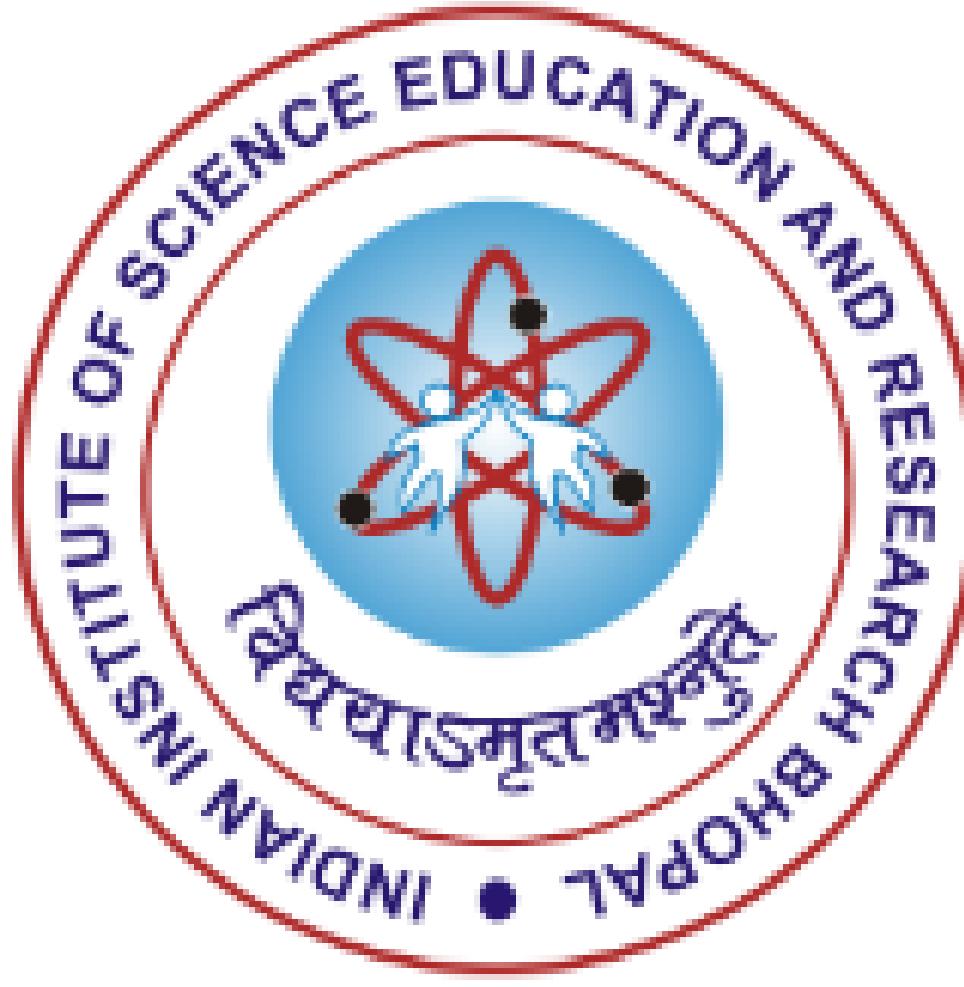


# Machine Learning

## Summer Internship2024,IISERBhopal



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# ABOUT

**Autonomous Cars** are the self driven cars that are capable of sensing the environment and navigating without human effort or input

## ADVANTAGES -

- **Safety:** Reduced human error, leading to fewer accidents.
- **Efficiency:** Optimized traffic flow and reduced congestion.
- **Accessibility:** Enhanced mobility for the elderly and disabled.
- **Environmental Impact:** Lower emissions due to efficient driving patterns.

# PARTS OF AUTONOMOUS VEHICLE



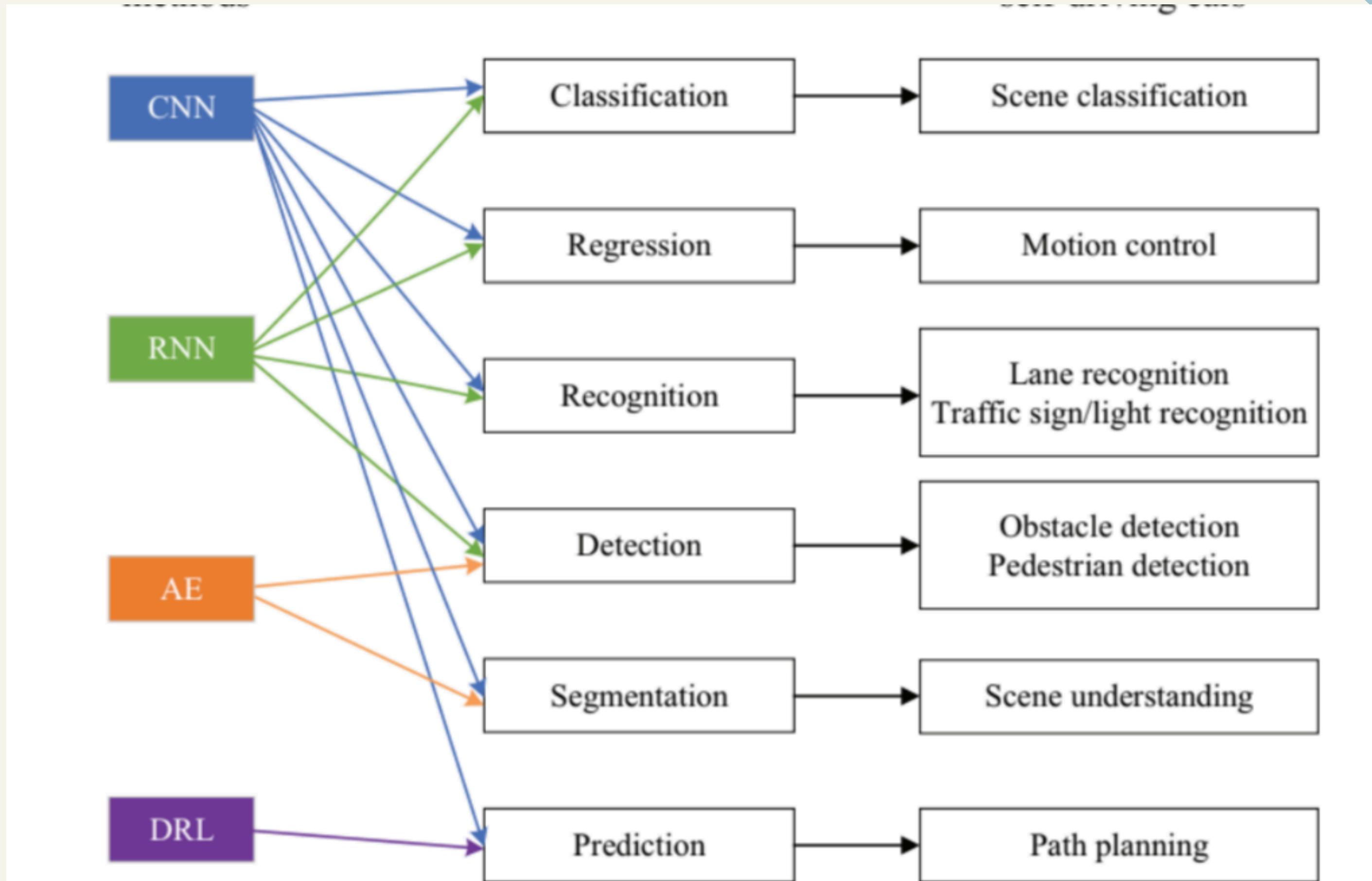
# COMPONENTS

Sensors-Collect data from the environment.

Cameras: Capture visual information.

- LIDAR: Provides high-resolution 3D mapping.
- Radar: Detects objects and their speed.
- Ultrasonic Sensors: For close-range object detection.
- GPS: Provides precise location data.

# ML IN AUTONOMOUS CARS



# NEED OF ML IN AUTONOMOUS CARS

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## 1.Object Detection

ML algorithms analyze data from cameras and LIDAR to identify and classify objects like pedestrians, other vehicles, traffic signs, and lane markings.

## 2 Decision Making and Planning

ML is used to predict the behavior of other road users, which helps in making informed decisions about speed, lane changes, and turns.

## 3.Anomaly Detection and Safety

ML algorithms can detect anomalies in the vehicle's systems and predict potential failures before they occur, enhancing reliability and safety.

## 4.Traffic Management and Optimization

ML allows autonomous vehicles to communicate with traffic management system.

## 5. Human-Machine Interaction

ML enables natural interaction between passengers and the vehicle.

## YOLOv DETECTION-

YOLOv (You Only Look Once version n) is a family of deep learning models used for object detection.

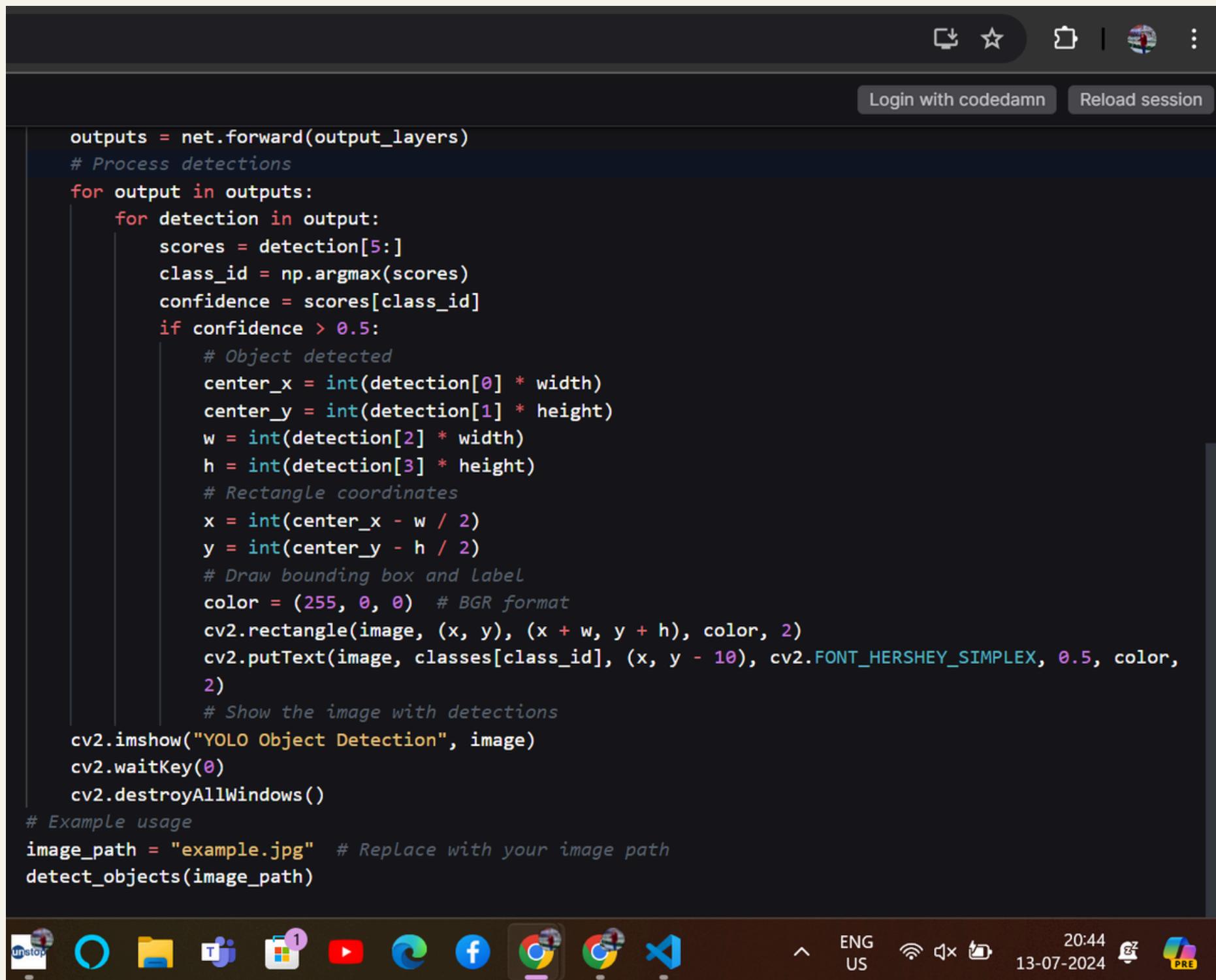
The key idea behind YOLO is to divide the input image into a grid and predict bounding boxes and probabilities for each grid cell. YOLO (You Only Look Once) models can be integral to the functionality of autonomous vehicles by providing real-time object detection capabilities. These models are adept at recognizing and localizing various objects in a vehicle's environment, such as pedestrians, other vehicles, traffic signs, and obstacles.

Versions of YOLOv are-

YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, and YOLOv7, YOLOv8, YOLOv10

YOLOv10 is high accuracy while being faster and more lightweight than previous YOLO versions and other state-of-the-art object detection models.

# Code Snippet



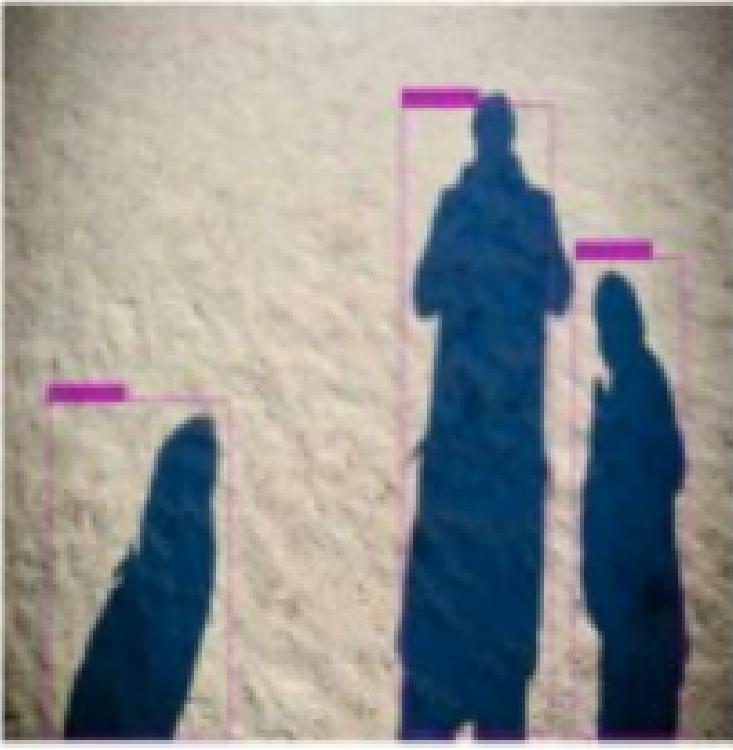
The screenshot shows a code editor window with a dark theme. The code is written in Python and performs YOLO object detection on an image. It uses OpenCV and NumPy libraries. The code processes network outputs, iterates through detections, and draws bounding boxes and labels on the image. It also includes example usage with a specific image path.

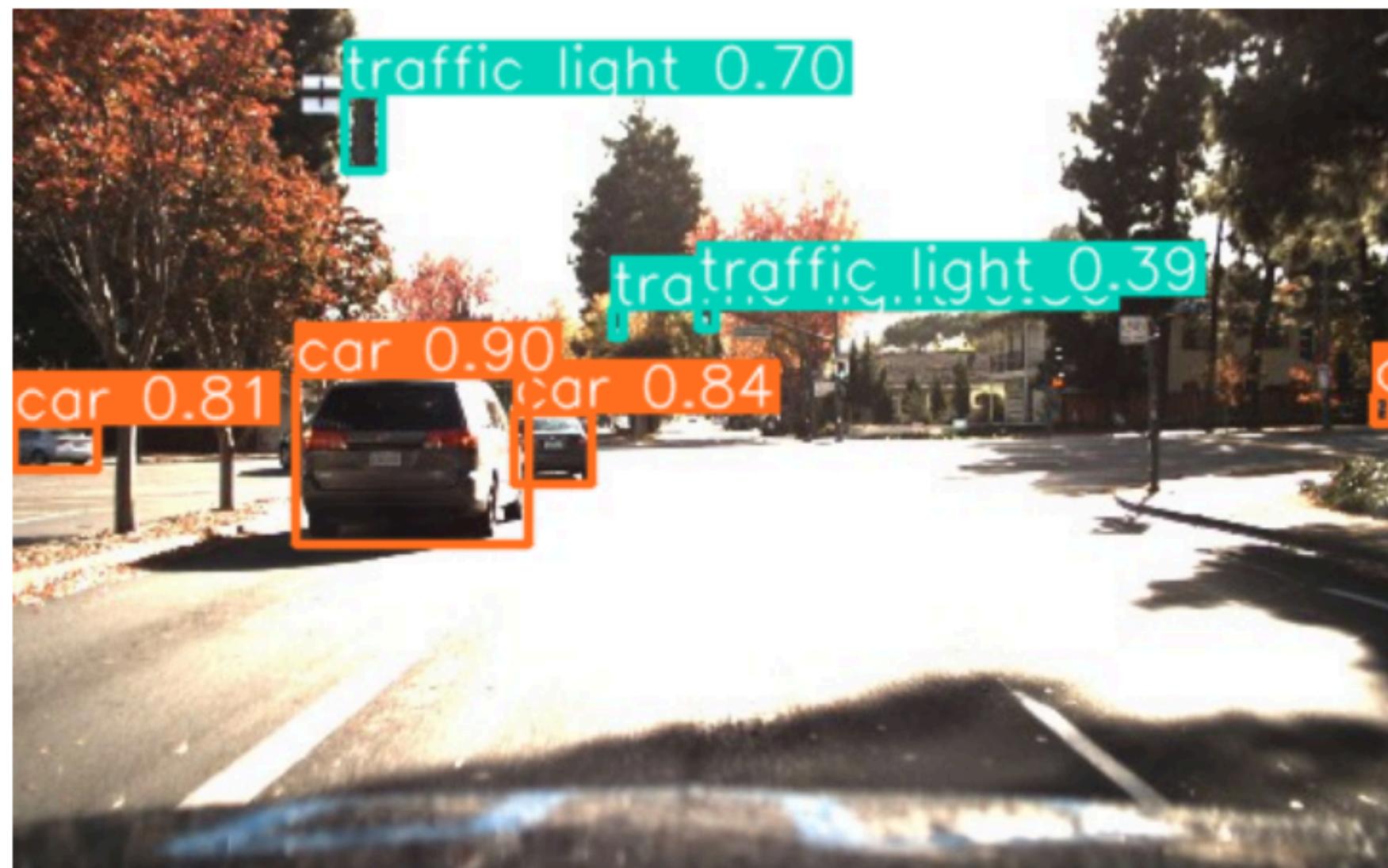
```
outputs = net.forward(output_layers)
# Process detections
for output in outputs:
    for detection in output:
        scores = detection[5:]
        class_id = np.argmax(scores)
        confidence = scores[class_id]
        if confidence > 0.5:
            # Object detected
            center_x = int(detection[0] * width)
            center_y = int(detection[1] * height)
            w = int(detection[2] * width)
            h = int(detection[3] * height)
            # Rectangle coordinates
            x = int(center_x - w / 2)
            y = int(center_y - h / 2)
            # Draw bounding box and Label
            color = (255, 0, 0) # BGR format
            cv2.rectangle(image, (x, y), (x + w, y + h), color, 2)
            cv2.putText(image, classes[class_id], (x, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)
            # Show the image with detections
            cv2.imshow("YOLO Object Detection", image)
            cv2.waitKey(0)
            cv2.destroyAllWindows()
# Example usage
image_path = "example.jpg" # Replace with your image path
detect_objects(image_path)
```

# Seat Yolo Detection

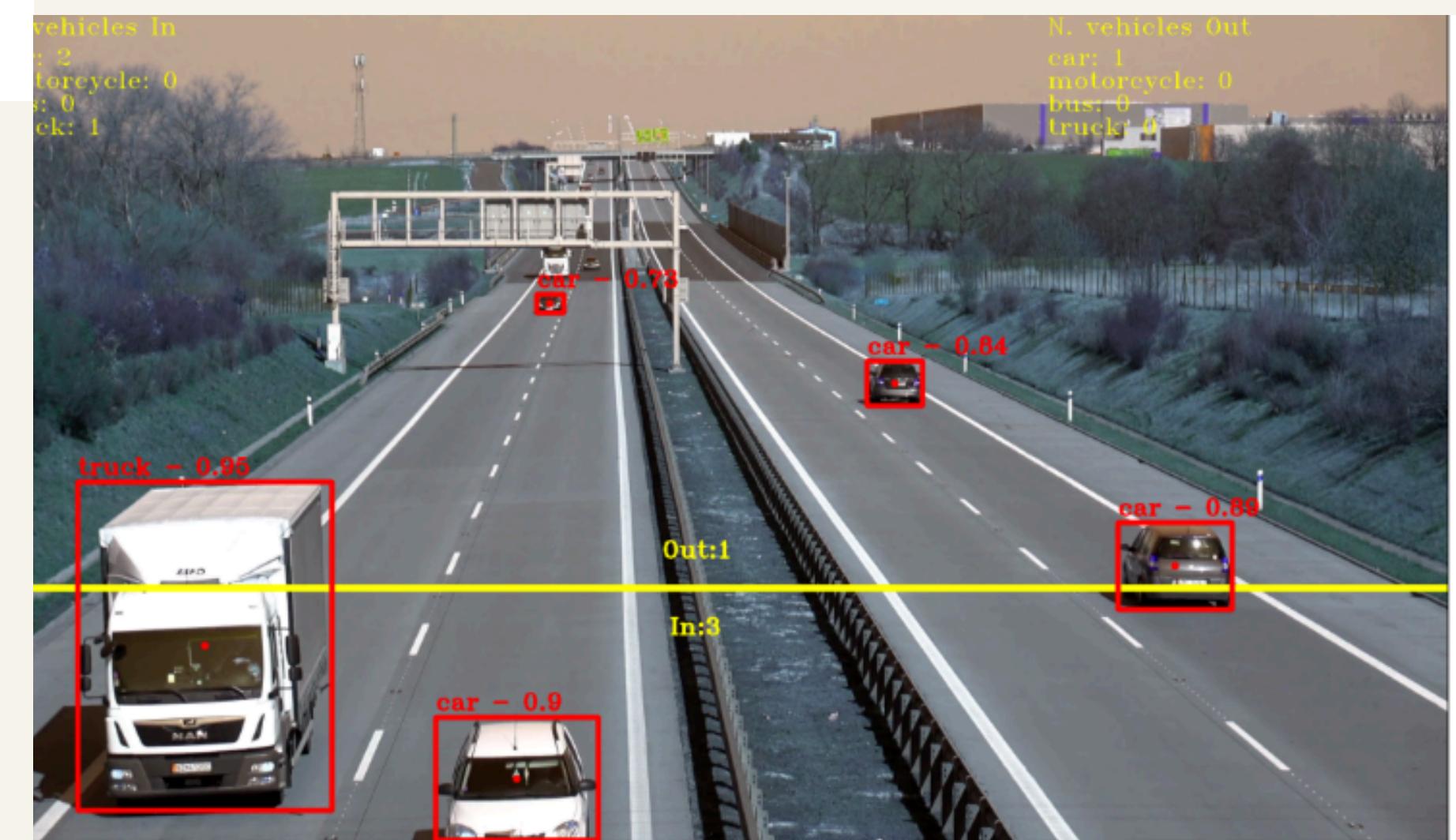
Seat yolo detection is a technique that is used in YOLO for detecting seats and shadows in an autonomous vehicle context.

SEAT-YOLO architecture for shadow detection. The SEAT-YOLO is a novel deep learning architecture that combines squeeze-excite blocks, spatial attention module, and spatial pyramid pooling along with three YOLO detection heads for accurate detection of shadow regions in images and videos.





## VIDEO DETECTION USING YOLOv METHOD

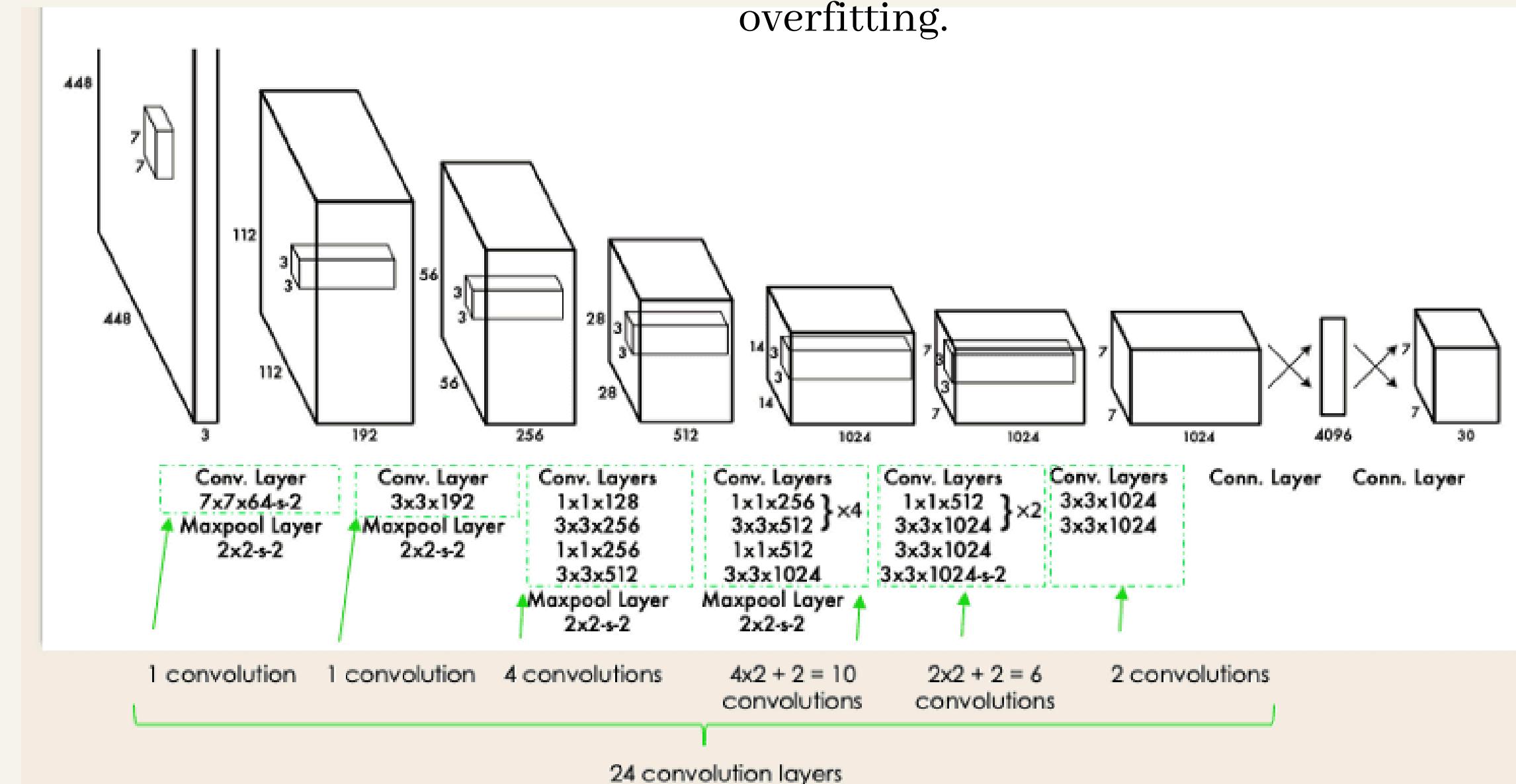


## YOLO ARCHITECHTURE-

YOLO architecture is similar to GoogleNet. As illustrated below, it has overall 24 convolutional layers, four max-pooling layers, and two fully connected layers

Resizes the input image into 448x448 before going through the convolutional network.

- A 1x1 convolution is first applied to reduce the number of channels, which is then followed by a 3x3 convolution to generate a cuboidal output.
- The activation function under the hood is ReLU, except for the final layer, which uses a linear activation function.
- Some additional techniques, such as batch normalization and dropout, respectively regularize the model and prevent it from overfitting.



## **ALGORITHM BEHIND YOLOv DETECTION-**

**1.Dividing the image** -The input image is divided into a grid. This grid can vary in size depending on the YOLO version and configuration.

**2.Predictions for Each Grid Cell**-For each grid cell the YOLOv model then predicts the probability for each grid respectively.Each bounding box consists of five components: (x, y, w, h, confidence).

- a. (x, y) represent the coordinates of the center of the bounding box relative to the grid cell.
- b. (w, h) represent the width and height of the bounding box relative to the entire image.
- c. confidence represents the confidence score that the bounding box and the accuracy of the bounding box.

**3.Class Prediction**-For each bounding box, YOLO predicts the probability distribution over classes.

This means that for each bounding box, YOLO provides a score for each class indicating the likelihood of the object belonging to that class.

**4.Final Detection**-YOLO combines the bounding box predictions with their confidence scores and class predictions.

**After this it is trained on large datasets where the predictions are calculated.**

# DESCRIPTION

## 1.OBJECT DETECTION -

To detect cars in images using automated techniques, we can combine Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for handling sequential data. Although RNNs are not typically used for object detection tasks directly, they can be used for tracking objects across video frames. For standard object detection, CNN-based models like Faster R-CNN, SSD, and YOLO are more suitable. This is how ML models can be used in the object detection purposes in the area of automated driving.

Epoch: 38:- TrainLoss: 2.9258378446102142

100%

80/80 [08:53<00:00, 6.17s/it]

Epoch: 39:- TrainLoss: 2.936946827173233

100%

80/80 [08:53<00:00, 6.22s/it]

Epoch: 40:- TrainLoss: 2.9451949432492257

DONE.

TrainLoss: 2.9013238146901132



Cardetection

Draft saved

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Draft Ses

```
best_train_loss=train_loss
```

```
print(f"Done.\nTrainLoss: {best_train_loss}")
```

100% 80/80 [08:20<00:00, 5.70s/it]

Epoch: 1:- TrainLoss: 6.285768777132034  
Model Updated

100% 80/80 [08:27<00:00, 5.99s/it]

Epoch: 2:- TrainLoss: 4.563216876983643  
Model Updated

100% 80/80 [08:21<00:00, 5.74s/it]

Epoch: 3:- TrainLoss: 4.153026843070984  
Model Updated

2% 2/80 [00:12<08:04, 6.21s/it]

+ Code + Markdown

# TRAFFIC SIGN DETECTION

For Traffic sign detection in Automated driving we can use and train a neural network model and CNN model to recognise traffic signs that can be helpful in Traffic Sign Recognition, Improving Road Safety and Enabling Autonomous Navigation. The specific type of model used here is a Convolutional Neural Network (CNN). CNNs are well-suited for image recognition tasks due to their ability to capture spatial hierarchies in images through convolutional layer.

Data shape: (26640, 30, 30, 3), Labels: (26640,)



Training Data: (18648, 30, 30, 3), Training labels: (18648,)

Validation Data: (7992, 30, 30, 3), Validation labels: (7992,)

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X **Code** ▾

| Layer (type)                               | Output Shape        | Param #   |
|--|---------------------|-----------|
| conv2d_3 (Conv2D)                          | (None, 30, 30, 64)  | 832       |
| batch_normalization_3 (BatchNormalization) | (None, 30, 30, 64)  | 256       |
| conv2d_4 (Conv2D)                          | (None, 30, 30, 64)  | 16,448    |
| batch_normalization_4 (BatchNormalization) | (None, 30, 30, 64)  | 256       |
| max_pooling2d_2 (MaxPooling2D)             | (None, 15, 15, 64)  | 0         |
| conv2d_5 (Conv2D)                          | (None, 15, 15, 128) | 32,896    |
| batch_normalization_5 (BatchNormalization) | (None, 15, 15, 128) | 512       |
| max_pooling2d_3 (MaxPooling2D)             | (None, 7, 7, 128)   | 0         |
| dropout_1 (Dropout)                        | (None, 7, 7, 128)   | 0         |
| flatten_1 (Flatten)                        | (None, 6272)        | 0         |
| dense_4 (Dense)                            | (None, 256)         | 1,605,888 |

# 3D Object Detection

Detecting 3D objects for autonomous vehicles typically involves using machine learning (ML) techniques, often in conjunction with sensor data such as LiDAR point clouds and camera images.



Cancel Run Code Draft Session (41m) D P A M :

```
583/583 63s 108ms/step - categorical_accuracy: 0.9938 - loss: 0.0390 - mse: 3.2301e-04 - val_categorical_accuracy: 0.9836 - val_loss: 0.0817 - val_mse: 6.7342e-04
Epoch 23/25
583/583 0s 100ms/step - categorical_accuracy: 0.9958 - loss: 0.0333 - mse: 2.5931e-04
Epoch 23: val_loss did not improve from 0.08173
583/583 64s 110ms/step - categorical_accuracy: 0.9958 - loss: 0.0333 - mse: 2.5933e-04 - val_categorical_accuracy: 0.9820 - val_loss: 0.0820 - val_mse: 6.8124e-04
Epoch 24/25
583/583 0s 99ms/step - categorical_accuracy: 0.9963 - loss: 0.0302 - mse: 2.3794e-04
Epoch 24: val_loss improved from 0.08173 to 0.08088, saving model to traffic_sign_model.keras
583/583 63s 109ms/step - categorical_accuracy: 0.9963 - loss: 0.0302 - mse: 2.3798e-04 - val_categorical_accuracy: 0.9837 - val_loss: 0.0809 - val_mse: 6.6918e-04
Epoch 25/25
583/583 0s 98ms/step - categorical_accuracy: 0.9963 - loss: 0.0285 - mse: 2.1492e-04
Epoch 25: val_loss improved from 0.08088 to 0.07901, saving model to traffic_sign_model.keras
583/583 63s 108ms/step - categorical_accuracy: 0.9963 - loss: 0.0285 - mse: 2.1492e-04 - val_categorical_accuracy: 0.9831 - val_loss: 0.0790 - val_mse: 6.4823e-04
[In progress] Loading Keras model and history file...
[Done] Loading Keras model and history file...
```

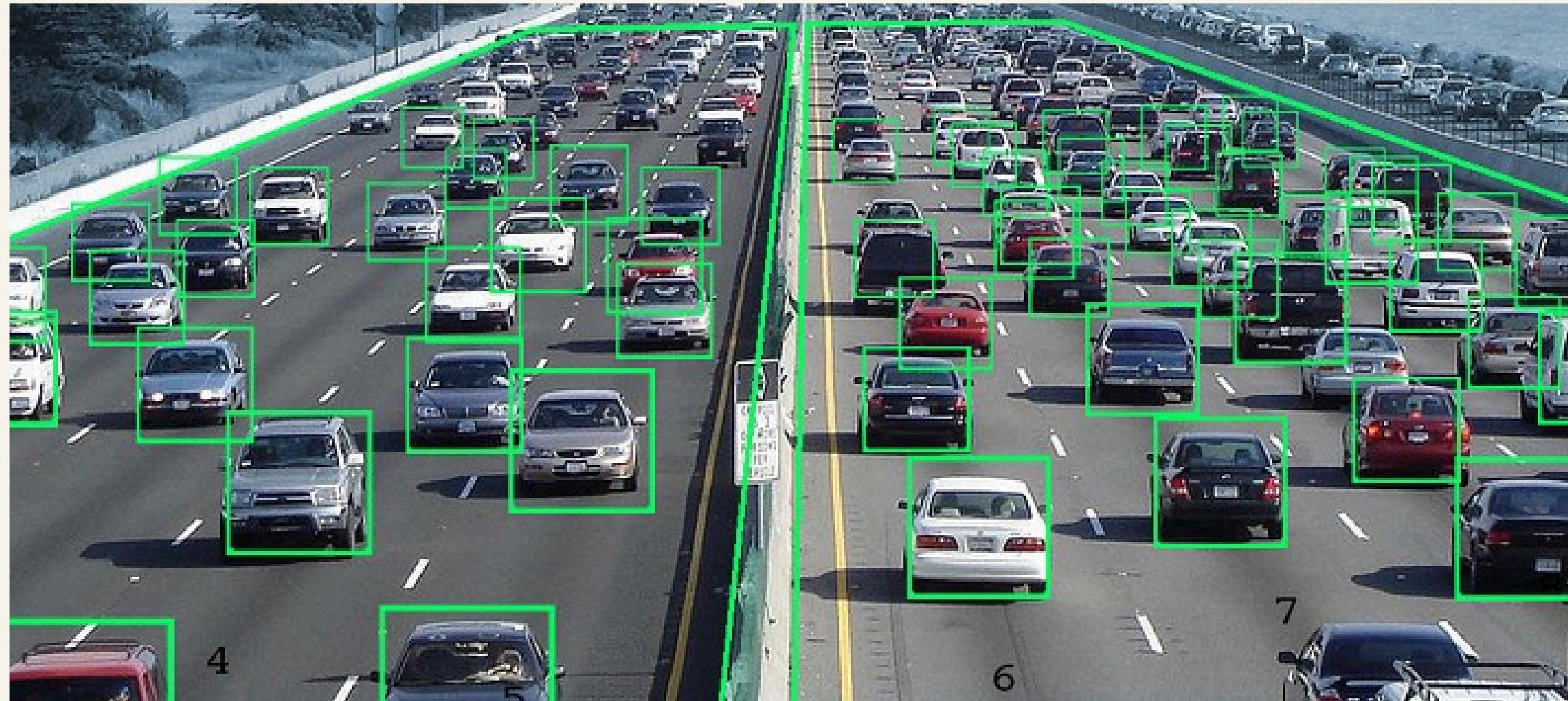
+ Code + Markdown

# LANE DETECTION AND ROAD BOUNDARY

Lane Detection can also be done with the help of various ml algorithm and Lane detection helps in maintaining the vehicle within its lane by providing feedback to automated steering systems. This is essential for implementing lane-keeping assistance features, where the vehicle autonomously adjusts its steering to stay centered within the lane. Automated vehicles equipped with lane detection systems can alert the driver or autonomously take corrective action if the vehicle begins to drift out of its lane unintentionally.

## MOTION DETECTION

Machine learning can be effective for motion detection, it's not the only approach. Traditional computer vision techniques like background subtraction or optical flow are also commonly used for motion detection tasks.



LINK TO GITHUB-<https://github.com/t-abs/Autonomous-cars-IISER-Intern>

## SUMMARY AND FUTURE WORKS-

Machine learning in autonomous cars is essential for enabling the vehicle to perceive and interpret its environment, make informed decisions, and navigate safely. It involves computer vision techniques to process data from cameras and sensors, allowing the car to recognize and track objects, lane markings, and traffic signs. Sensor fusion combines information from various sources for a comprehensive situational awareness. Additionally, machine learning algorithms predict the behavior of other road users and plan the car's path accordingly, ensuring safe and efficient driving. YOLO (You Only Look Once) is a real-time object detection algorithm widely used in autonomous driving. It processes an image in a single pass to detect and classify objects with high speed and accuracy. YOLO divides the image into a grid and predicts bounding boxes and probabilities for each grid cell, allowing the vehicle to identify and locate multiple objects simultaneously. This capability is crucial for real-time navigation and decision-making in dynamic environments.

## **FUTURE WORK AND REFERENCE PAPERS-**

- 1.Trying to train various weather detection using yolo technique real time analysis**
- 2.Working on other detection and aspects**

## **References-**

- 1.)[https://www.researchgate.net/publication/350486877\\_Autonomous\\_vehicles\\_A\\_study\\_of\\_implementation\\_and\\_security](https://www.researchgate.net/publication/350486877_Autonomous_vehicles_A_study_of_implementation_and_security)**
- 2.)<https://journalofbigdata.springeropen.com/articles/10.1186/s40537-023-00701-y>**

**THANK YOU**