INDUSTRIAL ORIENTED MINI PROJECT

Report

On

SMART TRAFFIC LIGHT CONTROL SYSTEM USING YOLOv3

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

INFORMATION TECHNOLOGY

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CERTIFICATE

This is to certify that the **Industrial Oriented Mini Project** entitled **SMART TRAFFIC LIGHT CONTROL SYSTEM USING YOLOv3** submitted by **Maroju Krishna Sahee (23265A1205)** and **Pinninti Soumya (23265A1206)** in partial fulfillment of the requirements for the Award of the Degree of Bachelor of Technology in Information Technology as specialization is a record of the bona fide work carried out under the supervision of **Mrs. A. V. L. PRASUNA**, and this has not been submitted to any other University or Institute for the award of any degree or diploma.

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DECLARATION

We hear by declare that the **Industrial Oriented Mini Project** entitled **SMART TRAFFIC LIGHT CONTROL SYSTEM USING YOLOv3** is an original and bona fide work carried out by us as a part of fulfilment of Bachelor of Technology in Information Technology, Mahatma Gandhi Institute of Technology, Hyderabad, under the guidance of **Mrs. A. V. L. PRASUNA, Assistant Professor,** Department of IT, MGIT.

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ABSTRACT

Urban traffic congestion, particularly at intersections, poses a persistent challenge due to the reliance on conventional fixed-timer traffic light systems. These systems operate based on predetermined schedules that do not account for real-time road conditions, often leading to unnecessary delays, increased fuel consumption, and safety concerns for both vehicles and pedestrians. To address these inefficiencies, this project introduces a Smart Traffic Light Control System that utilizes computer vision to dynamically adjust traffic signal timings based on actual traffic density.2f

The system integrates YOLOv3, a fast and accurate object detection algorithm, with OpenCV to process live or recorded video feeds. It detects and counts the number of vehicles and pedestrians approaching an intersection in real time. Based on the object counts, the system intelligently calculates the appropriate duration for the red signal, ensuring smoother traffic flow and safer pedestrian crossings. This adaptive mechanism replaces static timing with a more responsive and efficient control strategy.

This smart traffic system reduces congestion, lowers emissions by minimizing vehicle idling, and enhances pedestrian safety through dynamic signal adjustments. It improves overall traffic efficiency using real-time object detection and analysis. Designed for scalability, the system can integrate with live CCTV feeds, Arduino or Raspberry Pi controllers, and broader smart city networks, offering a modern, AI-powered solution for safer and more sustainable urban traffic management.

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1. INTRODUCTION

1.1 Motivation

Modern cities are increasingly grappling with complex traffic challenges stemming from rapid urbanization and the growing number of vehicles and pedestrians. Traffic congestion, road safety concerns, and environmental degradation have become pressing issues in most urban areas. One of the key contributors to these problems is the reliance on traditional traffic light systems, which operate on predetermined, fixed timers. These static systems do not account for real-time fluctuations in traffic density or pedestrian movement. As a result, vehicles are often left idling at intersections even when there is no cross-traffic, while roads with heavier congestion may receive insufficient green light time. This inefficiency not only causes unnecessary delays and commuter frustration but also results in increased fuel consumption, higher carbon emissions, and a greater likelihood of road accidents.

Pedestrians face similar challenges. Traditional signal systems may not provide sufficient crossing time or fail to detect the actual presence of people waiting to cross, putting them at risk and compromising safety. The disconnect between actual road usage and fixed signal patterns leads to an imbalance in traffic management that affects everyone on the road.

Witnessing these shortcomings in real-world traffic scenarios, we were motivated to design a smart solution capable of adapting to live traffic dynamics. Our approach leverages **YOLOv3 (You Only Look Once)** — a powerful, real-time object detection algorithm — in conjunction with **OpenCV**, a robust computer vision library. This combination enables our system to detect and count vehicles and pedestrians from live video feeds with high accuracy and speed.

Our system uses real-time visual data to dynamically adjust traffic signals based on actual road conditions, reducing idle wait times and prioritizing flow where needed. This improves vehicle movement, enhances pedestrian safety, and lowers fuel use and emissions. The goal is a scalable, cost-effective solution for smarter, safer, and more efficient urban traffic control.

1.2 PROBLEM STATEMENT

In today’s rapidly urbanizing world, the efficient management of road intersections has become a pressing challenge. Intersections serve as critical points within urban transportation networks, where multiple streams of traffic converge. However, they often become major bottlenecks due to the reliance on outdated, time-based traffic signal systems. These conventional systems operate on pre-programmed schedules that do not adapt to the dynamic nature of real-world traffic. They lack the situational awareness necessary to respond to varying road conditions, resulting in scenarios where green lights are underutilized, red signals persist unnecessarily, and road users — both pedestrians and drivers — are subjected to excessive delays.

This rigid and non-adaptive control mechanism contributes to a host of urban issues. Commuters experience increased frustration due to prolonged wait times, which in turn leads to a loss in productivity. The unnecessary idling of vehicles at traffic signals also leads to higher fuel consumption and emissions, exacerbating urban air pollution and contributing to climate change. Furthermore, inefficient signal timing compromises pedestrian safety, especially at busy crosswalks where pedestrians may be forced to wait longer or may cross unsafely due to impatience.

The core challenge lies in designing a smart, adaptive system that can perceive and respond to traffic conditions in real-time. Such a system must be capable of accurately detecting and analyzing the flow of vehicles and pedestrians at intersections using advanced sensors or video feeds. It should intelligently assess the density and movement patterns of road users and dynamically adjust signal timings to optimize traffic flow. Crucially, this process must operate autonomously, without the need for manual intervention, and be robust enough to handle the complex, unpredictable nature of urban environments.

Solving this challenge necessitates the integration of fast and accurate object detection algorithms — such as those powered by deep learning frameworks like YOLO (You Only Look Once) — with adaptive traffic control logic. These algorithms must be deployed in a real-time processing pipeline capable of functioning on embedded systems or edge devices. Additionally, the system must be scalable, cost-effective, and easily integrable with existing infrastructure to ensure widespread adoption.

By bridging the gap between traditional traffic management and intelligent automation, cities can significantly enhance their transportation efficiency, reduce environmental impact, and improve safety for all road users. The adoption of such smart traffic control systems represents a vital step toward building sustainable and intelligent urban infrastructure for the future.

1.3 EXISTING SYSTEM

Most traffic lights used in cities today work on fixed timers. This means the lights change colors after a set amount of time, no matter how many cars or pedestrians are waiting. Because of this, sometimes vehicles and people have to stop and wait even when there is no traffic coming from other directions. This can waste time and make people impatient.

These fixed-timer systems also struggle during busy times like rush hours or special events. They cannot adjust to the increase in traffic, which leads to long lines of cars and traffic jams at intersections. Pedestrian signals also do not always match the number of people waiting to cross. Sometimes they give too much crossing time when no one is there, or not enough time when many people want to cross.

Because of these problems, cars often have to idle longer, which wastes fuel and increases air pollution. Since fixed systems cannot respond to real-time traffic conditions, there is a clear need for smarter traffic lights. These advanced systems would use sensors or cameras to detect how many vehicles and pedestrians are waiting and adjust the light timings accordingly, making traffic flow better and safer for everyone.

1.3.1 Limitations

- **Inefficient Waiting Times:** Fixed-timer traffic lights change signals after a set duration without considering the actual number of vehicles or pedestrians waiting. This often results in unnecessary waiting, where vehicles and people remain stopped even when there is little or no traffic coming from other directions. Such delays waste time and reduce the overall efficiency of road use, frustrating drivers and pedestrians alike.
- **Inability to Handle Traffic Variations:** Traffic volumes change throughout the day due to factors like rush hours, special events, or accidents. Fixed-timer systems cannot adjust their signal timings based on these fluctuations, which causes long queues and traffic jams during peak periods or unexpected situations. This lack of flexibility leads to poor traffic flow and increased congestion.
- **Lack of Prioritization for Emergency Vehicles:** Emergency vehicles such as ambulances, fire trucks, and police cars need quick passage through intersections to respond to urgent situations. Traditional fixed systems do not have the ability to detect these vehicles or give them priority by changing lights in their favor. This delay can slow down emergency response times, potentially risking lives and property.

- **Increased Fuel Consumption and Pollution:** When vehicles idle for longer periods at red lights due to poorly timed signals, they consume more fuel and emit higher levels of harmful gases like carbon dioxide and nitrogen oxides. This contributes to air pollution and environmental degradation, especially in densely populated urban areas with heavy traffic.
- **No Real-Time Adaptability:** Traditional systems operate in isolation and are not integrated with real-time traffic monitoring tools. They cannot detect sudden changes in traffic behavior such as roadblocks, accidents, or weather-related disruptions, resulting in delayed responses and poor adaptability.
- **Lack of Pedestrian Safety Measures:** Pedestrians may not get adequate crossing time or may be forced to wait excessively due to unresponsive signals. In some cases, crosswalk lights may not be synchronized with actual foot traffic, increasing the risk of accidents and reducing pedestrian confidence in the system.

1.4 PROPOSED SYSTEM

The proposed system for signal control uses smart technology called YOLOv3 and OpenCV to watch the roads through cameras. It can detect and count how many vehicles and pedestrians are waiting at the traffic lights by recorded video. This helps the system understand the current traffic situation accurately.

Based on the number of vehicles and people detected, the system changes the length of the red light automatically. If there are fewer vehicles or pedestrians, the red light will be shorter, so they don’t have to wait unnecessarily. This helps reduce traffic jams and makes moving through intersections faster and smoother. It also prioritizes safety by ensuring enough time is given for pedestrians to cross during busy periods.

The system also has an easy-to-use display that shows the number of cars and pedestrians waiting, along with the timing of the lights, right on the video screen. This makes it simple for traffic controllers to keep an eye on what’s happening and quickly respond to any unusual traffic situations.

Moreover, by reducing unnecessary waiting and vehicle idling, the system helps lower fuel consumption and decrease harmful emissions, contributing to a cleaner environment. The adaptive nature of the system also makes it suitable for various traffic conditions, including peak hours, emergencies, and special events.

1.4.1 ADVANTAGES

- **Reduces Waiting Time:** The system adjusts traffic light durations based on the actual number of vehicles and pedestrians detected at the intersection. This reduces unnecessary red light waiting time, helping commuters move more efficiently and with less frustration.
- **Improves Traffic Flow:** By dynamically updating signal timings according to real-time traffic conditions, the system minimizes bottlenecks and keeps traffic moving smoothly, especially during peak hours or events. This results in faster and more consistent travel times.
- **Increases Efficiency of Traffic Management:** Real-time data and analytics are provided to traffic operators, helping them monitor and manage multiple intersections more effectively. This leads to quicker and smarter decisions, improving the responsiveness of traffic control systems.
- **Easy Monitoring and Control:** A user-friendly interface displays live counts of vehicles and pedestrians, current light statuses, and traffic trends. This simplifies oversight and allows operators to intervene when needed with minimal effort.
- **Emergency Vehicle Prioritization:** The system can detect approaching emergency vehicles like ambulances or fire trucks and instantly adjust signals to give them priority. This helps reduce emergency response times and can save lives during critical situations.
- **Enhanced Pedestrian Safety:** By detecting the actual presence of pedestrians at crosswalks, the system ensures safe crossing times and reduces the risk of pedestrian-related accidents, especially in crowded or high-speed traffic zones.
- **Fuel and Emissions Reduction:** Less idling time at intersections means reduced fuel consumption and lower emissions of harmful gases. This contributes to a cleaner environment and supports sustainable urban development.
- **Scalability and Integration with Smart Cities:** The system is modular and scalable, making it easy to deploy across multiple intersections. It can also be integrated with IoT devices, surveillance systems, and other smart city technologies for a holistic traffic management solution.
- **Adaptability to Unusual Situations:** Whether it's an accident, a public gathering, or road construction, the system can adapt to sudden changes in traffic conditions, helping avoid unexpected congestion or dangerous traffic buildup.
- **Cost-Effective in the Long Run:** Although initial deployment may require investment, the long-term benefits — such as reduced fuel usage, fewer traffic personnel, lower

maintenance of outdated infrastructure, and better traffic flow — lead to substantial cost savings for municipalities.

1.5 OBJECTIVES

- Develop a real-time vehicle and pedestrian detection system using YOLOv3 and OpenCV.
- Dynamically adjust signal timings based on traffic density to reduce congestion.
- Provide a user-friendly interface for real-time traffic data and signal monitoring.
- Enhance traffic management with real-time analytics and responsive control.
- Improve traffic flow, reduce idle time, and lower fuel consumption and emissions.

1.6 HARDWARE AND SOFTWARE REQUIREMENTS

1.6.1 SOFTWARE REQUIREMENTS

- **Software**
  The system is developed using VS Code as the integrated development environment (IDE) for Python. VS Code offers a lightweight and flexible platform for writing, debugging, and running real-time video processing and detection scripts.
- **Primary Language**
  The project is developed in Python, a powerful programming language widely used in computer vision and real-time image processing. Python's compatibility with OpenCV and other AI libraries makes it ideal for this traffic monitoring application.
- **Object Detection Libraries**
  The detection of pedestrians and vehicles is implemented using OpenCV and pre-trained models such as YOLO (You Only Look Once) or Haar Cascade classifiers, allowing for fast and accurate recognition in real-time video streams.
- **Data Visualization & UI Display**
  The interface showing live detection, red light timer, and status indicators is created using OpenCV GUI functions, which allow overlays of text and visuals directly onto the video frame—commonly done by layering transparent overlays using cv2.addWeighted() methods .
- **Supporting Libraries**
  - **NumPy**: For matrix operations and frame processing
  - **time**: For calculating red light intervals

    - **os, cv2, etc.**: For basic file, camera access, and image handling

- **Installation Tools**
  Python libraries are installed using pip, and all dependencies can be listed in a requirements.txt file for easy environment setup.

1.6.2 HARDWARE REQUIREMENTS

- **Operating System:**
  The system is compatible with Windows and Linux-based operating systems. It can run on any platform supporting Python and OpenCV.
- **Processor:**
  An Intel Core i5 or above is recommended to support real-time video processing and object detection tasks without lag.
- **RAM:**
  Minimum 8 GB RAM is required to efficiently manage frame capture, object detection, and GUI display in real-time. Higher RAM (e.g., 16 GB) is preferred for faster performance during long sessions or higher frame resolutions.
- **Storage:**
  At least 2 GB of free disk space is recommended to store scripts, detection logs, and temporary processing files.

2. LITERATURE SURVEY

Wet Zhcu et al. proposed a surveillance-based pedestrian intention prediction system that offers over-the-horizon safety alerts and effectively anticipates pedestrian behavior. While promising, the approach depends heavily on existing surveillance infrastructure and raises significant privacy concerns. Additionally, integrating such systems with vehicle platforms in real-time remains a major challenge.[1]

Mahbubul Alam Palash and Duminda Wijesekera introduced an adaptive traffic signal control framework leveraging CNNs for traffic signal recognition. Their method demonstrated potential in reducing traffic congestion through real-time signal optimization. However, the reliance on Cellular Vehicle-to-Everything infrastructure and associated privacy issues limits its practical deployment, especially in areas with limited network capabilities.[2]

Iswarlya Logeswaran et al. contributed to the field by combining CNN-based pedestrian detection with traffic sign recognition for autonomous vehicles (AVs). This integrated approach is suitable for real-time application and contributes toward safer AV operations. Nevertheless, the absence of adaptive learning or intelligent decision-making in the system presents a notable limitation, particularly in complex urban environments where dynamic responses are crucial.[3]

Chenyao Bai et al. focused on pedestrian tracking and trajectory analysis for security applications. Their solution proved highly accurate in crowded environments but lacked adaptability to varying camera angles, limiting its broader usability. Similarly, Mohammed S.A. Muthanna et al. (2020) developed a real-time pedestrian detection system aimed at enhancing safety in smart cities. Despite its benefits, the approach suffers from high computational requirements, underscoring the need for lightweight, low-cost implementations for wider adoption.[4]

Table 2.1 Literature Survey of Research papers

References	**Author(s) & Year**	**Journal / Conference & Publisher**	**Methodology / Techniques Used**	**Merits**	**Demerits**	**Research Gaps**
[1]	Wet Zhcu et al., 2023	IEEE Trans. on Intelligent Transportation Systems	Deep Learning on pedestrian posture & motion using surveillance video	Enhances pedestrian safety with accurate crossing prediction	Needs high-quality surveillance; privacy concerns	Limited to areas with installed surveillance systems
[2]	Mahbubul Alam Palash & Duminda Wijesekera, 2023	IEEE VTC 2023 – Fall	CNNs trained on SPaT data	Dynamic and adaptive signal control; responsive to real-time traffic	High training data requirement; can miss edge scenarios	CNNs are not always interpretable or optimal under unseen conditions
[3]	Iswarlya Logeswaran et al., 2023	IEEE Access	Deep Q-Network (Reinforcement Learning)	Learns and optimizes over time; reduces vehicle wait time	Requires large training time and computing power	Initial training phase delays practical deployment
[4]	Chenyao Bai, Yi Gong, Xiaojie Cao, 2020	IEEE Access	Multi-agent system for intersection coordination	Decentralized, scalable; good for urban networks	Complex agent communication; potential delays	Needs robust communication protocols for real-world deployment
[5]	M.S.A. Muthanna, Y.T. Lyachek, A.M.O. Musaeed, 2020	IEEE Internet of Things Journal	IoT sensors + Edge Computing	Real-time processing; reduces network latency	Sensor calibration & hardware maintenance issues	Data accuracy depends on sensor conditions and environment

3. ANALYSIS AND DESIGN

The Smart Traffic Light Control System is developed to solve the problem of traffic congestion caused by fixed-timer traffic lights. Traditional systems do not respond to real-time traffic, leading to unnecessary delays and safety risks. In this project, we use YOLOv3 to detect and count pedestrians and vehicles from video input. Based on this count, the red light duration is calculated dynamically using a simple formula. This helps reduce wait times and improve traffic flow.

The system is designed with multiple modules. The Object Detection Module uses YOLOv3 to identify and count objects in the video. The Duration Calculation Module takes the counts and calculates the red light timing. The Video Display Module shows bounding boxes, object counts, and the red light duration on the screen using OpenCV. The Signal Simulation Module displays the red signal status using visuals like a red circle and text overlays.

The design is modular and easy to extend. It currently works with recorded videos but can be upgraded to live CCTV feeds. In the future, it can be connected to real traffic lights using Arduino or Raspberry Pi. It can also support features like emergency vehicle detection and 4-way traffic control. The system combines computer vision, simple logic, and a web server to provide a smart, scalable solution for better traffic management.

3.1 MODULES

Object Detection Module

- The Object Detection Module is responsible for identifying and classifying real-time objects such as vehicles and pedestrians from a live webcam feed or a pre-recorded video file. It uses a pre-trained YOLOv3 model, which includes the configuration file (yolov3.cfg), the weights file (yolov3.weights), and the class labels (coco.names) trained on the COCO dataset. OpenCV handles video capture and frame processing. As each frame is passed through the model, it detects and draws bounding boxes around objects like cars, bikes, and people. These objects are then classified and counted separately as vehicles and pedestrians.

- Input to this module is the video feed and YOLO model files, while the output is a list of detected objects, their labels, bounding boxes, and real-time counts that are forwarded to the next module.

Traffic Duration Calculation Module

- The Traffic Duration Calculation Module determines how long the red signal should stay on, depending on the number of vehicles detected in the current frame. It uses a simple rule-based formula such as red_duration = base_time + (vehicle_count * weight), where base_time is the minimum red light duration and weight is the number of seconds added per detected vehicle. This adaptive logic ensures that areas with higher traffic congestion receive longer red signals to manage flow more efficiently.
- The input to this module is the vehicle count from the object detection module and predefined constants for calculation. The output is the calculated red light duration (in seconds), which is passed to the signal simulation module.

Video Processing and Display Module

- The Video Processing and Display Module is responsible for showing the live video feed with detection results and enabling user interaction. It overlays bounding boxes, labels, and object counts (vehicles and pedestrians) onto each video frame using OpenCV's GUI display functions like cv2.imshow(). It enhances user experience by displaying a clean visual of what's happening in real-time.

Signal Simulation and Timer Module

- Finally, the Signal Simulation and Timer Module simulates the red light phase based on the red light duration calculated earlier. This module displays a countdown timer on the video frame that visually informs how long vehicles must stop. The countdown is updated each second and provides an intuitive simulation of how a smart traffic signal would operate. Though currently limited to red light, it can be extended to include green and yellow signal phases for more realism.
- The input to this module is the red light duration in seconds, and the output is a dynamic, real-time visual timer overlaid on the video feed, demonstrating adaptive traffic light behavior.

3.2 ARCHITECTURE

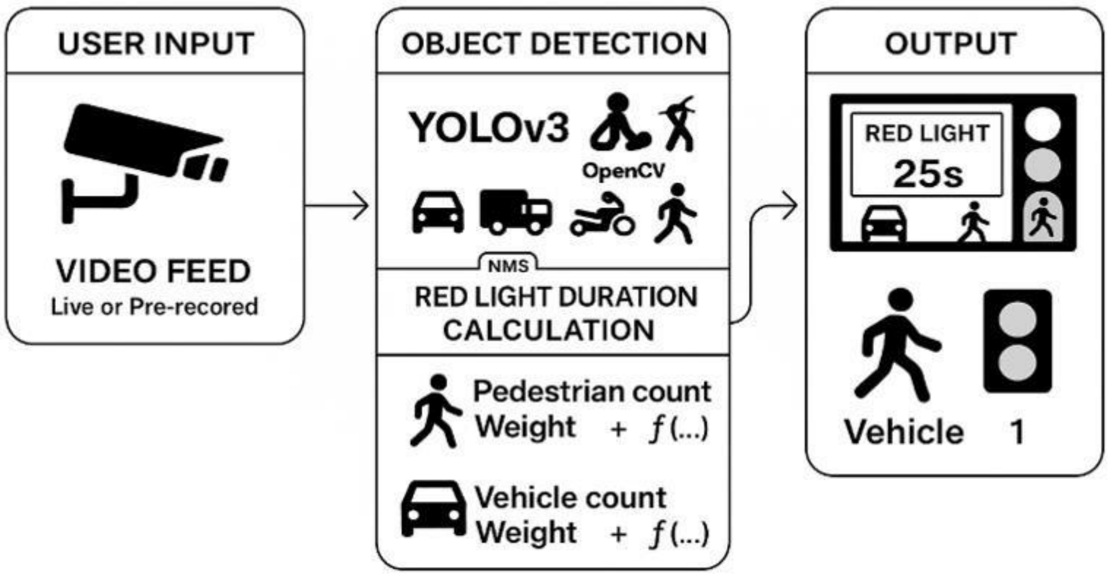


Fig. 3.2.1 Architecture of Smart Traffic Light Control System

The architecture of the Smart Traffic Signal Control System is structured into three main components: User Input, Object Detection and Red Light Duration Calculation, and Output. Each part plays a critical role in enabling the system to function intelligently and respond dynamically to real-time traffic conditions.

The process begins with the User Input stage, where a surveillance camera captures a video feed from a traffic intersection. This feed can be either live or pre-recorded. The purpose of this input is to continuously monitor the traffic environment, providing the system with up-to-date visual data on both vehicular and pedestrian activity. This raw video footage forms the basis for the system's analysis and decision-making.

Next, the video feed is passed into the Object Detection and Red Light Duration Calculation module. This is the heart of the system. Here, the video frames are processed using a deep learning model called YOLOv3 (You Only Look Once version 3), which is capable of detecting multiple objects in real time with high speed and accuracy. YOLOv3 identifies vehicles, pedestrians, bikes, and other relevant objects within the traffic scene. OpenCV, a computer vision library, is used alongside YOLOv3 to handle image processing tasks. To enhance accuracy, Non-Maximum Suppression (NMS) is applied to filter out overlapping detection boxes and retain only the most precise object detections.

Once the objects are detected, the system moves on to calculating the red light duration. This is done using a formula that considers the number of detected pedestrians and vehicles, each weighted according to importance or urgency. For example, a high number of waiting pedestrians might increase the red light duration for vehicles, giving pedestrians more time to cross safely. Similarly, heavy vehicle traffic might adjust the timing in favor of reducing congestion. The function used for calculation ensures the system adapts dynamically based on real-time traffic conditions. Finally, the calculated result is passed to the Output module. This module controls and displays the traffic signal based on the computed duration.

3.3 UML DIAGRAMS

3.3.1 USE CASE DIAGRAMS

A use case diagram is a visual representation that depicts the interactions between various actors and a system, capturing the ways in which users or external entities interact with the system to achieve specific goals. It is an essential tool in system analysis and design, often used in software engineering and intelligent system development. In a use case diagram, actors are entities external to the system that interact with it, and use cases are specific functionalities or features provided by the system, as seen in Fig. 3.3.1.2. These interactions are represented by lines connecting actors to use cases. The diagram helps to illustrate the scope and behavior of a smart traffic control system, providing a high-level view of how external components like cameras and AI models interact with it.

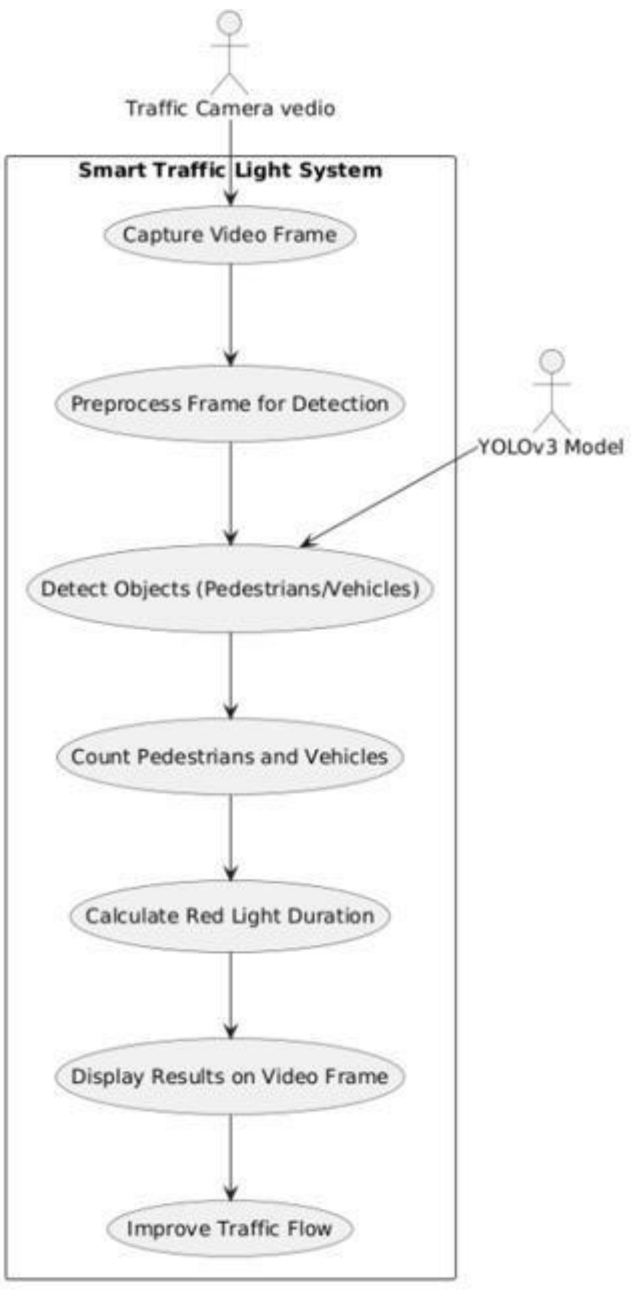

Traffic Camera vedio
Smart Traffic Light System
Capture Video Frame
Preprocess Frame for Detection
YOLOv3 Model
Detect Objects (Pedestrians/Vehicles)
Count Pedestrians and Vehicles
Calculate Red Light Duration
Display Results on Video Frame
Improve Traffic Flow

Fig. 3.3.1.1 Use Case Diagram

Actors:

1. **Traffic Camera Vedio**:
   An external device that captures live video footage of the road or intersection and continuously feeds it into the Smart Traffic Light System. It acts as the system's visual input source.

2. **YOLOv3 Model**:
   A machine learning-based object detection model that assists the system in detecting and identifying key objects, such as pedestrians and vehicles, within each video frame

Use Cases:

1. **Capture Video Frame**:
   The system receives and captures a continuous stream of video frames from the traffic camera, which serves as the input data for processing.
2. **Preprocess Frame for Detection**:
   The system enhances and prepares the captured video frames through preprocessing techniques like resizing, filtering, and normalization to improve object detection accuracy.
3. **Detect Objects (Pedestrians/Vehicles)**:
   Using the YOLOv3 model, the system detects and classifies objects in the video frame, specifically identifying pedestrians and different types of vehicles.
4. **Count Pedestrians and Vehicles**:
   After detection, the system counts the number of pedestrians and vehicles in the scene, which becomes the basis for signal timing decisions.
5. **Calculate Red Light Duration**:
   Based on the count data, the system calculates the optimal red light duration using predefined logic or a weighted formula, aiming to balance traffic flow and pedestrian safety.
6. **Display Results on Video Frame**:
   The system overlays the calculated signal timing and traffic status information (e.g., red light countdown) directly on the video feed for monitoring or display purposes.
7. **Improve Traffic Flow**:
   The overall goal of the system is achieved through real-time, adaptive traffic signal control, which helps reduce congestion and waiting time while improving urban traffic efficiency.

3.3.2 CLASS DIAGRAM

A class diagram is a visual representation that models the static structure of a system, showcasing the system's classes, their attributes, methods (operations), and the relationships between them, as seen in Fig. 3.3.2.2. It is a key tool in object-oriented design and widely used in software engineering to define the architecture and responsibilities of system components. The class diagram for the **Smart Traffic Light System** illustrates how different classes work together to process traffic video data, detect and count objects, and compute traffic signal durations to improve traffic flow.

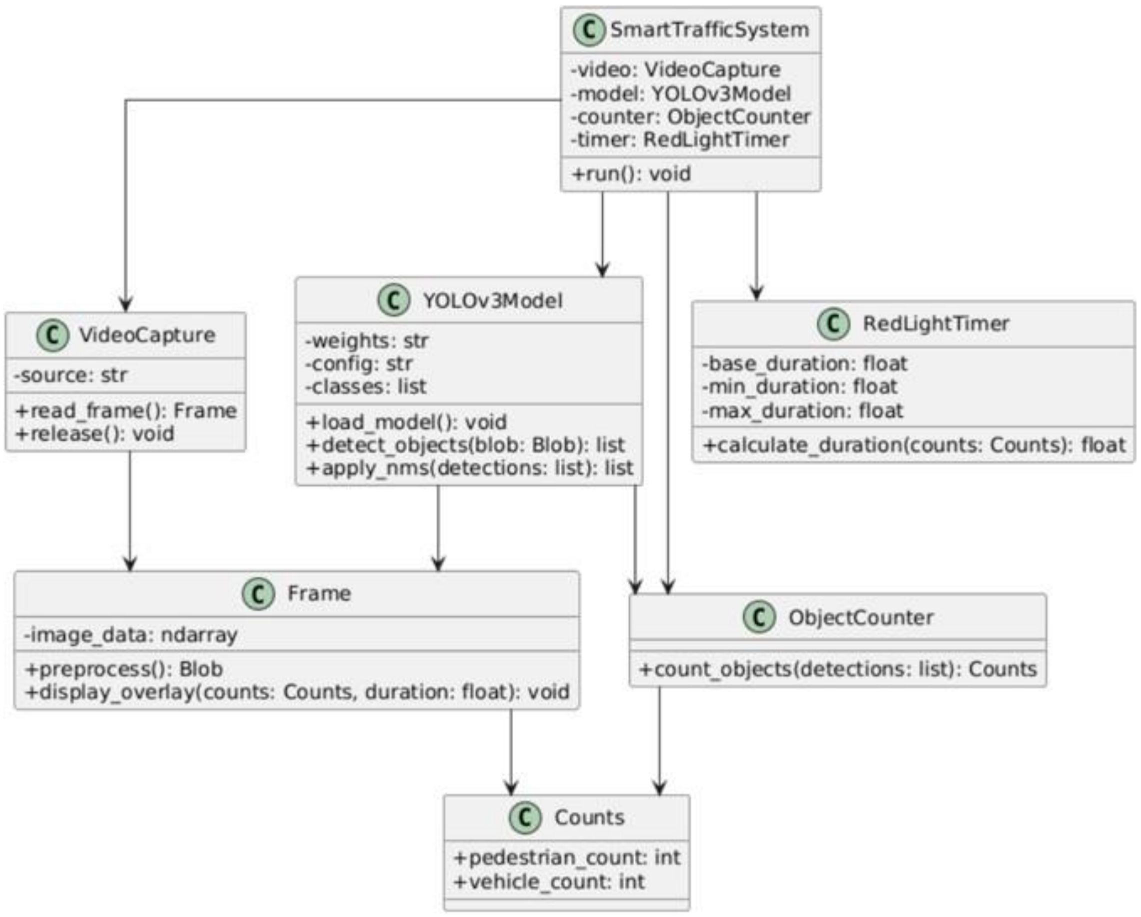


Fig. 3.3.2.1 Class Diagram

Relationships:

1. **SmartTrafficSystem → VideoCapture**
   - The SmartTrafficSystem class utilizes the VideoCapture class to read video frames from a given source.
   - VideoCapture contains attributes like source (a string representing the video feed location) and provides methods like read_frame() and release() to interact with the video stream.
2. **SmartTrafficSystem → YOLOv3Model**
   - The system uses the YOLOv3Model class to detect objects (vehicles and pedestrians) in a video frame.

- This class includes attributes such as weights, config, and classes and offers methods like load_model(), detect_objects(), and apply_nms() for detection and noise reduction.

3. **SmartTrafficSystem → ObjectCounter**
   - The system passes detection outputs to the ObjectCounter, which counts the number of detected vehicles and pedestrians.
   - It provides the method count_objects() that returns an instance of the Counts class.
4. **SmartTrafficSystem → RedLightTimer**
   - This relationship defines how the system calculates the red light duration based on object counts.
   - The RedLightTimer class includes parameters like base_duration, min_duration, and max_duration, and a method calculate_duration() which uses the counts to determine signal timing.
5. **VideoCapture → Frame**
   - Each call to read_frame() produces a Frame object which holds image_data and provides methods like preprocess() to prepare the frame for detection and display_overlay() to show counts and timer data.
6. **YOLOv3Model → Frame**
   - The model uses the preprocessed blob from the Frame class for object detection, indicating dependency.
7. **ObjectCounter → Counts**
   - The ObjectCounter returns an instance of the Counts class which encapsulates pedestrian_count and vehicle_count as integer attributes.
8. **Frame → Counts, RedLightTimer**
   - The Frame class uses the Counts and RedLightTimer data in its display_overlay() method to annotate the video output.

System Flow:

1. **Video Frame Acquisition:** The system begins by acquiring video frames from a traffic camera through the VideoCapture class. Each frame is passed on for further processing.
2. **Preprocessing and Detection:** The frame is preprocessed into a format usable by the YOLOv3Model. The object detection model identifies pedestrians and vehicles within the frame using deep learning techniques.

3. **Counting and Analysis:** Detected objects are counted using the ObjectCounter class, producing a Counts object which provides data about the number of pedestrians and vehicles present in the frame.
4. **Duration Calculation:** Based on the count values, the RedLightTimer calculates an optimal red light duration. This duration is derived within defined bounds (minimum, maximum, and base duration).
5. **Output Overlay:** Finally, the results, including object counts and computed red light duration, are overlayed on the frame using the display_overlay() method, providing real-time visual feedback.

3.3.3 ACTIVITY DIAGRAM

An activity diagram is a visual representation used in software engineering to model the workflow or sequence of activities within a system or process. It illustrates how different tasks or actions flow from one to another, showing decisions, parallel processes, and the overall dynamic behavior of the system. Activity diagrams help in understanding, documenting, and analyzing how a process operates by clearly depicting the order of activities, the branching of decisions, and the synchronization of concurrent tasks. They are widely used to represent business workflows, system functions, or algorithms, making complex processes easier to communicate and optimize.

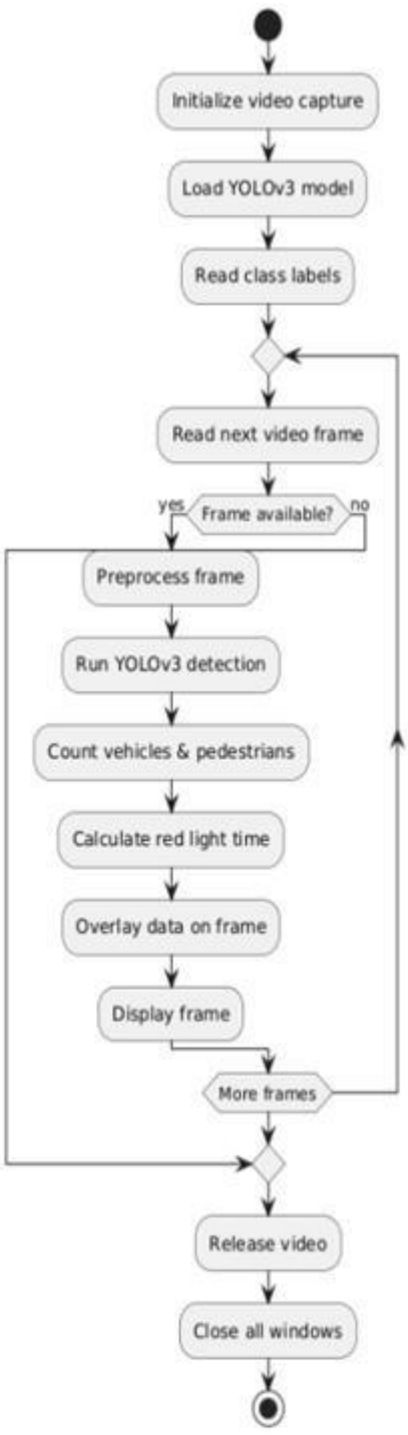


Fig. 3.3.3.1 Activity Diagram

Flow Explaination

1. **Start System**

   The system begins when the Smart Traffic Light application is launched or activated.

2. **Initialize Video Capture**

   The system initializes the video input, typically from a traffic surveillance camera or a stored video file.

3. **Load YOLOv3 Model**

   The deep learning model (YOLOv3) used for object detection is loaded into memory. This step prepares the system for analyzing frames.

4. **Read Class Labels**

   The system loads a file containing object class names (e.g., "car", "bus", "person") to label detected objects correctly.

5. **Read Next Video Frame:**

   The system attempts to read the next frame from the video input.

6. **Frame Available**

   A decision is made:

   - **Yes:** If a video frame is successfully read, processing continues.
   - **No:** If no frame is available (end of video), the system moves to termination steps.

7. **Preprocess Frame:**

   The current frame is preprocessed to prepare it for the YOLOv3 model (e.g., resizing, normalization).

8. **Run YOLOv3 Detection:**

   The preprocessed frame is passed through the YOLOv3 model to detect objects such as vehicles and pedestrians.

9. **Count Vehicles & Pedestrians:**

   The system processes YOLOv3's output to count the number of vehicles and pedestrians present in the frame.

10. **Calculate Red Light Time:**

    Based on the number of detected objects, the system dynamically calculates the appropriate red light duration using a predefined algorithm.

11. **Overlay Data on Frame:**

    The computed red light time and object counts are drawn or overlayed on the video frame as visual feedback.

12. **Display Frame:**

    The annotated frame is displayed to the user, showcasing detection results and timing recommendations.

13. **More Frames?**

    A decision is made:

    - **Yes:** If more frames remain, the system loops back to read the next frame.

    - **No:** If there are no more frames, the system proceeds to shut down.

14. **Release Video:**
    The video capture object is released, freeing resources.
15. **Close All Windows:**
    Any display windows or graphical interfaces are closed to complete the execution.
16. **End of Workflow:**
    The process terminates, having analyzed all video frames and performed the necessary detections and calculations.

3.3.4 SEQUENCE DIAGRAM

The sequence diagram illustrates the interactions between various system components and an external actor (Traffic Camera) to manage traffic light timing dynamically using object detection and counting. The diagram emphasizes the order of messages exchanged between components to detect vehicles, count them, compute the red light duration accordingly, and display the processed frames.

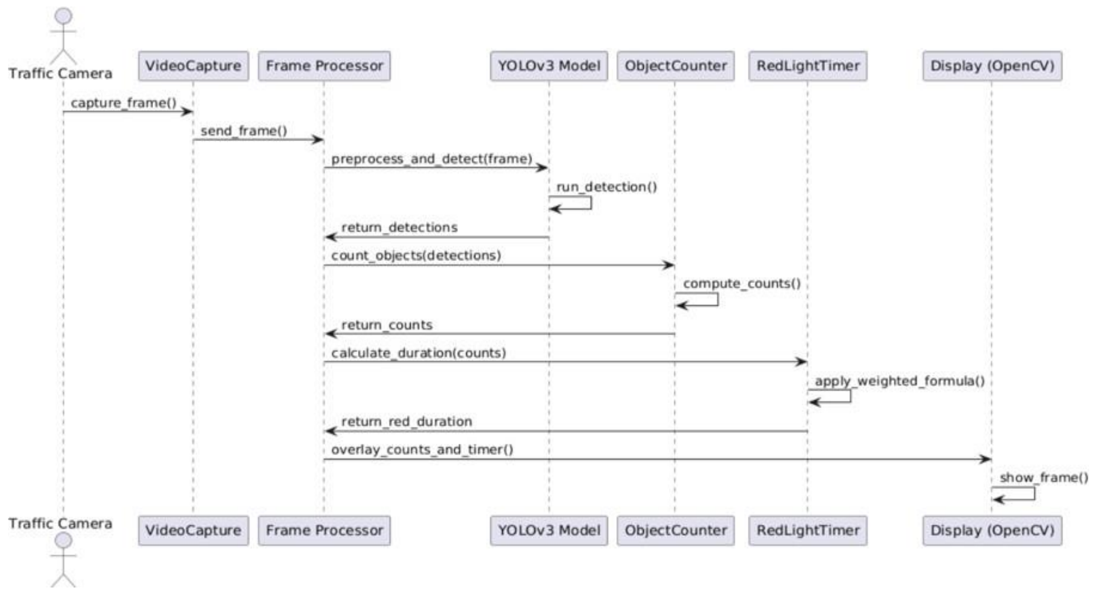


Fig. 3.3.4.1 Sequence Diagram

Key Interactions and Relationships

Traffic Camera and System Components:

- **Frame Capture and Transmission:**
    - The Traffic Camera captures a video frame (capture_frame()).

    - The VideoCapture module receives this frame and forwards it to the Frame Processor via send_frame().

Frame Processor and YOLOv3 Model:

- **Object Detection:**
    - The Frame Processor preprocesses the frame and requests object detection by sending preprocess_and_detect(frame) to the YOLOv3 Model.
    - The YOLOv3 Model runs detection (run_detection()) on the frame and returns detected objects (return_detections).

Frame Processor and Object Counter:

- **Counting Objects:**
    - The Frame Processor sends the detections to the ObjectCounter with count_objects(detections).
    - The ObjectCounter computes the count of vehicles or pedestrians (compute_counts()) and returns these counts (return_counts).

Frame Processor and Red Light Timer:

- **Red Light Duration Calculation:**
    - The Frame Processor forwards the counts to the RedLightTimer using calculate_duration(counts).
    - The RedLightTimer applies a weighted formula to determine the appropriate red light duration (apply_weighted_formula()).
    - It then returns the calculated duration (return_red_duration).

Frame Processor and Display Module:

- **Displaying Processed Frame:**
    - The Frame Processor overlays the counts and timer information on the frame (overlay_counts_and_timer()).
    - This annotated frame is sent to the Display (OpenCV) module.
    - The Display component shows the processed frame to the user or traffic controller (show_frame()).

3.3.5 COMPONENT DIAGRAM

A Component Diagram is a type of structural diagram used in software engineering to visualize the organization and interrelationships among the components of a software system. Each component encapsulates a specific set of functionalities and communicates with other components via clearly defined interfaces. This provides a high-level overview of system architecture, module dependencies, and system behavior.

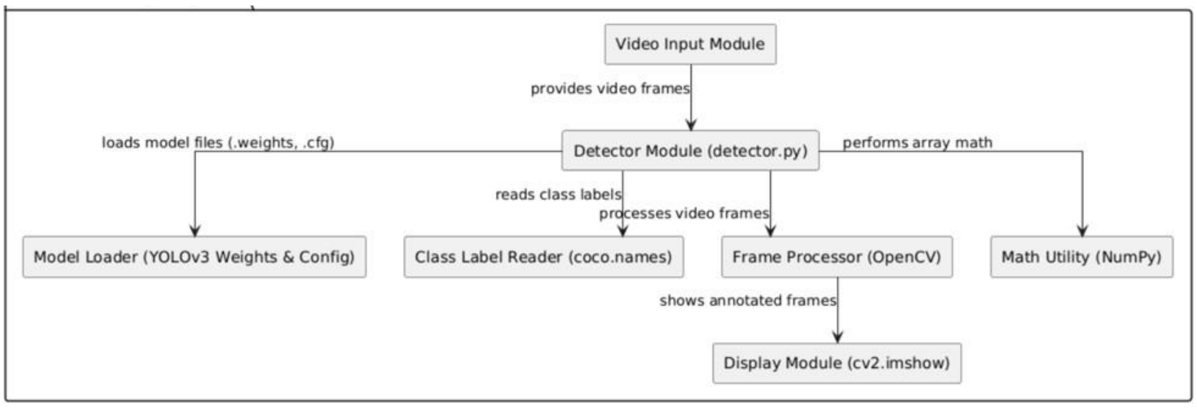


Fig. 3.3.5.1 Component Diagram

Main Components:

- **Video Input Module**
  - **Description**: Captures or reads video input (e.g., from a camera or a pre-recorded video file like sampleinput3.mp4). It serves as the data source for object detection.
- **Detector Module (detector.py)**
  - **Description**: The core logic of the system. This Python script:
    - Loads YOLOv3 model files.
    - Reads object class labels (like car, person, traffic light).
    - Processes video frames to detect objects.
    - Uses libraries like OpenCV and NumPy for efficient frame manipulation and mathematical operations.
- **Model Loader (YOLOv3 Weights & Config)**
  - **Description**: Loads the pre-trained YOLOv3 model (yolov3.weights and yolov3.cfg) used for object detection. These files define the neural network architecture and its learned parameters.
- **Class Label Reader (coco.names)**
  - **Description**: Provides the class names that the YOLOv3 model can detect (e.g., 80 object classes like bicycle, car, bus, etc.). Used to annotate frames with human-readable labels.

- **Frame Processor (OpenCV)**
  - **Description**: Uses the OpenCV library to process each video frame. This includes tasks like resizing, drawing bounding boxes, and converting between color spaces.

- **Math Utility (NumPy)**
  - **Description**: Performs numerical operations on frame data (arrays), such as coordinate transformations, filtering, or handling model outputs.
- **Display Module (cv2.imshow)**
  - **Description**: Visual output module that displays the processed and annotated video frames on the screen in real time using OpenCV's cv2.imshow() function.

3.3.6 DEPLOYMENT DIAGRAM

A Deployment Diagram models the physical deployment of software components on hardware nodes. It shows how software artifacts are distributed across various physical resources and how they interact at runtime. In this context, the Smart Traffic Light System leverages YOLOv3 for object detection and OpenCV for video frame processing.

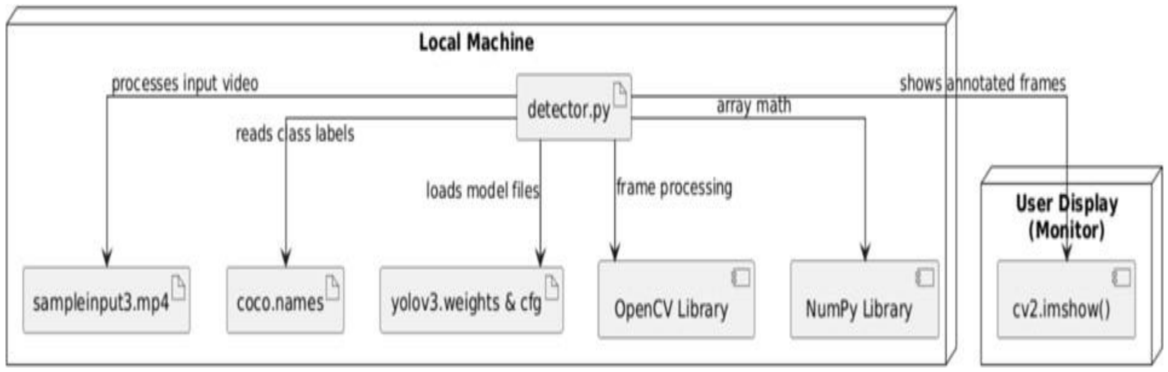


Fig. 3.3.6.1 Deployment Diagram

The **deployment architecture** is divided into two main nodes:

1. Local Machine

The **Local Machine** serves as the central computational environment where all core processing occurs. It hosts the following components:

- **detector.py**:
  The main execution script that coordinates the entire detection pipeline. It performs the following tasks:
  - Loads input video (sampleinput3.mp4)
  - Reads class labels from coco.names
  - Loads pretrained YOLOv3 model weights and config files (yolov3.weights & cfg)
  - Utilizes **OpenCV** for processing video frames
  - Performs mathematical operations using **NumPy**
- **sampleinput3.mp4**:
  A video file used as input for the detection process.
- **coco.names**:
  A file containing the class labels used for object classification (e.g., person, car, traffic light).
- **yolov3.weights & cfg**:
  These files include the pretrained weights and configuration of the YOLOv3 model necessary for object detection.
- **OpenCV Library**:
  Used for reading, processing, and displaying video frames.
- **NumPy Library**:
  Used to handle mathematical and array-based operations required during detection.

2. User Display (Monitor)

The **User Display** node is a visual output device where the results of the object detection process are shown. It includes:

- **cv2.imshow()**:
  An OpenCV function responsible for displaying the annotated video frames in real time to the user.

3.4 METHODOLOGY

Data Acquisition

- **Video Input**: The system processes input video data from a prerecorded video file or live camera feed using OpenCV's VideoCapture. Each frame represents the current traffic situation for analysis.

- **Purpose**: Video frames provide the raw data for detecting pedestrians and vehicles, which is essential for dynamic traffic signal control.

Object Detection and Counting

- **Frame Processing**: To maintain real-time performance, the system processes every alternate frame. Each frame is resized and preprocessed into a blob compatible with the YOLOv3 deep learning model.
- **YOLOv3 Model**: The pretrained YOLOv3 model identifies objects within each frame, focusing on relevant traffic participants such as pedestrians (person) and vehicles (car, bus, truck, motorbike).
- **Non-Maximum Suppression**: Applied to filter out duplicate bounding boxes and improve detection accuracy.

Counting Logic

- Pedestrians are counted by detecting bounding boxes labeled as person, ensuring no overlap in counting.
- Vehicles are counted by detecting bounding boxes labeled as car, bus, truck, or motorbike.

Dynamic Red Signal Duration Calculation

- **Algorithm**: The system calculates the red signal duration dynamically based on the detected number of pedestrians and vehicles.
- **Inputs**: Base time, pedestrian count, vehicle count, and respective weight factors.
- **Constraints**: The calculated duration is bounded within minimum and maximum limits (e.g., 5 to 60 seconds) to maintain practical signal timings.
- **Output**: The adjusted red signal time helps balance pedestrian safety with traffic flow efficiency.

Visualization

- **On-Screen Display**: The system annotates each processed frame by drawing bounding boxes around detected pedestrians and vehicles, color-coded for easy distinction.
- **Information Overlay**: Real-time counts of pedestrians and vehicles and the current red signal duration are displayed on the video frames.
- **Signal Indicator**: A visual cue (e.g., a colored circle) indicates whether the red signal is active, providing immediate feedback.

Models Used

1. YOLOv3 (You Only Look Once, version 3)

- **Description:**
  YOLOv3 is a state-of-the-art deep learning model for object detection. It detects objects in images and videos by predicting bounding boxes and class probabilities in a single evaluation, making it extremely fast and suitable for real-time applications.
- **How It Works:**
  - YOLOv3 divides the input image into a grid and predicts bounding boxes and confidence scores for each grid cell.
  - It uses a convolutional neural network backbone (Darknet-53) to extract features.
  - The network outputs bounding boxes at three different scales, allowing it to detect objects of various sizes.
  - For each bounding box, YOLOv3 predicts the class probabilities (like person, car, bus, truck, motorbike).
  - Non-Maximum Suppression (NMS) is applied to remove overlapping boxes, keeping only the best predictions.
- **Why It's Used:**
  - **Real-time detection:** Can process video frames quickly, ideal for live traffic monitoring.
  - **Multi-class detection:** Can detect different vehicle types and pedestrians simultaneously.
  - **High accuracy and robustness:** Performs well in various lighting and weather conditions, crucial for traffic systems.

2. Rule-based Counting and Traffic Signal Duration Calculation

- **Description:**
  This is a custom, rule-based logic module implemented in Python. It is not a machine learning model but uses counts of detected objects to dynamically adjust traffic light timings.
- **How It Works:**
  - Counts the number of detected pedestrians and vehicles from YOLOv3 output per video frame.

    - Applies heuristic formulas (with weights and thresholds) to calculate the appropriate red light duration based on traffic density.
    - For example, if pedestrian count exceeds a threshold, it increases red light time proportionally, weighted differently than vehicle counts.
    - Ensures red light duration stays within set minimum and maximum limits.
- **Why It’s Used:**
    - **Adaptive traffic control:** Dynamically manages traffic signals based on real-time traffic flow without needing complex predictive models.

4. CODE AND IMPLEMENTATION

4.1 CODE

detector.py:

```
import cv2
import numpy as np
import requests

vehicle_model = cv2.dnn.readNet('./models/yolov3.weights', './models/yolov3.cfg')

layer_names = vehicle_model.getLayerNames()
output_layers = [layer_names[i - 1] for i in vehicle_model.getUnconnectedOutLayers()]

with open('coco.names', 'r') as f:
    classes = [line.strip() for line in f.readlines()]

cap = cv2.VideoCapture('sampleinput3.mp4')

def calculate_red_signal_duration(pedestrian_count, vehicle_count,
                                  base_duration=10, adjustment_pedestrian=0.5, adjustment_vehicle=0.3,
                                  min_duration=5, max_duration=60,
                                  pedestrian_threshold=5, vehicle_threshold=5,
                                  pedestrian_weight=1.2, vehicle_weight=1.1):
    if pedestrian_count == 0:
        return 0

    if pedestrian_count > pedestrian_threshold:
        T_P = pedestrian_count * adjustment_pedestrian * pedestrian_weight
    else:
        T_P = pedestrian_count * adjustment_pedestrian

    if vehicle_count > vehicle_threshold:
        T_V = vehicle_count * adjustment_vehicle * vehicle_weight
    else:
        T_V = vehicle_count * adjustment_vehicle

    T_red = base_duration + T_P + T_V
    T_red = max(min_duration, min(T_red, max_duration))

    return T_red

frame_count = 0

while cap.isOpened():
    ret, frame = cap.read()
    if not ret:
        break
    frame_count += 1

    if frame_count % 2 == 0:
        height, width, channels = frame.shape
        blob = cv2.dnn.blobFromImage(frame, 0.00392, (320, 320), (0, 0, 0), True, crop=False)
        vehicle_model.setInput(blob)
        detections = vehicle_model.forward(output_layers)

        pedestrian_count = 0
        vehicle_count = 0
        detected_pedestrians = []
        boxes = []
        confidences = []
        class_ids = []

        for detection in detections:
            for obj in detection:
                scores = obj[5:]
                class_id = np.argmax(scores)
                confidence = scores[class_id]
                if confidence > 0.6:
                    center_x = int(obj[0] * width)
                    center_y = int(obj[1] * height)
                    w = int(obj[2] * width)
                    h = int(obj[3] * height)
                    x = int(center_x - w / 2)
                    y = int(center_y - h / 2)

                    boxes.append([x, y, w, h])
                    confidences.append(float(confidence))
                    class_ids.append(class_id)

        indices = cv2.dnn.NMSBoxes(boxes, confidences, 0.6, 0.4)

        if len(indices) > 0:
            for i in indices.flatten():
                box = boxes[i]
                x, y, w, h = box
                class_id = class_ids[i]
                label = str(classes[class_id])

                if label == 'person':
                    center_x = x + w // 2
                    center_y = y + h // 2
                    if not any((abs(center_x - px) < w / 2 and abs(center_y - py) < h / 2) for px, py in
detected_pedestrians):
                        pedestrian_count += 1
                        detected_pedestrians.append((center_x, center_y))
                        cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)
                elif label in ['car', 'truck', 'bus', 'motorbike']:
                    vehicle_count += 1
                    cv2.rectangle(frame, (x, y), (x + w, y + h), (255, 0, 0), 2)

        total_red_time = calculate_red_signal_duration(pedestrian_count, vehicle_count)

        data = {
            "pedestrian_count": pedestrian_count,
            "vehicle_count": vehicle_count,
            "red_light_duration": total_red_time
        }
        cv2.putText(frame, f'Pedestrians: {pedestrian_count}', (10, 50),
cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 0, 0), 2)
        cv2.putText(frame, f'Vehicles: {vehicle_count}', (10, 100),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2)
        cv2.putText(frame, f'Red Light Time: {total_red_time:.1f} sec', (10, 150),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2)

        if total_red_time == 0:
            cv2.circle(frame, (width - 50, 50), 20, (0, 255, 0), -1)
        else:
            cv2.circle(frame, (width - 50, 50), 20, (0, 0, 255), -1)

        cv2.imshow('Frame', frame)

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

cap.release()
cv2.destroyAllWindows()
```

app.py:

```
from flask import Flask, render_template, jsonify, request, Response
import threading
import cv2

app = Flask(_name_)

# Shared data for pedestrian count, vehicle count, and red light duration
shared_data = {
    "pedestrian_count": 0,
    "vehicle_count": 0,
    "red_light_duration": 10
}

def generate_video():
    # Open the video file
    cap = cv2.VideoCapture('videoo.mp4')
    while True:
        ret, frame = cap.read()
        if not ret:
            break

        # Encode the frame as JPEG
        ret, jpeg = cv2.imencode('.jpg', frame)
        if not ret:
            continue

        # Yield the frame in the format needed for video streaming
        yield (b'--frame\r\n'
               b'Content-Type: image/jpeg\r\n\r\n' + jpeg.tobytes() + b'\r\n')

    cap.release()

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/data', methods=['GET'])
def data():
    return jsonify(shared_data)

@app.route('/video_feed')
def video_feed():
    return Response(generate_video(),
                    mimetype='multipart/x-mixed-replace; boundary=frame')

@app.route('/increase_duration', methods=['POST'])
def increase_duration():
    shared_data["red_light_duration"] += 10
    return jsonify(success=True)

def run_flask():
    app.run(debug=True, use_reloader=False)

# Start Flask server in a separate thread
if _name_ == "_main_":
    threading.Thread(target=run_flask).start()
```

index.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Real-Time Video Feed</title>
    <style>
```

```
        body {
            font-family: Arial, sans-serif;
            display: flex;
            flex-direction: column;
            align-items: center;
            justify-content: center;
            height: 100vh;
            margin: 0;
        }
        #video-container {
            position: relative;
        }
        #video {
            max-width: 100%;
        }
        #info {
            margin-top: 10px;
            font-size: 18px;
        }
    </style>
</head>
<body>
    <div id="video-container">
        <h1>Real-Time Vehicle and Pedestrian Count</h1>
        <img id="video" src="{{ url_for('video_feed') }}" />
        <div id="info">
            <p>Pedestrians: <span id="pedestrian-count">0</span></p>
            <p>Vehicles: <span id="vehicle-count">0</span></p>
        </div>
    </div>

    <script>
        function updateCounts() {
            fetch('/data')
                .then(response => response.json())
                .then(data => {
                    document.getElementById('pedestrian-count').textContent =
data.pedestrian_count;
                    document.getElementById('vehicle-count').textContent = data.vehicle_count;
                })
                .catch(error => console.error('Error fetching data:', error));
        }

        setInterval(updateCounts, 1000);
    </script>
</body>
</html>
```

4.2 IMPLEMENTATION

Create a directory folder as following and copy relevant pieces of code into the required parts: -

```
TrafficControl/
│
├── app.py                  # Main Flask or app entry point
├── requirements.txt           # Python dependencies (Flask, OpenCV, etc.)
│
├── data/
│   └── detection_data.db        # (If applicable: for storing results/logs)
│
├── src/
│   ├── detector.py            # Core detection logic
│   ├── yolov3.cfg             # Model configuration
│   ├── yolov3.weights           # Trained YOLO model (if available)
│   ├── coco.names             # Class labels for object detection
│
├── static/
│   ├── css/
│   │   └── style.css          # Styles for UI (if any used)
│   └── img/
│      └── sample_frame.png      # Example detections / frames from videos
│
├── templates/
│   ├── index.html             # Video upload interface (if used)
│   └── results.html           # Results page for detected objects
│
├── videos/
│   ├── dfghj.mp4
│   ├── video.mp4
│   ├── videoo.mp4
│   └── oiytdfn.mp4             # Uploaded or sample videos for detection
│
└── README.md
```

Installing Python Packages

Open your terminal and run the following command to install all required packages:

pip install flask opencv-python numpy

If you're using a requirements.txt, you can also run:

pip install -r requirements.txt

Optional: If you're using VS Code, make sure your virtual environment is activated before installing.

Run the App

1. Open your terminal
2. Navigate to the folder:
   ```
   cd TrafficControl
   ```
3. Run the Python script (which shows detection window):
   ```
   python app.py
   ```
4. The video window will pop up with object detection running.
   Press Q to close the video window when it's done.

5. TESTING

5.1 INTRODUCTION TO TESTING

Testing ensures the core functionality of video object detection works as expected under different scenarios. It is a vital part of the development lifecycle, helping to identify bugs, ensure performance, and improve the overall reliability of the system before deployment. Testing confirms that individual modules such as model loading, video frame processing, object detection, and user interaction behave correctly and consistently under real-time conditions.

It verifies that the detection logic, model loading, frame-by-frame processing, and output rendering operate smoothly without crashing or producing incorrect results. This phase also includes edge-case analysis to test the application's robustness—such as how it responds to invalid file formats, missing resources, or videos with dense object populations.

The main goal is to make sure the application:

- Loads models correctly (YOLO config, weights, class names)
- Processes uploaded or live video feeds frame by frame
- Accurately detects and displays labeled objects in real time
- Handles invalid video formats or missing files gracefully

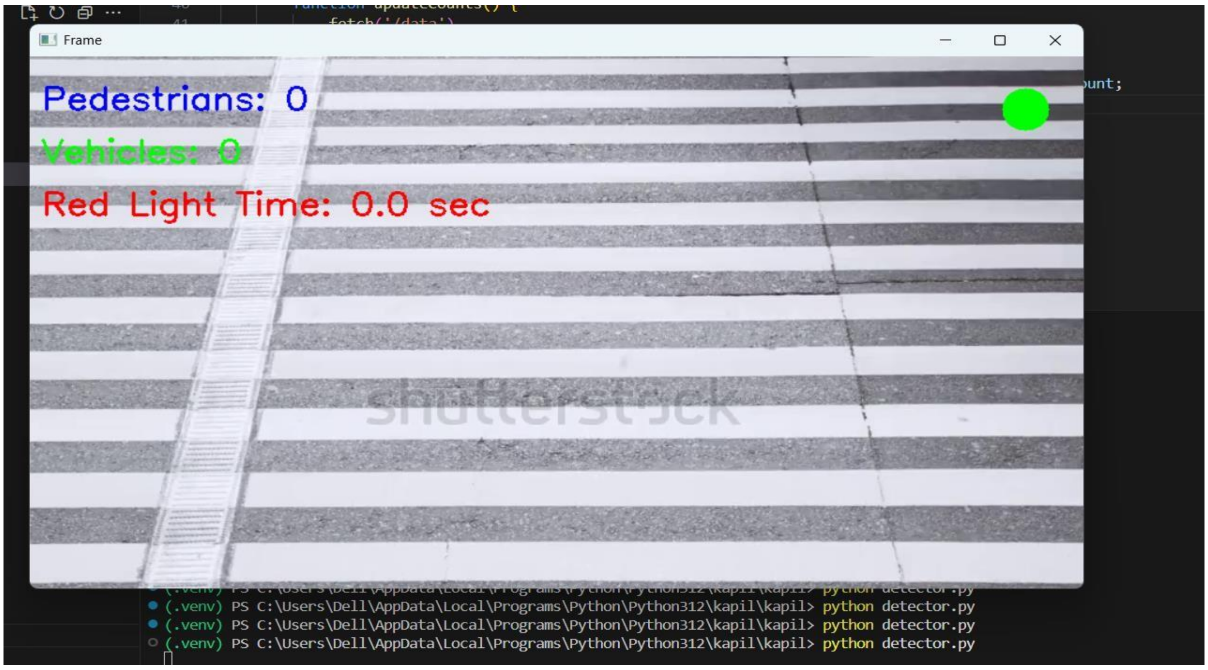
A well-structured set of test cases ensures the functionality and quality of the system. Each test case includes the conditions to be tested, the expected behavior, and a comparison with the actual results.

5.2 TEST CASES:

Table 5.1 Test Cases of Smart Traffic Light Control System

Test Case ID	**Test Case Name**	**Test Description**	**Expected Output**	**Actual Output**	**Remarks**
TC_01	App Launch	Run `app.py` in terminal	Detection window launches with video feed	Detection window launches with video feed	Success
TC_02	Model Load	Check if YOLO weights/config load properly	No errors; model loads and is ready	Model loaded successfully	Success
TC_03	Video Input (Valid File)	Provide valid `.mp4` file as input	Objects detected and labeled on video frames	Objects detected and labeled correctly	Success
TC_04	Video Input (Invalid File)	Pass unsupported or corrupted video	Application should handle error gracefully	Displays error message, no crash	Success
TC_05	Object Labels Display	Observe object label rendering	Class names (like person, car, etc.) shown on detected objects	Labels shown accurately	Success
TC_06	Multiple Object Detection	Test video with many objects	All detectable objects are marked and labeled	Multiple objects detected and labeled	Success
TC_07	Error Handling - Missing Files	Delete `yolov3.weights` and run	Display error, avoid crashing	Error displayed, app exits cleanly	Success
TC_08	Exit Detection Window	Press `Q` to quit during video playback	Video window closes and program exits	Quit works as expected	Success
TC_09	Detection Accuracy	Use known object-rich sample video	Expected objects are correctly identified	Good accuracy on common objects	Success

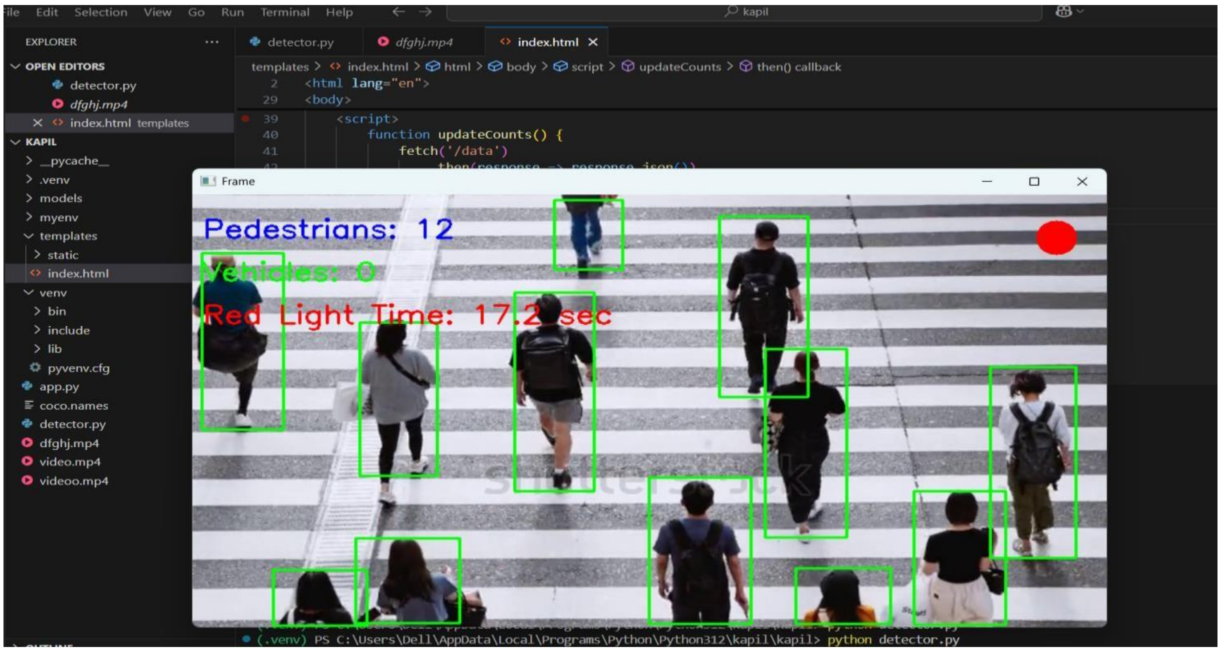
6. RESULTS



```
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
```

Fig. 6.1 Initial Count and Light

The fig 6.1 shows the initial count and light which uses real-time object detection to control traffic lights. The live video displays a pedestrian crossing, with counters for detected pedestrians and vehicles (both zero currently). It shows the red light duration and indicates the green light is active. The system adjusts traffic signals automatically based on detected road users to improve safety.



```
<html lang="en">
<body>
    <script>
        function updateCounts() {
            fetch('/data')
```

```
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
```

Fig. 6.2 Pedistrain Count

The fig 6.2 shows the system detects and counts pedestrians crossing a zebra crossing, marking each person with a green bounding box. The display indicates 12 pedestrians detected and 0 vehicles. The red text shows the red light duration counting up to 17.2 seconds, while a red circle at the top right likely signals the red light status. This real-time object detection interface helps manage traffic signals by adjusting light timings based on pedestrian presence, enhancing road safety.

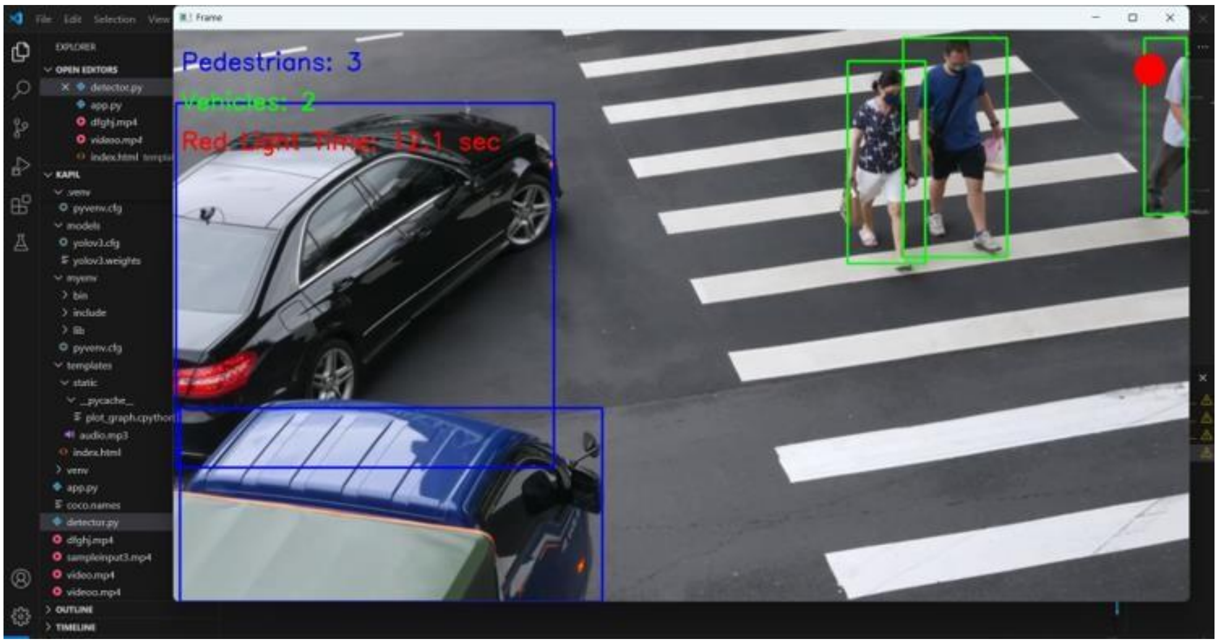
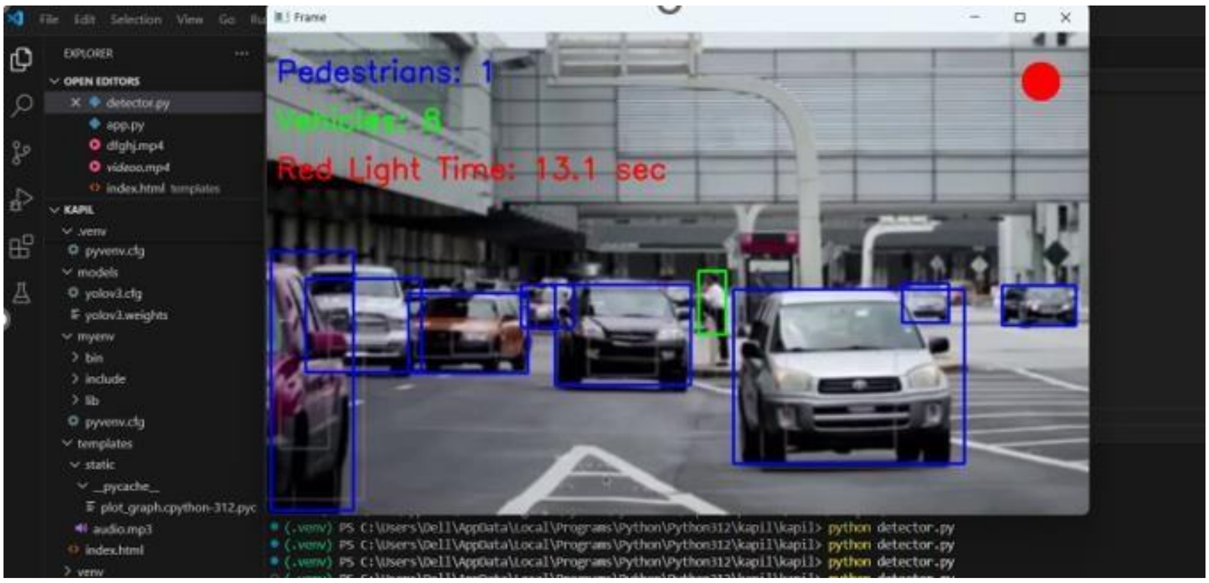


Fig. 6.3 Pedistrain and Vechicle Count

Figure 6.3 shows the system detecting and counting 2 pedestrians crossing a zebra crossing, each marked with a green bounding box. The display shows 2 pedestrians and 2 vehicles detected. A red text indicates the red light duration as 11.6 seconds, and a red circle at the top right likely represents the red light status.



```
Pedestrians: 1
Vehicles: 8
Red Light Time: 13.1 sec
```

```
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
(.venv) PS C:\Users\Dell\AppData\Local\Programs\Python\Python312\kapil\kapil> python detector.py
```

Fig. 6.4 Pedistrain and Vechicle Count

Figure 6.4 shows a real-time traffic monitoring system detecting 1 pedestrian and 8 vehicles. The pedestrian is marked with a green bounding box, while vehicles are outlined in blue. The display indicates a red light duration of 13.1 seconds, shown in red text. A red circle in the top-right corner likely signals that the red light is active or that the system is recording.

7. CONCLUSION AND FUTURE ENHANCEMENTS

7.1 CONCLUSION

The Smart Traffic Light System revolutionizes urban traffic management by combining real-time data processing with advanced AI techniques. Unlike traditional fixed-timer traffic lights that often cause unnecessary delays and congestion, this system uses YOLOv3 for precise detection and counting of vehicles and pedestrians through live video feeds. OpenCV facilitates the real-time analysis of this data, enabling the system to continuously monitor traffic conditions and respond dynamically. By adjusting signal timings based on actual traffic flow, the system reduces wait times, prevents traffic jams, and optimizes the overall movement of vehicles and pedestrians at intersections.

This adaptive approach not only improves traffic efficiency but also enhances safety by ensuring pedestrians receive timely crossing opportunities and congested lanes get appropriate green-light durations. In addition to lowering fuel consumption and emissions through smoother traffic flow, the system serves as a stepping stone for future smart city initiatives. Its scalable design allows integration with emerging technologies, supporting sustainable and intelligent urban mobility that benefits both commuters and the environment.

7.2 FUTURE ENHANCEMENTS

- Live CCTV Integration - Utilize real-time video streams from existing street CCTV cameras instead of webcams or prerecorded videos to get continuous and accurate traffic data in varied conditions.
- Arduino Traffic Light Control - Interface the system with Arduino or Raspberry Pi to control actual traffic lights, enabling automated, real-world signal changes based on AI analysis.
- Emergency Vehicle Detection - Detect emergency vehicles like ambulances and fire trucks using unique visual or audio cues, and prioritize their passage by switching signals to green.
- Traffic Data Storage - Save detailed traffic counts and signal timing data for historical analysis, reporting, and informed urban traffic planning.

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