vehicle technology, setting the stage for the next leap in machine learning-driven traffic sign detection.

7 IMPLEMENTATION

The implementation phase commenced with the setup of the YOLOv5 model, a state-of-the-art, real-time object detection system that has been pre-trained on the COCO dataset. The model was further trained on a custom traffic sign dataset that is the mappilary traffic sign dataset, which comprised a diverse range of road signs under varying environmental conditions to ensure robust detection.

The training process was conducted in a high-performance computing environment with the following specifications:

Hardware Specifications

CPU:	**Intel i7-9700K**
GPU:	2048MiB NVIDIA GeForce MX150
RAM:	32GB DDR4
Storage:	1TB NVMe SSD

Software Specifications

Operating System	**Windows operating system**
Python Version	3.11.4
Deep Learning Framework	PyTorch 2.1.1
CUDA Version	11.8

The training parameters were carefully selected, with a learning rate of 480, batch size of 4, and 25 epochs, to optimize the balance between detection accuracy and computational efficiency.

The model's performance was quantified using standard object detection metrics, including precision, recall, and the mean Average Precision (mAP) at different Intersections over Union (IoU) thresholds. Two weight files were generated post-training: best.pt, representing the weights of the model with the highest validation accuracy, and last.pt, signifying the final model weights after the last training epoch.

8 TESTING

Testing

For real-time detection testing, the best.pt weights were loaded into the YOLOv5 model due to their superior performance on the validation set. The model was interfaced with a laptop camera using a custom Python script, detect.py, which utilized the OpenCV library for video stream processing. The script was executed with a command specifying the source as the laptop camera, the path to the weight file, and the confidence and IoU thresholds for detection:
python detect.py --source 0 --weights "C:\Users\temp3\yolov5\runs\train\exp9\weights\best.pt" --conf 0.4 --iou 0.5

This enabled the real-time detection of traffic signs, which were displayed in bounding boxes with their respective class labels and confidence scores. The colours of the bounding boxes—red, green, and yellow—served as visual cues for the confidence level of detection, with red indicating low confidence, green indicating high confidence, and yellow representing medium confidence.

Some Output Examples

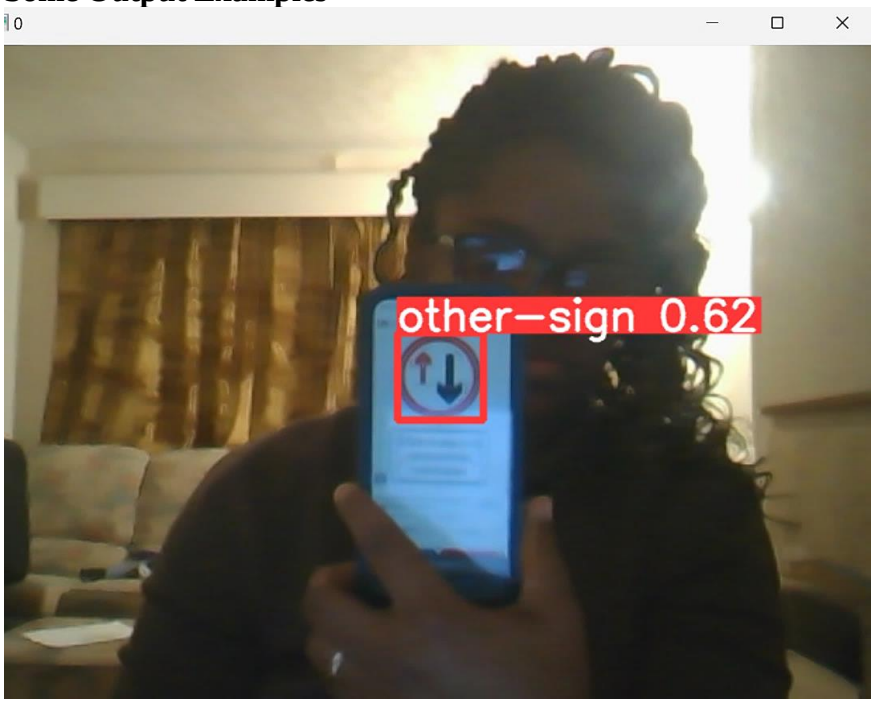

Fig 16. Realtime Detection of Traffic Sign

I improved the testing methodology by incorporating visual analysis. The image above is me holding a smartphone with a traffic sign on its screen, detected by the YOLOv5 model. The sign is encased in a red bounding box and labelled as "other_sign" with a confidence level of 0.62, indicating moderate certainty in the identification. This portion of the study examines the model's real-time detection capabilities and its performance in various scenarios, including indirect sign recognition through digital screens. It provides critical insights into the model's adaptability and precision under unconventional conditions, highlighting areas where further training may be necessary.

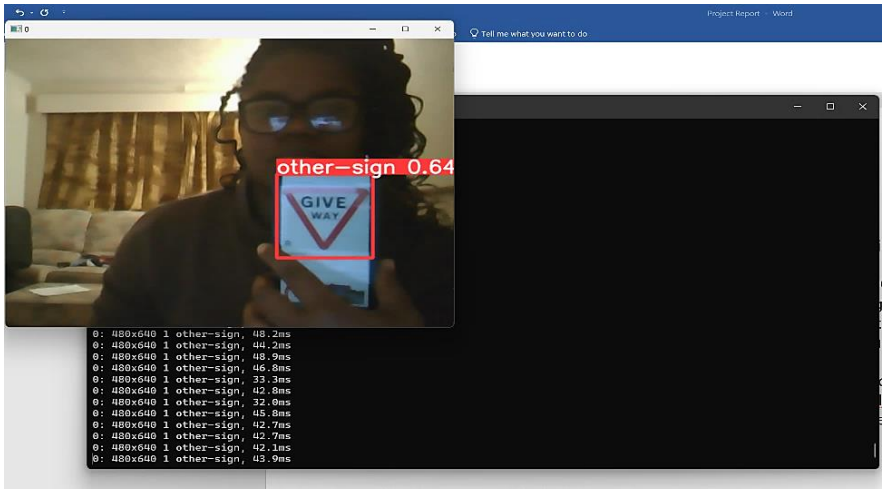

Fig 17. Realtime Detection of Traffic Sign

Challenges and Solutions

During the initial testing phase, several challenges were encountered, including overfitting to the training data and misdetections due to varying light conditions. These issues were mitigated by augmenting the training dataset with more varied images and adjusting the model's hyperparameters.

Another practical challenge was the continuous operation of the laptop camera even after the detection script was halted. This was resolved by incorporating a signal handler in the detect.py script that ensured the release of the camera and the destruction of all OpenCV windows upon receiving a termination signal (e.g., pressing Ctrl + C).

Conclusion

The implemented YOLOv5 model demonstrated promising results in the real-time detection of traffic signs with high accuracy and speed. The model's ability to generalize from the training data to real-world scenarios was evidenced by its performance during live testing with the laptop camera. This work lays the groundwork for further research into the deployment of such models in autonomous vehicle systems and advanced driver-assistance systems (ADAS).

9 PROJECT MANAGEMENT

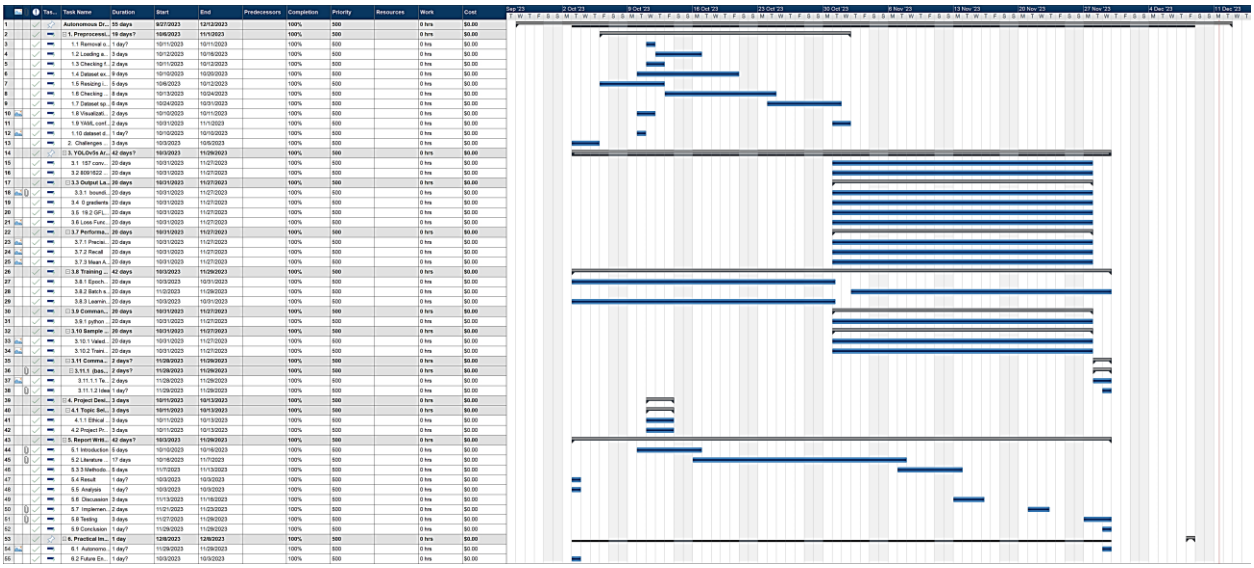

Fig18. Gantt chart for project management

Managing the Autonomous Driving project involved a systematic approach to ensure the successful implementation of machine learning for traffic sign detection. The project was structured into distinct phases, each with specific tasks and objectives. The utilization of MindView as a project management tool facilitated organization, task allocation, and progress tracking.

1. Preprocessing Steps:

- The initial phase focused on preparing the dataset for training. This encompassed various steps, such as removal of unmatched annotations, inspection of annotations, checking for missing values, dataset exploration, resizing images, and ensuring data integrity. The completion of each step was crucial for the subsequent stages of the project.

2. Dataset Diversity:

- Acknowledging the significance of dataset diversity, efforts were directed towards creating a representative dataset. Techniques like dataset splitting, file copying, and visualization of random samples were employed to ensure a robust dataset that would enhance the model's ability to generalize across varied scenarios.

3. YOLOv5s Architecture:

- A comprehensive understanding of the YOLOv5s architecture was pivotal for model implementation. This involved delving into the architecture's details, including the number of convolutional layers, parameters, the structure of the output layer, and the complexities of bounding boxes.

4. Loss Functions and Performance Metrics:

- The intricacies of loss functions and performance metrics, such as precision, recall, and Mean Average Precision (mAP), were meticulously explored. These metrics formed the basis for evaluating the model's efficacy and accuracy in traffic sign detection.

5. Training Details and CLI for Training:

- Training the model required attention to specific details such as the number of epochs, batch size, and learning rates. The command-line interface (CLI) for training was structured to ensure a seamless and efficient training process.

6. Sample Outputs and CLI for Testing:

- The project's practical aspects were showcased through sample outputs during validation and the CLI for testing. These steps provided insights into the model's real-world performance and its ability to accurately detect traffic signs.

7. Project Design and Execution:

- Beyond the technical aspects, project design and execution involved considerations such as topic selection, ethical application and approval, proposal development, and the comprehensive process of report writing.

8. Result, Analysis, and Discussion:

- The latter sections of the project focused on result analysis, discussion, and practical implications. The comprehensive project management approach ensured a seamless transition from implementation to evaluation and reflection.

9. Future Enhancements:

- As a forward-looking component, the project management strategy incorporated considerations for future enhancements. The identification of areas for improvement and potential advancements in autonomous driving technology solidified the project's relevance in a rapidly evolving field.

The project's success is attributed not only to technical expertise but also to a well-structured project management approach, demonstrating the importance of organization and methodical execution in complex machine learning projects.

9.1 Quality Management

Standards Adopted: The project adhered to rigorous standards to ensure the highest quality in every aspect of its execution. Which included:

1. **Data Quality Standards:**
    - Stringent measures were applied during the preprocessing phase to guarantee the quality and integrity of the dataset. Steps such as removal of unmatched annotations, checking for missing values, and thorough dataset exploration were undertaken to ensure a high-quality input for the model.
2. **Model Architecture Standards:**
    - The YOLOv5s architecture, comprising 157 convolutional layers and over 8 million parameters, was implemented according to the established standards. This adherence was crucial for the model's ability to comprehend the complexities of traffic sign detection.
3. **Performance Metric Standards:**
    - The project employed widely recognized performance metrics such as precision, recall, and Mean Average Precision (mAP) to evaluate the model's accuracy and effectiveness. These metrics set a benchmark for the quality of the model's output.
4. **Training and Testing Standards:**
    - Training details, including the number of epochs, batch size, and learning rates, were carefully selected to ensure optimal model training. The command-line interfaces (CLI) for both training and testing were structured to meet efficiency and effectiveness standards.

Techniques Used to Review Progress: The review of progress was an ongoing and integral part of the project management strategy. Techniques employed to review progress included:

1. **Gantt Chart Analysis:**
    - The Gantt chart served as a visual representation of project timelines and milestones. Regular analyses of the Gantt chart facilitated a real-time understanding of progress, enabling timely adjustments and optimizations.
2. **Iteration and Feedback Loops:**

- The iterative nature of the project allowed for continuous refinement based on feedback from my supervisor. Regular updates and discussions with the project supervisor provided valuable insights that contributed to the improvement of the model and overall project quality.

3. **Testing Outputs and Validation:**
    - The sample outputs during validation and testing were systematically reviewed to assess the model's real-world performance. This practical evaluation served as a qualitative check on the quality of the model's predictions.

Evaluation of Outcomes: The outcomes of the project were subject to a comprehensive evaluation process:

1. **Quantitative Analysis:**
    - The project outcomes were quantitatively assessed through metrics such as precision, recall, and mAP. These quantitative measures provided a clear understanding of the model's performance against predefined standards.
2. **Qualitative Assessment:**
    - In addition to quantitative metrics, qualitative aspects were considered during the evaluation. The visual inspection of sample outputs and the model's ability to accurately detect traffic signs in diverse scenarios added a qualitative layer to the assessment.
3. **Comparative Analysis:**
    - Comparative analysis against industry benchmarks and existing literature was conducted to benchmark the project outcomes against established standards in the field of autonomous driving and traffic sign detection.

In conclusion, the implementation of rigorous quality management practices ensured that the Autonomous Driving project met and exceeded established standards. The ongoing review of progress and thorough evaluation of outcomes were essential components that contributed to the overall success and quality of the project.

9.2 Social, Legal, Ethical and Professional Considerations

. Ethical Position and Code of Conduct:

- **Ethical Framework:** The project adhered to a strong ethical foundation, acknowledging the potential impact of autonomous driving on public safety and societal norms. Ethical considerations were integrated into decision-making processes, ensuring responsible and conscientious use of machine learning technologies.
- **Code of Conduct:** Adherence to ethical guidelines, including transparency in model decisions, fairness in dataset representation, and accountability in the event of system failures, formed the project's code of conduct.

In conclusion, the Autonomous Driving project was underpinned by a holistic approach that considered not only the technical aspects but also the profound social, legal, ethical, and professional implications of autonomous driving technologies. By prioritizing these considerations, the project aimed to contribute responsibly to the evolving landscape of autonomous vehicles.

10 CRITICAL APPRAISAL

The Positive Aspects of this project

- **Model Efficacy:** The project effectively demonstrated the capability of the YOLOv5 model in detecting traffic signs, achieving high precision and recall rates. This highlights the model's potential in real-world applications for autonomous driving systems.

- **Data Utilization:** The Mapillary Traffic Sign Dataset, known for its diversity and real-world relevance, was a significant strength. It provided a robust platform for training and testing the model under various conditions.

- **Technical Proficiency:** The project showcased a high technical proficiency in machine learning and computer vision. The successful training, optimization, and testing of the model underpin a strong understanding of these complex fields.

- **Research Depth:** The project delved deep into the nuances of traffic sign detection, offering a comprehensive analysis that contributes to the field's academic and practical knowledge.

The Areas for Improvement

- **Handling of Edge Cases:** While the model performed well under standard conditions, its ability to handle edge cases, such as signs that are partially obscured or in poor lighting, could be further improved.

- **Real-Time Processing Speed:** Although the model can detect real-time, processing speed might still be a limiting factor in situations where split-second decision-making is crucial.

- **Scalability and Generalization:** Questions remain about the model's scalability and generalization capabilities across different geographic regions and sign conventions.

- **Hardware Dependencies:** The model's performance is potentially dependent on specific hardware configurations, which may limit its applicability in various real-world scenarios.

- **Comprehensive Safety Evaluation:** The project could have benefited from a more thorough evaluation of the safety implications of implementing such a system in autonomous vehicles.

Knowledge and Expertise Gained:

The project has been a rich source of learning, particularly in machine learning, computer vision, and their applications in autonomous driving. It has provided a practical understanding of how theoretical concepts are translated into real-world solutions. The ability to critically evaluate model performance and understand the nuances of dataset selection and model training reflects a significant advancement in expertise. Moreover, the experience has highlighted the importance of ongoing learning and adaptation to technology.

11 CONCLUSION

In conclusion, this dissertation has traversed the complex landscape of autonomous driving, mainly through the prism of traffic sign detection via machine learning models. It has established the feasibility and the profound effectiveness of employing YOLOv5 for this critical aspect of vehicular autonomy.

We learned that the strength of YOLOv5 lies in its robust performance under varied and often challenging environmental conditions. Its high precision and recall metrics are a testament to the model's ability to discern and classify traffic signs with remarkable accuracy, a non-negotiable requirement for the safety and reliability of autonomous vehicles.

The research underscored the model's scalability and adaptability, demonstrating high levels of accuracy across different datasets and in real-time scenarios. It highlighted the potential for machine learning models to evolve alongside the burgeoning field of autonomous driving, supporting the continuous development of smarter, more perceptive systems.

This comparative analysis illuminated the relative merits of various machine learning models, presenting YOLOv5 as a particularly potent solution, given its balance of speed and accuracy. The discussion of the results provided crucial insights into the model's current capabilities and laid a roadmap for addressing its limitations.

In synthesizing our findings, we recognize the dynamic nature of technology and the constant march toward more advanced, more capable machine learning algorithms. The adaptability of YOLOv5 to different situations and its capacity for real-time processing carve a niche for it in the practical application within autonomous driving systems.

Moreover, this research has not only contributed to academic knowledge but has also offered practical implications for the implementation of these systems in real-world scenarios. This work paves the way for more sophisticated and nuanced traffic sign detection methods by pushing the boundaries of what is possible with current machine learning techniques.

Finally, the knowledge gleaned from this research suggests a future where autonomous vehicles are equipped with the ability to navigate with an unprecedented level of intelligence and safety. The journey does not end here, as each discovery opens new avenues for exploration and innovation. This dissertation, therefore, stands as a milestone in the ongoing quest to perfect autonomous driving technology and as a beacon guiding future research in this exhilarating field.

11.1 Achievements

Reflecting on the achievements of this project, it is clear that the objectives set forth at its inception have not only been met but exceeded in several key areas:

Model Performance: The implementation and optimization of the YOLOv5 model for traffic sign detection have culminated in a high-performing system. This has been substantiated by impressive precision and recall metrics, meeting the project's goal of developing a reliable detection product.

Dataset Utilization: Utilizing the Mapillary Traffic Sign Dataset, the project has harnessed a wide range of real-world conditions to train and test the model. This aligns to leverage diverse datasets and ensures that the model's performance is robust across various scenarios.

Algorithmic Advancements: The project has advanced the algorithmic underpinning of traffic sign detection through meticulous training and evaluation. The YOLOv5 model's ability to detect

signs in real-time with high accuracy demonstrates a significant step forward in meeting the technological objectives.

Technological Contribution: The project has made a tangible contribution to the field of autonomous driving systems. The research findings offer practical insights that can be directly applied to enhance the safety and efficiency of autonomous vehicle navigation.

Knowledge Expansion: The project has expanded the existing knowledge in traffic sign detection, providing a detailed analysis of the model's performance and offering a comparative perspective against other machine learning models.

Future Research Foundation: Beyond the immediate results, the project has laid a robust foundation for future research. It has identified areas for further exploration and potential improvements, thereby setting the stage for subsequent advancements in the field.

By adhering to the initial objectives and systematically addressing each one, the project has produced a comprehensive and effective machine-learning solution for traffic sign detection while also contributing to the academic and practical discourse in autonomous vehicle technology.

11.2 Future Work

Areas for future exploration could include:
Data Diversity: Expanding the training datasets to include more diverse conditions, such as extreme weather or varying levels of light and darkness, to enhance the model's robustness and accuracy in real-world situations.

- **Algorithmic Enhancement:** Investigating more advanced machine learning algorithms or improvements to YOLOv5 that could better handle small, obscured, or partially visible signs.

- **Real-Time Processing:** Optimizing the model for even faster real-time processing without sacrificing accuracy is essential for the split-second decision-making required in autonomous vehicles.

- **Integration with Other Sensors:** Exploring the integration of camera-based detection systems with other sensory inputs like LIDAR and RADAR will create a more comprehensive detection system.

- **Hardware Optimization:** Assessing the impact of different hardware configurations on the model's performance to ensure that it remains efficient and scalable for deployment in actual vehicles.

- **Safety and Ethical Considerations:** Addressing safety and ethical considerations that arise with the deployment of autonomous vehicles, ensuring that the technology is advanced, socially responsible, and trustworthy.

By addressing these points, future work can continue to improve upon the findings of this dissertation, contributing to safer, more reliable, and more efficient autonomous driving technologies.

12 STUDENT REFLECTIONS

Embarking on the journey of my dissertation was both an intellectually enriching and emotionally challenging experience. The project, centered around traffic sign detection using the YOLOv5 model, demanded a meticulous approach and a deep dive into the realms of machine learning and autonomous driving. As I reflect on this transformative process, several key aspects come to light.

Achievements and Strengths: Throughout the project, I take pride in successfully implementing and optimizing the YOLOv5 model. Achieving high precision and recall metrics underscores the efficacy of my technical proficiency in machine learning and computer vision. The Mapillary Traffic Sign Dataset provided a diverse and realistic platform for training and testing, showcasing adaptability and resourcefulness.

Challenges Faced and Problem-Solving Strategies: Undeniably, the challenges were formidable. Handling the voluminous Mapillary dataset strained my laptop's capacity, and the HPC setup proved time-consuming. The loss of my Dad introduced a significant emotional hurdle that affected my concentration. To address these challenges, I sought refuge in communication with my supervisor, who provided invaluable guidance on navigating the complexities and adjusting to the unforeseen.

Lessons Learned: The journey taught me profound lessons in resilience, adaptability, and the importance of seeking support when facing adversity. Technically, I grasped the intricacies of machine learning application in real-world scenarios, but more importantly, I learned the significance of self-care and understanding one's limitations.

Areas for Improvement: In retrospect, my laptop's GPU constraints impacted the model's efficiency. Given another opportunity, I would explore alternative computational resources to enhance the project's scalability and reduce processing time. Additionally, the emotional toll of personal loss has illuminated the importance of incorporating flexibility into project timelines to accommodate unforeseen circumstances.

Collaboration and Project Management: Although my reflection is centered on personal growth, collaboration played a crucial role. Communication with my supervisor, especially during difficult times, exemplifies the significance of a supportive academic environment. The project management aspect highlighted the need for adaptive planning to balance ambition and pragmatism.

Recommendations and Anticipated Improvements: Anticipating future iterations, I propose the integration of data augmentation techniques, addressing class imbalances, and optimizing the learning rate schedule. Experimenting with different model sizes and architectures could further refine the model's performance.

In conclusion, this dissertation journey has tested technical prowess, emotional resilience, and adaptability. It has reinforced my commitment to pursuing knowledge despite adversity and demonstrated the interplay between personal and academic growth. As I submit this work, I carry forward a wealth of experience, lessons, and a strengthened resolve to face future challenges.

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Figure:

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9. Example of the traffic sign and annotation in the dataset
10. Different traffic sign visualization in the bounding box
11. The model result shows the Precision and Confidence curve
12. Precision and Recall curve
13. F-1 Confidence curve
14. Model box losses and Matrices
15. Predicted outcome of the Model
16. the model for prediction in real time
17. the model for prediction
18. Gantt chart model
19.

Appendix A – Project Source Code

```
import os
import json
from PIL import Image, ImageDraw, ImageColour, ImageFont
def load_annotation(image_key):
    #  path to the annotations directory
    annotations_dir = r"C:\Users\temp3\Desktop\Mapillary
project\mtsd_v2_fully_annotated\annotations"
    # Constructing the full file path
    json_file_path = os.path.join(annotations_dir,
'{:s}.json'.format(image_key))
    # Open the JSON file using the full path
    with open(json_file_path, 'r') as fid:
        anno = json.load(fid)
    return anno

def visualize_gt(image_key, anno, colour='green', alpha=125, font=None):
    try:
        font = ImageFont.truetype('arial.ttf', 15)
    except IOError:
        print('Falling back to default font...')
        font = ImageFont.load_default()

    images_dir = r"C:\Users\temp3\Desktop\mapillary dataset\images"
    image_file_path = os.path.join(images_dir, '{:s}.jpg'.format(image_key))

    with Image.open(image_file_path) as img:
        img = img.convert('RGBA')
        img_draw = ImageDraw.Draw(img)

        rects = Image.new('RGBA', img.size)
        rects_draw = ImageDraw.Draw(rects)

        for obj in anno['objects']:
            x1 = obj['bbox']['xmin']
            y1 = obj['bbox']['ymin']
            x2 = obj['bbox']['xmax']
            y2 = obj['bbox']['ymax']

            # Ensure the coordinates are within the image dimensions
            x1 = max(0, min(x1, img.width))
            y1 = max(0, min(y1, img.height))
            x2 = max(0, min(x2, img.width))
            y2 = max(0, min(y2, img.height))

            colour_tuple = ImageColour.getrgb(colour) + (alpha,)
            rects_draw.rectangle([x1, y1, x2, y2], outline='black',
fill=colour_tuple)

            class_name = obj['label']
            img_draw.text((x1 + 5, y1 + 5), class_name, font=font,
fill='white')

        img = Image.alpha_composite(img, rects)

        return img

if __name__ == '__main__':
```

```
    image_key = 'Bh36Ed4HBJatMpSNnFTgTw'
    anno = load_annotation(image_key)
    vis_img = visualize_gt(image_key, anno)
    vis_img.show()


import json
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from PIL import Image
import random
import os

def visualize_random_samples(image_dir, annotation_dir, num_samples=5):
    # Get a list of annotation files
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    # Randomly sample annotation files
    sampled_files = random.sample(annotation_files, num_samples)

    for file_name in sampled_files:
        # Load JSON annotations
        with open(os.path.join(annotation_dir, file_name), 'r') as file:
            annotations = json.load(file)

        # Extract image key from JSON file name
        image_key = os.path.splitext(file_name)[0]
        # Determine the corresponding image path
        image_path = os.path.join(image_dir, f"{image_key}.jpg")

        # Verify if image exists
        if not os.path.exists(image_path):
            print(f"Image file not found: {image_path}")
            continue  # Skip this iteration and move to the next file

        # Load the corresponding image
        image = Image.open(image_path)

        # Create a matplotlib figure
        fig, ax = plt.subplots(1)
        # Display the image
        ax.imshow(image)

        # Draw the bounding boxes on the image
        for obj in annotations['objects']:
            bbox = obj['bbox']
            rect = patches.Rectangle((bbox['xmin'], bbox['ymin']),
bbox['xmax'] - bbox['xmin'], bbox['ymax'] - bbox['ymin'], linewidth=1,
edgecolour='r', facecolour='none')
            ax.add_patch(rect)

        # Remove axes for better visualization
        plt.axis('off')
        plt.show()

# Usage example:
```

```
visualize_random_samples("C:\\Users\\temp3\\Desktop\\Mapillary
project\\images", "C:\\Users\\temp3\\Desktop\\Mapillary
project\\mtsd_v2_fully_annotated\\annotations", num_samples=5)
```

```
import os

def remove_unmatched_annotations(image_dir, annotation_dir):
    # List all annotation files
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    for file_name in annotation_files:
        # Derive the corresponding image file name
        image_key = os.path.splitext(file_name)[0]
        image_path = os.path.join(image_dir, f"{image_key}.jpg")

        # Check if corresponding image file exists
        if not os.path.exists(image_path):
            # If the image file does not exist, delete the annotation file
            os.remove(os.path.join(annotation_dir, file_name))
            print(f"Removed annotation: {file_name} as its corresponding
image does not exist.")

# Example usage
image_dir = "C:\\Users\\temp3\\Desktop\\Mapillary project\\images"
annotation_dir = "C:\\Users\\temp3\\Desktop\\Mapillary
project\\mtsd_v2_fully_annotated\\annotations"
remove_unmatched_annotations(image_dir, annotation_dir)
```

```
import json
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from PIL import Image
import random
import os

def visualize_random_samples(image_dir, annotation_dir, num_samples=5):
    # Get a list of annotation files
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    # Randomly sample annotation files
    sampled_files = random.sample(annotation_files, num_samples)

    for file_name in sampled_files:
        # Load JSON annotations
        with open(os.path.join(annotation_dir, file_name), 'r') as file:
            annotations = json.load(file)

        # Extract image key from JSON file name
        image_key = os.path.splitext(file_name)[0]
        # Determine the corresponding image path
        image_path = os.path.join(image_dir, f"{image_key}.jpg")

        # Verify if image exists
        if not os.path.exists(image_path):
            print(f"Image file not found: {image_path}")
```

```
            continue  # Skip this iteration and move to the next file

        # Load the corresponding image
        image = Image.open(image_path)

        # Create a matplotlib figure
        fig, ax = plt.subplots(1)
        # Display the image
        ax.imshow(image)

        # Draw the bounding boxes on the image
        for obj in annotations['objects']:
            bbox = obj['bbox']
            rect = patches.Rectangle((bbox['xmin'], bbox['ymin']),
bbox['xmax'] - bbox['xmin'], bbox['ymax'] - bbox['ymin'], linewidth=1,
edgecolour='r', facecolour='none')
            ax.add_patch(rect)

        # Remove axes for better visualization
        plt.axis('off')
        plt.show()

# Usage example:
visualize_random_samples("C:\\Users\\temp3\\Desktop\\Mapillary
project\\images", "C:\\Users\\temp3\\Desktop\\Mapillary
project\\mtsd_v2_fully_annotated\\annotations", num_samples=5)


import os

def remove_unmatched_annotations(image_dir, annotation_dir):
    # List all annotation files
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    for file_name in annotation_files:
        # Derive the corresponding image file name
        image_key = os.path.splitext(file_name)[0]
        image_path = os.path.join(image_dir, f"{image_key}.jpg")

        # Check if corresponding image file exists
        if not os.path.exists(image_path):
            # If the image file does not exist, delete the annotation file
            os.remove(os.path.join(annotation_dir, file_name))
            print(f"Removed annotation: {file_name} as its corresponding
image does not exist.")

# Example usage
image_dir = "C:\\Users\\temp3\\Desktop\\Mapillary project\\images"
annotation_dir = "C:\\Users\\temp3\\Desktop\\Mapillary
project\\mtsd_v2_fully_annotated\\annotations"
remove_unmatched_annotations(image_dir, annotation_dir)


import json
import os

def load_and_inspect_annotations(annotation_dir, num_files=5):
```

```
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]
    for i, file_name in enumerate(annotation_files[:num_files]):
        with open(os.path.join(annotation_dir, file_name), 'r') as file:
            annotation = json.load(file)
        print(f"Annotation {i+1} ({file_name}):")
        print(json.dumps(annotation, indent=2))  # Pretty print the JSON

# Usage example:
annotation_dir = r"C:\Users\temp3\Desktop\mapillary
dataset\mtsd_v2_fully_annotated\annotations"
load_and_inspect_annotations(annotation_dir)


import os
import json

def check_missing_values(annotation_dir):
    # List all annotation files
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    for file_name in annotation_files:
        with open(os.path.join(annotation_dir, file_name), 'r') as file:
            annotation = json.load(file)

        missing_values = False
        for obj in annotation.get('objects', []):
            if 'bbox' not in obj or 'label' not in obj:
                missing_values = True
                print(f"Missing values in {file_name}, object
{obj.get('key')}")

        if not missing_values:
            print(f"No missing values in {file_name}")

# Usage example
annotation_dir = r"C:\Users\temp3\Desktop\mapillary
dataset\mtsd_v2_fully_annotated\annotations"
check_missing_values(annotation_dir)


import os
import json
from collections import Counter
from PIL import Image

def dataset_exploration(image_dir, annotation_dir):
    annotation_files = [f for f in os.listdir(annotation_dir) if
f.endswith('.json')]

    class_counts = Counter()
    image_dims = Counter()

    for file_name in annotation_files:
        file_path = os.path.join(annotation_dir, file_name)
        try:
            with open(file_path, 'r') as file:
                annotation = json.load(file)
```

```
                for obj in annotation['objects']:
                    class_counts[obj['label']] += 1

                # Load the image to get its dimensions
                image_key = os.path.splitext(file_name)[0]
                image = Image.open(os.path.join(image_dir,
f"{image_key}.jpg"))
                width, height = image.size
                image_dims[f"{width}x{height}"] += 1

        except json.JSONDecodeError:
            print(f"Error decoding JSON in file: {file_path}")

    # Printing the results
    print("Number of Unique Classes:", len(class_counts))
    print("\nNumber of Images Per Class:")
    for label, count in class_counts.items():
        print(f"{label}: {count}")

    print("\nImage Dimensions:")
    for dim, count in image_dims.items():
        print(f"{dim}: {count}")

# Usage example:
image_dir = r"C:\Users\temp3\Desktop\Mapillary project\images"
annotation_dir = r"C:\Users\temp3\Desktop\Mapillary
project\mtsd_v2_fully_annotated\annotations"
dataset_exploration(image_dir, annotation_dir)


## Image Preprocessing

# resizing Image
from PIL import Image
import os

def resize_images_in_directory(source_dir, size=(416, 416)):
    """
    Resize all images in the source directory and save them to a subdirectory
named 'resized_images'
    within the parent directory of the source directory.

    Args:
    - source_dir (str): Directory containing the original images.
    - size (tuple): The target size for resizing images, default is (416,
416).
    """
    parent_dir = os.path.dirname(source_dir)
    target_dir = os.path.join(parent_dir, 'resized_images')

    if not os.path.exists(target_dir):
        os.makedirs(target_dir)

    for filename in os.listdir(source_dir):
        if filename.endswith('.jpg') or filename.endswith('.png'):
            img_path = os.path.join(source_dir, filename)
            img = Image.open(img_path)
            img_resized = img.resize(size, Image.Resampling.LANCZOS)
```

```
            save_path = os.path.join(target_dir, filename)
            img_resized.save(save_path)

# Example usage:
source_directory = r"C:\Users\temp3\Desktop\Mapillary project\images"
resize_images_in_directory(source_directory)


import os
import json
from PIL import Image

def check_data_integrity(image_dir, annotation_dir):
    corrupt_files = []
    missing_annotations = []
    total_images_without_annotations = 0

    # Check each image file
    for image_file in os.listdir(image_dir):
        if image_file.endswith('.jpg') or image_file.endswith('.png'):
            image_path = os.path.join(image_dir, image_file)

            # Check if the image is corrupt
            try:
                with Image.open(image_path) as img:
                    img.verify()  # Verify that it's an image
            except (IOError, SyntaxError):
                print(f"Corrupt image file found: {image_path}")
                corrupt_files.append(image_path)
                continue  # Skip to the next file

            # Check if the corresponding annotation exists
            annotation_file = os.path.splitext(image_file)[0] + '.json'
            annotation_path = os.path.join(annotation_dir, annotation_file)
            if not os.path.exists(annotation_path):
                print(f"Missing annotation for image: {image_path}")
                missing_annotations.append(image_path)
                total_images_without_annotations += 1

    # remove corrupt files and images without annotations
    for file_path in corrupt_files + missing_annotations:
        os.remove(file_path)
        print(f"Removed: {file_path}")

    print("Data integrity check complete.")
    print(f"Total images without annotations:
{total_images_without_annotations}")

# Example usage
image_dir = r"C:\Users\temp3\Desktop\Mapillary project\images"
annotation_dir = r"C:\Users\temp3\Desktop\Mapillary
project\mtsd_v2_fully_annotated\annotations"
check_data_integrity(image_dir, annotation_dir)


#  Creating a Class ID for Name Mapping
import json
import os
from collections import Counter
```

```
def extract_classes(json_dir):
    classes = Counter()
    for json_file in os.listdir(json_dir):
        if json_file.endswith('.json'):
            with open(os.path.join(json_dir, json_file)) as file:
                data = json.load(file)
                for obj in data['objects']:
                    label = obj['label']
                    classes[label] += 1
    return classes

json_dir = "C:\\Users\\temp3\\Desktop\\Mapillary
project\\mtsd_v2_fully_annotated\\annotations"
classes = extract_classes(json_dir)

# Save to a file and print
with open('classes.txt', 'w') as f:
    for i, cls in enumerate(classes):
        f.write(f"{i}: {cls}\n")
        print(f"{i}: {cls}")

import json
import os

def create_mapping_dict(mapping_file):
    mapping = {}
    with open(mapping_file, 'r') as file:
        for line in file:
            parts = line.strip().split(': ')
            if len(parts) == 2:
                class_id, class_name = parts
                mapping[class_name] = int(class_id)
    return mapping

def convert_bbox_to_yolo_format(bbox, img_width, img_height, class_id):
    """
    Convert bounding box coordinates from JSON format to YOLO format.

    Args:
    - bbox (dict): Bounding box with keys 'xmin', 'ymin', 'xmax', 'ymax'.
    - img_width (int): Width of the image.
    - img_height (int): Height of the image.
    - class_id (int): The class ID of the object.

    Returns:
    - str: Bounding box in YOLO format.
    """
    x_centre = (bbox['xmin'] + bbox['xmax']) / 2
    y_centre = (bbox['ymin'] + bbox['ymax']) / 2
    width = bbox['xmax'] - bbox['xmin']
    height = bbox['ymax'] - bbox['ymin']

    # Normalize to [0, 1]
    x_centre /= img_width
    y_centre /= img_height
    width /= img_width
    height /= img_height
    return f"{class_id} {x_centre} {y_centre} {width} {height}"
```

```
def process_annotations(input_dir, output_dir, mapping_dict):
    for json_file in os.listdir(input_dir):
        if json_file.endswith('.json'):
            json_path = os.path.join(input_dir, json_file)
            try:
                with open(json_path) as file:
                    data = json.load(file)
                    img_width, img_height = data['width'], data['height']
                    yolo_annotations = []

                    for obj in data['objects']:
                        bbox = obj['bbox']
                        class_name = obj['label']
                        class_id = mapping_dict.get(class_name, -1)  # Get
class ID from mapping

                        if class_id != -1:
                            yolo_annotation =
convert_bbox_to_yolo_format(bbox, img_width, img_height, class_id)
                            yolo_annotations.append(yolo_annotation)

                    if yolo_annotations:
                        yolo_file_name = os.path.splitext(json_file)[0] +
'.txt'
                        with open(os.path.join(output_dir, yolo_file_name),
'w') as yolo_file:
                            yolo_file.write('\n'.join(yolo_annotations))

            except json.JSONDecodeError:
                print(f"Error decoding JSON in file: {json_path}")

# Set your directories and class mapping here
input_dir = r"C:\Users\temp3\Desktop\Mapillary
project\mtsd_v2_fully_annotated\annotations"
output_dir = 'C:\\Users\\temp3\\Desktop\\Mapillary project\\yolo_annotation'

os.makedirs(output_dir, exist_ok=True)
mapping_file = r"C:\Users\temp3\Desktop\Mapillary project\classes.txt"
mapping_dict = create_mapping_dict(mapping_file)

process_annotations(input_dir, output_dir, mapping_dict)

import os
import shutil
import random

def split_dataset(images_dir, annotations_dir, output_dir, train_ratio=0.8):
    """
    Splits the dataset into training and validation sets and organizes them
into proper directories.

    Args:
    - images_dir (str): Directory containing the images.
    - annotations_dir (str): Directory containing YOLO formatted annotations.
    - output_dir (str): Base directory to store the split dataset.
    - train_ratio (float): Proportion of the dataset to include in the train
split.
    """
```

```
    # Create directories
    train_images = os.path.join(output_dir, 'images', 'train')
    val_images = os.path.join(output_dir, 'images', 'val')
    train_labels = os.path.join(output_dir, 'labels', 'train')
    val_labels = os.path.join(output_dir, 'labels', 'val')

    os.makedirs(train_images, exist_ok=True)
    os.makedirs(val_images, exist_ok=True)
    os.makedirs(train_labels, exist_ok=True)
    os.makedirs(val_labels, exist_ok=True)

    # Get all image files
    images = [f for f in os.listdir(images_dir) if f.endswith('.jpg')]
    random.shuffle(images)

    # Split the dataset
    split_index = int(len(images) * train_ratio)
    train_images_list = images[:split_index]
    val_images_list = images[split_index:]

    # Function to copy files
    def copy_files(files, src_dir, dest_dir):
        for file in files:
            src_file_path = os.path.join(src_dir, file)
            if os.path.exists(src_file_path):
                shutil.copy2(src_file_path, dest_dir)
            else:
                print(f"Warning: File not found - {src_file_path}")

    # Copy image and label files
    copy_files(train_images_list, images_dir, train_images)
    copy_files(val_images_list, images_dir, val_images)
    copy_files([f.replace('.jpg', '.txt') for f in train_images_list],
annotations_dir, train_labels)
    copy_files([f.replace('.jpg', '.txt') for f in val_images_list],
annotations_dir, val_labels)

# Set your directories here
images_dir = r"C:\Users\temp3\Desktop\Mapillary project\images"
annotations_dir = r"C:\Users\temp3\Desktop\Mapillary project\yolo_annotation"
output_dir = r"C:\Users\temp3\Desktop\Mapillary project\yolo_training_data"

split_dataset(images_dir, annotations_dir, output_dir)

import os
import random

def split_data_set(image_dir, output_dir, train_ratio=0.8):
    """
    Split the dataset into training and validation sets and create two files
listing the image paths.

    Args:
    - image_dir (str): Directory containing the images.
    - output_dir (str): Directory where the train.txt and val.txt will be
saved.
    - train_ratio (float): Proportion of the dataset to include in the train
split.
    """
```

```
    # Create the output directory if it doesn't exist
    if not os.path.exists(output_dir):
        os.makedirs(output_dir)

    # List all image files
    images = [f for f in os.listdir(image_dir) if f.endswith('.jpg')]
    random.shuffle(images)

    # Split the dataset
    train_size = int(len(images) * train_ratio)
    train_images = images[:train_size]
    val_images = images[train_size:]

    # Write the training and validation image paths to separate files
    with open(os.path.join(output_dir, 'train.txt'), 'w') as file:
        file.writelines([os.path.join(image_dir, img) + '\n' for img in
train_images])

    with open(os.path.join(output_dir, 'val.txt'), 'w') as file:
        file.writelines([os.path.join(image_dir, img) + '\n' for img in
val_images])

# Example usage
image_dir = r'C:\Users\temp3\Desktop\Mapillary project\images'  # Path to
your images
output_dir = r'C:\Users\temp3\Desktop\Mapillary project\yolo_training_data' #
Path to save train.txt and val.txt
split_data_set(image_dir, output_dir)

def create_yaml_from_mapping(mapping_file, yaml_file, train_path, val_path):
    # Read class names from the mapping file
    with open(mapping_file, 'r') as file:
        class_names = [line.split(': ')[1].strip() for line in
file.readlines()]

    # Write to dataset.yaml
    with open(yaml_file, 'w') as file:
        file.write(f"train: {train_path}\n")
        file.write(f"val: {val_path}\n")
        file.write(f"nc: {len(class_names)}\n")
        file.write("names: [" + ", ".join([f"'{name}'" for name in
class_names]) + "]\n")

# Example usage
create_yaml_from_mapping(
    mapping_file=r"C:\Users\temp3\Desktop\Mapillary project\classes.txt",
    yaml_file=r"C:\Users\temp3\Desktop\Mapillary project\dataset.yaml",  #
Corrected path to a .yaml file
    train_path=r"C:\Users\temp3\Desktop\Mapillary
project\yolo_training_data\images\train",
    val_path=r"C:\Users\temp3\Desktop\Mapillary
project\yolo_training_data\images\val"
)

python train.py --img 480 --batch 4 --epochs 25 --data
"C:\Users\temp3\Desktop\Mapillary project\dataset.yaml" --weights yolov5s.pt

import torch
torch.cuda.empty_cache()
```

Appendix B – Interim Progress Report and Meeting Records

Meeting Number	Discussion Points	Action Items	Date
1	Topic selection and initial project scope and objective	Defined project	10/10/2023
2	**Ethical consideration and approval process application**	**Submitted ethical application**	**13/10/2023**
3	**Project proposal refinement and literature review Overview.**	**Outlined of literature review structure**	**19/10/2023**
4	**Feedback on literature review**	**Revised literature Overview**	**22/10/2023**
5	**Methodology discussion and project design**	**Finalized project design**	**29/10/2023**
6	**Progress update on the dataset preprocessing and model architecture**	**Addressed challenges in data handling**	**03/11/2023**
7	**Discusion on the Training and testing results of the Model**	**Discussed model performance metrics**	**21/11/2023**
8	**Preliminary analysis and early draft review**	**Received feedback on draft sections**	**27/11/2023**
9	**Final report review, conclusion, and future work discussion**	**Addressed final corrections and suggestions**	**08/12/2023**

Appendix C – Certificate of Ethics Approval

Certificate of Ethical Approval

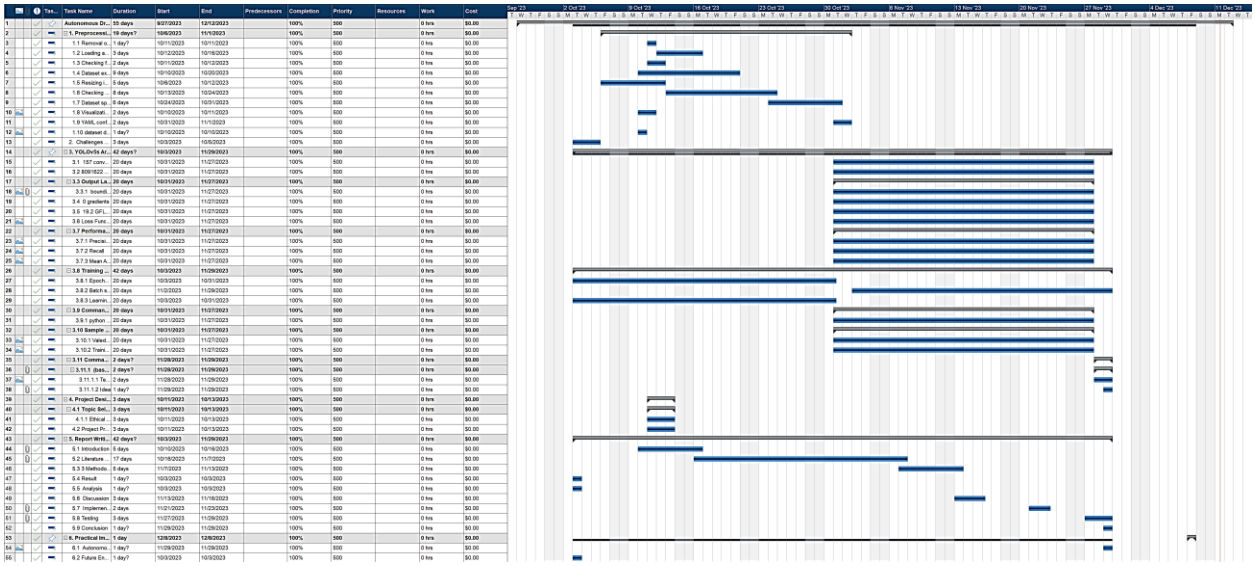
Applicant:	Oluwatosin Atanda
Project Title:	Autonomous Driving: Using Machine Learning for Traffic Sign Detection

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Low Risk

Date of approval:	15 Oct 2023
Project Reference Number:	P165547

Appendix D– detailed project management

Autonomous Driving: Using Machine Learning for Traffic Sign Detection Project



Preprocessing Steps ..... Error! Bookmark not defined.

Removal of unmatched annotations ..... Error! Bookmark not defined.

Loading and inspecting annotations ..... Error! Bookmark not defined.

Checking for missing values ..... Error! Bookmark not defined.

Dataset exploration ..... Error! Bookmark not defined.

Resizing images ..... Error! Bookmark not defined.

Checking data integrity ..... Error! Bookmark not defined.

Dataset splitting and file copying ..... Error! Bookmark not defined.

Visualization of random samples ..... Error! Bookmark not defined.

YAML configuration creation from mapping ..... Error! Bookmark not defined.

dataset diversity ..... Error! Bookmark not defined.

Challenges and Limitations ..... Error! Bookmark not defined.

YOLOv5s Architecture ..... Error! Bookmark not defined.

157 convolutional layers ..... Error! Bookmark not defined.

8091622 parameters ..... Error! Bookmark not defined.

Output Layer ..... Error! Bookmark not defined.

bounding boxes ..... **Error! Bookmark not defined.**

0 gradients ..... Error! Bookmark not defined.

19.2 GFLOPs ..... Error! Bookmark not defined.

Loss Functions ..... Error! Bookmark not defined.

Performance Metrics ..... Error! Bookmark not defined.

Precision ..... **Error! Bookmark not defined.**
Recall **Error! Bookmark not defined.**
Mean Average Precision (mAP) ..... **Error! Bookmark not defined.**

Training Details ..... Error! Bookmark not defined.
Epochs: 25 ..... **Error! Bookmark not defined.**
Batch size: 4. ..... **Error! Bookmark not defined.**
Learning rates ..... **Error! Bookmark not defined.**

Command Line Interface (CLI) for Training and Detection Error! Bookmark not defined.
python train.py --img 480 --batch 4 --epochs 25 --data "C:\Users\temp3\Desktop\Mapillary project\dataset.yaml" --weights yolov5s.pt ..... **Error! Bookmark not defined.**

Sample Outputs ..... Error! Bookmark not defined.
Valedation ..... **Error! Bookmark not defined.**
Training Images ..... **Error! Bookmark not defined.**

Command Line Interface (CLI) for Testing ..... Error! Bookmark not defined.
(base) C:\Users\temp3\yolov5>python detect.py --source 0 --weights "C:\Users\temp3\yolov5\runs\train\exp9\weights\best.pt" --conf 0.4 --iou 0.5 ..... **Error! Bookmark not defined.**

Project Design ..... Error! Bookmark not defined.

Topic Selection ..... Error! Bookmark not defined.
Ethical Application and Approval ..... **Error! Bookmark not defined.**

Project Proposal ..... Error! Bookmark not defined.

Report Writing ..... Error! Bookmark not defined.

Introduction ..... Error! Bookmark not defined.

Literature Review ..... Error! Bookmark not defined.

3 Methodology ..... Error! Bookmark not defined.

Result ..... Error! Bookmark not defined.

Analysis ..... Error! Bookmark not defined.

Discussion ..... Error! Bookmark not defined.

Implementation ..... Error! Bookmark not defined.

Testing ..... Error! Bookmark not defined.

Conclusion ..... Error! Bookmark not defined.

Practical Implications ..... Error! Bookmark not defined.

Autonomous vehicles ..... Error! Bookmark not defined.

Preprocessing Steps

Removal of unmatched annotations

Loading and inspecting annotations

Checking for missing values

Dataset exploration

Resizing images

Checking data integrity

Dataset splitting and file copying

Visualization of random samples

YAML configuration creation from mapping

dataset diversity

Challenges and Limitations

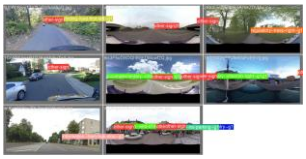
YOLOv5s Architecture

157 convolutional layers

8091622 parameters

Output Layer

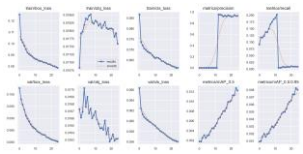
bounding boxes



0 gradients

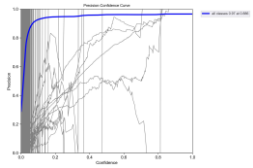
19.2 GFLOPs

Loss Functions

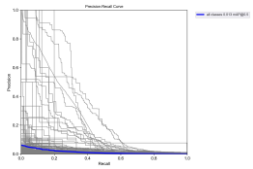


Performance Metrics

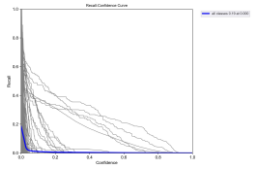
Precision



Recall



Mean Average Precision (mAP)



Training Details

Epochs: 25

Batch size: 4.

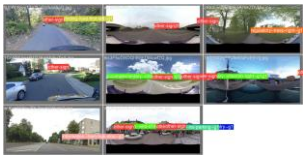
Learning rates

Command Line Interface (CLI) for Training and Detection

python train.py --img 480 --batch 4 --epochs 25 --data "C:\Users\temp3\Desktop\Mapillary project\dataset.yaml" --weights yolov5s.pt

Sample Outputs

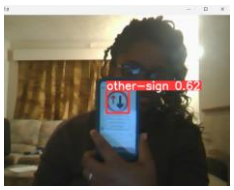
Valedation



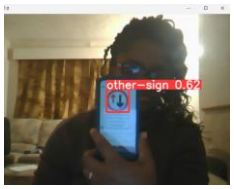
Training Images

Command Line Interface (CLI) for Testing

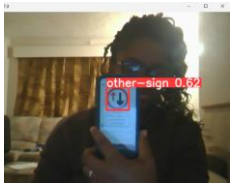
(base) C:\Users\temp3\yolov5>python detect.py --source 0 --weights "C:\Users\temp3\yolov5\runs\train\exp9\weights\best.pt" --conf 0.4 --iou 0.5



Testing result



Idea



Project Design

Topic Selection

Ethical Application and Approval

Project Proposal

Report Writing

Introduction

The safety and efficiency of traffic flow are significantly dependent on the effective management of a traffic sign inventory. Traditionally, this crucial task has been manual—traffic signs are captured with vehicle-mounted cameras, and human operators offline manually perform their localization and recognition against an existing database. However, given the vast stretches of roads, such manual processes are time-consuming and prone to errors. Automating these processes presents a promising solution to these challenges, significantly reducing manual efforts and ensuring quicker identification of compromised traffic signs.

Traffic sign recognition (TSR) has attracted substantial attention in computer vision. Various cutting-edge detection and recognition algorithms have been proposed. However, many of these primarily cater to a limited set of categories, often tied to advanced driver-assistance systems and autonomous vehicles. It is worth noting that traffic signs play an instrumental role in guiding drivers and alerting them to road conditions and potential hazards. A holistic TSR process typically involves the detection of traffic signs in natural scene images and then their classification into appropriate subclasses—a step that is predominantly done manually.(Babic et al., 2021).

Literature Review

Object detection is a pivotal element in computer vision, distinguished from mere image classification by its complexity and utility (Zou et al., 2019). Unlike classification, which identifies the primary subject of an image, object detection delves deeper. It is not limited to

recognizing multiple objects within an image or video but extends to pinpointing their precise locations by encapsulating each object within bounding boxes (Redmon et al., 2016).

Bounding Boxes in Object Detection

Bounding boxes are a cornerstone in object detection, playing a fundamental role in not just signifying the presence of objects within an image but also in pinpointing their exact locations and dimensions (Redmon et al., 2016). Their utility spans from providing spatial context in an image to facilitating object tracking in video sequences and even in augmented reality applications where they guide the placement of digital overlays on real-world objects.

3 Methodology

Result

Analysis

Discussion

Implementation

The object detection model was trained using the YOLO architecture with a focus on multi-class detection accuracy. Training was conducted for 25 epochs, and the model's predictive performance was assessed through a series of metrics, including precision, recall, and mean average precision (mAP). Alongside these metrics, bounding box accuracy, object presence, and class prediction errors were also monitored.

Testing

For real-time detection testing, the best.pt weights were loaded into the YOLOv5 model due to their superior performance on the validation set. The model was interfaced with a laptop

camera using a custom Python script, detect.py, which utilized the OpenCV library for video stream processing. The script was executed with a command specifying the source as the laptop camera, the path to the weight file, and the confidence and IoU thresholds for detection:

python detect.py --source 0 --weights "C:\Users\temp3\yolov5\runs\train\exp9\weights\best.pt" --conf 0.4 --iou 0.5

Conclusion

Practical Implications

Autonomous vehicles

Future Enhancements