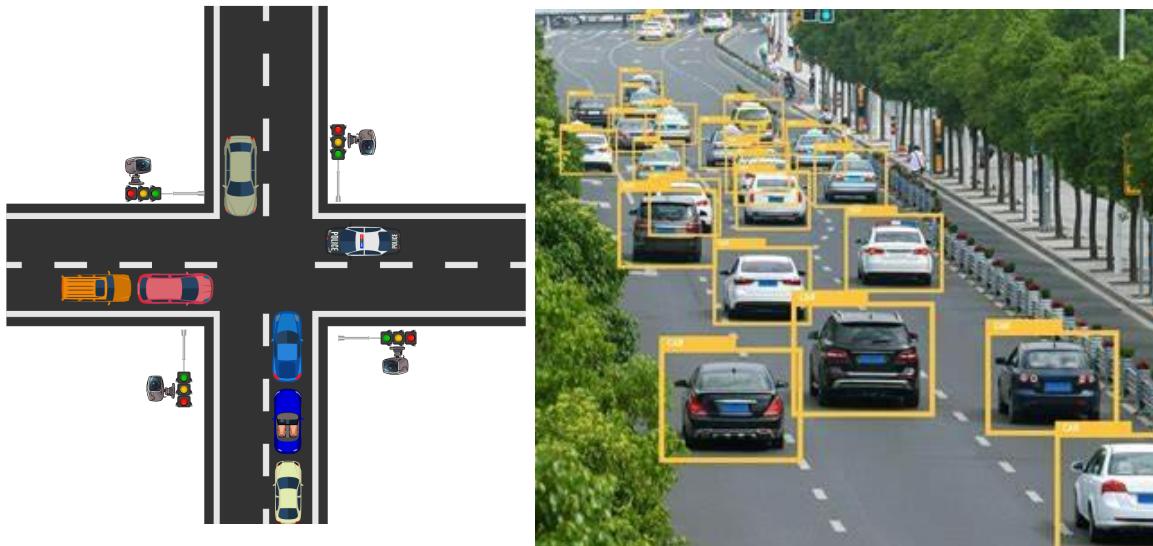


Smart Traffic Management System for Curry Avenue and Arteche Boulevard Intersection in Catbalogan City: A Raspberry Pi-Based Approach.

A Raspberry Pi-based traffic monitoring system with cameras and machine learning that analyzes traffic patterns, congestion, and optimizes traffic signal timing.



YOLOv5 is a model in the You Only Look Once (YOLO) family of computer vision models. YOLOv5 is commonly used for detecting objects. YOLOv5 comes in four main versions: small (s), medium (m), large (l), and extra large (x), each offering progressively higher accuracy rates. Each variant also takes a different amount of time to train.

In the context of our project YOLO applies in many ways.

- **Vehicle Detection:** YOLOv5 can be used to detect vehicles in live traffic footage captured by cameras installed at **Curry Avenue and Arteche Boulevard Intersection in Catbalogan City**. This information can be used to monitor traffic flow, identify congestion hotspots, and optimize signal timings at intersections.
- **Lane Congestion:** it allows the model to identify areas of traffic congestion and alleviate traffic flow issues. YOLOv5 involves adapting the object detection capabilities of the model to identify congested areas within specific lanes in traffic footage.

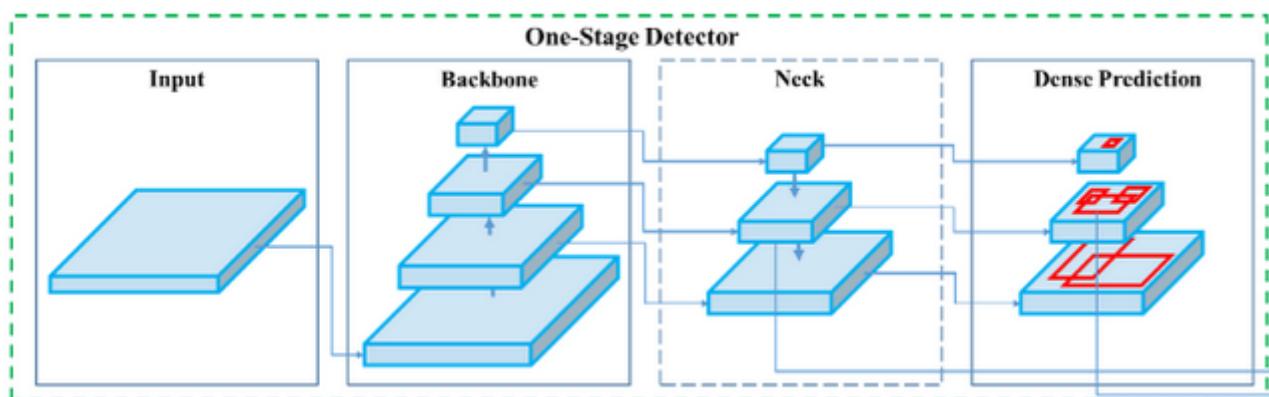
Utilizing the YOLOv5 (You Only Look Once) algorithm for the Smart Traffic Management System in Catbalogan City, particularly at critical intersections like Curry Ave and Arteche Boulevard, is an ideal choice due to its real-time processing capabilities, efficiency, and accuracy.

YOLOv5's ability to rapidly detect and classify objects such as vehicles and pedestrians in traffic images or video frames enables continuous monitoring and immediate adjustments to signal timing, crucial for effectively managing congestion. Moreover, YOLO's computational efficiency makes it well-suited for deployment on

devices like Raspberry pi, ensuring fast inference speeds despite limited processing power. Operating with a single forward pass through the neural network, YOLOv5 achieves high accuracy without sacrificing speed, thereby reliably detecting objects in varying traffic conditions. YOLO also offers flexibility for customization to the unique traffic scenarios of Catbalogan City, ensuring optimal performance of the traffic management system at intersections in Curry Ave and Arteche Boulevard.

1. High-level architecture for single-stage object detectors

There are two types of object detection models : two-stage object detectors and single-stage object detectors. Single-stage object detectors (like YOLO) architecture are composed of three components: **Backbone**, **Neck** and a **Head** to make dense predictions as shown in the figure below.



Model Backbone

The backbone is a pre-trained network used to extract rich feature representation for images. This helps **reduce the spatial resolution** of the image and **increases its feature** (channel) **resolution**.

Model Neck

The model neck is used to extract feature pyramids. This helps the model to generalize well to objects on different sizes and scales.

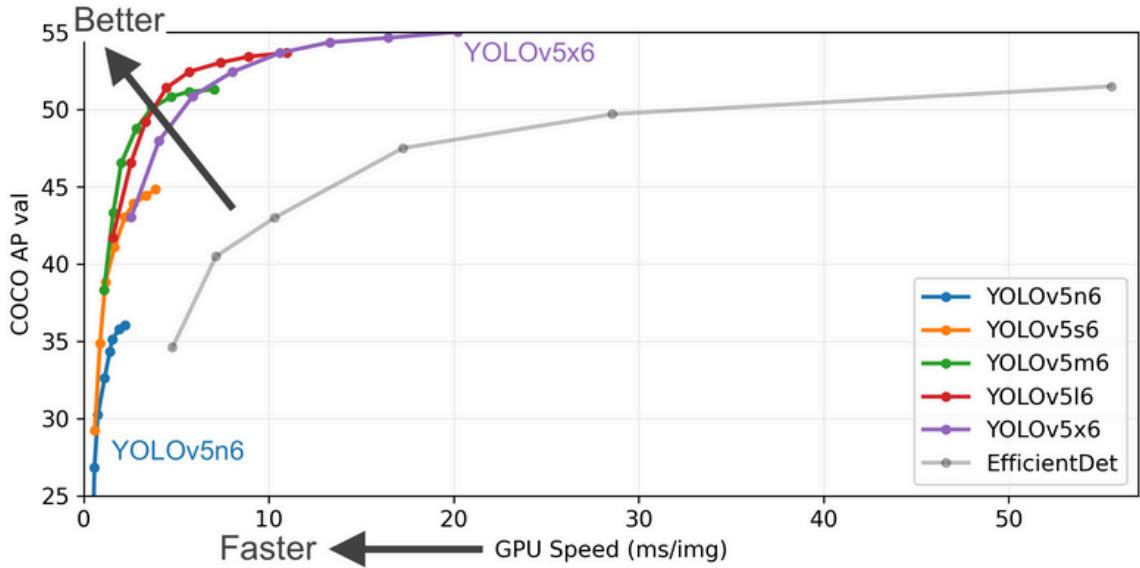
Model Head

The model head is used to perform the final stage operations. It applies anchor boxes on feature maps and renders the final output: **classes**, **objectness scores** and **bounding boxes**.

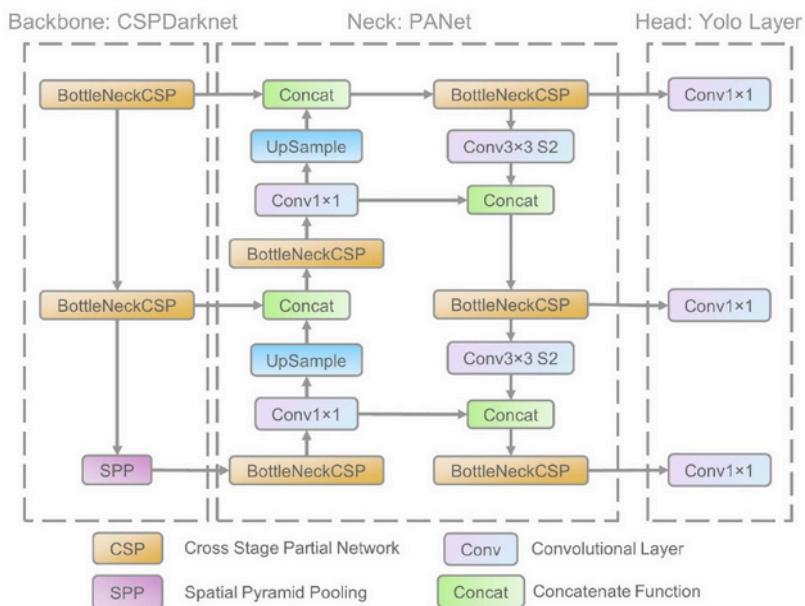
2. YOLOv5 Architecture

- **n** for an extra small (nano) size model.
- **s** for small size models.

- **m** for medium size models.
- **I** for large size model
- **x** for extra large size model



All the YOLOv5 models are composed of the same 3 components: **CSP-Darknet53** as a backbone, **SPP** and **PANet** in the model neck and the **head** used in YOLOv4.



Head of the network

YOLOv5 uses the same head as YOLOv3 and YOLOv4. It is composed from three convolution layers that predicts the location of the bounding boxes (x,y,height,width), the scores and the objects classes. The equation to compute the target coordinates for the bounding boxes have changed from previous versions, the difference is shown in the figure below.

$$\begin{aligned} b_x &= \sigma(t_x) + c_x \\ b_y &= \sigma(t_y) + c_y \\ b_w &= p_w \cdot e^{t_w} \\ b_h &= p_h \cdot e^{t_h} \end{aligned}$$

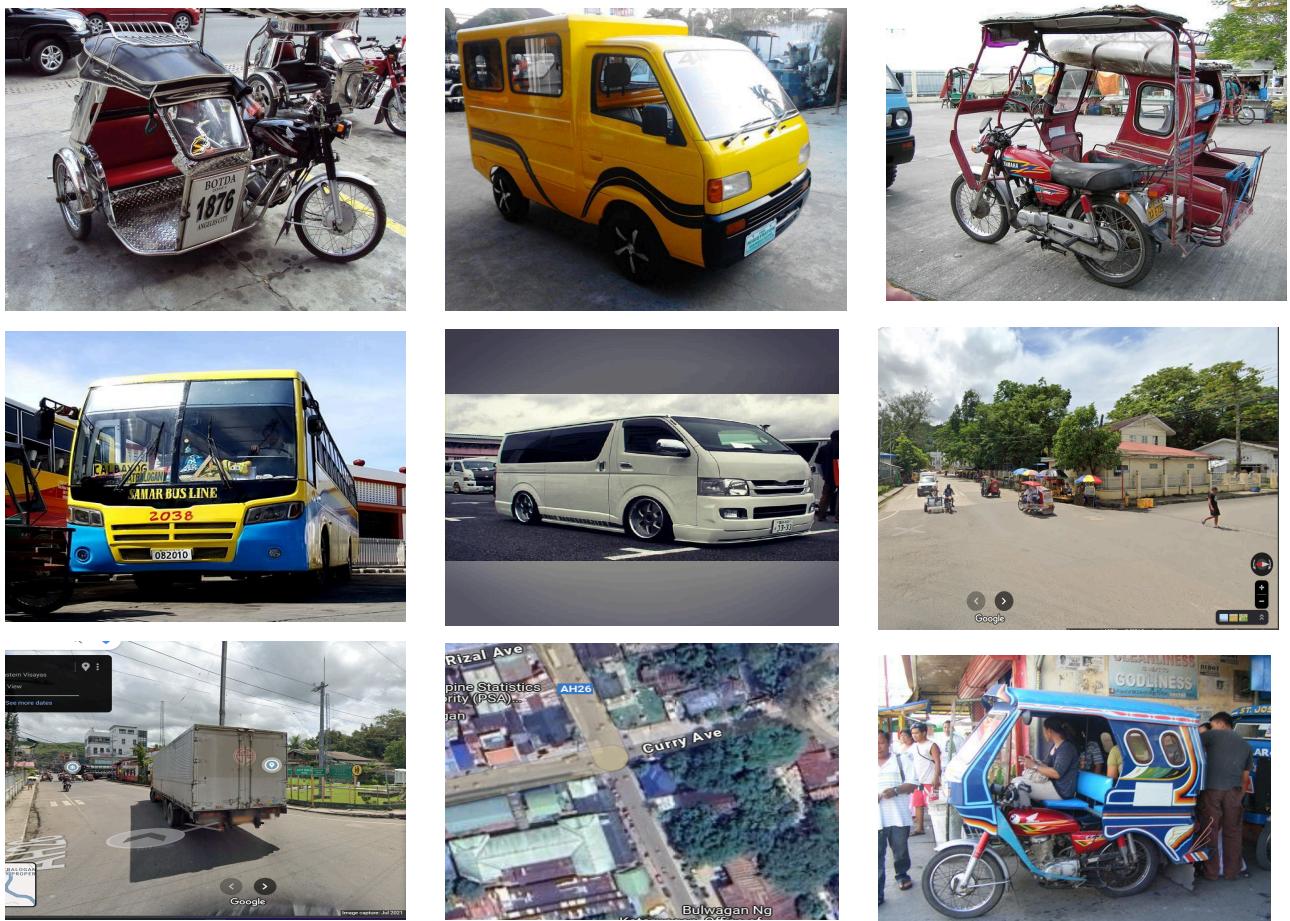
(a)

$$\begin{aligned} b_x &= (2 \cdot \sigma(t_x) - 0.5) + c_x \\ b_y &= (2 \cdot \sigma(t_y) - 0.5) + c_y \\ b_w &= p_w \cdot (2 \cdot \sigma(t_w))^2 \\ b_h &= p_h \cdot (2 \cdot \sigma(t_h))^2 \end{aligned}$$

(b)

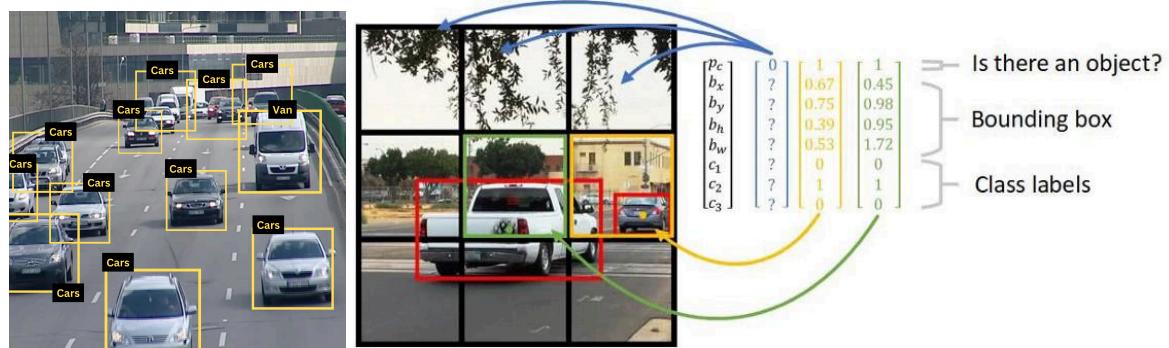
Step-by-step process in applying the algorithm (from data gathering to data processing and forecasting etc. - up to meeting your respective objectives)

1. **Data Gathering:** we will use cameras and drones at the intersection of Curry Avenue and Arteche Boulevard, and vehicles existing in Catbalogan City. These cameras will capture traffic data, and will proceed to the labeling process to create data that machine learning can understand and be able to train the model



2. **Data Preprocessing:** The raw data captured by the cameras will likely need some preprocessing. This could involve cleaning the data, selecting relevant features

(like the number of cars, their speed, etc.), and formatting the data in a way that can be used to train the model of machine learning.

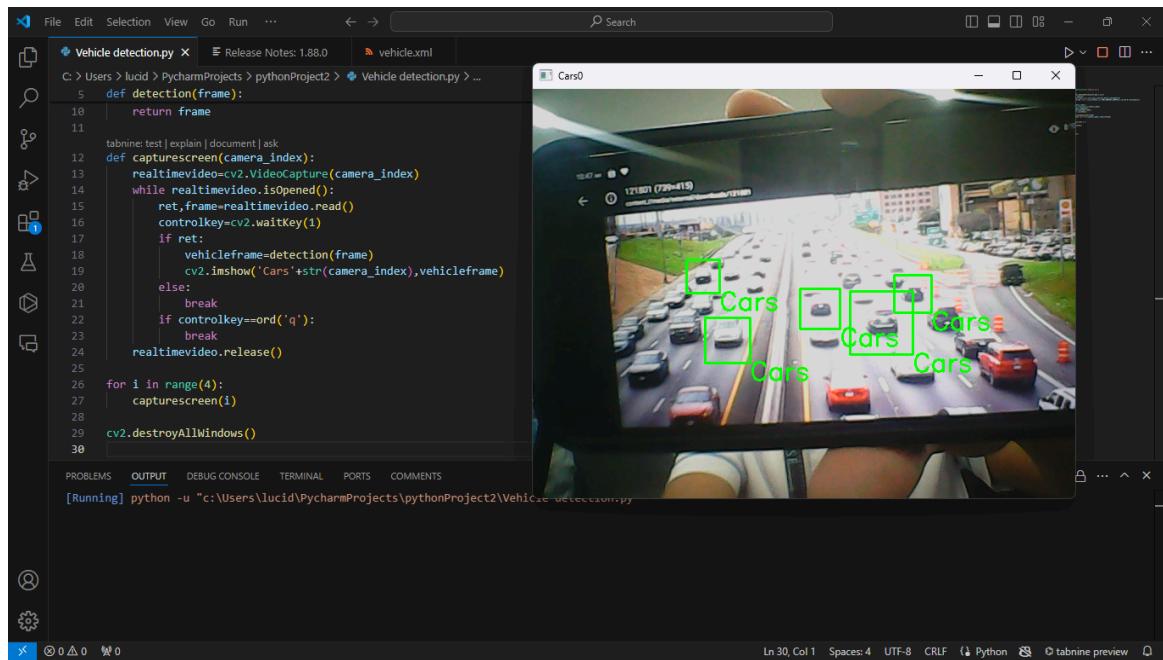


3. **Model Training:** Use the preprocessed data to train a machine learning model. This model should be designed to analyze traffic patterns and detect congestion.



4. **Model Testing and Validation:** After the model has been trained, it should be tested and validated. This involves using a separate set of data (not used in the training phase) to evaluate the model's performance.

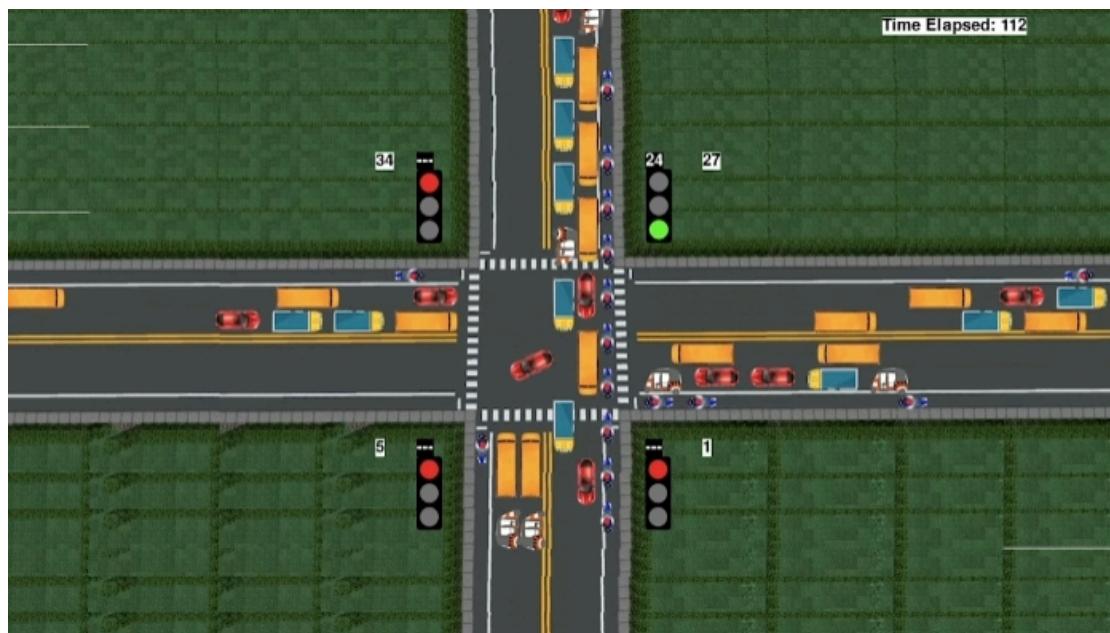
A screenshot of a dual-monitor setup. The left monitor displays a code editor with the file 'Vehicle detection.py'. The code uses OpenCV's VideoCapture module to read from camera index 0, detect frames, and draw bounding boxes around cars. The right monitor shows a live video feed from a camera, with several green bounding boxes drawn around cars in the scene. A small red trash can is also visible.



The screenshot shows the PyCharm IDE interface. On the left, the code editor displays a Python script named 'Vehicle detection.py'. The code implements a vehicle detection system using OpenCV, specifically the 'VideoCapture' module. It captures frames from a camera, detects vehicles, and displays them in a window titled 'Cars0'. The right side of the interface shows the resulting video frame with several cars highlighted by green bounding boxes and labeled with the word 'Cars'. Below the code editor, the status bar indicates the script is running with the command: [Running] python -u "c:/Users/lucid/PycharmProjects/pythonProject2/Vehicle detection.py".

```
File Edit Selection View Go Run ... Search
C:\Users\lucid\PycharmProjects\pythonProject2> Release Notes: 1.88.0 vehicle.xml
10     return frame
11
12 tabnine: test | explain | document | ask
13 def capturescreen(camera_index):
14     realtimevideo=cv2.VideoCapture(camera_index)
15     while realtimevideo.isOpened():
16         ret,frame=realtimevideo.read()
17         controlkey=cv2.waitKey(1)
18         if ret:
19             vehicleframe=detection(frame)
20             cv2.imshow('Cars'+str(camera_index),vehicleframe)
21         else:
22             break
23         if controlkey==ord('q'):
24             break
25     realtimevideo.release()
26
27 for i in range(4):
28     capturescreen(i)
29
30 cv2.destroyAllWindows()
```

5. Signal Optimization: Based on the traffic forecasts, the traffic signals at the intersection can be optimized. For example, if the model predicts heavy traffic on Curry Avenue at a certain time of day, the signal timings could be adjusted to give more green light time to Curry Avenue during that period.



6. Meeting Objectives: The ultimate objective of this system is to develop the working system that improves traffic flow and reduces congestion at the intersection of Curry Avenue and Arteche Boulevard.

