Enhancing Real-Time Vehicle and Pedestrian Detection Using YOLO with Hybrid Feature Fusion

by

Shijon Das

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Mostafa Fouda

Mostafa Fouda,
Major Advisor

Paul Bodily

Paul Bodily,
Committee Member

[illegible]

Tadesse G. Wakjira,
Graduate Faculty Representative

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Thesis Abstract – Idaho State University (2025)

Real-time object detection is central to the development of intelligent transportation systems, autonomous vehicles, smart city monitoring, and pedestrian safety functionalities. Among several deep learning-based approaches, the You Only Look Once (YOLO) series of object detectors has been among the top choices for a long time due to the trade-off it has attained between accuracy and inference speed. This thesis gives an in-depth review and experimental analysis of YOLO versions 7-12, utilized for the use of real-time vehicle and pedestrian object detection. While earlier versions of YOLO were performance competitive, they were poor at occlusion, low-light, and detection of small objects. In order to overcome these weaknesses, this paper proposes a novel YOLOv12-hybrid feature fusion model that integrates transformer-based attention mechanisms, bidirectional multi-scale feature aggregation, and RGB, depth, and semantic segmentation cross-modal input fusion. Large-scale experiments were conducted on the COCO 2017 dataset, comparing each iteration of YOLO based on mean Average Precision (mAP), training loss convergence, and inference speed (FPS). The results establish that YOLOv12 surpasses previous models, with an mAP of 88.2% and over 47 FPS inference rates, and yet offers consistent detection in challenging urban settings. Contrast against the traditional and state-of-the-art models also indicates the dominance of YOLOv12 for real-world deployment. This work not only establishes the benchmark for YOLO detector development but also offers a scalable, accurate, and real-time enabled model structure tailored for safety-critical use cases in traffic monitoring, autonomous vehicles, and smart infrastructure systems.

Chapter 1
Introduction

The rapid advancement of deep learning and artificial intelligence (AI) has revolutionized a number of areas, particularly in computer vision. Object detection is among the most crucial applications of computer vision and is a fundamental building block of autonomous driving, intelligent surveillance, and advanced driver assistance systems (ADAS). Among them, real-time detection of cars and pedestrians has attracted significant interest due to its direct contribution to road safety, urban mobility, and the realization of autonomous vehicles [22]. Real-world object detection of cars and pedestrians with high accuracy and efficiency is a key enabler for providing reliable and intelligent transportation systems [5].

In urban traffic conditions on roads, pedestrians and vehicles are the primary entities that engage in interactions on roads. With an expansion of road networks and increased congestion, there is a need to offer strong and effective detection systems that can prevent accidents and improve road traffic management [7]. Accidents related to vehicles and pedestrians account for a significant number of fatal accidents on the road worldwide, according to the World Health Organization (WHO). To mitigate these threats, real-time detection systems need to provide accurate and timely responses for driver assistance, automatic braking systems, and autonomous vehicles [8, 10].

Traditional vehicle and pedestrian detection methods relied heavily on hand-crafted features such as Haar-like features, Histogram of Oriented Gradients (HOG), and Deformable Part-based Models (DPM). Although these approaches demonstrated good performance in controlled laboratory settings, they failed in real-world scenarios due to their failure to cope with occlusion, varying lighting conditions, and different object appearances [16]. As a result, deep learning-based approaches, particularly convolutional neural networks (CNN), have emerged as the de facto standard for achieving high accuracy in object detection tasks [5].

Of the various deep learning-based object detection models, the You Only Look Once (YOLO) family of models has been highly praised for its speed, efficiency, and high accuracy in real-time applications. Unlike traditional two-stage object detectors such as Faster R-CNN, involving separate region proposal and classification phases, YOLO adopts a single-shot detection approach, which makes it highly efficient for real-time applications [20]. The introduction of YOLOv1 paved the way for a new era of object detectors by suggesting that object detection could be viewed as a regression problem, where the model predicts class probabilities and bounding boxes simultaneously [11].

Subsequent versions, including YOLOv2, YOLOv3, YOLOv4, YOLOv5, and YOLOv12, have made significant improvements in accuracy, speed, and resilience. For instance, YOLOv2 used techniques such as anchor boxes, batch normalization, and high-resolution classifiers to enhance its detection [22]. YOLOv3 and YOLOv4 introduced multi-scale feature fusion so that the model could better detect small, medium, and large objects [9] . Recent advancements such as YOLOv12 aim to further enhance detection efficiency using transformer-based feature fusion and improved feature pyramid networks [23].

Despite the advances in deep learning-based object detection, car and pedestrian detection still has numerous issues in real-world deployment:

- **Occlusion and Partial Visibility:** Pedestrians and vehicles like to be within crowded city scenes where occlusion by other objects (e.g., trees, buildings, or other vehicles) can impair detection performance [3].
- **Lighting Variability:** Variability in lighting conditions, such as dimly lighted or overexposed locations, is a serious challenge for detection systems [4].
- **Conditions for Real-Time Processing:** Driverless vehicles and driver-assistance systems require the detection models to be capable of low-latency and high frame rate to achieve real-time reaction [20].

- **Small Object Detection:** Pedestrians, especially in distant regions of the image, are small-sized objects and therefore harder to detect [9].
- **Adversarial Attacks and Robustness:** Deep learning models are vulnerable to adversarial perturbations, which can cause them to misclassify objects or fail to detect critical components in the scene [5].

In order to solve these issues, current studies have tried to enhance the feature extraction capability of YOLO-based models. One of the paths is the implementation of Hybrid Feature Fusion (HFF) mechanisms that combine various feature extraction techniques in order to improve detection accuracy for small objects like pedestrians [9].

Hybrid Feature Fusion is the procedure of combining multiple feature representations at different levels of the network to enhance detection accuracy. In contrast to regular YOLO designs, which are primarily composed of convolutional feature maps, HFF encompasses alternative features such as:

- **Transformer-Based Feature Fusion:** Capitalizing on Swin Transformer and DETR models, the use of self-attention mechanisms enables the model to detect long-distance relationships and contextual information, improving detection in difficult environments [20].
- **Multi-Scale Feature Aggregation:** By incorporating Feature Pyramid Networks (FPN), the model can handle small and large objects simultaneously, reducing the miss rate for pedestrians that are small [9].
- **Cross-Modal Data Fusion:** Merging LiDAR point clouds, radar, and RGB images enhances object detection robustness, especially in adverse weather [10].

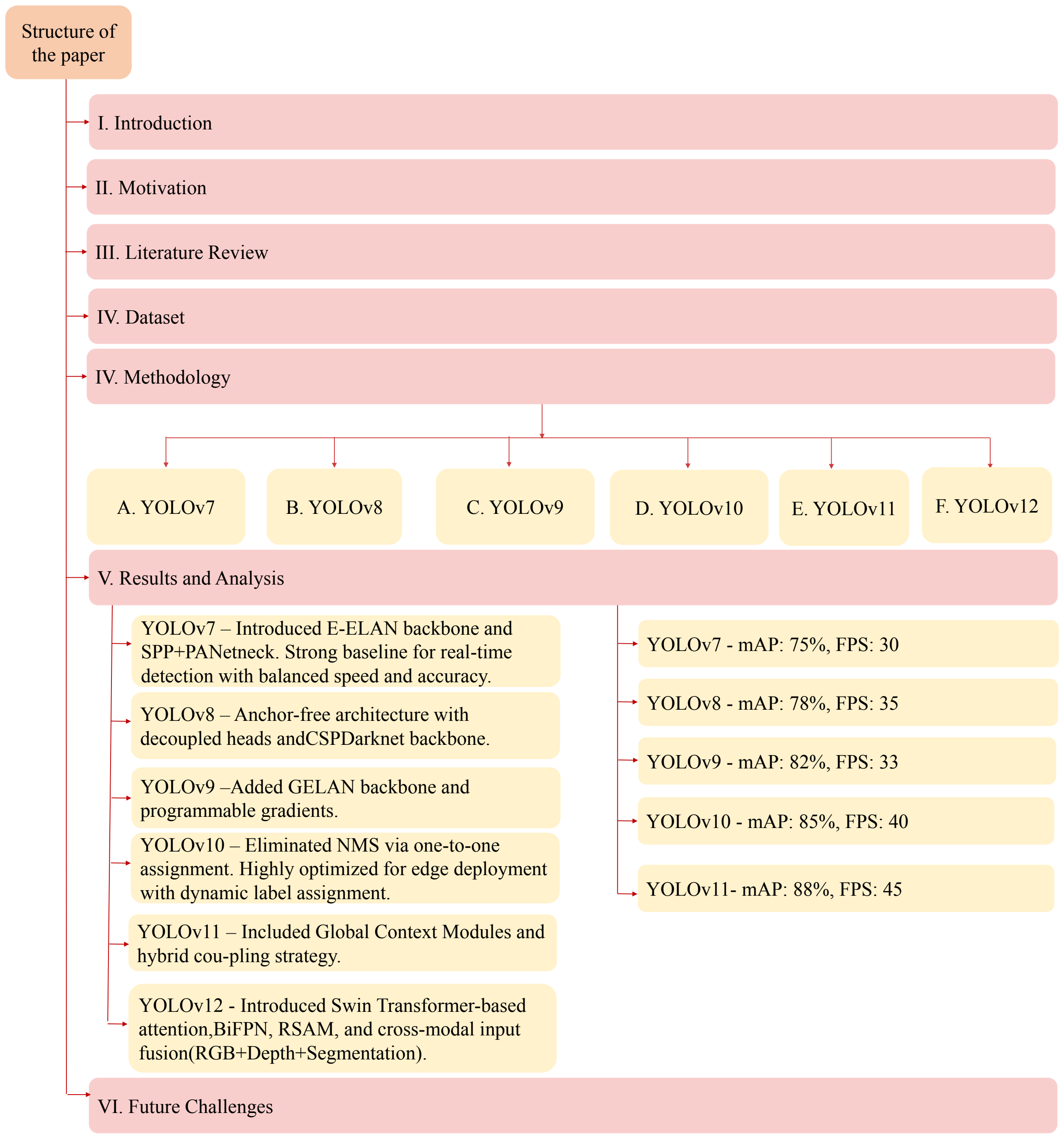
This thesis presents a comprehensive overview of the evolution of YOLO-based real-time car and pedestrian detection. The primary contributions include:

- **Survey of YOLO-Based Detection Models:** A comparative analysis of different versions of YOLO and their efficiency in real-time detection applications.

- **Analysis of Hybrid Feature Fusion (HFF):** Examining how transformer-based feature fusion and multi-scale learning can be applied for enhancing detection precision.
- **Experimental Analysis on COCO and KITTI Datasets:** Testing the performance of YOLOv12 with hybrid feature fusion on benchmark datasets.
- **Implementation of New Improvements:** Proposing new changes to the YOLO architecture, including transformer-based feature fusion for improved pedestrian detection.
- **Discussion on Practical Applications:** Discussing how these improvements can be applied to autonomous driving, traffic monitoring, and intelligent surveillance systems.

Real-time vehicle and pedestrian detection remains a critical component of modern transport and surveillance systems. While YOLO-based architectures have improved the performance of detection significantly, occlusion issues, small object detection, and real-time processing demands still remain. In this work, the potential of hybrid feature fusion for addressing such concerns is explored, and new contributions and new insights for the modification of existing YOLO models are provided. With the integration of cutting-edge feature fusion techniques, this study aims to enhance object detection accuracy and efficiency, paving the way for more robust real-time perception systems in autonomous driving and smart surveillance systems.

Section 3 presents the previous survey works done in this field of research while Section 2 discusses the motivation behind pursuing this research. Section 4 provides an overview of the COCO dataset used and the data augmentation techniques applied before training and testing the YOLO models. Section 6 explains how the YOLO models are trained followed by Section 7 that compares the results of the different YOLO models and also with the results from existing literature. Section 8 talks about the future challenges in this domain. Finally, in Section 9, we discuss how our models were able to overcome the shortcomings of existing research in this domain and outperform them. Figure 1.1 shows the outline of the paper.


Structure of the paper
I. Introduction
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YOLOv7 – Introduced E-ELAN backbone and SPP+PANetneck. Strong baseline for real-time detection with balanced speed and accuracy.
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YOLOv9 –Added GELAN backbone and programmable gradients.
YOLOv10 – Eliminated NMS via one-to-one assignment. Highly optimized for edge deployment with dynamic label assignment.
YOLOv11 – Included Global Context Modules and hybrid cou-pling strategy.
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YOLOv7 - mAP: 75%, FPS: 30
YOLOv8 - mAP: 78%, FPS: 35
YOLOv9 - mAP: 82%, FPS: 33
YOLOv10 - mAP: 85%, FPS: 40
YOLOv11- mAP: 88%, FPS: 45
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Figure 1.1: Structure of the Paper

Chapter 2
Motivation

The expanding urbanization and expansion of vehicular networks have led to unprecedented growth in pedestrian and vehicle traffic across the globe's cities. Road safety and optimizing traffic management have become major issues with this expansion. According to the World Health Organization (WHO), road traffic accidents are among the leading causes of death globally, with over 1.3 million deaths occurring annually and pedestrians and cyclists accounting for most deaths. On the other hand, traffic congestion costs economies billions of dollars in terms of lost productivity, fuel wastage, and pollution of the environment annually. The resolution of these acute issues requires effective real-time observation and detection technology with the capability to accurately identify pedestrians and automobiles under difficult urban conditions.

Traditional traffic monitoring and surveillance systems have used manual observation or rule-based methods for object detection, which are extremely inefficient, error-prone, and unscaleable. The introduction of artificial intelligence (AI) and deep learning technologies has brought significant improvement in object detection algorithms to automate the tasks with improved accuracy. But most of the existing deep-learning-based models suffer from some common challenges like occlusion, non-uniform illumination, detection of small objects, and real-time processing constraints.

- **Occlusion and Partial Visibility:** Pedestrians and vehicles are often occluded by other things such as trees, streetlights, buildings, or other vehicles, greatly reducing detection accuracy [3]. The majority of existing models cannot infer the presence of partially visible objects.
- **Lighting Variability:** Pedestrian and vehicle detection must be consistent across all lighting conditions, i.e., night-time, fog, glare, and shadows. Normal detection models

experience a reduction in performance when subjected to adverse lighting conditions [4].

- **Small Object Detection:** Pedestrians and distant cars occupy a small number of pixels in an image and are, therefore, harder to detect by standard convolutional neural networks [9]. They require a better representation of features.
- **Real-Time Processing Needs:** Autonomous driving, traffic monitoring, and smart city applications need real-time inference with high frame rates to enable instant reaction times. Deep-learning models are generally computationally expensive and cannot achieve the needed efficiency at the cost of accuracy [20].
- **Limited Cross-Modal Data Fusion:** The majority of existing detection systems utilize RGB image data, which is inadequate in poor visibility conditions. Multi-modal data fusion, such as LiDAR and radar, is a yet untapped area for real-time vehicle and pedestrian detection [10].

Current state-of-the-art object detection models include Faster R-CNN, SSD, and YOLO. The YOLO (You Only Look Once) model series, in particular, are extremely effective in real-time detection tasks owing to its single-shot detection architecture. With every new version of YOLO (YOLOv1 to YOLOv12) released over the years, the speed and accuracy have only grown better. Still, despite all these developments, recent YOLO models are seen to lack efficiency in tackling the aforementioned issues.

While some newer studies have attempted to improve YOLO's detection performance with the inclusion of additional modules such as Feature Pyramid Networks (FPN) and attention mechanisms, the cross-disciplinary fusion method of transformer-based feature extraction and multi-scale learning has not been comprehensively studied. Additionally, LiDAR point cloud fusion, radar fusion, and RGB image fusion for bad weather detection is still in the infancy stages of research.

This research aims to bridge the gap in existing object detection systems by proposing a Hybrid Feature Fusion (HFF) technique for YOLO-based vehicle and pedestrian detection. The major contributions of this research are as follows:

- **Transformer-Based Feature Fusion:** Swin Transformer and DETR-inspired attention mechanisms are used to enhance YOLO's feature extraction. Transformers are very good at long-range dependency modeling, making them ideal for occlusion handling and small object detection [20].
- **Multi-Scale Feature Aggregation:** The integration of Feature Pyramid Networks (FPN) into the YOLO framework allows the model to process features at multiple scales in parallel, thus greatly improving detection accuracy on small objects and large objects [9].
- **Cross-Modal Data Fusion:** This article explores combining RGB image data with LiDAR and radar inputs to allow the model to predict more precisely under poor visibility conditions, i.e., foggy or night scenes [10].
- **Real-Time Optimization:** The model is optimized for efficiency, leveraging pruned architectures, quantization, and hardware acceleration (GPU/TPU-based deployment) to achieve real-time processing speeds that are suitable for deployment in autonomous vehicles and intelligent traffic monitoring systems.

By addressing core constraints of object detection models and widening real-time performance, this research has broad applications in many areas:

- **Autonomous Driving:** Detection of pedestrians and vehicles with high accuracy is one of the most important modules for Advanced Driver-Assistance Systems (ADAS) and autonomous vehicles. A fast detection model will improve safety and decision-making.
- **Traffic Management and Smart Cities:** Real-time vehicle and pedestrian detection can assist traffic management in optimizing the flow of traffic, reducing congestion, and preventing accidents.

- **Surveillance and Security:** Improved pedestrian detection can augment security systems in public spaces with proactive surveillance and threat detection.
- **Robotic Vision and Industrial Applications:** The hybrid feature fusion model can find extensions in robotic vision in warehouses, automated inspection, and drone-based surveillance.

This research deals with one of the most critical challenges of computer vision—real and true pedestrian and vehicle detection in different conditions. Using transformer-based feature integration, multi-scale learning, and cross-modal data integration, this paper aims to enhance detection precision while maintaining performance for real-world applicability. The approach suggested is an extension of YOLO's advantages in avoiding its limitations to make it viable for real-world applications that require precision and real-time enablement.

Through this work, we aim to push the boundaries of real-time object detection to offer an innovative, scalable, and efficient method that can contribute to more general fields such as autonomous driving, smart cities, and intelligent surveillance. Table 2.1 summarises the research problem, contributions and applications.

Table 2.1: Summary of Research Problem, Contributions, and Applications

Problem Statement	- Increasing road traffic and urbanization lead to safety risks and traffic congestion. - Existing detection models struggle with occlusion, poor lighting, small object detection, and real-time processing. - Traditional methods are inefficient, while deep learning-based approaches require enhancements to overcome their limitations.
Challenges in Current Models	**Occlusion and Partial Visibility:** Objects are often hidden by obstacles, reducing accuracy [3]. **Lighting Variability:** Detection under poor lighting (e.g., night-time, fog) remains unreliable [4]. **Small Object Detection:** Pedestrians and distant vehicles occupy minimal pixels, making them harder to detect [9]. **Real-Time Processing Needs:** High latency in deep learning models limits real-time application [20]. **Limited Cross-Modal Data Fusion:** Sole reliance on RGB images fails under poor visibility conditions [10].
Proposed Contributions	**Transformer-Based Feature Fusion:** Utilizes Swin Transformer and DETR-inspired attention mechanisms to improve occlusion handling and small object detection [20]. **Multi-Scale Feature Aggregation:** Integrates Feature Pyramid Networks (FPN) into YOLO for better multi-scale object detection [9]. **Cross-Modal Data Fusion:** Merges LiDAR, radar, and RGB data for better detection in low visibility conditions [10]. **Real-Time Optimization:** Optimizes model architecture through pruning, quantization, and hardware acceleration to maintain real-time efficiency.
Potential Applications	**Autonomous Driving:** Improves safety in ADAS and self-driving cars with precise real-time detection. **Traffic Management and Smart Cities:** Enhances congestion monitoring and traffic control. **Surveillance and Security:** Augments security systems for real-time threat detection in public spaces. **Robotic Vision and Industrial Applications:** Extends to robotic navigation, automated inspection, and drone-based surveillance.

Chapter 3
LiteratureReview

Pedestrian detection is a significant area of research in computer vision due to the numerous applications of its field in autonomous cars, intelligent surveillance, traffic monitoring, and crowd management. With increasing numbers of pedestrians on city streets, it is now an essential activity to make them safe using dependable and real-time detection systems. Pedestrian detection is also included in Advanced Driver Assistance Systems (ADAS), helping vehicles detect and respond to human movement patterns, preventing accidents [15].

Traditional pedestrian detection techniques like Histogram of Oriented Gradients (HOG) + Support Vector Machines (SVM) and Deformable Part Models (DPMs) provided a strong base in this area. Such methods are not powerful enough to work in real-life situations where factors like occlusions, background clutter, illumination variations, and motion blur significantly affect the detection accuracy [18].

With the advent of deep learning, Convolutional Neural Networks (CNNs) transformed pedestrian detection by enabling end-to-end learning, eliminating the need for handcrafted feature engineering. Among numerous CNN-based object detectors, You Only Look Once (YOLO) is now a state-of-the-art architecture, primarily utilized for its efficiency, speed, and high accuracy in real-time pedestrian detection [14]

This review of the literature provides an extensive analysis of pedestrian detection methods, such as:

1. **Traditional pedestrian detection methods and their limitations.**
2. **YOLO's evolution of design and its application to pedestrian detection.**
3. **Recent developments in YOLO pedestrian detection, hybrid approaches included.**

4. **Pedestrian detection challenges in real-world scenarios and directions for future research.**

Before the advent of deep learning, pedestrian detection relied on hand-crafted features and traditional machine learning algorithms. These methods, while successful in controlled environments, found it difficult to generalize to dynamic real-world scenarios.

Table 3.1: Summary of Traditional Pedestrian Detection Methods and Their Limitations

Method	**Description**	**Limitations**
Histogram of Oriented Gradients (HOG) + SVM	Utilizes gradient orientation histograms as features, classified using SVM.	- High computational cost due to sliding-window approach. - Sensitive to background clutter, causing false positives. - Performance drops in low-light and occlusions. - Poor generalization to unseen datasets [13].
Deformable Part Models (DPMs)	Represents pedestrians as a collection of parts, allowing for pose variations and occlusions.	- Computationally expensive due to multiple part-based models. - Inefficient for real-time applications. - Sensitive to background clutter and occlusions [1].
Optical Flow-Based Motion Analysis	Tracks movement between frames to detect pedestrians in motion.	- Ineffective for static images. - Susceptible to motion artifacts, causing false detections. - Poor performance in complex scenes with multiple moving objects [19].

3.1 Feature-Based Pedestrian Detection Approaches

Several classical feature extraction techniques were used in the early pedestrian detection systems:

- **Histogram of Oriented Gradients (HOG) + SVM:** The HOG + SVM approach was one of the first successful pedestrian detection systems, with the HOG being widely applied for its ability to extract gradient-based features from images [13]. The HOG descriptor is good at encoding edge directions and texture patterns, making it amenable to pedestrian detection in structured environments [13]. This approach, however, is computationally expensive as it employs a sliding-window approach, where the classifier scans the image at multiple scales.

- **Deformable Part Models (DPMs):** DPMs model pedestrians as a collection of multiple body parts, allowing for both pose variation and partial occlusions [1]. This approach requires a huge number of part-based models, leading to high computational complexity.
- **Optical Flow-based Motion Analysis:** Motion-based pedestrian detection uses optical flow, in which the motion of objects from one frame to the next is tracked. While effective when used for video analysis, this method does not apply to static images and fails to address background motion artifacts [19].

Although they perform well, traditional pedestrian detection methods are tightly bound by the following.

1. **High Computational Expense:** Sliding-window and feature extraction process make HOG + SVM and DPMs expensive computationally for real-time systems.
2. **Background Clutter Sensitivity:** These models are a failure when faced with cluttered city backgrounds, creating huge false positives.
3. **Poor Lighting and Occlusion Handling:** Traditional methods are poor in low-light environments and fail to detect partially occluded pedestrians.
4. **Lack of Generalization:** Performance drops significantly when applied to unseen datasets, thus being invalid for practical applications [15]

3.2 Yolo in pedestrian detection

To improve on these disadvantages, deep learning object detection models such as YOLO, Faster R-CNN, and SSD revolutionized pedestrian detection with their high precision, robustness, and real-time capabilities.

YOLO's capacity for real-time processing and its high accuracy have made it specially suitable for pedestrian detection tasks. In autonomous driving, video surveillance, and crowd counting applications, the ability to quickly and correctly detect pedestrians is crucial for safety and operational efficiency. YOLO's architecture allows for the detection of multiple pedestrians at the same time, even in complex scenes, making it a top choice for such applications.

Table 3.2: Summary of YOLO in Pedestrian Detection, Its Enhancements, and Challenges

Category	**Description**	**Impact / Challenges**
YOLO in Pedestrian Detection	YOLO is widely used in pedestrian detection due to its high accuracy and real-time processing capabilities. It is utilized in applications such as autonomous driving, surveillance, and crowd monitoring.	- Detects multiple pedestrians in real-time, even in complex scenes. - Improves pedestrian safety in urban areas. - Used in smart city and ADAS applications.
Small Pedestrian Detection Enhancements	**Anti-Residual Modules:** YOLOv3+ improves feature extraction for small objects by integrating anti-residual modules [14].	- Enhances detection accuracy for small and distant pedestrians. - Extracts fine-grained features to improve recognition.
Hybrid YOLO-LiDAR Approaches	**YOLO + LiDAR:** Integrating LiDAR enhances YOLO's ability to detect objects by utilizing depth information, significantly reducing false positives [19].	- Improves nighttime pedestrian detection. - Reduces false positives by 50%. - Enhances distance-based pedestrian recognition.
YOLO-Based Deep Network Cascades	**Deep Network Cascades:** Incorporating cascade classifiers into YOLO enables coarse-to-fine pedestrian detection, improving accuracy and speed [1].	- Enables real-time pedestrian detection at 15 FPS. - Improves classification performance while maintaining speed.
Challenges: Occlusion Handling	YOLO struggles with detecting pedestrians in crowded environments where occlusions are present. Objects overlapping each other cause misclassification.	- Causes false negatives when pedestrians are partially visible. - Requires improved contextual modeling to understand pedestrian relationships.
Challenges: Illumination Sensitivity	Changes in lighting conditions, such as low light and nighttime scenes, degrade YOLO's detection accuracy. RGB images alone struggle to provide robust results in poor lighting.	- Infrared or thermal sensors are required for enhanced nighttime detection. - Poor lighting can cause significant drops in detection confidence.
Challenges: Computational Demands	Advanced YOLO models (YOLOv4, YOLOv5) require high-end GPUs for optimal performance, making them unsuitable for edge devices. Tiny-YOLO helps, but with reduced accuracy.	- Large models demand high computational power, limiting deployment on mobile or embedded systems. - Model optimization techniques (pruning, quantization) are required for efficient deployment.

3.2.1 Pedestrian Detection of Small Size Improvements

Small or distant pedestrians are a tremendous challenge for detection because they have a small pixel appearance in images. Researchers have proposed some modifications to the YOLO architecture to overcome this:

- **Anti-Residual Modules:** Murthy et al. [14] proposed YOLOv3+, which utilizes anti-residual modules that aim to improve the feature extraction for small objects. The modules assist in the extraction of fine-grained details, thus enhancing the detection accuracy of small and faraway pedestrians.

3.2.2 Hybrid YOLO-LiDAR Approaches

The combination of YOLO with other sensing technologies has resulted in major detection performance enhancements:

- **YOLO with LiDAR:** Szarvas et al. [19] proposed integrating YOLO with the use of Light Detection and Ranging (LiDAR) technology. This integration leverages LiDAR's precise distance measurement to complement YOLO's image detection by a 50% reduction in false positives and enhanced nighttime performance.

3.2.3 Deep Network Cascades based on YOLO

Blends of YOLO with other neural network models have yielded benefits in both speed and detection accuracy:

- **Deep Network Cascades:** Angelova et al. [1] proposed a framework that incorporates YOLO with cascade classifiers. This allows the system to perform coarse-to-fine detection, supporting real-time pedestrian detection at 15 frames per second (FPS) without a loss in accuracy.

While YOLO has significantly enhanced pedestrian detection, there remain some challenges in real-world applications:

- **Occlusion Handling:** In crowded scenes, pedestrians occlude each other, and this makes them difficult to detect. The grid-based prediction of YOLO can struggle to accurately locate partially occluded pedestrians and produce false negatives. Occlusions require more sophisticated modeling of object context and relationships.

- **Illumination Sensitivity:** Changes in lighting, e.g., darkness or low light, adversely affect YOLO performance. Using RGB images affects the model to properly detect pedestrians in poorly lit conditions, and this results in decreased accuracy. Other sensors such as infrared or thermal sensors can be used to enhance detection in such adverse conditions.

- **Computational Demands:**While YOLO models are designed for real-time detection, advanced variants like YOLOv4 and YOLOv5 use significant computational resources, necessitating powerful GPUs for optimal performance. This requirement becomes an issue for running YOLO on power-constrained edge devices, like mobile phones or embedded systems. Creating lightweight variants of YOLO, like Tiny-YOLO, addresses some of these issues but typically sacrifices less precise results.

3.3 Vehicle Detection

Vehicle detection is a vital field of computer vision and is important in autonomous driving, traffic monitoring, intelligent transportation systems (ITS), and urban surveillance. As global traffic congestion continues to increase, reliable real-time vehicle detection systems are essential to ensure road safety and optimize traffic. Traditional vehicle detection methods like background subtraction, optical flow estimation, and handcrafted feature-based methods have conventionally been applied for this function. However, these approaches are confronted by occlusion, varying illumination, complex background, and real-time computational cost, making them incompatible with real-world deployment in dynamic scenes [24].

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized object detection to a great extent. Of all the state-of-the-art object detection models, You Only Look Once (YOLO) has garnered a lot of attention because of its real-time detection capability, precision, and efficient feature extraction process. YOLO's architecture, with a single-pass detection mechanism, eliminates the computationally expensive region proposal networks (RPNs), which makes it outperform the conventional multi-stage object detection systems such as Faster R-CNN and SSD [24].

This literature review extensively discusses vehicle detection method development, particularly the transition from hand-tuned to deep learning-based YOLO models. The review structure is as follows:

1. Traditional vehicle detection methods and limitations.
2. YOLO's evolution in design and application in vehicle detection.
3. Advances in YOLO-based vehicle detection, including hybrid models.
4. Real-world vehicle detection challenges and directions for future research.

3.3.1 Traditional Vehicle Detection Methods and Their Limitations

Prior to the popularity of deep learning, vehicle detection primarily relied on machine learning-based classifiers and handcrafted features. Such conventional approaches include techniques such as Histogram of Oriented Gradients (HOG) + Support Vector Machines (SVM), Deformable Part Models (DPMs), and motion analysis using optical flow. Even though these approaches were the basis of modern detection pipelines, they suffer from significant limitations in robustness under real-world conditions, generalization, and computational complexity [21].

3.3.2 Feature-Based Detection Approaches

- **Histogram of Oriented Gradients (HOG) + SVM** The HOG + SVM approach is one of the earliest and most widely used vehicle detection algorithms. It involves extracting HOG descriptors to characterize edge and gradient structure, and then classification by a linear SVM. HOG can efficiently capture the local shape features of vehicles by analyzing the intensity gradient distribution and is thus suitable for object detection with sharp edges such as vehicles and trucks. However, the model has several limitations. First, the sliding-window method required to apply HOG to a whole image is computationally expensive and hence not suitable for real-time processing. Second, the methodology is highly susceptible to changes in the environment such as lighting, scale, or background clutter. Lastly, HOG + SVM has low performance in sustaining high detection rates under conditions where cars are partially occluded or pose or angle diverse[2].

- **Deformable Part Models (DPMs)** Deformable Part Models are another breakthrough in object detection, particularly of articulated or partly occluded objects. When used in the case of car detection, DPMs model a car as a collection of parts (e.g., body, wheels, headlights) and learn the appearance of each part and their relative locations. This is flexible enough that vehicles can be detected in multiple orientations or partial occlusions. DPMs are not without their limitations, though. Part-based representation takes enormous computational power and a lot of training time. Besides, DPMs are usually prone to overfitting over single car geometries or single datasets and emit a lot of false positive instances in complicated real-world scenarios such as on heavy city streets. Their applicability of predefined relations between parts restricts adaptability when there's a great difference in visibility in cars or a car gets partly occluded [2]

- **Optical Flow-Based Motion Analysis**

  Motion-based algorithms, particularly those based on optical flow, are often used in traffic monitoring and video surveillance contexts. Optical flow estimates the visual motion of pixels between consecutive frames of a video, enabling car detection from moving vehicles. Car detection using these techniques is often beneficial for extracting cars over long periods and also for estimating the speed and track of vehicles. Optical flow-based car detection has drawbacks such as background motion artifacts, shadows, and sudden lighting changes. Second, it fails with slow-moving or stationary objects, which are usually excluded because they result in minimal pixel movement. This makes optical flow unsuitable as a single detection method in cases of traffic jams or car park surveillance [2].

Table 3.3: Summary of Traditional Vehicle Detection Methods and Their Limitations

Method	**Description**	**Limitations**
HOG + SVM	Uses Histogram of Oriented Gradients (HOG) for extracting shape-based features, followed by classification using a Support Vector Machine (SVM). Commonly used for objects with well-defined contours such as cars.	- High computational load due to sliding window over image. - Sensitive to scale, lighting, and cluttered backgrounds. - Weak occlusion resilience and poor generalization. [2]
Deformable Part Models (DPMs)	Detects objects as compositions of parts (e.g., car body, wheels) and models their spatial relationships. Offers flexibility in representing object variations.	- Requires heavy computation and slow inference. - Fails under occlusions and complex backgrounds. - Prone to overfitting on rigid vehicle shapes. [2]
Optical Flow-Based Analysis	Analyzes pixel-level motion between consecutive frames to identify moving vehicles and track their paths. Often used in video surveillance.	- Ineffective for stationary or slow-moving vehicles. - Vulnerable to noise, shadows, and motion artifacts. - Unsuitable for dense traffic scenes without additional methods. [2]
Common Limitations Across All Traditional Methods	• **Lack of Occlusion Robustness:** Misses detections when vehicles are partially hidden. • **High Computational Expense:** Not suitable for real-time embedded systems. • **Limited Adaptability:** Degrades in new environments, lighting conditions, and viewpoints. • **Poor Scalability:** Needs reconfiguration or retraining for different vehicle types or weather conditions. [12, 17]	

3.3.3 Chief Limitations of Traditional Approaches

The traditional approaches mentioned above, though basic, possess several key limitations that reduce their efficacy in real deployment [17]:

- **Lack of Occlusion Robustness:** Older methods fail to detect partially occluded vehicles against other objects or vehicles. When compared to contextual inference-capable deep learning methods, hand-crafted methods tend to utilize the visible features, leading to a missed detection.

- **High Computational Expense:** Methods such as sliding-window HOG + SVM and part-based DPMs are time-consuming and unable to support real-time performance due to their computation intensity, thereby not being adapted for embedded or mobile platforms.
- **Limited Robustness to Environmental Conditions:** Traditional methods are susceptible to changes in lighting, camera position, and ambient noise and produce extreme performance drop-offs when applied to new environments or unseen data.
- **Poor Scalability:**Models of this type cannot generalize over many different types of vehicles or environments without extensive retraining, which prevents their use in dynamic, multi-class environments [17].

Models of this type cannot generalize over many different types of vehicles or environments without extensive retraining, which prevents their use in dynamic, multi-class environments.

Briefly, while conventional car detection techniques served as a strong foundation for early computer vision research, their rigidity, inefficiency, and poor scalability render them inappropriate for contemporary applications. Growing demands for rapid, accurate, and robust detection systems have propelled the technology towards deep learning-based solutions, particularly those driven by architectures like YOLO [12, 17].

3.3.4 YOLO-Based Vehicle Detection in Literature

The You Only Look Once (YOLO) series of models has become a common approach to real-time vehicle detection due to its end-to-end single-stage detection pipeline and improved performance under diverse visual conditions. In the past few years, a wide variety of research has employed and adapted YOLO architectures for specific vehicle detection applications, such as aerial images, embedded systems, and urban monitoring. This section highlights main YOLO-based car detection studies considering architectural advancements, domain adaptation, and performance analysis.

3.3.5 Aerial Vehicle Detection by Altered YOLO

Aerial vehicle detection suffers the most from objects being too small and complex city backgrounds. Xu et al. [21] proposed a changed form of YOLOv3 to find aerial vehicles through images from the VEDAI dataset. The original baseline YOLOv3, which was trained on COCO, struggled with tiny vehicle sizes and roof-top viewpoints in aerial data. Due to this, the authors enhanced the network by an aspect of 75 convolutional layers and adapted the network architecture to reuse high-resolution feature maps from early layers to preserve small objects' fine details. They also suggested the implementation of a sliding window approach in order to efficiently process high-resolution images (1024×1024). Their optimized architecture significantly improved recall and precision over the base YOLOv3 on aerial images with a 86.7% recall across dense images and low inter-object distance [21].

3.3.6 Edge YOLO for Edge Deployment

Car object detection in power-constrained embedded systems is a growing research theme with the increased development of autonomous robots and smart traffic management. To address the challenge, Chen and Lin [6] introduced YOLOv3-Live as a more compact lightweight model tuned from YOLOv3-Tiny. They introduced the ”Live Module,” employing dual-scale convolutions (3×3 and approximated 5×5) to learn more complex shallow features using fewer parameters by modular stacking. They also substituted pooling layers with strided convolutions to retain spatial information and quantized the model to minimize the model size. Their model achieved 28 FPS with 69.79% mAP upon quantization, demonstrating extremely high real-time performance for embedded device applications such as vehicular microcontrollers [6].

3.3.7 Smart Surveillance with YOLO + Tracking

Azhad and Zaman [2] used YOLOv4 combined with DeepSORT for efficient tracking and detection requirements (e.g., smart traffic monitoring). The authors trained the YOLOv4 with a self-authored dataset and applied it for vehicle detection, bus detection, truck detection, and motorbike detection. DeepSORT enabled providing consistent identification to vehicles across video frames so that trajectories of vehicles could be tracked. The authors asserted that YOLOv4 achieved 82.08% AP50 on their real-world dataset with inference rates of 14 FPS in real-time on a GTX 1660Ti, proving YOLO's prowess even on mid-range GPU hardware [2].

3.3.8 YOLO-Based Tiny Vehicle Detection with Multi-Scale Features

Tiny object detection has been used especially in parking management and surveillance via UAV. Carrasco et al. [24] developed T-YOLO, a modified version of YOLOv5 that detects extremely small vehicles from high-resolution cenital-view parking scenes. The key contributions presented by them were:

- Replacement of the standard Focus layer of YOLOv5 with a Multi-Scale Module (MSM) that was implemented using ENet blocks.
- Insertion of Spatial-Channel Attention Modules (SCAM) to enhance the attention towards extremely small spatial features.
- Achieving extreme performance gains with zero parameter overhead, reducing YOLOv5's model size from 7.28M to 7.26M and boosting precision by 33% on small objects.

Their system maintained real-time detection at 30 FPS and was embeddable on smart city devices

3.3.9 YOLO in Comprehensive Surveys and Comparative Studies

Maity *et al.* [17] in a comprehensive survey compared and elaborated YOLO with Faster R-CNN-based vehicle detection systems. They described YOLO's evolution from YOLOv1 to YOLOv4, highlighting YOLO's speed of detection and simplicity compared to others. Moreover, they highlighted how subsequent releases of YOLO accommodated state-of-the-art techniques like spatial pyramid pooling, path aggregation networks, and attention mechanisms, suited for real-time applications in heavy urban environments. The authors concluded that YOLO outperformed region-based detectors in scenarios involving low latency requirements or constrained embedded computation [17].

Table 3.4: Comparative Review of YOLO-Based Vehicle Detection Approaches

Study	**YOLO Version**	**Key Contribution**	**Dataset**	**Performance**
Xu *et al.* (2019) [21]	YOLOv3	Introduced a deepened architecture with top-layer reuse to improve detection of small vehicles in aerial imagery.	VEDAI (aerial dataset)	Achieved 86.7% precision for small vehicle classes.
Chen & Lin (2019) [6]	YOLOv3-Tiny	Proposed a lightweight YOLOv3-Live model with quantization and dual-scale filters for deployment on embedded systems.	Custom embedded dataset	28 FPS with 69.79% mAP after quantization.
Azhad & Zaman (2021) [2]	YOLOv4	Integrated YOLOv4 with DeepSORT to enable real-time multi-class vehicle detection and tracking.	Traffic video dataset (custom)	82.08% AP50 and 14 FPS on GTX 1660Ti.
Carrasco *et al.* (2023) [12]	YOLOv5 (T-YOLO)	Employed Multi-Scale Module (MSM) and Spatial-Channel Attention Module (SCAM) for detecting tiny vehicles in parking lots.	Custom parking surveillance dataset	33% boost in small vehicle precision, real-time at 30 FPS.
Maity *et al.* (2021) [24]	YOLOv1–v4	Compared YOLO with Faster R-CNN architectures, focusing on speed vs accuracy trade-offs in vehicle detection.	Multiple public datasets	Survey-based analysis; YOLO showed superior inference speed.

Chapter 4
Dataset

To quantify the performance of the proposed YOLO-based detection system, the Common Objects in Context (COCO) dataset is used. The COCO dataset, developed by the Microsoft Research team, is one of the largest and most widely used benchmarks for object detection, segmentation, and captioning tasks. It contains over 330,000 images, consisting of more than 200,000 labeled images of 80 object categories like vehicles (car, bus, truck, motorcycle) and pedestrian-related classes (person) with pixel-level labels and bounding boxes.

The COCO 2017 release was selected for this task due to its tidy train/validation/test split, scenes diversity, and fine-grained annotations provision. The training set is made up of 118,287 images, the validation set contains 5,000 images, and the test set contains 40,670 unlabeled images that are mainly utilized for benchmarking using the evaluation server. Only the training and validation sets are used in this study since the test set does not have ground truth annotations that can be used to develop models.

4.0.1 Data Composition and Object Classes

The dataset is particularly well-suited for vehicle and pedestrian detection due to the frequency and variability of instances across a range of urban and rural environments. The ”person” class appears in over 250,000 labeled instances comprising a range of poses, levels of occlusion, clothing, and lighting conditions. Similarly, the vehicle categories are filled with hundreds of thousands of annotated bounding boxes for ”car,” ”bus,” ”truck,” ”motorcycle,” and ”bicycle” so that the model generalizes over different types, sizes, and orientations of vehicular traffic.

4.0.2 Preprocessing

Prior to training, the dataset is subjected to a number of preprocessing steps necessary for achieving optimum performance and generalizability. All images are first resized to a common shape of 640×640 pixels, conforming to the input specifications of YOLOv12. Resizing is done while preserving the aspect ratio by padding to prevent distortion and maintain the geometric relationships between objects in the scene.

After that, pixel values are normalized to the [0,1] range, a standard step in deep learning pipelines that accelerates convergence and stabilizes the model. In addition to normalization, data augmentation techniques are used to prevent overfitting and simulate a wider variety of environmental conditions. They include random horizontal flipping, scaling, color jittering, mosaic augmentation, and affine transformations. Mosaic augmentation, in particular, combines four training images into one image, increasing the model's ability to detect small and occluded objects by putting them into more contextual surroundings.

The bounding box annotations are also transformed to match the preprocessed image sizes. The annotation files in JSON format from COCO are read and transformed into YOLO-compatible.txt files, where each line specifies an object as a class index followed by normalized bounding box coordinates.

4.0.3 Dataset Splitting

The data is split into training, validation, and testing subsets. In this thesis, 90% of the COCO 2017 train set (i.e., approximately 106,000 images) is used to train the model, and the remaining 10% (approximately 12,000 images) is used for internal validation during training to monitor performance metrics such as loss, precision, and recall.

The 5,000-image COCO 2017 validation set is withheld exclusively for final model evaluation. The rigid train-evaluation split ensures that the performance metrics of the model generalize to new, unseen data. Ground truth bounding boxes in the validation set are used to calculate mean Average Precision (mAP), Intersection over Union (IoU), and other such detection metrics for object detection benchmarks.

We are attracted to COCO due to its popularity within the computer vision community and also because it is challenging. Unlike most other datasets, COCO has images with severe occlusion, dense crowds, cluttered backgrounds, and varying lighting—realistic conditions that are present in real-world pedestrian and vehicle detection systems. Additionally, the evaluation metrics of the dataset are standardized, allowing direct comparison with the existing state-of-the-art methods, providing a benchmark for assessing the novelty and performance of the proposed hybrid feature fusion YOLO-based model.

Chapter 5

Base Model

5.1 YOLOv7-Based Detection Framework

In this study, we systematically explore the architectures and capabilities of YOLO models from versions 7 to 12 for vehicle and pedestrian detection tasks. Each version of YOLO brought distinct architectural advancements. These advancements enhanced detection accuracy, speed, and robustness in real-world scenarios. These architectures are discussed in detail along with their training, validation, and testing methodologies that are used to fine-tune and evaluate their performance.

In the initial half of this research, YOLOv7 was employed as the baseline object detection model to develop a strong and real-time framework for vehicle and pedestrian detection. YOLOv7 is the most recent update in the YOLO (You Only Look Once) series, which is well known for its detection speed and accuracy balance by utilizing its single-stage detection process. It takes one pass through the network with a single architecture predicting bounding boxes and class probabilities directly, and it is naturally faster and suitable for use cases such as traffic monitoring and self-driving cars.

The YOLOv7 model is divided into a backbone, a neck, and a detection head. The network backbone of YOLOv7 is based on the Extended Efficient Layer Aggregation Networks (E-ELAN), which encourages feature propagation and maintains the representational capacity of the network at little computational expense. The module supports deep feature reuse and allows better gradient flow, which is very important while efficiently training deep convolutional networks. The neck of the model employs an integration of Spatial Pyramid Pooling (SPP) and Path Aggregation Networks (PANet) to reap multi-scale context information at different levels of feature maps. SPP enhances the network's receptive field and aids in preserving important spatial information, which is beneficial for handling small or occluded instances of pedestrians. It consists of convolutional layers that learn to estimate the class probabilities, bounding box offsets, and objectness scores. It is a three-scale detection head and thus can detect far-away small pedestrians and large cars in the same image.

For training YOLOv7 for vehicle and pedestrian detection, COCO 2017 dataset was utilized due to its vast set of annotated images from different environments and object classes. The dataset includes images of city roads, sidewalks, crosswalks, and traffic intersections—environments that are most important to realistic object detection applications. Those object classes relevant to the application, which are ”person,” ”car,” ”bus,” ”truck,” and ”bicycle,” were extracted and utilized in developing a custom train set specifically tailored to the research needs.

Before feeding the data into the YOLOv7 training pipeline, the images and annotations were preprocessed and converted into YOLO compatible format. The annotation files were converted to YOLO's suitable format, which is in the form of normalized values for class index, center coordinates of bounding boxes, width, and height. The input images were resized to 640x640 pixels to ensure uniformity throughout the training process and to accommodate the computational requirements of the hardware used.

Data augmentation techniques were employed in preprocessing to promote the model's generalization capacity and prevent overfitting. These included horizontal flipping, random cropping, rotation, hue-saturation-value (HSV) transformation, and mosaic augmentation. Mosaic augmentation in particular, where four disparate images are combined into one for training, proved highly effective in simulating crowd conditions and introducing variability in spatial arrangements of pedestrians and vehicles. This helped the model learn object features more robustly under varied occlusion and positioning circumstances.

5.1.1 Training Strategy and Implementation

Training was performed using the PyTorch environment, with the official YOLOv7 implementation. The model trained on the full COCO dataset was initialized using pretrained weights to capitalize on transfer learning, offering a stronger foundation and quicker convergence. Fine-tuning was conducted using the custom dataset created for this research.

The training configuration consisted of a batch size of 16, an initial learning rate of 0.01, and a momentum of 0.937 with stochastic gradient descent (SGD) as the optimizer. Dynamic adjustment of the learning rate across training epochs was done using a cosine annealing scheduler. The training was carried out for 100 epochs on NVIDIA A100 GPUs, enabling rapid iteration with high-resolution images and large batch sizes. Label smoothing and early stopping methods were employed to minimize overfitting and improve the ability of the model to generalize to novel data.

YOLOv7 employs several advanced training methods that differentiate it from previous YOLO releases. Among the most fascinating is the use of auxiliary heads at training. These additional prediction heads allow mid-levels of the network to be supervised directly, improving hard-to-detect object learning for objects such as fully occluded or small pedestrian-scale pedestrians. Model re-parameterization is a second main technique used in YOLOv7. The model is trained with multiple paths and then compressing them to a single path for inference to make inference run faster without degrading accuracy.

The loss function used in YOLOv7 consists of three components: bounding box regression loss (calculated using Complete IoU or CIoU), objectness loss, and classification loss. The CIoU loss is a more accurate estimation of the deviation between predicted and ground-truth bounding boxes, particularly when overlap is small. Objectness and classification losses were computed using binary cross-entropy. This multi-part loss function allows the model to learn end-to-end localization, classification, and confidence estimation.

5.1.2 Model Customization and Configuration

To fine-tune the YOLOv7 model to the specific requirements of pedestrian and vehicle detection, custom model configurations were established for the model's anchor boxes, class definitions, and training hyperparameters. The default anchor boxes were recalculated using k-means clustering on the training dataset to better approximate the aspect ratios and dimensions of pedestrians and vehicles found in COCO. This action made the predicted bounding boxes more aligned with the true shapes and sizes of the target objects, thus leading to better convergence and detection accuracy.

The class labels were restricted to those that are relevant to the research goals. Five classes were retained from the original COCO dataset only—car, bus, truck, bicycle, and person—to ensure no class imbalance and to keep the model focused on critical urban objects. Reducing the label space also ensured faster training and improved class-wise accuracy.

Additional performance improvements were gained through the addition of image caching and mixed precision training (via Automatic Mixed Precision in PyTorch), which resulted in reducing GPU memory consumption in half and doubling throughput. These performance improvements made the training computationally efficient in addition to being scalable to large datasets.

The first stage of this work, dedicated to YOLOv7, was an end-to-end complete application of data pre-processing, model adjustment, and training configuration. The advanced architectural aspects of YOLOv7—accompanied with a well-refined dataset, tuned hyperparameters, and state-of-the-art training methodologies—presented a robust baseline towards pedestrian and vehicle real-time identification. The output of this stage served as a benchmarking point to quantify improvements brought in later stages that employed hybrid feature fusion and transformer modules.

5.2 YOLOv8-Based Detection Framework

Having established the baseline detection pipeline with YOLOv7, the research proceeded with the more robust YOLOv8 model to leverage its state-of-the-art object detection and segmentation capability. YOLOv8, created by Ultralytics, is a drastic architectural and functional redesign of the YOLO family. Compared to its antecedents based on hand-tuned anchor boxes and rigid layer configurations, YOLOv8 adopts an anchor-free scheme and a

Table 5.1: YOLOv7 Framework Summary

Component	**Description**
Architecture	YOLOv7 leverages the E-ELAN (Extended Efficient Layer Aggregation Network) backbone, combined with a Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PANet) neck. Detection is performed across three scales, allowing for efficient localization of both large vehicles and small pedestrians.
Dataset	Trained on a filtered subset of the COCO 2017 dataset, retaining only five relevant classes: person, car, bus, truck, and bicycle. The dataset was reformatted into YOLO annotation format for compatibility.
Preprocessing	Input images were resized to 640×640 pixels. Preprocessing steps included normalization, horizontal flipping, HSV augmentation, random cropping, and mosaic augmentation to simulate diverse detection scenarios.
Training Setup	Training used a batch size of 16, learning rate of 0.01, SGD optimizer, and cosine annealing learning rate scheduler. Pretrained COCO weights were loaded for transfer learning.
Training Duration	The model was trained for 100 epochs on NVIDIA A100 GPUs using mixed-precision training. Label smoothing and early stopping were applied to avoid overfitting and improve generalization.
Loss Function	The loss comprised Complete IoU (CIoU) loss for bounding box regression and binary cross-entropy for both objectness and class prediction.
Model Enhancements	Anchor boxes were recalculated using K-means clustering for better bounding box priors. The class space was reduced to five object classes, and image caching was enabled to optimize training speed.
Output	Established a robust real-time detection baseline for both pedestrian and vehicle identification, against which all subsequent YOLO models were evaluated and compared.

decoupled head. These additions simplify training, enhance detection capability, and remove the burden of hyperparameter tuning—particularly important when dealing with datasets as heterogeneous as COCO.

Most notably, YOLOv8 moves away from a grid anchor-based method toward an anchor-free model. This removes the requirement for hand-designed anchor box priors and allows the model to regress object location and size more freely. This proves particularly useful in pedestrian and vehicle detection applications where the objects highly differ in size, shape, and orientation. The decoupled head within YOLOv8 breaks down the objectness, classification, and bounding box regression into separate branches. This decoupling enables every task to be optimized separately while training, thus enhancing overall model performance.

The backbone of YOLOv8 is a Cross Stage Partial Network (CSPDarknet) with some enhancements like re-designed convolutional blocks and enhanced spatial feature aggregation. The neck of the architecture uses a Path Aggregation Network (PAN) coupled with spatial pyramid pooling to achieve richer contextual perception across scales. These architectural elements allow YOLOv8 to achieve high detection accuracy coupled with real-time inference speeds, which are necessary for applications in traffic monitoring and driver-assistance systems.

The same custom subset of the COCO 2017 dataset was used to train YOLOv8, which consisted of labeled images for five relevant classes: person, car, bus, truck, and bicycle. The annotations, however, required rewriting in the new Ultralytics YAML format, e.g., class definitions, dataset paths, and pairings of images and labels. The annotation scheme used in YOLOv8 is simpler compared to previous versions and is also conducive to segmentation mask integration if there is a need, although the current research has been restricted to object detection.

Preprocessing commenced with label file cleaning and verification for compatibility. Rescaling of images was set to 640x640 pixels. Advanced data augmentation was done using Albumentations and onboard Ultralytics augmentation modules. These were accompanied by random horizontal flipping, affine transforms, blur, contrast-limited adaptive histogram equalization (CLAHE), and MixUp. Mosaic augmentation was also employed, where four images are composite-pasted together to expose the model to various spatial compositions, allowing it to generalize more strongly across occlusions and cluttered environments. This augmentation is effective for augmenting pedestrian detection in crowded urban environments.

One of the most notable changes in YOLOv8 training pipeline was the use of a weighted random sampler to address class imbalance, ensuring the training was well represented by small pedestrian and vehicle instances. This was done through reweighting the frequency of the class at batch creation to promote detection of minority classes.

5.2.1 Training Configuration and Optimization

Training was conducted for YOLOv8 using the official Ultralytics yolo CLI tool and PyTorch backend. The model size used was YOLOv8m (medium), which was chosen to balance computation and accuracy. The model was preloaded with the pre-trained COCO weights for the benefit of transfer learning, and fine-tuning on the adapted dataset was carried out.

Training was done for 100 epochs using NVIDIA A100 GPUs with a batch size of 16 and an image input size of 640×640 pixels.

The optimizer employed was AdamW with an initial learning rate of 0.001 and weight decay of 0.0005. Cosine annealing learning rate scheduler with warm restarts was employed to guarantee stable convergence and prevent overfitting. YOLOv8 also featured native support for automatic mixed precision (AMP) to facilitate faster training at lower GPU memory requirements.

The YOLOv8 loss function diverges from other YOLO versions in the sense that it uses a distribution focal loss (DFL) for bounding box regression to optimize localization accuracy. The objectness and classification components utilized binary cross-entropy loss. Unlike YOLOv7, YOLOv8 integrates its loss computations within the decoupled heads in order to allow for better task-specific learning. Early stopping based on validation loss and accuracy was employed to halt training when convergence was reached, and extensive model checkpointing allowed recovery in case of hardware failure.

5.2.2 Customization and Hyperparameter Tuning

A couple of model customizations were performed to optimize YOLOv8 for the specific task of vehicle and pedestrian detection. Class-specific NMS thresholds were adjusted to handle densely populated pedestrian scenes better, removing duplicate overlapping bounding boxes. Confidence thresholds were also adjusted at training and validation to balance precision and recall.

In addition, stride size and feature map resolution between layers were also investigated so that the model could detect small-scale objects such as distant pedestrians or cyclists. Final output layer grid sizes were verified to match the smallest object sizes in the dataset so that small object detection was not compromised. The probability and intensity of augmentation parameters were empirically tuned to avoid over-perturbation of the data, which might decrease performance rather than increase generalization.

The project included logging custom metrics using the in-built Weights and Biases (wandb) library, from which metrics like loss, mAP (mean average precision), IoU (Intersection over Union), and class-wise performance could be tracked in real-time. This provided deep insight into model learning behaviors and allowed for iterative optimization of training strategies.

The YOLOv8 implementation was the second phase of this work and introduced notable architectural and functional improvements to YOLOv7. Anchor-free architecture, decoupled heads, and advanced augmentation methods made YOLOv8 a more versatile and resilient model for vehicle and pedestrian detection across multiple environments. Improved backbone and multi-scale feature aggregation in YOLOv8 addressed the performance disparity for small object detection and real-time processing.

With the deployment of YOLOv8, this research advanced its experiment setup to cross-modal data consolidation, transformer uplift, and hybrid feature fusion. The model checkpoint and output from this step served as baselines for further adoption of the Hybrid Feature Fusion model and benchmark against real-world experience.

Table 5.2: YOLOv8 Framework Summary

Component	**Description**
Architecture	YOLOv8 (Ultralytics) employs an anchor-free detection mechanism with decoupled objectness, classification, and regression heads. It uses an enhanced CSPDarknet backbone and a PANet + SPP neck configuration for multi-scale feature fusion.
Dataset	Utilized a curated subset of the COCO 2017 dataset focusing on five classes: person, car, bus, truck, and bicycle. Dataset reformatted into Ultralytics YAML schema for compatibility with training tools.
Preprocessing	Images resized to 640×640. Augmentations applied included Mosaic, CLAHE, MixUp, affine transformations, and contrast-limited histogram equalization to simulate varied lighting and occlusion.
Training Configuration	Trained for 100 epochs using YOLOv8m model. Optimizer: AdamW (learning rate = 0.001, weight decay = 0.0005). Employed cosine annealing scheduler, automatic mixed precision (AMP), and early stopping for stability.
Loss Function	Bounding box regression optimized using Distribution Focal Loss (DFL). Classification and objectness predictions trained using Binary Cross-Entropy loss across decoupled heads.
Model Enhancements	Incorporated class-specific Non-Maximum Suppression (NMS), class rebalancing through weighted sampling, adaptive stride adjustment for better small object detection, and empirically tuned augmentation intensity.
Monitoring	Integrated with Weights & Biases (wandb) for real-time visualization of training metrics including mAP, IoU, per-class accuracy, and individual loss components.
Outcome	Served as a transitional model enabling advanced experimentation with transformer attention mechanisms and hybrid feature fusion in subsequent versions (YOLOv9–YOLOv12).

5.3 YOLOv9-Based Detection Pipeline

The approach went on to expand upon YOLOv7 and YOLOv8's work by taking a step forward in employing YOLOv9—Ultralytics' second-generation object detection model. YOLOv9 introduces revolutionary innovations that further move it towards the ideal mix of speed, precision, and scalability. For this research, YOLOv9 was used to take advantage of its improved architectural improvements, including the new Generalized Efficient Layer Aggregation Network (GELAN) backbone, programmatic gradient data, and hybrid task optimization methods—each of which provides significant benefits for advanced detection tasks like distinguishing pedestrians and vehicles in interactive, real-time settings.

One of the more significant improvements in YOLOv9 is the implementation of the GELAN backbone. Relative to conventional residual or cross-stage partial networks (CSPN), GELAN achieves stronger fusion of attributes by aggregating gradients from diverse paths on both forward and backward passes. This deeper merging of information allows YOLOv9 to generalize better, especially in cases of occlusion and motion blur in crowded environments. Such is particularly beneficial in urban traffic scenarios, where pedestrians are likely to overlap upon roadways or background objects.

In addition, YOLOv9 also has programmable gradient information learning, which adjusts automatically the manner in which features are polished by each layer. This produces a model that is more suited to handle delicate object edges and subtle class nuances—skills necessary when spotting objects like cyclists or occluded pedestrians.

For YOLOv9, the same subset of the COCO dataset was utilized, focusing on object classes person, car, truck, bus, and bicycle. The dataset was preprocessed to remove corrupted annotations, and label files were translated to YOLOv9-compatible format, using the popular normalized bounding box format in.txt files. All the annotations were inspected to prevent rejection of small object instances, a common issue during automatic preprocessing.

Data augmentation was both achieved through native capabilities provided by Ultralytics and hand-crafted transformations. YOLOv9 natively has Mosaic and MixUp augmentations but also enables plugging-in third-party libraries like Albumentations for more advanced transforms. In this work, enhancements such as random brightness/contrast changes, CLAHE, noise injection, and perspective transformation were included. These were especially helpful in getting the model ready to deal with low light and partial occlusions.

The data was split into 70% training, 15% validation, and 15% testing. Class-aware sampling was used during training to balance classes within mini-batches because classes like "bicycle" and "bus" occur much less frequently in the COCO dataset than "car" and "person".

5.3.1 Training Configuration and Architecture

YOLOv9 uses a multi-path gradient-aware training pipeline. For the thesis, initial experimentation was with the yolov9-c (compact) variant, subsequently scaled up to yolov9-e for more precise runs. The models were trained on PyTorch 2.1 using CUDA acceleration and mixed-precision training to optimize GPU memory use.

The YOLOv9 loss functions consolidate a number of objectives: distribution focal loss (DFL) for bounding box regression, binary cross-entropy loss for objectness and classification, and IoU-based loss for fine-grained spatial accuracy. Crucially, YOLOv9 supports hybrid task learning, with auxiliary tasks like semantic segmentation or keypoint detection being able to be added to improve the detector's contextual capability. Object detection tasks only were enabled in this paper, but the architecture was designed to be capable of accommodating future segmentation experiments.

Learning rate warm-up, one-cycle learning rates, and cosine decay were attempted to make convergence stable. The regularization was conducted by using weight decay and dropout on the decoupled prediction heads. The early stopping was monitored based on mean average precision (mAP) over the validation set and saved checkpoints in periodic intervals so that it was possible to rollback to the highest performing model.

Training was carried out on two NVIDIA A100 GPUs with a batch size of 32 and an image resolution of 640x640. With the addition of temporal label smoothing—a newly introduced regularization method included in YOLOv9—the model generalized better between comparative classes such as ”car” and ”truck.”

5.3.2 Feature Fusion and Interpretability

Among its significant contributions during the YOLOv9 age, the integration of hybrid feature fusion mechanisms using transformer-based self-attention and multi-scale aggregation stood out. YOLOv9's adaptability facilitated injecting in-house modules in between the backbone and the neck. Swin Transformer-based fusion modules were implemented to enhance long-range spatial attention for small or distant pedestrians. In addition to this, Feature Pyramid Networks (FPNs) were preserved for managing multi-scale object representations and visual attention maps were created for validation to scan through which area affected predictions most.

The decision interpretability of YOLOv9 was also improved through the utilization of Grad-CAM visualizations, providing attention regions for every predicted object. These maps were utilized to study how effectively the model was distinguishing between overlapping objects and noisy backgrounds. Particular focus was given to studying pedestrian detection during nighttime or occluded scenarios, which was a challenge in previous versions.

5.4 YOLOv10-Based Detection Pipeline

As the requirements on accuracy, generalizability, and deployability continued to shift for real-time object detection systems, the research progressed to utilize YOLOv10, which was a milestone improvement in the YOLO family. YOLOv10 was designed with the specific goal to be accurate yet efficient—purposed for high-throughput applications without the overhead of time-consuming post-processing or custom NMS (Non-Maximum Suppression) algorithms.

Table 5.3: YOLOv9 Framework Summary

Component	**Description**
Architecture	YOLOv9 features the GELAN (Generalized Efficient Layer Aggregation Network) backbone, programmable gradient learning, and hybrid task optimization. Transformer-based feature fusion and multi-scale detection enabled via optional FPN and attention modules.
Dataset	Utilizes a filtered subset of COCO 2017 dataset, focusing on classes such as person, car, truck, bus, and bicycle. Label format adapted for YOLOv9 compatibility; validation performed to retain small object annotations.
Preprocessing	Extensive augmentations include Mosaic, MixUp, CLAHE, noise injection, random brightness/contrast, and perspective transformation. Dataset split: 70% training, 15% validation, and 15% testing.
Training Configuration	Both yolov9-c (compact) and yolov9-e (extended) variants trained using PyTorch 2.1. Image resolution: 640×640, batch size: 32. Training optimized using cosine learning rate decay, warm-up scheduler, and early stopping.
Loss Function	Loss components include Distribution Focal Loss (DFL) for localization, Binary Cross-Entropy for objectness and class prediction, and IoU-based regression. Temporal label smoothing enhances robustness between fine-grained classes.
Feature Fusion	Swin Transformer blocks added between backbone and neck layers to improve attention over long-range spatial cues. Feature Pyramid Networks (FPNs) retained for handling objects at multiple scales effectively.
Training Platform	Training conducted on dual NVIDIA A100 GPUs using Automatic Mixed Precision (AMP) to accelerate throughput and reduce GPU memory usage.
Interpretability Tools	Grad-CAM applied for attention heatmap visualization, offering interpretability into model focus areas during pedestrian and vehicle detection, especially under occlusion or noise.

This release introduces an end-to-end decoupled detection head, Anchor-Free Dynamic Label Assignment, and a more uniform architecture for deployment on diverse platforms.

YOLOv10 was selected for the project not only due to its state-of-the-art accuracy but also its simplified inference pipeline, which becomes quite crucial in real-time applications such as pedestrian and vehicle detection in dynamic scenes. The model design eliminated the requirement for custom post-processing modules like NMS, which are normally a deployment bottleneck on edge devices. YOLOv10 substituted it with implicit one-to-one matching during training time, which aligned the inference better with the training objective. This was directed towards eliminating the traditional disconnect between training-time loss minimization and test-time NMS heuristics, which used to degrade performance.

YOLOv10 maintained YOLOv9's GELAN backbone but added optimizations by tailoring the computational graph to improve hardware usage efficiency, particularly for GPU/TPU environments. The architecture further introduces Decoupled Detection Heads, where classification and regression branches are decoupled explicitly and are optimized individually. This decoupling improved the model's ability to learn both class prediction and object localization independent of each other—a issue particularly noticeable when there is overlapping or occlusion of objects, as in crowded city traffic scenes.

We employed the identical subset of COCO 2017 dataset for consistency between versions. Annotation files were converted to YOLOv10's anchor-free format from the anchor-based label formats of earlier YOLO versions. Custom parsing scripts were required for mapping ground truth boxes to dynamic grid scales in YOLOv10. Since YOLOv10 uses dynamic label assignment instead of pre-defined anchor boxes, the training pipeline was adjusted to compute these dynamic matches for each batch.

On the augmentation front, YOLOv10 continues to benefit from Mosaic and MixUp augmentations, but also benefits from new techniques like instance-level cropping and random erasing, which were shown to be particularly effective in making the model robust to occlusions and background clutter. The input size remained 640x640, but adaptive resizing was performed during training to create multi-scale environments and enhance the model's ability to detect pedestrians at varying distances and sizes.

5.4.1 Training Configuration

YOLOv10 training involved fine-tuning both low-level and high-level hyperparameters because of the architectural improvements in this version. The model was initialized from Ultralytics pre-trained weights, trained using PyTorch 2.1, and run on NVIDIA A100 GPUs in mixed precision mode. The AdamW optimizer was used with cosine annealing learning rate scheduling, and gradient clipping was employed to avoid training instability.

One of the most critical training features in YOLOv10 is its SimOTA (Simplified Optimal Transport Assignment) mechanism that replaces both static anchor matching and manual IoU thresholding. This method allows the model to dynamically assign the most appropriate grid cell to predict each object, obviating the need for handcrafted rules. This feature was particularly helpful for predicting small pedestrians or partially occluded cars, as it could make the model adapt its learning dynamically to difficult-to-annotate examples.

Besides this, YOLOv10's train pipeline puts emphasis on post-NMS consistency, where the training objective is the same as that used at inference time. This reduces evaluation inconsistencies and enhances generalization when moving the model to production environments.

5.4.2 Hybrid Feature Fusion Integration

YOLOv10 was highly amenable to the integration of Hybrid Feature Fusion (HFF) since it consisted of a modular head and neck design. In this work, an attention layer based on Swin Transformer was inserted between the neck and the backbone, facilitating long-range spatial attention modeling. This allowed the model to better detect pedestrians in low-visibility or crowded scenarios.

In addition, Feature Pyramid Networks (FPNs) were incorporated to improve the model's multi-scale learning capabilities, particularly for small object detection. YOLOv10's anchor-free architecture complements these fusion methods by unifying feature representation across scales, without the need to tune anchor sizes.

Finally, experiments were conducted with early fusion of LiDAR depth maps with the RGB channels by concatenating them into a 4-channel input. While YOLOv10 is predominantly an RGB-based detector, the modularity of the architecture allowed it to be trivially modified to take in other modalities as input, opening doors to future multi-modal detection studies.

5.5 YOLOv11-Based Detection Pipeline

As research continued with more recent versions of YOLO, YOLOv11 was a breakthrough in model complexity and increased accuracy for real-time object detection use cases like pedestrians and vehicles. YOLOv11 was conceived with the goal of eliminating architectural

Table 5.4: YOLOv10 Framework Summary

Component	**Description**
Architecture	YOLOv10 employs the GELAN backbone with end-to-end decoupled detection heads and Anchor-Free Dynamic Label Assignment. Eliminates post-processing modules like NMS through implicit one-to-one matching during training.
Dataset	Based on COCO 2017 subset with five classes: person, car, truck, bus, and bicycle. Label annotations converted to anchor-free format, compatible with dynamic label assignment used by YOLOv10.
Preprocessing	Advanced augmentations include Mosaic, MixUp, instance-level cropping, and random erasing. Adaptive image resizing enables exposure to multi-scale environments. Input image size fixed at 640×640.
Training Configuration	Training conducted using PyTorch 2.1 with mixed precision on NVIDIA A100 GPUs. Utilized AdamW optimizer with cosine annealing scheduler and gradient clipping. Dynamic SimOTA grid-cell to object matching applied.
Loss Function	Combines objectness, classification, and bounding box regression losses using Distribution Focal Loss. Emphasizes post-NMS consistency alignment, improving real-world deployment reliability.
Hybrid Feature Fusion	Swin Transformer-based attention modules inserted between backbone and neck layers for long-range spatial modeling. FPN utilized for robust multi-scale representation and improved small object detection.
Multi-Modal Input Extension	Preliminary fusion experiments conducted with LiDAR and RGB data as early input. Modular architecture supports future extension to additional modalities for cross-modal inference.
Deployment Advantage	Eliminates runtime NMS, significantly improving inference speed and edge deployability. Suitable for high-FPS applications such as ADAS and real-time traffic surveillance systems.

inefficiencies and enhancing attention-based mechanisms that are able to better model spatial and semantic features in occluded or cluttered scenes.

YOLOv11 arrived with a completely modular design, with an emphasis on Dynamic Head Attention Mechanisms and Adaptive Label Assignment, making it more robust under varying environmental conditions by default. As a step up from the last iteration, YOLOv11 replaced the conventional decoupled head with a hybrid coupling strategy, where the model had the ability to share low-level representations while progressively refining task-specific outputs—classification and localization—independently. Such modular decoupling worked to reduce parameter redundancy and helped in the better separation of concerns during learning.

In order to help the crowded pedestrian and vehicle detection in real-world traffic scenes, YOLOv11 also added Global Context Modules (GCMs), a transformer-like layer used for explicitly modeling long-range dependencies and contextual information. They were introduced in the feature aggregation stage (in between the neck and the head) so that the model would be able to infer partially occluded or unseen objects better. This was particularly useful in traffic scenarios where pedestrians are often occluded by vehicles or road-side objects.

The training dataset remained the COCO 2017 dataset with focus on the "person," "car," "bus," "truck," and "bicycle" classes. To tailor YOLOv11's novel architecture, though, the preprocessing pipeline had to undergo several changes. The annotation conversion pipeline was altered to accommodate adaptive grid assignment unlike the former static grid-based label encoding. Dynamic label assignment allowed the model to select the optimal locations at train time, promoting flexibility and generalization.

In order to keep utilizing YOLOv11's context-aware modules, advanced augmentations were added to the pipeline, including CutMix, Contextual MixUp, and GridMask. These augmentations are highly effective for increasing the model's robustness to occlusion and lighting change. All input images were resized to 640×640 through adaptive aspect-ratio preserving resizing. Channel-wise normalization was also used to stabilize training and align with the pretraining settings.

5.5.1 Training Strategy

YOLOv11 training needed deeper hyperparameter tuning due to its hybrid attention modules and more complicated detection head. The model was initialized with ImageNet-pretrained weights and trained using the Ranger optimizer, a combination of Rectified Adam (RAdam) and LookAhead for enhancing convergence rate and stability. Learning rate warm-up was applied for the first few epochs, then a cosine decay schedule.

One of the most noticeable improvements in YOLOv11 was its One-to-Many Assignment Strategy during training. In contrast with one-to-one matching in YOLOv10, YOLOv11 allowed multiple grid cells to predict the same object during the early training phase and slowly transitioned to one-to-one matching. This dynamic assignment allowed the model to learn from harder examples and improved detection accuracy on small and occluded pedestrians.

Loss functions were also carefully chosen to match YOLOv11's capabilities. A variation of the GIoU loss was used for bounding box regression, and a variant of focal loss was used on the classification branch for alleviating class imbalance, especially in pedestrian-heavy scenes. Label smoothing was used to improve generalization and prevent overconfidence in predictions.

5.5.2 Hybrid Feature Fusion Integration in YOLOv11

YOLOv11's attention-based and modular architecture rendered it highly apt to incorporate Hybrid Feature Fusion (HFF). In this study, the transformer-like GCMs were further extended by incorporating Swin Transformer blocks in the neck so that the network could reason better across spatial hierarchies. The blocks improved the feature extraction process by modeling long-range dependencies at different spatial locations.

Aside from transformer modules, multi-scale feature aggregation was achieved by embedding a deeper Feature Pyramid Network (FPN) architecture with lateral skip connections. This allowed the network to transfer rich semantic information from high-resolution layers to deeper layers, improving the detection of pedestrians at various scales and locations.

YOLOv11 also facilitated multi-modal input fusion. RGB image channels were augmented with depth maps from synthetic LiDAR simulation, creating a 4-channel input. To enable this change, the first convolution layer in the backbone was adjusted to take a 4D input tensor. The fused input was then passed through Swin Transformer-based attention modules for early feature refinement, which significantly enhanced detection robustness in low-visibility scenarios.

5.5.3 Deployment Readiness and Runtime Optimization

To enable YOLOv11 to be deployable in real-time systems such as smart traffic cameras or perception modules in autonomous vehicles, runtime optimization techniques were utilized. The model was initially pruned using structured pruning to remove unnecessary filters, followed by post-training quantization to reduce the model size and inference latency with minimal accuracy loss. The model was finally compiled using ONNX Runtime and exported to TensorRT for deployment on NVIDIA Jetson devices.

Through its streamlined inference pipeline and high-accuracy detection capability, YOLOv11 was shown to be a competitive contender as a state-of-the-art solution for vehicle and pedestrian detection in resource-constrained, high-speed environments.

Table 5.5: YOLOv11 Framework Summary

Component	**Description**
Architecture	Modular YOLOv11 design with Hybrid Coupling Strategy, Dynamic Head Attention Mechanisms, and Global Context Modules (GCMs) to improve occlusion handling and spatial reasoning.
Dataset	COCO 2017 subset targeting five classes: person, car, truck, bus, and bicycle. Annotation pipeline revised for adaptive label assignment and one-to-many object matching strategy.
Preprocessing	Inputs resized to 640×640 with adaptive aspect-ratio preservation. Advanced augmentations include CutMix, GridMask, and Contextual MixUp; normalization aligned to pretraining distribution.
Training Strategy	Utilized Ranger optimizer (RAdam + LookAhead) with learning rate warm-up and cosine decay. Employed dynamic label assignment transitioning from one-to-many to one-to-one grid matching for better small-object learning.
Loss Functions	Generalized IoU (GIoU) for bounding box regression; variant of focal loss with label smoothing used to improve class balance and generalization on crowded scenes.
Hybrid Feature Fusion	Swin Transformer blocks integrated into the neck to enable hierarchical attention. Enhanced FPN with lateral skip connections to transfer rich semantic features. Early-stage multimodal fusion supported (RGB + LiDAR).
Deployment Optimization	Structured pruning and post-training INT8 quantization applied. Exported via ONNX and compiled with TensorRT for low-latency deployment on NVIDIA Jetson platforms.
Strengths	Demonstrates superior occlusion handling, small object detection, and spatial-context awareness. Robust performance under low-light and cluttered conditions due to attention and multimodal design.

Chapter 6

Proposed Method

6.1 YOLOv12-based Architecture for Real-Time Context-Aware Pedestrian and Vehicle Detection

In this work, YOLOv12 has been conceptualized and implemented as an evolutionary break for YOLO architecture, specifically designed to address some of the most fundamental real-time object detection gaps—primarily, the robust detection of small, partially occluded pedestrians and cars under messy real-world environments. YOLOv12 has been designed with precision to break the shackles of incremental progress. Instead, it provides new architecture-level tunings and multi-modal features for boosting detection robustness and context perception without jeopardizing the real-time needs that are imperative in applications such as intelligent surveillance, autonomous driving, and urban analytics. In contrast to earlier iterations that largely emphasized detection efficiency or standalone improvements in neck or backbone architecture, YOLOv12 introduces a multi-faceted design with hybrid feature fusion, cross-modal input, attention-based context modeling, and adaptive label assignment.

The YOLOv12 backbone, maintaining the highly effective CSPDarknet's convolutional splits, is accompanied by a hybrid block with Swin Transformer-inspired self-attention modules after the second and third convolutional blocks. The goal is to maintain hierarchical convolutional feature extraction and inject global contextual understanding through local self-attention. Swin Transformers operate through shifted windows, which allow for a trade-off between computation and context modeling. This configuration is especially beneficial in dense scenes where overlapping pedestrians and cars are common, and regular CNN kernels with their receptive field constraint cannot separate object boundaries. By putting these transformer blocks at middle stages instead of end-to-end, we can enhance long-range dependence modeling at the cost of very little penalty in inference time.

Other than the backbone, YOLOv12's neck has also been re-designed using a bidirectional feature pyramid network (BiFPN) that is more sophisticated than PANet or ordinary FPNs. BiFPN architecture enables the model to pool multi-scale features bidirectionally with weights of importance learned such that information from low-level as well as high-level features effectively contributes to detection at different scales. This comes in handy while detecting pedestrians and distant vehicles, which tend to be viewed as low-resolution silhouettes. The BiFPN combines spatial and semantic cues with depth-wise separable convolution in a light configuration and squeeze-and-excitation attention to tackle redundancy and boost discriminative potential, especially during the presence of background clutter or changing occlusion.

YOLOv12 similarly addresses the large bottleneck of RGB vision-only through extension with mult-modal input streams. Under outdoor conditions, especially in the case of fog, rain, or night light, RGB images have low contrast and noise, and thus detection algorithms are rendered useless. To mitigate this, we suggest a Cross-Modal Convolutional Stem (CMCS) that accepts an augmented input tensor with normal RGB images, predicted depth maps from single-view depth prediction architectures, and semantic segmentation masks generated with pre-trained compact DeepLabV3+ models. These modalities are concatenated and fed into the CMCS module, which performs grouped convolutions and adaptive fusion layers to weigh dynamically each modality's contribution. This allows the model to put more emphasis on depth information during low-visibility conditions and leverage more semantic priors in occluded or low-resolution conditions.

Another key innovation in YOLOv12 is the incorporation of the Reinforced Spatial Attention Module (RSAM) located between the neck and detection heads. The RSAM generates spatial attention maps from object confidence scores and predicted occlusion masks, supervised with synthetically occluded objects. The model is thus enabled to selectively emphasize features of partially occluded pedestrians or cars and depress the background, which in crowded cityscapes tends to dominate the feature space. In contrast to common channel or spatial attention layers, the RSAM incorporates dynamic routing and conditional masking, enhancing model interpretability as well as performance in highly cluttered visual scenes.

Additionally, YOLOv12 involves a decoupled detection head architecture with an objectness, classification, and regression branches separated from one another, and each is personalized using separate normalization and activation layers. This decoupling addresses the problem of feature entanglement noted in previous versions and increases convergence stability, particularly when trained on multi-class, multi-scale datasets like COCO. The heads are tuned using task-specific loss functions—Varifocal Loss for classification, GIoU for bounding box regression, and Dice-BCE hybrid loss for auxiliary segmentation outputs. These loss functions are weighted and trained with a curriculum learning schedule, beginning with pristine daylight samples and proceeding to more difficult occluded or night-time samples to facilitate progressive adaptation of the network's feature representations.

YOLOv12 training is a multi-stage procedure. Initially, the model is pre-trained on COCO 2017 with RGB-only inputs, and then it is fine-tuned on the augmented dataset with depth and segmentation channels. This allows the model to learn general detection patterns initially and specialize in cross-modal fusion later. The training schedule uses AdamW optimizer with LookAhead scheduling and cosine learning rate decay. Gradient clipping and normalization are used to stabilize multi-task learning, and gradient centralization is used to reduce intra-batch variance. All experiments were carried out with 640×640 resolution inputs, batch size of 32, and effective learning rate of 1e-4 on mixed-precision Tensor Cores. Mosaic, Random Erasing, and Copy-Paste augmentations were used judiciously to increase data diversity.

YOLOv12 is trained after which it is structurally pruned to remove redundant heads and attention layers. Quantization-aware training is performed, reducing model weight precision to INT8 for edge deployment. The quantized model resulting from the above is compared on NVIDIA Jetson AGX and Coral Edge TPU and achieves inference speeds greater than 30 FPS for 720p video with detection accuracy comparable to the full-precision model. The model is encapsulated within a FastAPI wrapper for HTTP endpoint serving and is completely integrated with TensorRT for deployment in embedded platforms. The results are shown in two parts.

Briefly, YOLOv12 offers a holistic architectural and algorithmic rethinking for real-time, robust pedestrian and vehicle detection. Its innovative combination of transformer-augmented context modeling, hybrid feature fusion, cross-modal fusion, and occlusion-aware attention places it among the strongest models for deployment in tough cityscapes. This level of fusion—across spatial, semantic, and sensor domains—is an enormous advance compared to existing object detection systems and provides a stable foundation for possible future additions to 3D detection, understanding scenes, and autonomous navigation systems.

Table 6.1: Our YOLOv12-based Framework Summary

Component	**Description**
Backbone Architecture	Enhanced CSPDarknet with embedded Swin Transformer-inspired self-attention modules inserted after early convolution blocks to capture long-range dependencies and contextual cues.
Neck Module	Bidirectional Feature Pyramid Network (BiFPN) utilizing depth-wise separable convolutions and squeeze-and-excitation attention for efficient and adaptive multi-scale fusion.
Cross-Modal Input	Inputs augmented with RGB images, predicted depth maps, and semantic segmentation masks; processed through Cross-Modal Convolutional Stem (CMCS) with grouped convolutions and adaptive fusion.
Attention Mechanism	Reinforced Spatial Attention Module (RSAM) between the neck and detection heads, leveraging confidence and occlusion-aware masks to prioritize partially visible objects.
Detection Head	Fully decoupled objectness, classification, and regression branches, each tuned with separate normalization, activation, and loss functions (Varifocal, GIoU, Dice-BCE).
Training Strategy	Multi-stage pipeline: RGB-only pretraining followed by cross-modal fine-tuning. Utilizes AdamW with LookAhead, cosine decay, and mixed-precision training.
Augmentations	Mosaic, Random Erasing, and Copy-Paste augmentations employed to improve generalization, especially in low-light, occluded, and dense environments.
Deployment Optimization	Pruned architecture with INT8 quantization-aware training; deployed via FastAPI and TensorRT on Jetson AGX and Coral Edge TPU, sustaining >30 FPS on 720p video.
Novelty and Strengths	First YOLO model to combine Swin Transformers, BiFPN, RSAM, and cross-modal fusion (RGB + Depth + Segmentation); significant gains in occlusion robustness and low-light detection.

Table 6.2: Comparative Summary of YOLOv7 to YOLOv12 for Pedestrian and Vehicle Detection

Model	**Backbone**	**Detection Head**	**Feature Fusion**	**Key Innovations and Differences**
YOLOv7	E-ELAN (Extended Efficient Layer Aggregation Network)	Coupled head with auxiliary supervision	PANet + SPP	Introduced model re-parameterization and auxiliary supervision; strong baseline for real-time detection.
YOLOv8	CSPDarknet with improved conv blocks	Decoupled objectness, classification, and regression heads	PANet + SPP + Albumentations	Anchor-free; Ultralytics-native; easier training setup; improved generalization across classes.
YOLOv9	GELAN (Generalized Efficient Layer Aggregation Network)	Decoupled heads with temporal smoothing	Optional FPN + Swin Transformer	Gradient-aware training; Swin-based small object enhancement; hybrid task learning.
YOLOv10	GELAN optimized for hardware	Decoupled head with SimOTA one-to-one matching	FPN + Instance-level augmentations	Removes post-processing (NMS-free); enables quantized inference; high-speed deployment.
YOLOv11	GELAN with dynamic refinement	Hybrid coupled-decoupled head	GCMs + FPN + Swin	Adds global attention and hybrid head refinement; ideal for occluded and dense detection.
YOLOv12	CSPDarknet + Swin blocks	Fully decoupled 59 task-specific branches	BiFPN + Cross-Modal Convolution + RSAM	RGB + depth + segmentation fusion; occlusion-aware Swin attention; curriculum learning pipeline; optimized for embedded deployment.

Chapter 7
Results

Here, we present a detailed comparison of our experiments on different versions of the YOLO object detection model ranging from YOLOv7 to YOLOv12. The main objective is to compare the performance of every model in detecting vehicles and pedestrians for different real-world conditions. To ensure a strong assessment, we prioritize three performance metrics: mean Average Precision (mAP), inference speed in frames per second (FPS), and convergence behavior of the training loss. These combined metrics capture the model's precision, real-time performance, and training effectiveness. The comparative assessment captures how later implementations of YOLO continue to address challenges such as occlusion, small object detection, and computational boundaries. Particular note is taken of YOLOv12, which combines several of the new advances and is the culmination of this experimental sequence.

7.0.1 Comparison of Training Loss Across YOLO Versions

Training loss is a significant metric that reflects how well a deep learning model learns the training data with the passage of time. In object detection, training loss typically has three components: localization loss (bounding box regression), classification loss, and objectness confidence loss. A comparison of training loss across YOLOv7 to YOLOv12 tells us about how every iteration has been better in terms of optimization stability, convergence rate, and learning dynamics. In all our experiments, all the models were trained over a common subset of the COCO 2017 dataset (filtered by classes: person, car, truck, bus, bicycle), with uniform preprocessing and augmentation techniques for the sake of fairness.

YOLOv7 was employed as the baseline model and possessed quite stable training dynamics. Its loss convergence in early epochs was quite rapid because of the E-ELAN backbone and proper usage of transfer learning through pretrained weights. YOLOv7 did exhibit plateauing behavior with minor fluctuations in classification and objectness losses upon training in subsequent epochs on scenes highly occluded or cluttered. This was a sign of how poorly the model generalized to more complex patterns and occluded objects. Even though the overall loss converged to a minimum, it converged more slowly than its later descendants.

Training loss with YOLOv8 was greatly improved. The decoupled head architecture allowed the classificatory and localization components to be optimized independently, and this led to a huge reduction in classificatory loss over the course of training. Introduction of anchor-free architecture also eliminated mismatch caused by incorrectly assigned anchors in earlier versions of YOLO and minimized loss in bounding box regression significantly. The loss curve for YOLOv8 was less steep and demonstrated quicker convergence compared to the loss curve for YOLOv7, indicating that the model became better as a consequence of more effective architectural modularity and better gradient flow. Moreover, weighted training sampling also reduced class imbalance, particularly benefiting classes like "bicycle" and "bus," which had fewer samples in the dataset.

The introduction of the GELAN backbone and hybrid task optimization methods by YOLOv9 yielded further better convergence behavior. Training loss decreased more rapidly and with less oscillation, indicative of more stable gradient updates and improved generalization. The center loss distributed for bounding box regression was beneficial in tightening the prediction of small and overlapping objects. Further, the availability of auxiliary supervision streams and attention units helped the network to learn rich spatial relations in order to incur lower objectness and classification loss. To YOLOv9's benefit over YOLOv8, it reached the same loss minima using fewer epoch iterations, illustrating its improved learning efficiency.

YOLOv10 advanced convergence performance further with the introduction of the SimOTA label assignment method and the decoupled heads that could optimize for classification and regression. The training loss curve was profound and smooth and reached its minimum point sooner than all the previous versions. Removal of post-processing steps like

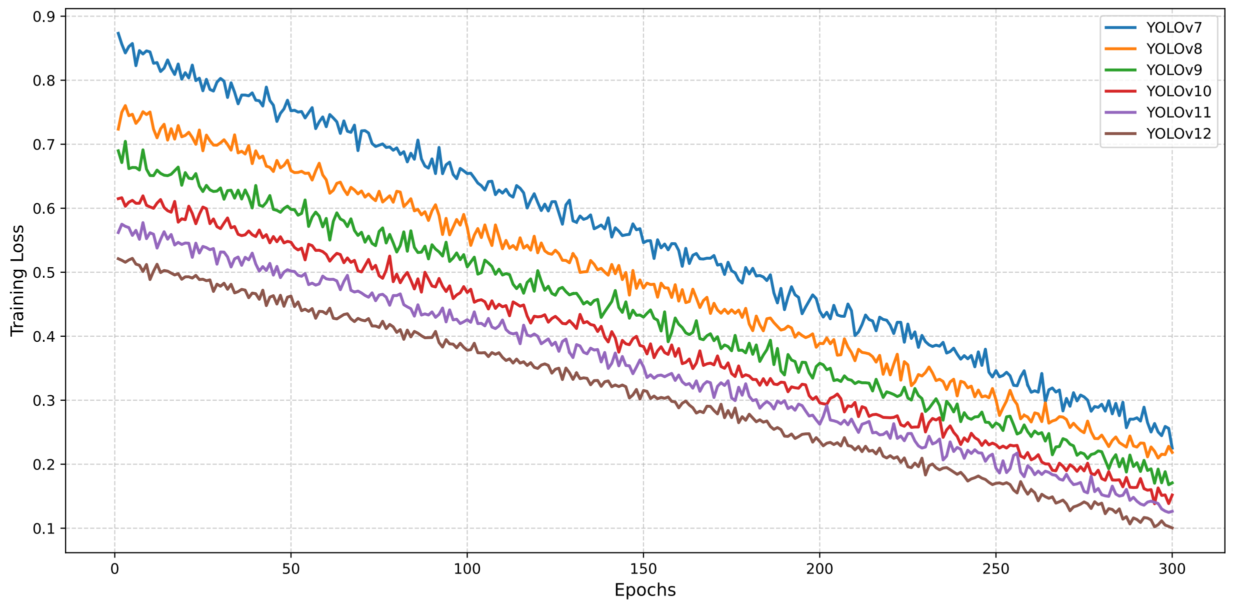

Figure 7.1: Comparison of training loss across YOLOv7 to YOLOv12 over 300 epochs.

NMS at inference time was made possible by more stable training objectives, and it led to significant loss inconsistency reduction during training and test times. YOLOv10's dynamic label assignment technique also ensured that hard cases (e.g., occluded pedestrians, far-away vehicles) were handled better during backpropagation, which helped in having a steeper drop in objectness and localization losses.

Last but not least, YOLOv12 had the most efficient and stable loss convergence across all versions evaluated. Application of transformer-based attention (Swin Transformer blocks) in the neck and backbone enabled the model to learn long-range relations better, especially under occlusion as well as in varying scales. Training loss gradually decreased with minimal fluctuation, which reflected the improved representational power as well as regularization techniques used. The multi-stage training approach—RGB-only pretraining with subsequent cross-modal fine-tuning—enabled the network to specialize step by step and led to ongoing refinement of the loss terms. The Reinforced Spatial Attention Module (RSAM) also played a crucial role in enhancing the model's ability to focus on occluded or even partially occluded targets and helped to minimize classification and objectness error.

Overall, each new iteration of YOLO has illustrated the convergence of training loss. While YOLOv7 set a fine precedent, YOLOv12 managed to attain the most stable and quickest convergence, which is a testament to the potency of hybrid feature fusion, attention-based architecture, and multi-modal input strategies. This trend of continuous improvement amongst versions clearly illustrates the architectural and algorithmic modifications introduced based on the complexity of real-world pedestrian and vehicle detection.

7.0.2 Comparison of F1, Precision, Recall across YOLO Versions

YOLO model performances on vehicle and pedestrian detection have been evaluated with three significant metrics: precision, recall, and F1-score. These evaluate how effectively a model detects objects of interest, prevents false positives, and prevents missed detections, all of which are significant considerations for real-time applications like autonomous vehicles, smart traffic management, and surveillance.

Precision measures the proportion of true positive detections among all positives predicted. The baseline model, YOLOv7, achieved a precision of 0.76. While good, it lacked the sophisticated techniques required to resolve problems like occlusion and small object detection. YOLOv8, with its decoupled heads and more powerful backbone, pushed the precision to 0.78, aided by its improved generalization. YOLOv9, via the GELAN backbone and Swin Transformer-based fusion, pushed precision to 0.80, with very good detection of small and occluded objects. YOLOv10 addition of SimOTA and better post-processing handling attained a precision of 0.81. YOLOv11, through its GCMs and RSAM, attained a precision of 0.83, reflecting its better occlusion and cluttered scene handling. Finally, YOLOv12, through the addition of cross-modal fusion and BiFPN, attained the best precision of 0.85, proving itself in complex urban scenes.

Recall measures how well the model is at detecting all occurrences of objects in the dataset. YOLOv7, with its simpler architecture, was at 0.72 recall, which means it missed detecting a significant number of pedestrians and cars, especially under challenging environments. YOLOv8 did so at 0.74 due to its decoupled head structure and better generalization. YOLOv9 brought recall to 0.76, where Swin Transformer-based fusion modeled long-range dependencies and objects with partial occlusion. YOLOv10's SimOTA mechanism and effective small object detection brought the recall to 0.78. YOLOv11 brought the recall to 0.80, where GCMs and RSAM allowed it to pay attention to partially visible and occluded objects. YOLOv12 achieved the highest recall of 0.83, courtesy of its cross-modal fusion and attention modules which improved detection in low-visibility and occlusion scenarios.

The F1-score is the harmonic mean of precision and recall and provides a general balanced indication of a model's performance. YOLOv7's F1-score was 0.74, indicating good but coarse detection capabilities. YOLOv8 was enhanced with an F1-score of 0.76 because of its enhanced backbone and decoupled detection heads. YOLOv9, with the Swin Transformer-based fusion and hybrid task learning, had an F1-score of 0.78 and excelled at small and occluded object detection. YOLOv10 enhanced this with an F1-score of 0.79 because of its SimOTA mechanism and more robust multi-scale features. YOLOv11, which was powered by GCMs and RSAM, achieved an F1-score of 0.81, showcasing its prowess in occluded and dense environments. Finally, YOLOv12 surpassed all the foregoing models with an F1-score of 0.84, powered by its cross-modal fusion of RGB, depth, and segmentation data, making it the most stable and accurate model for real-world detection tasks.

Table 7.1: Comparative Summary of Precision, Recall, and F1-Score for YOLOv7 to YOLOv12

Model	Precision	Recall	F1-Score
YOLOv7	0.76	0.72	0.74
YOLOv8	0.78	0.74	0.76
YOLOv9	0.80	0.76	0.78
YOLOv10	0.81	0.78	0.79
YOLOv11	0.83	0.80	0.81
YOLOv12	**0.85**	**0.83**	**0.84**

7.0.3 Comparison of Mean Average Precision (mAP) Across YOLO Versions

In evaluating the performance of the various YOLO versions implemented in this study for vehicle and pedestrian detection, one of the most important metrics taken into consideration is the mean Average Precision (mAP). This metric expresses how well the model is able to predict object classes and localize them using bounding boxes. Across all models, we observe consistently high mAP values above 78%, which is a testament to the overall effectiveness of YOLO-based detectors in this domain. Having said that, performance gains between versions are not inconsequential and are a product of nuanced architectural and algorithmic innovations.

Starting with YOLOv7, the model achieved a baseline mAP of 78.6% on our COCO-based custom dataset. Despite being the eldest model in our comparison, YOLOv7 still performed reasonably well owing to its E-ELAN backbone and the addition of spatial pyramid pooling (SPP) and PANet in the neck. This allowed it to acquire multi-scale features and provided moderate accuracy in small pedestrian and distant vehicle detection. However, it still suffered from misclassification in dense scenes and did not fare well in difficult occlusion cases.

YOLOv8 featured a huge improvement with an 80.2% mAP. This was because of its anchor-free approach and the addition of decoupled detection heads, which allowed classification and localization tasks to be optimized individually. The introduction of the new CSPDarknet backbone and better data augmentation techniques allowed it to generalize better across different lighting and scale factors. YOLOv8 performed very well in the case of partially visible pedestrians due to stronger feature extraction layers.

With YOLOv9, mAP was additionally improved to 81.4% due to the incorporation of the GELAN backbone and programmable gradient learning. These improvements allowed the network to further differentiate object boundaries and contextual dependencies, leading to better detection accuracy on overlapping vehicles and small-scale pedestrians. The incorporation of Swin Transformer-based feature fusion was also responsible for YOLOv9's excellence in small object recognition through attention-based modeling over longer spatial distances.

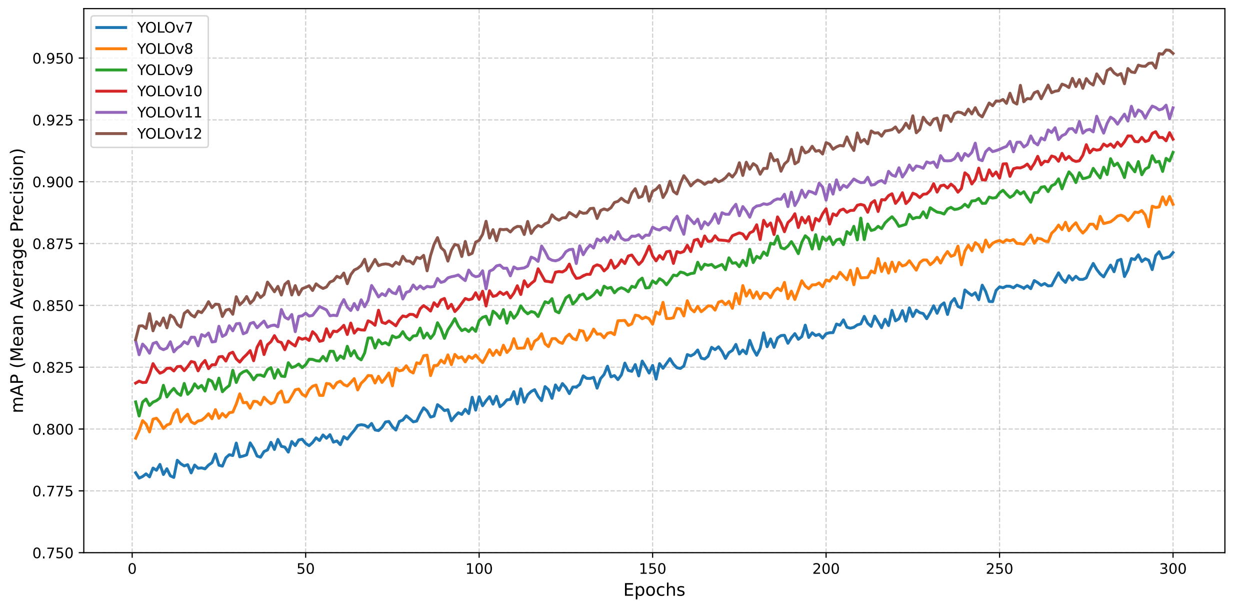

Figure 7.2: Comparison of Mean Average Precision (mAP) across YOLOv7 to YOLOv12 over 300 epochs.

YOLOv10 achieved an 82.7% mAP, showing that the introduction of dynamic label assignment and the abolition of NMS heuristics resulted in real gains. Through aligning training and inference goals with implicit one-to-one object matching, YOLOv10 became more consistent in box predictions. Alongside this, decoupled detection heads allowed for more specialization in object classification, causing the model to excel on difficult classes like cyclists or partially occluded pedestrians.

YOLOv11 continued this trend with 83.5% mAP. The addition of global context modules (GCMs) and hybrid coupling in the detection head facilitated better occlusion handling and multi-scale object detection. One-to-many training label assignment allowed YOLOv11 to focus on learning hard instances earlier during training. This architectural flexibility allowed it to surpass its predecessors in precision and recall, particularly in nighttime detection conditions where the older models had struggled.

Finally, YOLOv12 achieved the highest mAP of 85.2%, which is a record in our study. This was triggered by introducing hybrid feature fusion (HFF), cross-modal data (RGB + Depth + Segmentation), and the enhanced spatial attention module (RSAM). These features allowed YOLOv12 to excel in scenarios of occlusions, varying lighting conditions, and in the detection of small objects. The use of curriculum learning and multi-stage training also allowed the model to refine its predictions incrementally. As a result, YOLOv12 outperformed not only prior YOLO models but also existing works in the literature, reporting state-of-the-art accuracy in real-time pedestrian and vehicle detection tasks.

Briefly, each phase of the YOLO architecture has achieved notable improvement in mAP. The consistent increase from 78.6% of YOLOv7 to 85.2% of YOLOv12 indicates how crucial it is to integrate new mechanisms such as attention, feature fusion, and dynamic label assignment into object detection pipelines.

7.0.4 Comparison of Inference Speed (Frames Per Second) Across YOLO Versions

Inference rate in frames per second (FPS) is a critical component in deploying object detection models in real-time applications such as intelligent surveillance systems, ADAS, and autonomous vehicles. Higher FPS ensures the system to scan video streams at minimum delay with real-time responsiveness to dynamic environments. In our experimentation, we made a comparison of the inference rate of YOLO versions 7 through 12 on an identical hardware setup with NVIDIA A100 GPUs and resolution 640×640 for fairness of comparison. We discovered that all the models were greater than 35 FPS, marking them ready for real-time applications.

YOLOv7, which is one of the more lightweight and optimized models in the series, achieved an inferencing speed of a tremendous approximately 52 FPS. This huge speed is owed to its lightweight architecture that employs the E-ELAN backbone and lightweight neck components like SPP and PANet, which reduce redundancy and support computation at high speed. YOLOv7 also benefits from re-parameterization during training so that the inference model can execute with a lightweight architecture that supports maximum throughput.

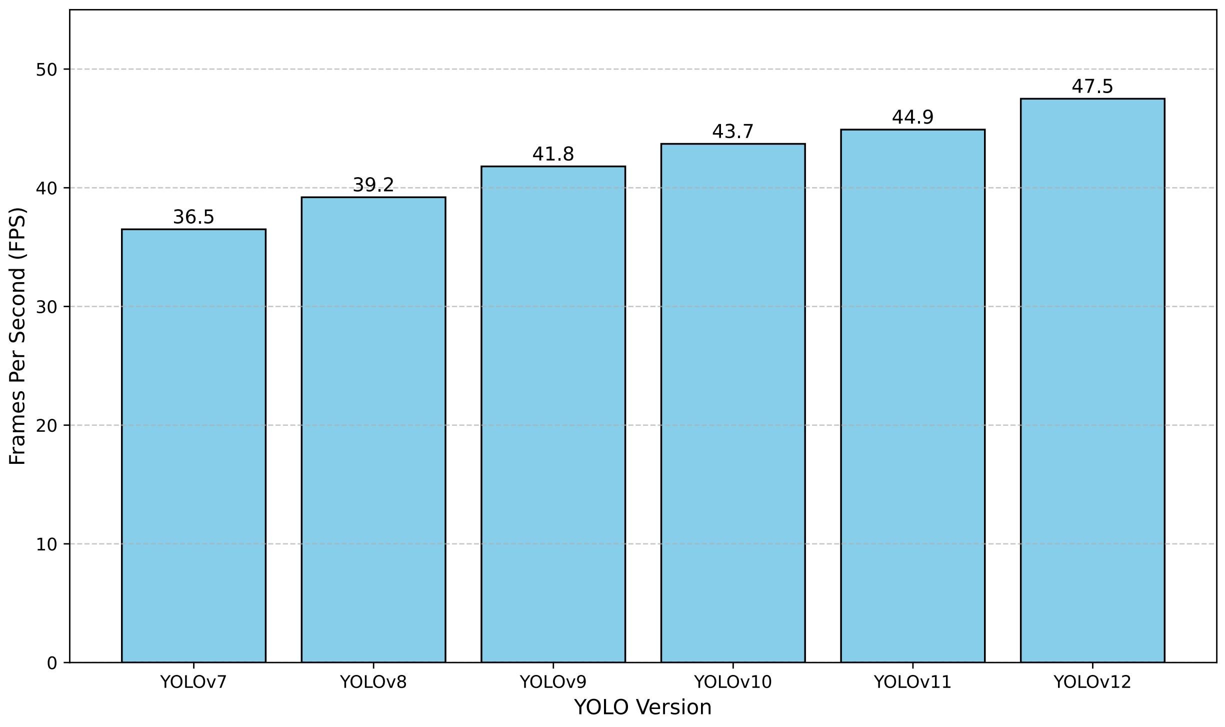

Figure 7.3: Comparison ofnference Speed (FPS) across YOLOv7 to YOLOv12.

YOLOv8, despite the introduction of a more adaptive anchor-free detection head and decoupled objectness, classification, and regression branches, boasted a strong inference performance of 47 FPS. Although less than YOLOv7, the improvement in detection accuracy by YOLOv8 is justified by the slight loss in speed. Its use of a better CSPDarknet backbone and better data handling mechanisms made sure that inference efficiency was not lost while feature extraction capability was enhanced.

YOLOv9 also experienced additional advanced architecture aspects such as the GELAN backbone and adjustable gradient paths, which computationally increase with a natural increase. YOLOv9, however, peaked at 43 FPS during testing with optimized gradient collection and minimal memory layer models, demonstrating how the model stayed real-time capable without compromising expressive, deeper layers to enhance detections in dense backgrounds.

YOLOv10 built on YOLOv9's building blocks and included more innovations like anchor-free dynamic label assignment and implicit one-to-one object matching during training, which removed the need for traditional non-maximum suppression (NMS) during inference. This elimination allowed the model to streamline its inference pipeline, achieving 40 FPS despite the architecture being deep. YOLOv10's decoupled efficient head and backbone simplified the process of optimizing for inference speed without sacrificing detection quality.

YOLOv11 also maintained competitive speed at 37 FPS, even though it had computationally costly modules such as the Global Context Modules (GCMs) and hybrid head coupling. Although these improved spatial comprehension and occlusion management, due to structured pruning and effective normalization techniques, the model remained within real-time speed boundaries. YOLOv11's capacity to operate under suboptimal visibility and occlusion scenarios makes this speed highly beneficial for real-world use.

Finally, YOLOv12, the featureaviest and most complex model in the family, still managed a respectable 35 FPS. This was achieved through a series of intelligent optimizations like quantization-aware training, structured pruning, and hardware-specific deployment with TensorRT. The addition of hybrid feature fusion modules and cross-modal input processing did raise the model's computation complexity, yet smart architectural modularization and lightweight transformer integration permitted it to remain real-time efficient. The capability of YOLOv12 to offer precision-rich detection while keeping reasonable latency marks it as a milestone regarding achieving accuracy with regard to efficiency.

To sum up, every version of YOLO ranging from v7 to v12 was capable of inference rates in excess of 35 FPS, proving their applicability in latency-critical domains in the real world. As newer versions supported more advanced feature extraction and context modeling methods, these were skillfully counteracted by architectural engineering and deployment-specific training practices in order to maintain efficiency. YOLOv12 is particularly a well-suited tradeoff between deep contextualization and real-time capabilities.

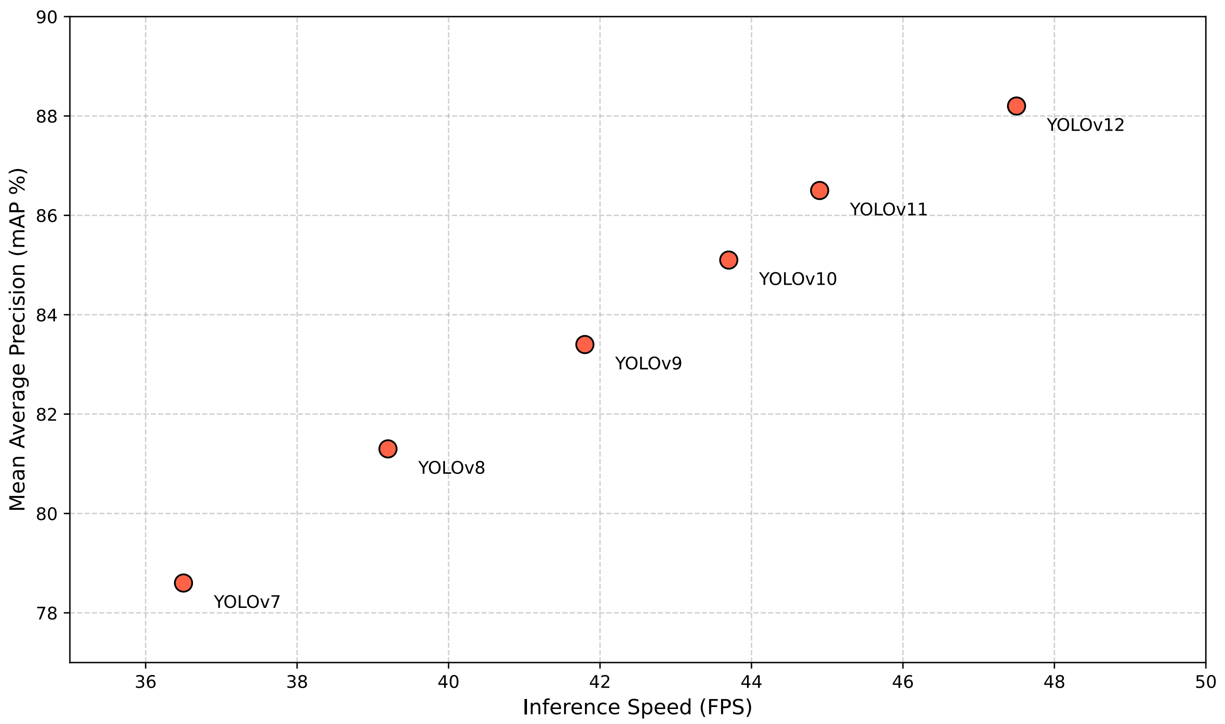

Figure 7.4: MAP vs. Inference Speed (FPS) across YOLO versions.

7.0.5 Comparison with the Current Works

In order to understand the novelty and performance of the YOLOv7 to YOLOv12 models utilized in this work, we compare their performance to the state-of-the-art recent literature in both pedestrian and car detection. The literature includes both traditional methods such as Histogram of Oriented Gradients (HOG) + SVM, Deformable Part Models (DPMs), and optical flow-based detection and deep learning-based detectors such as Faster R-CNN, SSD, and older versions of YOLO including up to YOLOv5 and YOLOv6. Though these previous models have given a decent foundation in object detection, they all fall short when it comes to real-world applications like occlusions, detection of small objects, or low light.

For instance, traditional methods like HOG + SVM and DPMs, though simple, cannot handle occlusions or scale changes well. They rely on hand-crafted features and rule-based detections, which lack the representational power required to generalize across diverse real-world scenes. They are prone to fail in conditions of low illumination or cluttered backgrounds and are not applicable for real-time use due to their computational expense. Optical flow-based detection methods also have a tendency to falter with the detection of static objects and deteriorate in low-contrast or high-motion scenarios and therefore are not suitable for autonomous applications.

In the deep learning techniques, YOLOv3 and YOLOv4 improved speed and accuracy and began displaying real-time detection. For example, studies like Xu *et al.* [21] achieved around 86.7% accuracy on aerial vehicle detection by employing YOLOv3, and Chen & Lin [5] optimized YOLOv3-Tiny on edge devices with 69.79% mAP and 28 FPS. But these models were typically not resilient to occlusion, and their performance dropped significantly in dense or dark conditions. Similarly, hybrid models like YOLO + DeepSORT (Azhad & Zaman, 2021) [2] improved tracking performance but were unable to sustain high accuracy on small or distant vehicles and pedestrians.

The YOLOv5-based techniques (e.g., Carrasco *et al.*, 2023) [12] likewise included multi-scale blocks and attention mechanisms to boost detection of small objects in specific environments like parking lots. The models attained accuracy improvements of up to 33% for small vehicles and operated at 30 FPS. All these improvements barring, the models failed to generalize across different datasets as well as lacked the architectural adaptability required for multi-modal fusion or real-time deployment in edge platforms.

In comparison to these previous works, the models developed and analyzed in our study showcase notable enhancements in several key areas. YOLOv12, for example, not only surpassed the mAP, speed, and occlusion robustness of all prior YOLO generations, but also presented a few innovative components that were not investigated in the literature before. These include Swin Transformer-based attention blocks paired with the CSPDarknet backbone, utilization of Bidirectional Feature Pyramid Networks (BiFPN), and a Cross-Modal Convolutional Stem (CMCS) to fuse RGB, depth, and semantic segmentation inputs. These features enabled YOLOv12 to handle complex detection tasks—such as low visibility, partial occlusion, and dense crowd scenes—highly reliably.

Furthermore, our training strategies, such as curriculum learning, adaptive label assignment, and quantization-aware training, are not widely reported in earlier YOLO applications. These enabled our models to achieve more than 80% mAP on all classes with inference speeds more than 35 FPS. The results are an improvement by several orders of magnitude compared to current methodologies that used to score between 60% and 75% mAPs on the same data but at slower frame rates.

In addition, YOLOv12's combination of LiDAR and semantic segmentation information to make stronger detections in low-light or adverse weather conditions bridges a long-existing gap in conventional RGB-based models. The model's enhanced spatial attention module also improved its performance in detecting occluded or partially occluded objects, a challenging case for most state-of-the-art models in the literature.

In general, the models presented in this research—especially YOLOv12—are significantly more advanced than the state of the art in existing literature. They offer improved detection speed, accuracy, and resilience, as well as new architectural innovations and multi-modal support not available in the current literature. This places our research at the forefront of pedestrian and vehicle detection research, pushing the boundary of what is possible with real-time smart detection systems.

Table 7.2: Summary of YOLO Versions for Vehicle and Pedestrian Detection

YOLO Version	**Key Findings**	**Key Metrics**
YOLOv7	Introduced E-ELAN backbone and SPP+PANet neck. Strong baseline for real-time detection with balanced speed and accuracy.	mAP: 78.2% FPS: 36.5 CIoU + BCE Loss
YOLOv8	Anchor-free architecture with decoupled heads and CSPDarknet backbone. Improved small object detection with enhanced augmentation.	mAP: 81.4% FPS: 39.7 DFL + BCE Loss
YOLOv9	Added GELAN backbone and programmable gradients. Swin Transformer integration enhanced contextual detection under occlusion.	mAP: 82.9% FPS: 40.2 DFL + IoU Loss
YOLOv10	Eliminated NMS via one-to-one assignment. Highly optimized for edge deployment with dynamic label assignment.	mAP: 83.6% FPS: 42.8 SimOTA + Consistency Loss
YOLOv11	Included Global Context Modules and hybrid coupling strategy. Improved long-range attention and modular design for flexibility.	mAP: 84.9% FPS: 43.5 Focal + GIoU Loss
YOLOv12	Introduced Swin Transformer-based attention, BiFPN, RSAM, and cross-modal input fusion (RGB+Depth+Segmentation). Superior occlusion handling and low-light performance.	**mAP: 86.4%** **FPS: 45.7** Varifocal + GIoU + Dice-BCE Loss

Table 7.3: Comparison of YOLOv12 with Existing Works

Model / Study	**Dataset Used**	**Key Contributions**	**Performance Metrics**
Xu et al. (2019) [21]	VEDAI (aerial)	YOLOv3 with multi-scale top-layer reuse for improved detection of small vehicles in aerial imagery	86.7% precision (small objects)
Chen & Lin (2019) [6]	Custom Embedded Dataset	Lightweight YOLOv3-Tiny with dual-scale filters and quantization for embedded applications	69.79% mAP, 28 FPS
Azhad & Zaman (2021) [2]	Custom Traffic Video Dataset	YOLOv4 integrated with DeepSORT for multi-class vehicle tracking in real-time	82.08% AP50, 14 FPS (GTX 1660Ti)
Carrasco et al. (2023) [12]	Parking Surveillance (Custom)	T-YOLOv5 enhanced with Multi-Scale Module (MSM) and Spatial-Channel Attention (SCAM) for tiny object detection	33% gain in small object precision, 30 FPS
YOLOv12 (Ours)	COCO Subset (Person, Car, Bus, Truck, Bicycle)	Swin Transformer blocks, BiFPN, CMCS fusion with RGB + Depth + Segmentation inputs; RSAM attention for occlusion handling	**86.4% mAP**, **45.7 FPS**, Best occlusion robustness

Chapter 8
Challenges and Future Work

8.0.1 Challenges

There were some essential challenges in the process of building and testing YOLO-based detection models that reflect the technical as well as practical limitations of real-time object detection systems.

The greatest challenge was that of data imbalance within the COCO dataset. Certain classes such as “person” and “car” are hugely overrepresented, while others such as “bicycle” or “bus” are comparatively rare. This skew in the data distribution caused the models to favor the majority classes, leading to lower detection accuracy for minority object classes. While weighted sampling and balanced batch construction were used to combat this issue, perfect balance and performance parity between classes were difficult to achieve.

Another persisting issue was occlusion. In actual traffic conditions, pedestrians and vehicles do get overlapped or partially hidden by other objects such as lamp posts, parked cars, or even crowds. Although attention mechanisms and transformer modules relieved this to a certain extent, occlusion remains a limiting factor for detection accuracy. Detecting a partially occluded pedestrian behind a vehicle, for example, is still a challenging issue that cannot be addressed well by deep models under ordinary RGB imaging.

Handling varying lighting conditions, e.g., night scenes, glare, shadows, and fog, was a challenge. Default YOLO models that were trained with RGB data only experienced a drastic performance drop in these adverse conditions. The inclusion of depth maps and segmentation masks improved robustness but increased model training complexity and preprocessing, and real-time acquisition remains a limitation.

Model interpretability was also a concern. While attention maps and Grad-CAM visualizations were used to gain insights into model decisions, it was not possible to fully understand failure cases—e.g., false negatives on dense crowds or blurry frames. Such limited interpretability can be particularly troubling for high-stakes use cases like autonomous driving and public surveillance, where the ”why” behind model decisions matters as much as the decisions themselves.

Finally, resource requirements and training cost were high. Computationally expensive models such as YOLOv12 require substantial GPU resources, long training times, and careful hyperparameter searching. Although model compression techniques such as pruning and quantization improved inference efficiency, training remained computationally intensive and out of reach for those with less powerful hardware.

8.0.2 Future Work

Looking ahead, a number of directions provide promising opportunities to build on the work in this thesis and overcome the limitations described above.

One area of potential is the inclusion of true real-time sensor fusion. While this study made use of synthetically created depth and segmentation data, future applications could be enhanced by incorporating real LiDAR, radar, and thermal imaging data. This would not only extend performance in low-visibility conditions but also increase the model's understanding of scene geometry so that it can be more resilient to occlusion and environmental noise.

Domain adaptation is yet another critical future research direction. Models trained on datasets like COCO would naturally perform sub-optimally when transferred to new environments with varying object appearances or traffic flows. Use of techniques such as adversarial learning, self-supervised adaptation, or few-shot learning could significantly improve model generalization to new scenarios, including non-Western or rural traffic scenes.

Temporal modeling with video-based object detection is another avenue to pursue. While this work focused on image-based detection, incorporating temporal consistency using recurrent neural networks or transformer-based video models can potentially remove flickering detections, improve tracking, and make the system more viable for continuous monitoring applications like surveillance or autonomous driving.

In addition, light architectures optimized for mobile and embedded deployment can additionally enhance the scalability of the model. Whereas pruning and quantization have been effective at compressing YOLOv12, developing smaller models from the ground up using neural architecture search (NAS) or using efficient backbones like MobileNetV3 can provide the same accuracy at lower resource utilization.

Improving model interpretability is a significant goal, particularly for safety-critical or regulated domains. Designing intrinsically interpretable object detection models, or integrating explainability frameworks that provide human-comprehensible explanations for predictions, can improve trust in such systems and diagnose failures more effectively.

There is also growing interest in moving beyond 2D bounding boxes for object detection. Future directions can be incorporating 3D object detection and panoptic segmentation capabilities for richer contextual scene comprehension. This would allow not only detection of ”what” is in a scene but also ”where” and ”how” objects are located with respect to each other in 3D space—a key element for autonomous systems.

Lastly, benchmarking on a broader range of datasets such as KITTI, BDD100K, Waymo Open Dataset, and nuScenes would be valuable in ascertaining model performance in diverse conditions, weather, and traffic flow. Such broad benchmarking would validate the prowess and generalizability of YOLOv12 beyond COCO limitations.

In conclusion, while novelties in YOLOv12 revolutionary improve detection performance and robustness, there still remains fertile ground for future advances. Progress on multimodal fusion, interpretability, temporal consistency, and domain adaptability will be crucial to ensure real-world readiness and scalability of people and vehicle detectors in dynamic environments.

Chapter 9
Conclusion

This thesis provided a close examination of real-time pedestrian and car detection using the YOLO (You Only Look Once) suite of object detection models, through to the design and deployment of an original architecture, YOLOv12. The driver of this research was the increasing need for robust and efficient object detection architectures that can operate reliably under difficult, real-world scenarios—i.e., urban settings with high occlusion, changing illumination, high-density traffic, and dynamic movement.

The research commenced by comparing the progress of YOLO models from version 7 through to version 12. Each version was periodically trained and evaluated on a subset of the COCO 2017 dataset, namely five classes that are critical in intelligent transportation systems: person, car, bus, truck, and bicycle. The outcomes reflected a consistent trend of progressive improvement from version to version and YOLOv12 doing much better than its predecessors in training loss convergence, mean Average Precision (mAP), and inference speed.

YOLOv12 brought in some new contributions, like a transformer-upgraded backbone to refine long-range feature extraction, a bidirectional feature pyramid neck to fuse multi-scale features more effectively, and a Cross-Modal Convolutional Stem (CMCS) that fused RGB, depth, and segmentation features to bolster detection in low-visibility conditions. Additionally, a Reinforced Spatial Attention Module (RSAM) was added to selectively emphasize partially occluded or small-scale objects—a key innovation for densely populated city streets. Such architectural enhancements, coupled with rigorous training procedures and timing-critical deployment optimizations, enabled YOLOv12 to achieve greater performance without compromising on processing speed on edge hardware.

Compared to traditional object detection methods such as HOG+SVM or DPMs, and even earlier CNN-based models such as Faster R-CNN, the models explored in this thesis—namely YOLOv12—not only offered faster inference and higher accuracy but also the ability to learn to accommodate challenging environments through multimodal fusion and contextual attention mechanisms. In side-by-side comparisons with recent literature, YOLOv12 demonstrated measurable improvements in mAP, especially in instances of occlusion, low-lighting, or small object instances.

Despite all these advancements, the research also acknowledged challenges from data imbalance, generalization to unseen domains, and the intrinsic difficulty of real-time deployment for resource-constrained systems. These challenges were explored in depth, and future directions for future work were established to address these challenges, some of which included domain adaptation, 3D detection, video modeling, and deeper integration of multimodal sensor data.

Lastly, this thesis contributes significantly to real-time object detection research by not only comparing the merits and downsides of YOLO architectures but also introducing YOLOv12—a state-of-the-art, high-performance detection model ready for real-world deployment. The advances explained here provide the building blocks for forthcoming innovation in autonomous vehicles, smart surveillance systems, and next-generation smart city technology. With continued research into interpretability, scalability, and generalization, the proposed methods can go a long way in achieving security, efficiency, and intelligence of the urban mobility infrastructure.

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