

# CREATIVE AND INNOVATIVE PROJECT

TEAM 4 -

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# ROAD LANE DETECTION AND OBSTACLE TRACKING

# OBJECTIVE

- To develop a vision-based real-time lane detection and tracking using PPHT, where different lighting conditions, and different road types, i.e., straight and curved, are considered.
- Using real world dataset to evaluate the lane boundary detection rate and the time complexity.
- Using YOLO algorithm to detect obstacles on the road and provide a robust object tracking system along with road lane detection.

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# INTRODUCTION

- Lane detection and tracking is an important component of the Advanced Driver Assistance System.
- Lane line detection and identification has become a basic and necessary functional module in the field of vehicle safety and intelligent vehicle navigation.
- The performance of various lane detection methods drops in the case of different lighting conditions
- Effective lane detection is challenging due to different types of roads as well as occlusion caused by various obstacles.
- Obstacle detection also plays a major role in avoiding accidents.

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# INTRODUCTION

The method proposed is as follows:

- In the pre-processing stage, images are transformed to grayscale image and smoothed. Edge detection is applied using Sobel filter. Finally, Otsu's thresholding is applied.
- A simple Adaptive Region of Interest (AROI) is used to reduce the computational complexity.
- PPHT is used as it reduces false positive rate.
- Kalman filter is used to track both borders of each lane markings. This additional lane-tracking step increases the probability to detect lane markings in poor conditions and improves efficiency.
- YOLO algorithm is then used to detect obstacles like vehicles, pedestrians, animals etc.

# LITERATURE SURVEY

	AUTHOR	METHODOLOGY	ADVANTAGES	DISADVANTAGES
1	Abdelh mid Mamme, Guangqian Lu et al	Uses PPHT and MSER for lane detection.	PPHT returns two end-points of the detected line markings.	MSER is more computationally expensive.
2	Yassin Kortli, Mehrez, J. Subash Chandra Bose et al	Uses RGB to grayscale image conversion, and a Gaussian filter.	Performs well in bad weather conditions.	Faces issue in case of blur lane marks and bent road surfaces.
3	Mohamed Aly	Inverse Perspective Mapping (IPM) is used as the algorithm.	Works at high rates of 50 Hz.	Presence of obstacles on road reduces accuracy.
4	Ziqiang Sun	Yellow & white lane lines are processed separately in HSV space and then combined.	Robust and adaptive.	High no. of false positives.

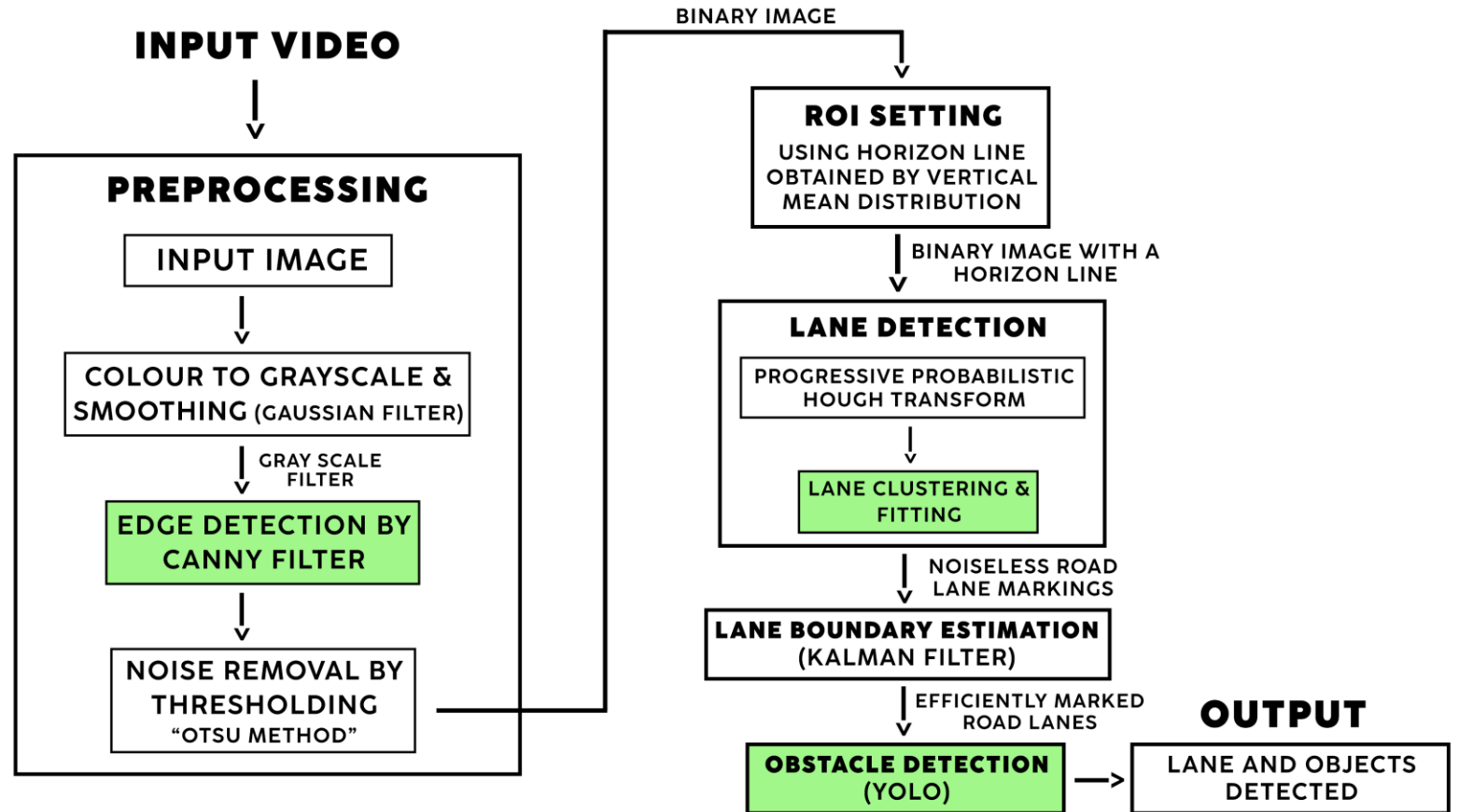
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# LITERATURE SURVEY

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5	Shahanaz Syed, Rudra Hota et al	Weighted regression to fit a curve is used here.	Better estimation of lane markings.	Does not work well under heavy traffic conditions and when the lane changes are fast.
6	Hiroyuki Komori, Kazunori Onoguchi	Detects various types of lane markings and road boundaries.	Detects blurred lane markings and shoulders with complicated shapes.	Cannot be evaluated using public datasets.
7	Ping Wei, Linhai Xu, Nanning Zheng	Incorporates prior spatial-temporal knowledge with lane appearance features.	Performs well under various challenging weather conditions.	May produce false results in some special traffic conditions.
8	Maurício Braga de Paula, Cláudio Rosito Jung	Lane boundaries are detected using a linear-parabolic lane model.	Consistent results for video sequences acquired with different devices.	Produces classification errors due to deviations of the lane tracker from the actual lane boundaries

# ARCHITECTURAL DIAGRAM



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# DETAILED MODULE DESIGN

## MODULE 1 - PRE-PROCESSING

1. Converting video to image sequences.
2. Converting an RGB image to grayscale images and smoothing. Smoothing is used to reduce noise or to produce a less pixelated image.
3. Edge detection is then performed using Sobel filter. It works by calculating the gradient of image intensity at each pixel within the image. It finds the direction of the largest increase from light to dark and the rate of change in that direction.
4. Image thresholding is done to remove noises using "Otsu method".

INPUT : Road Lane videos

OUTPUT : Binary Image

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# DETAILED MODULE DESIGN

## MODULE 1 - PRE-PROCESSING

ALGORITHM -

Conversion from RGB to Grayscale :

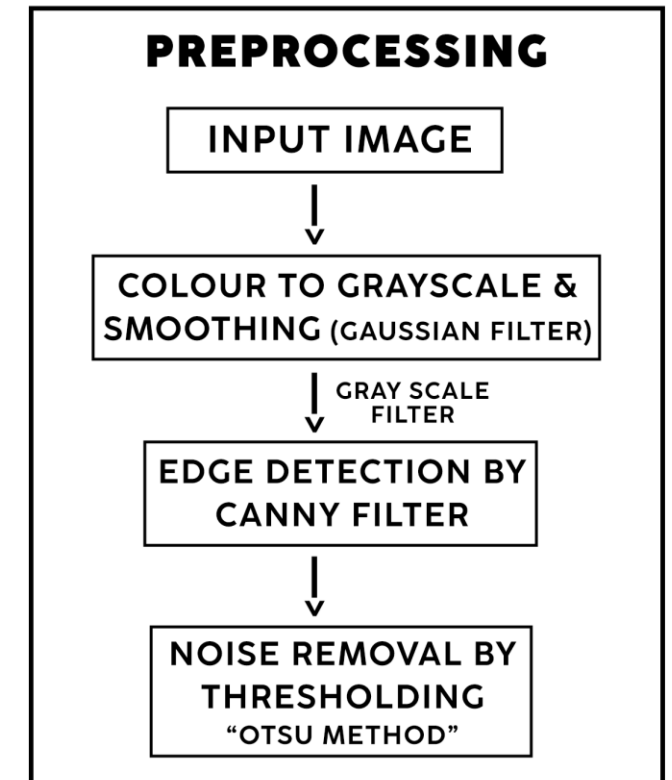
```
gray_img = cv.cvtColor(img,  
cv.COLOR_RGB2GRAY)  
blur = cv.GaussianBlur(gray_img,  
(5, 5), 0)
```

Edge detection :

```
edge_det = cv.Canny(gray_img, 50,  
100, apertureSize=3)
```

Otsu thresholding :

```
ret, thresh1 = cv.threshold(edge, 120, 255, cv.THRESH_BINARY +  
cv.THRESH_OTSU)
```



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# DETAILED MODULE DESIGN

## MODULE 2 - ROI SETTING

1. An AROI is established using a horizon line that effectively removes noisy line segments and reduces the computational complexity.
2. The horizon line is used to divide the scene into road region and sky region.

INPUT : Binary Image

OUTPUT : Binary Image with a horizon line

### ALGORITHM -

Setting the region of interest in our image :

```
region_of_interest_vertices = [(700, height), (width/2, height/1.37), (width-400, height)]
```

```
vertices = np.array([region_of_interest_vertices], np.int32)
```

```
mask = np.zeros_like(edge)
```

```
match_mask_color = (255)
```

```
cv.fillPoly(mask, vertices, match_mask_color)
```

```
masked_image = cv.bitwise_and(edge, mask)
```

### **ROI SETTING**

**USING HORIZON LINE  
OBTAINED BY VERTICAL  
MEAN DISTRIBUTION**

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# DETAILED MODULE DESIGN

## MODULE 3 - LANE DETECTION

1. Progressive Probabilistic Hough Transform (PPHT) is used to extract the straightest lines in the AROI.
2. The noisy lines (with unqualified angles) detected by PPHT can be removed using K-means clustering technique.

INPUT : Binary Image with a horizon line

OUTPUT : Noiseless road lane markings

### ALGORITHM -

PPHT algorithm :

PHT :

```
lines = cv.HoughLinesP(cropped_image, rho=2, theta=np.pi/180,  
threshold=50, lines=np.array([]), minLineLength=10, maxLineGap=30)
```

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# DETAILED MODULE DESIGN

## MODULE 3 - LANE DETECTION

### ALGORITHM -

K-Means clustering :

n\_clusters=4

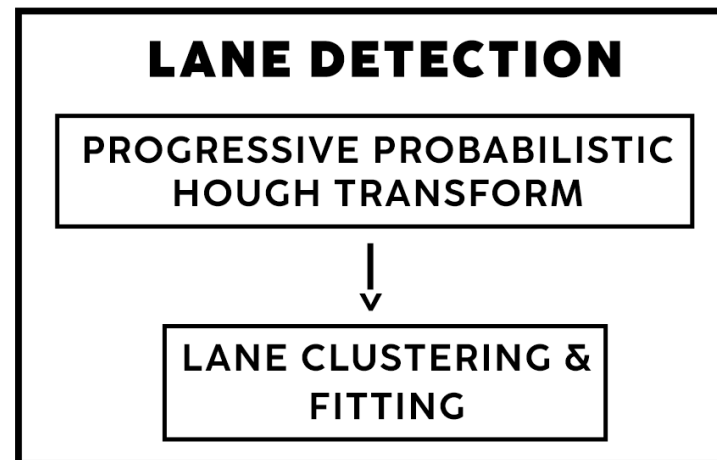
kmeans = KMeans(n\_clusters=n\_clusters, n\_init = 4)

kmeans.fit(lines)

centroids = kmeans.cluster\_centers\_

lines = scaler.inverse\_transform(lines)

centroids = scaler.inverse\_transform(centroids)



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# DETAILED MODULE DESIGN

## MODULE 4 - LANE BOUNDARY ESTIMATION

1. In order to increase the fidelity and the efficiency of lane detection system, Kalman Filter is used to track both limits of each lane markings extracted by PPHT.

INPUT : Extracted road lane markings

OUTPUT : Efficiently marked road lanes

ALGORITHM -

**LANE BOUNDARY ESTIMATION  
(KALMAN FILTER)**

Kalman filter algorithm :

```
cv.KalmanFilter(self.state_size, self.meas_size, self.contr_size)
self.kf.transitionMatrix = np.eye(self.state_size, dtype=np.float32)
self.kf.measurementMatrix = np.zeros((self.meas_size,
self.state_size), np.float32)
lt = LaneTracker(2, 0.1, 15)
```

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# DETAILED MODULE DESIGN

## MODULE 5 - OBSTACLE DETECTION

1. Detecting obstacles like vehicles, pedestrian etc. using the YOLO algorithm and providing a warning.

INPUT : Efficiently marked road lanes

OUTPUT : Obstacles Detected

ALGORITHM -

YOLO algorithm :

Divide the input images in various grids

Perform image classification

Predict the class probability of each vehicle present in the image

Detecting objects in video :

```
!./darknet detector demo cfg/coco.data cfg/yolov4.cfg yolov4.weights -  
dont_show /content/drive/MyDrive/video_2.mp4 -i 0 -out_filename  
/content/drive/MyDrive/video_out2.avi
```

**OBSTACLE DETECTION  
(YOLO)**

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# IMPLEMENTATION DETAILS

## MODULE 1 – PREPROCESSING

```
[ ] def get_vertices(image):
    rows, cols = image.shape[:2]
    bottom_left = [cols*0.15, rows]
    top_left = [cols*0.45, rows*0.6]
    bottom_right = [cols*0.95, rows]
    top_right = [cols*0.55, rows*0.6]

    ver = np.array([[bottom_left, top_left, top_right, bottom_right]], dtype=np.int32)
    return ver

def grayscale(img):
    gray_img = cv.cvtColor(img, cv.COLOR_RGB2GRAY)
    blur = cv.GaussianBlur(gray_img, (5, 5), 0)
    print("GrayScaled Image")
    cv2_imshow(blur)
    return blur

def edgeDetection(gray_img):
    edge_det = cv.Canny(gray_img, 50, 100, apertureSize=3)
    print("Edge Detection using Canny")
    cv2_imshow(edge_det)
    return edge_det

def noiseRemoval(edge):
    ret, thresh1 = cv.threshold(edge, 120, 255, cv.THRESH_BINARY + cv.THRESH_OTSU)
    print("OTSU thresholding")
    cv2_imshow(thresh1)
    return thresh1

def preprocessing(img):
    gray_img = grayscale(img)
    edge = edgeDetection(gray_img)
    edge = noiseRemoval(edge)
    #print("After pre-processing")
    #cv2_imshow(edge)
    return edge
```

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# IMPLEMENTATION DETAILS

## OUTPUT



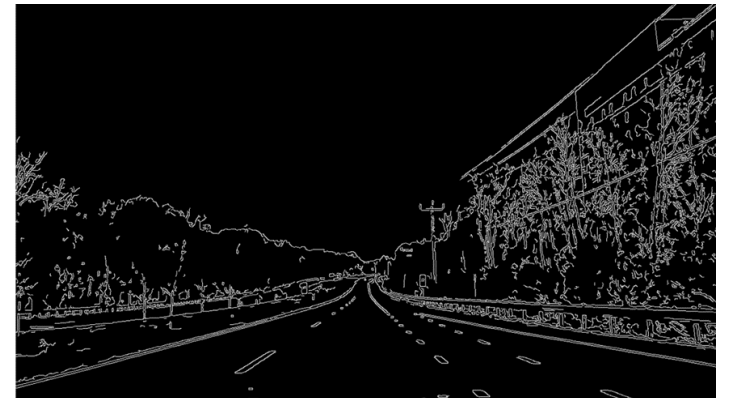
INPUT FRAME



GRAYSCALE IMAGE



CANNY FILTER



OTSU THRESHOLDING

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# IMPLEMENTATION DETAILS

## MODULE 2 – ROI SETTING

```
[ ] def regionOfInterest(img, edge):  
    height = img.shape[0]  
    width = img.shape[1]  
    #region_of_interest_vertices = [(700, height), (width/2, height/1.37), (width-400, height)]  
    region_of_interest_vertices = [(300, height), (width/2, height/1.37), (width-300, height)]  
    vertices = np.array([region_of_interest_vertices], np.int32)  
    mask = np.zeros_like(edge)  
    match_mask_color = (255)  
    cv.fillPoly(mask, vertices, match_mask_color)  
    masked_image = cv.bitwise_and(edge, mask)  
    print("ROI")  
    cv2_imshow(masked_image)  
    return masked_image
```

## OUTPUT



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# IMPLEMENTATION DETAILS

## MODULE 3 – LANE DETECTION

```
roi_theta = 0.4
road_horizon = 10
def draw_lines(img, lines):
    blank_image = np.zeros((img.shape[0], img.shape[1], 3), np.uint8)

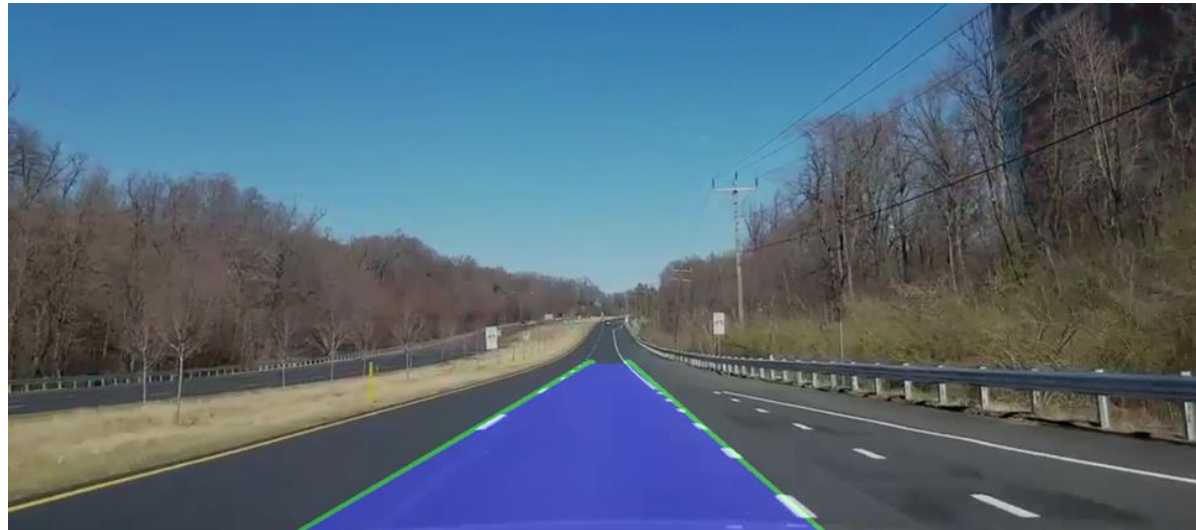
    for line in lines:
        for x1, y1, x2, y2 in line:
            cv.line(blank_image, (x1, y1), (x2, y2), (0, 255, 0), 2)

    return cv.addWeighted(img, 0.8, blank_image, 1, 0.0)

def laneDetectionPPHT(img, cropped_image):
    lines = cv.HoughLinesP(cropped_image, rho=2, theta=np.pi/180,
                           threshold=50, lines=np.array([]), minLineLength=10, maxLineGap=30)

    print("In ppht")
    print(lines)
    image_with_lines = draw_lines(img, lines)
    return lines, image_with_lines
```

## OUTPUT



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# IMPLEMENTATION DETAILS

## MODULE 3 – LANE DETECTION

```
def kmeans_clustering(lines):  
    print("in kmeans")  
    print(lines)  
    #preprocessing features to be in (0-1) range  
    scaler = MinMaxScaler()  
    lines = scaler.fit_transform(lines)  
  
    #checking K-Means Clustering Algorithm performance  
    n_clusters=4  
    kmeans = KMeans(n_clusters=n_clusters, n_init = 4)  
    kmeans.fit(lines)  
    centroids = kmeans.cluster_centers_  
  
    lines = scaler.inverse_transform(lines) #getting back our original values  
    centroids = scaler.inverse_transform(centroids) #scaling centroids to be similar to our original lines  
  
    plt.scatter(lines[:,0],lines[:,1])  
    plt.scatter(centroids[:,0],centroids[:,1])  
    plt.show()  
  
    print(centroids)  
    return centroids
```

## OUTPUT



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# IMPLEMENTATION DETAILS

## MODULE 4 – LANE BOUNDARY ESTIMATION

```
def _update_dt(self, dt):
    for i in range(0, self.state_size, 2):
        self.kf.transitionMatrix[i, i+1] = dt

def _first_detect(self, lanes):
    for l, i in zip(lanes, range(0, self.state_size, 8)):
        self.state[i:i+8:2, 0] = l
    self.kf.statePost = self.state
    self.first_detected = True

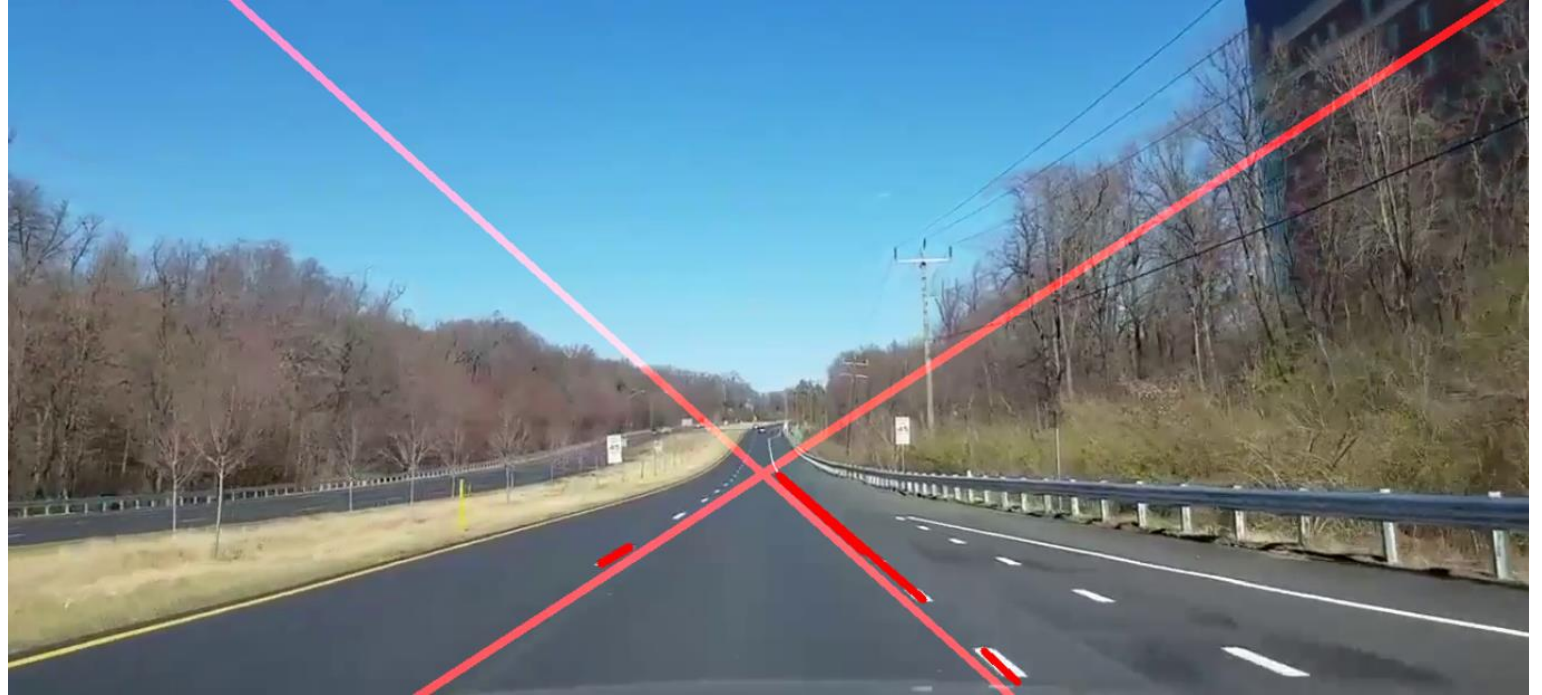
def update(self, lanes):
    if self.first_detected:
        for l, i in zip(lanes, range(0, self.meas_size, 4)):
            if l is not None:
                self.meas[i:i+4, 0] = l
            self.kf.correct(self.meas)
    else:
        lanes = lanes
        if lanes.count(None) == 0:
            self._first_detect(lanes)

def predict(self, dt):
    if self.first_detected:
        self._update_dt(dt)
        state = self.kf.predict()
        lanes = []
        for i in range(0, len(state), 8):
            lanes.append((state[i], state[i+2], state[i+4], state[i+6]))
        return lanes
    else:
        return None
```

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# IMPLEMENTATION DETAILS

## OUTPUT



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# IMPLEMENTATION DETAILS

## MODULE 5 – OBSTACLE DETECTION

```
[ ] #Download pre-trained YOLOv4 weights
!wget https://github.com/AlexeyAB/darknet/releases/download/darknet_yolo_v3_optimal/yolov4.weights

--2022-06-03 10:39:40-- https://github.com/AlexeyAB/darknet/releases/download/darknet_yolo_v3_optimal/yolov4.weights
Resolving github.com (github.com)... 140.82.112.4
Connecting to github.com (github.com)|140.82.112.4|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://objects.githubusercontent.com/github-production-release-asset-2e65be/75388965/ba4b6380-889c-11ea-9
--2022-06-03 10:39:40-- https://objects.githubusercontent.com/github-production-release-asset-2e65be/75388965/ba4b6
Resolving objects.githubusercontent.com (objects.githubusercontent.com)... 185.199.110.133, 185.199.108.133, 185.199
Connecting to objects.githubusercontent.com (objects.githubusercontent.com)|185.199.110.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 257717640 (246M) [application/octet-stream]
Saving to: 'yolov4.weights'

yolov4.weights      100%[=====>] 245.78M   238MB/s   in 1.0s

2022-06-03 10:39:41 (238 MB/s) - 'yolov4.weights' saved [257717640/257717640]
```



```
[ ] !./darknet detector demo cfg/coco.data cfg/yolov4.cfg yolov4.weights -dont_show /content/drive/MyDrive/ovideo.mp4 -i 0 -out_filename /content/drive/MyDrive/video_yolo_out.mp4

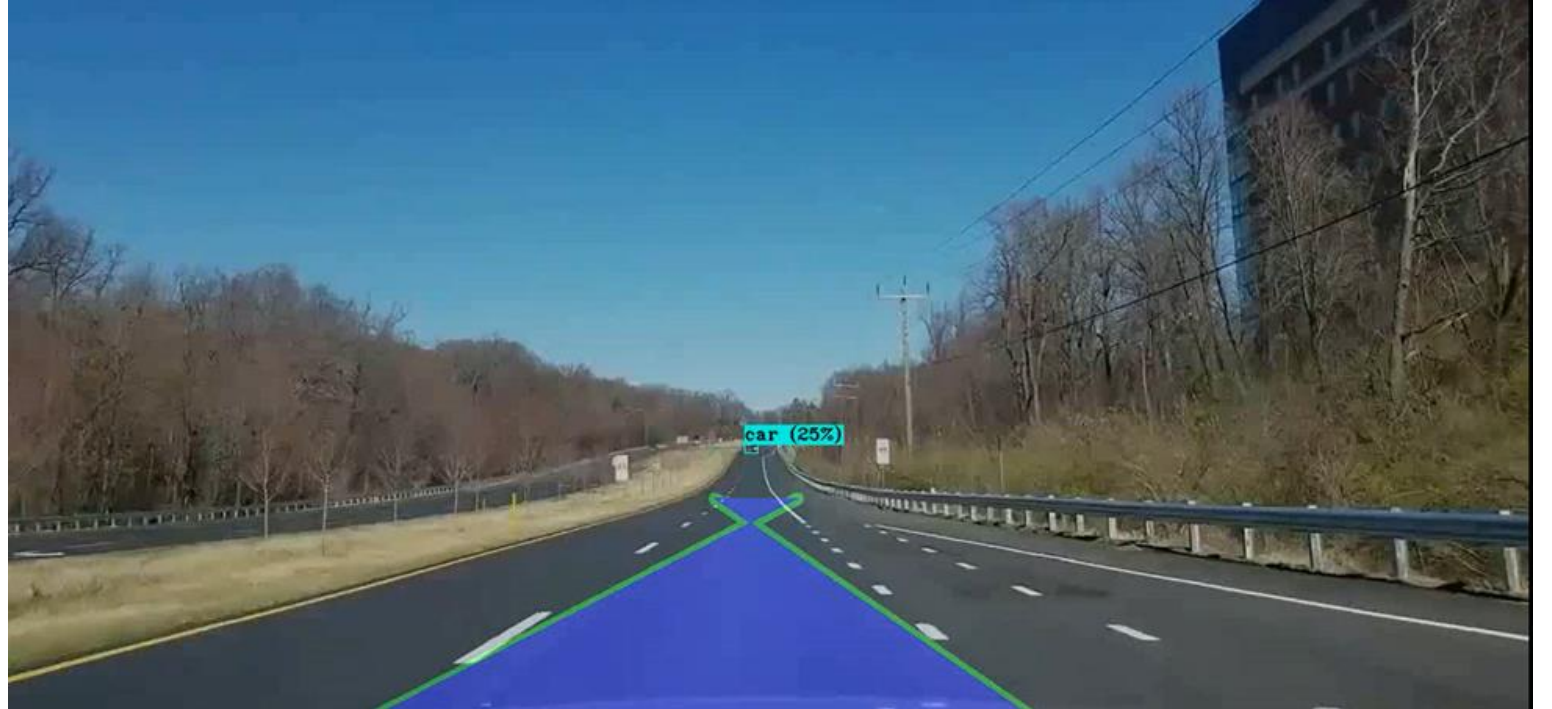
CUDA-version: 11010 (11020), cuDNN: 7.6.5, CUDNN_HALF=1, GPU count: 1
CUDNN_HALF=1
OpenCV version: 3.2.0
Demo
0 : compute_capability = 750, cudnn_half = 1, GPU: Tesla T4
net.optimized_memory = 0
mini_batch = 1, batch = 8, time_steps = 1, train = 0
layer filters size/strd(dil) input output
0 Create CUDA-stream - 0
Create cudnn-handle 0
conv 32 3 x 3/ 1 608 x 608 x 3 -> 608 x 608 x 32 0.639 BF
1 conv 64 3 x 3/ 2 608 x 608 x 32 -> 304 x 304 x 64 3.407 BF
2 conv 64 1 x 1/ 1 304 x 304 x 64 -> 304 x 304 x 64 0.757 BF
3 route 1 -> 304 x 304 x 64
4 conv 64 1 x 1/ 1 304 x 304 x 64 -> 304 x 304 x 64 0.757 BF
5 conv 32 1 x 1/ 1 304 x 304 x 64 -> 304 x 304 x 32 0.379 BF
6 conv 64 3 x 3/ 1 304 x 304 x 32 -> 304 x 304 x 64 3.407 BF
7 Shortcut Layer: 4, wt = 0, wn = 0, outputs: 304 x 304 x 64 0.006 BF
8 conv 64 1 x 1/ 1 304 x 304 x 64 -> 304 x 304 x 64 0.757 BF
9 route 8 2 -> 304 x 304 x 128
10 conv 64 1 x 1/ 1 304 x 304 x 128 -> 304 x 304 x 64 1.514 BF
11 conv 128 3 x 3/ 2 304 x 304 x 64 -> 152 x 152 x 128 3.407 BF
12 conv 64 1 x 1/ 1 152 x 152 x 128 -> 152 x 152 x 64 0.379 BF
.. ..
```

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# IMPLEMENTATION DETAILS

## OUTPUT



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# EVALUATION METRICS

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The criteria that are used in the evaluation of lane detection performance:

## ACCURACY

Accuracy indicates the fraction of predictions that the model made were correct.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

## PRECISION

Precision is defined as the ratio of correctly classified positive (True Positives) samples to a total number of classified positive samples (True Positives and False Positive).

$$Precision = \frac{TP}{TP + FP}$$

$TP$  = True positive

$TN$  = True negative

## RECALL

The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples

$$Recall = \frac{TP}{TP + FN}$$

$FP$  = False positive

$FN$  = False negative







## F1-SCORE

F1 Score is the weighted average of Precision and Recall.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$









# TEST CASES AND VALIDATION

Frame No.	Input Frame	Lane detected Frame	Binary output	Metrics
1				Precision : 0.806 Recall : 0.806 Accuracy : 0.963 F1-score : 0.806
2				Precision : 0.736 Recall : 0.736 Accuracy : 0.911 F1-score : 0.736

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# TEST CASES AND VALIDATION

3			 <p>Precision : 0.776 Recall : 0.776 Accuracy : 0.916 F1-score : 0.776</p>
4			 <p>Precision : 0.757 Recall : 0.757 Accuracy : 0.912 F1-score : 0.757</p>

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# TEST CASES AND VALIDATION

## OVERALL METRICS

ACCURACY – 0.925

PRECISION – 0.769

RECALL – 0.769

F1-SCORE – 0.769

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# REFERENCES

1. <https://ieeexplore.ieee.org/abstract/document/9085354>
2. <https://ieeexplore.ieee.org/document/9213624>
3. <https://ieeexplore.ieee.org/document/9412400>
4. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7905284>
5. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=4621152>
6. <https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.176.57&rep=rep1&type=pdf>
7. [https://mdpi-res.com/d\\_attachment/sensors/sensors-16-01276/article\\_deploy/sensors-16-01276.pdf](https://mdpi-res.com/d_attachment/sensors/sensors-16-01276/article_deploy/sensors-16-01276.pdf)
8. <https://ieeexplore.ieee.org/document/4580573>
9. <https://ieeexplore.ieee.org/document/7128388>