
ECEN 5763 Embedded Computer Vision: Final project Report

Exercise 6

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Introduction

Significant progress has been made in the field of computer vision in recent years, especially in the area of autonomous driving and Advanced Driver Assistance Systems (ADAS). These innovations are meant to advance driver comfort, increase vehicle safety, and lay the path for fully autonomous cars. These advancements are made possible by embedded computer vision, which allows for real-time processing and decision-making within the limitations of the systems installed inside the vehicle.

The creation of a dependable system for vehicle and lane detection was the main goal of this project. The method for lane detection required combining the probabilistic Hough line transform with Canny edge detection. This approach, which is covered in greater detail in the paper that goes with it, worked well for determining lane boundaries.

The first attempt used Haar Cascade classifiers for vehicle detection. But it soon became apparent that the accuracy was inadequate, and it was difficult to locate well-trained models online. YOLOv4 was used to solve this problem, which greatly increased detection accuracy. Unfortunately, the method is not practicable for real-time applications due to the excessively low frame rate caused by the significant computational burden on the CPU.

In order to address this problem, the approach shifted to YOLOv4-tiny, a scaled-down model intended for greater frames per second (FPS). Even if this was an improvement, the needed responsiveness was still not achieved. As a result, CUDNN (CUDA Deep Neural Network library) was included to expedite processing even more and improve the system's overall responsiveness and frame rate.

Comparing the performance and outcomes of these implementations with those obtained using OpenCV's CUDA implementation was also a major goal of this study. The purpose of this study was to evaluate the performance and efficacy of GPU-accelerated processing for real-time vehicle and lane recognition tasks.

Objectives

1. Implementation of lane detection and vehicle detection
2. Comparison of these algorithms with OpenCV's CUDA implementation.

Functional/Capability Requirements

Goal	Feature 1	Feature 2	Performance	Reliability
Minimum	Lane Detection	OpenCV CUDA basic algorithms comparison (canny, bgr to gray scale and Probabilistic Hough line)	8 frames/ Seconds	70%
Target	Steering based on center of the road with Incoming vehicle detection and distance estimation.	Implementing Lane detection algorithm using OpenCV's CUDA extension	12 frames/second	80%
Optimal	Lane detection and steering with broken center line/curves and generate warnings for braking based on vehicle detection.	Adaptation of the complete algorithm (lane detection, vehicle detection and warnings) using OpenCV's CUDA	20+ frames/second	90%+

Minimal Objective:

The bare minimum goal was achieved using the probabilistic Hough line algorithm and canny edge detection to develop a simple lane detection function. The basic algorithm was also implemented using OpenCV's CUDA extension.

Target Objective

Incoming vehicle detection was achieved by using Haar cascade. The same was implemented using OpenCV's CUDA extension.

Optimal Objective

The performance and reliability goals were achieved using both OpenCV and OpenCV's CUDA for lane detection. But Haar Cascade had around 5% of false positive rate, due to which alternate route of Yolo implementation was taken. By using the lane detection algorithm with yolo and CUDNN for car/truck detection, optimal goal was achieved.

Extra Implementation:

The yolov4 implementation was really slow due to which the yolov4-tiny was tested which gave faster frame rate as compared to yolov4 but was still not enough. Due to this, CUDNN was used to achieve the desired framerate and reliability.

Note:

Even though the CUDA implementation is straight forward, the OpenCV has to be reinstalled which took lot of effort and permutations of the CMAKE commands. This is the final configuration used for installation:

```
cmake -D CMAKE_BUILD_TYPE=Release -D CMAKE_INSTALL_PREFIX=/usr/local
-D OPENCV_EXTRA_MODULES_PATH=../../opencv_contrib/modules -D
WITH_CUDA=ON -D WITH_CUDNN=ON -D OPENCV_DNN_CUDA=ON -D
CUDA_ARCH_BIN=8.7 \ -D CUDA_ARCH_PTX=8.7 \ -D WITH_TBB=ON \ -D
WITH_EIGEN=OFF \ -D WITH_V4L=ON \ -D BUILD_TIFF=ON \ -D
WITH_FFMPEG=ON \ -D WITH_GSTREAMER=ON \ -D BUILD_TESTS=OFF \ -D
BUILD_PERF_TESTS=OFF \ -D BUILD_opencv_python2=OFF \ -D
BUILD_opencv_python3=ON \ -D BUILD_EXAMPLES=OFF -D WITH_CUBLAS=ON -D
ENABLE_FAST_MATH=ON ENABLE_NEON=ON -D WITH_OPENMP=ON -D
WITH_OPENCL=OFF -D BUILD_TBB=ON -D WITH_LIBV4L=ON -D
OPENCV_ENABLE_NONFREE=ON -D OPENCV_GENERATE_PKGCONFIG=ON -D
WITH_GTK=ON -D WITH_OPENGL=ON -S ~/opencv/ ..
```

Machine Vision Requirements

Canny Edge Detection

Canny edge detection is an edge detection algorithm that identifies the boundaries of objects within images. It functions in multiple stages: edge tracking via hysteresis, which uses dual thresholds to identify possible edges, gradient computation to detect edge intensity and direction, and non-maximum suppression to thin out the edges. The Gaussian filter is used for noise reduction.

Probabilistic Hough Line

The Probabilistic Hough Line Transform is a method for detecting lines in an image. It is more computationally efficient than the typical Hough Transform since it randomly samples a fraction of edge points to identify lines. The endpoint coordinates are obtained for detected lines and utilized to draw the lines.

Lane Detection

Lane detection is the process of identifying lane boundaries on roads in images or video streams, commonly used in autonomous driving. Usually, it starts with preprocessing operations such as edge detection and uses methods such as the Hough Line Transform to find and highlight lane markers.

Haar Cascade

Using Haar-like features, Haar Cascade is a machine learning-based object detection method that can identify faces and cars in images. In order to assess whether the window contains the object of interest, a window is slid across the image, and a classifier is used. Cascade steps are used to improve the efficiency and accuracy of detection.

YOLO (You Only Look Once)

YOLO is a real-time object detection algorithm that divides an image into a grid and predicts bounding boxes and class probabilities for objects within each grid cell. Because YOLO examines the full image in a single pass, unlike other detectors, it is incredibly quick and appropriate for real-time applications like as autonomous driving.

OpenCV's CUDA

Through the use of NVIDIA's CUDA API, OpenCV's CUDA extension speeds up image and video processing by shifting processing duties to the GPU. This feature is perfect for real-time applications that demand high computational performance since it enables significant speed improvements in tasks like object recognition, edge detection, and filtering.

Functional Design Requirements

Firstly, lane detection and Haar cascade were implemented using OpenCV and OpenCV's CUDA extension. The flow diagram for both the algorithms are attached below:

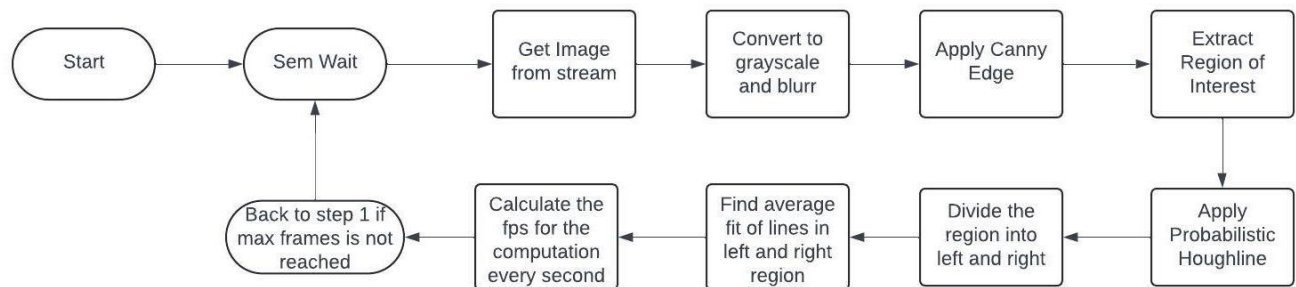


Figure 1 : Lane Detection Algorithm

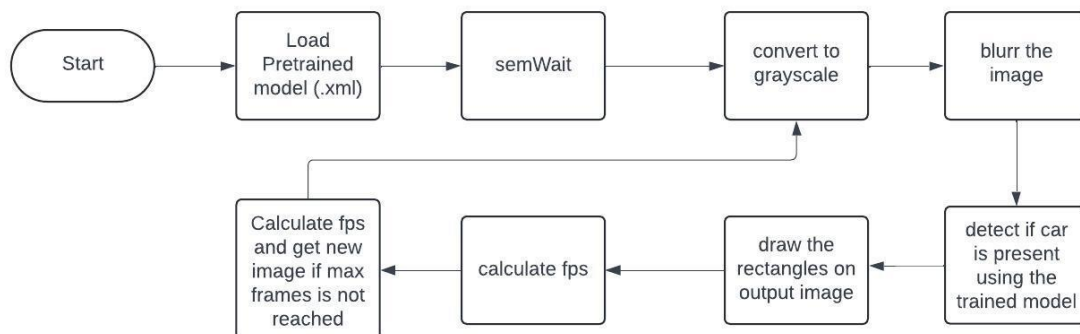


Figure 2 : Haar Cascade Implementation

As the Haar Cascade had around 5% False Positive rate, yolov4 was used. The implementation flow diagram is attached below:

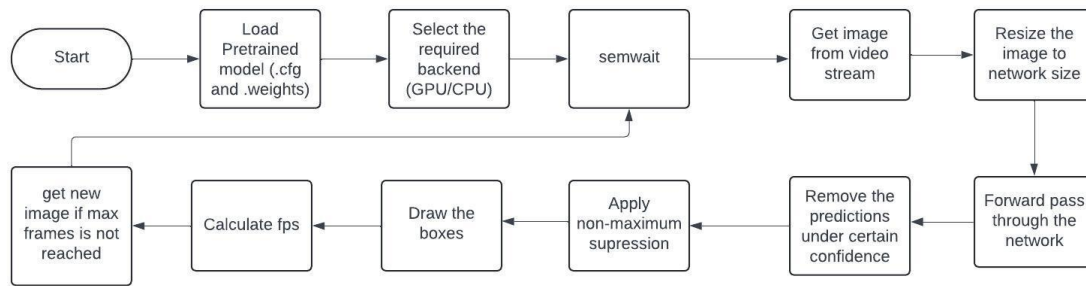


Figure 3 : Yolo implementation flow diagram

Three versions of the codes were prepared for comparison and real-time implementation. Initial goal was to run the codes on same core and use RM scheduling, but because of the fps bottleneck it was decided to use separate cores for each thread. Thus, the thread scheduling is straightforward was shown below.

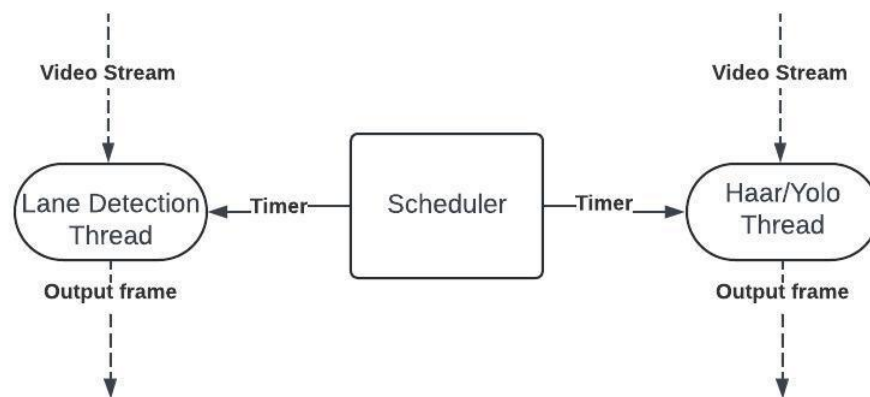


Figure 4 : Scheduler Flow

Three Implementations:

1. Lane Detection and Haar Cascade
2. CUDA Lane Detection and Haar Cascade
3. Lane Detection and CUDNN yolov4 tiny

All of the programs generate frames in prespecified location which are then encoded into a video using ffmpeg.

Results and Analysis

Lane detection:

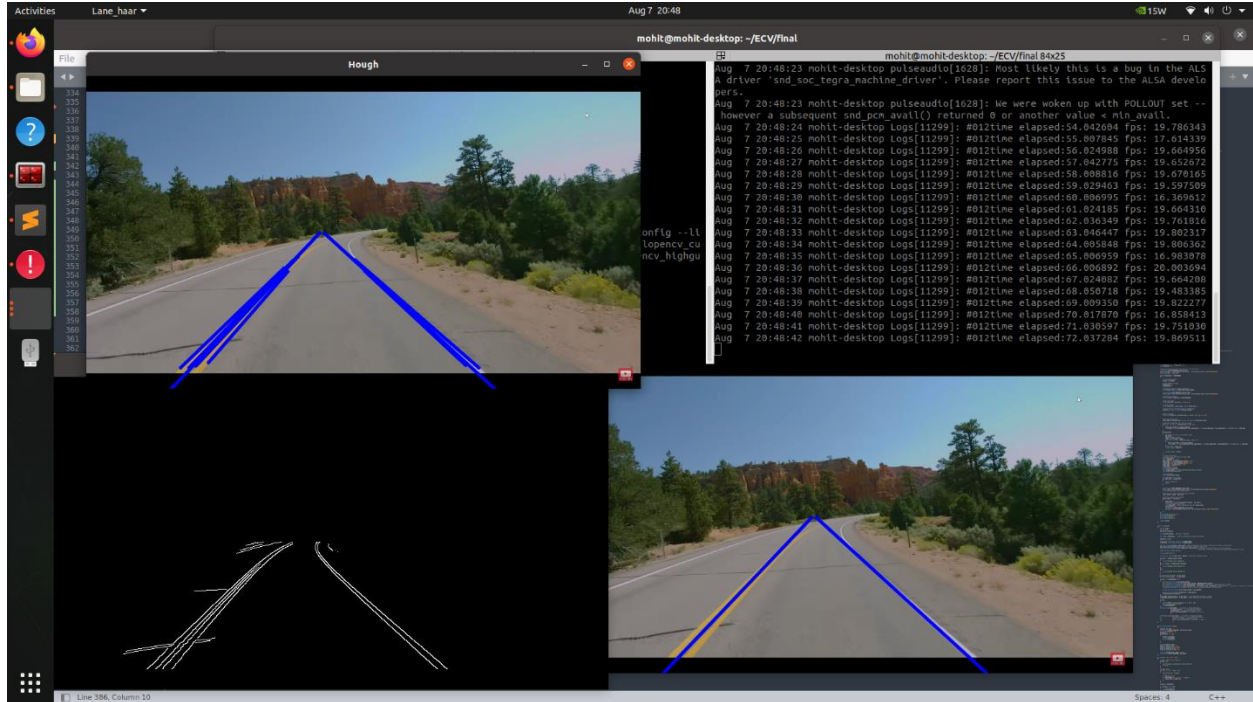


Figure 5 : Lane detection imshow and fps

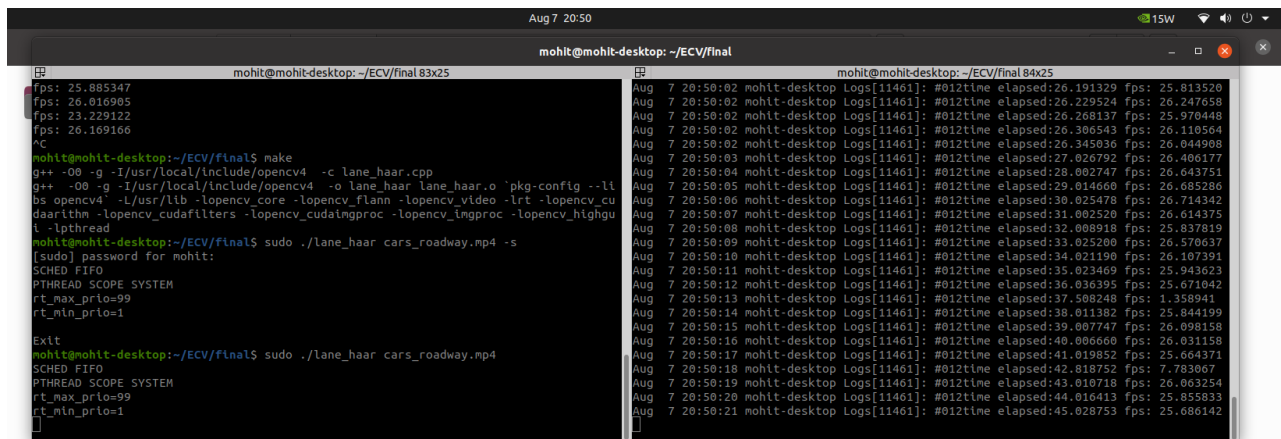


Figure 6 : Lane detection fps without imshow

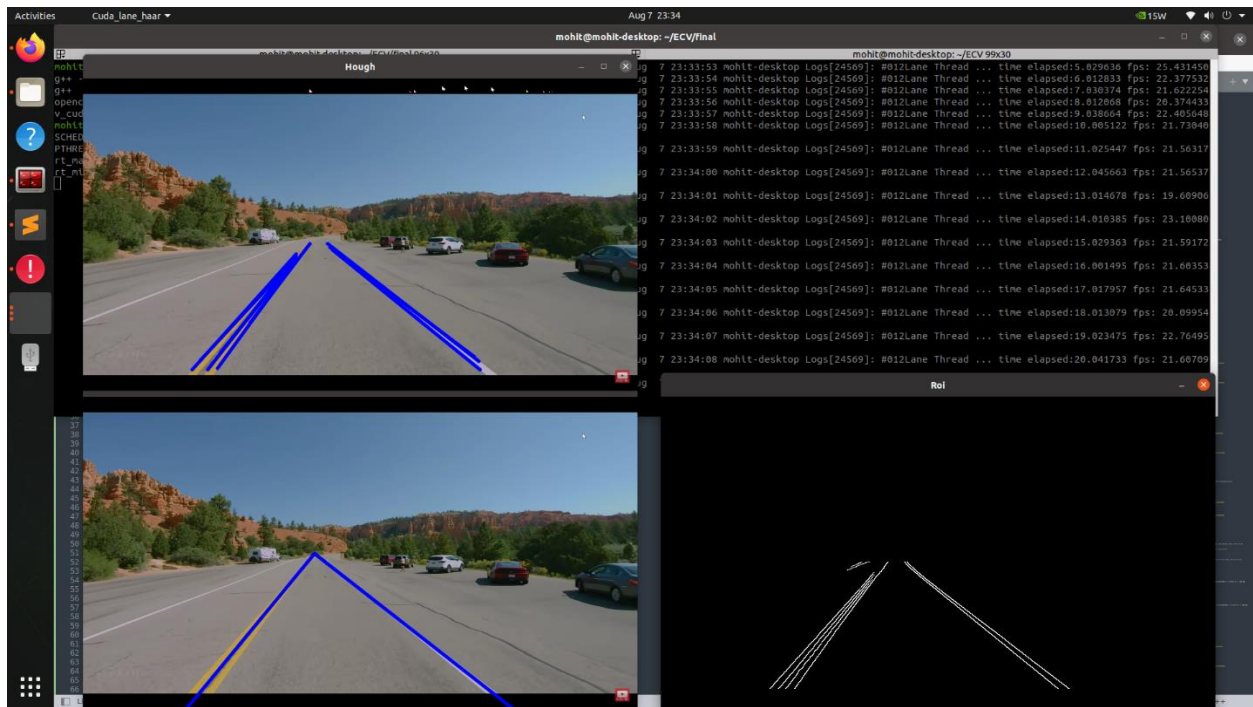


Figure 7 : CUDA Lane detection imshow and fps

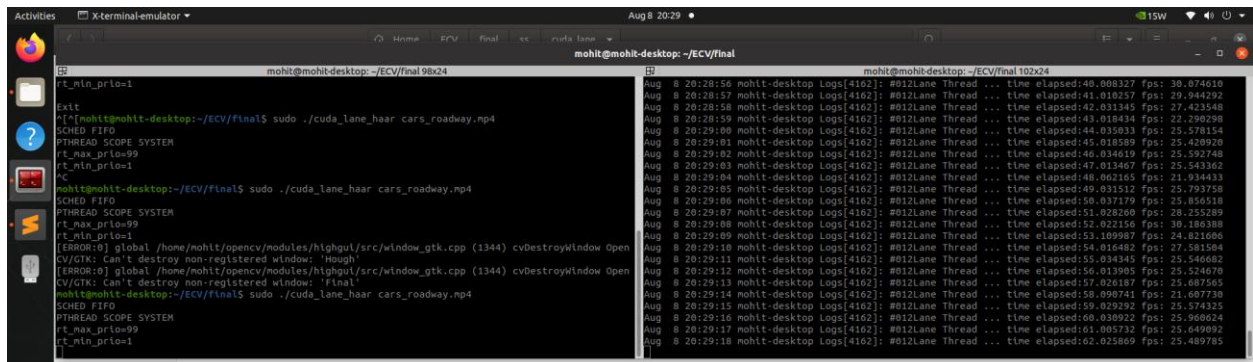


Figure 8 : CUDA Lane Detection fps without imshow

Haar Cascade:

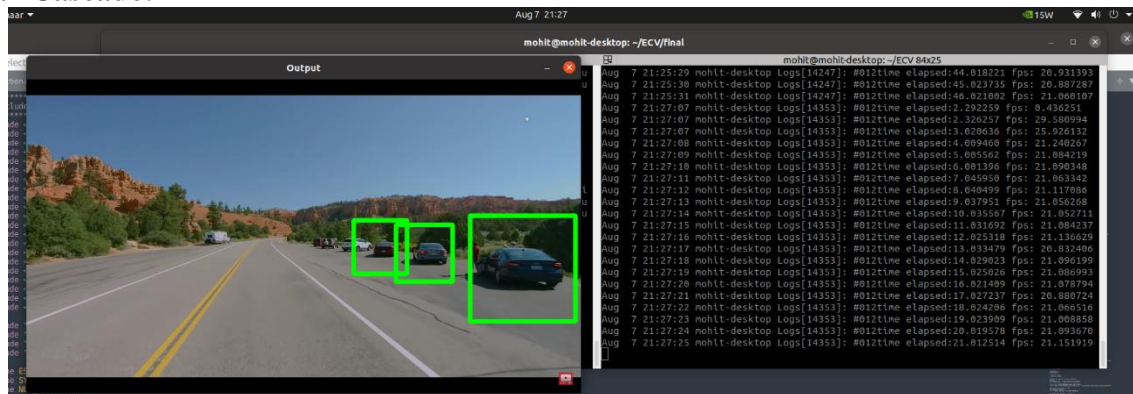


Figure 9 : Haar Cascade true positive imshow and fps

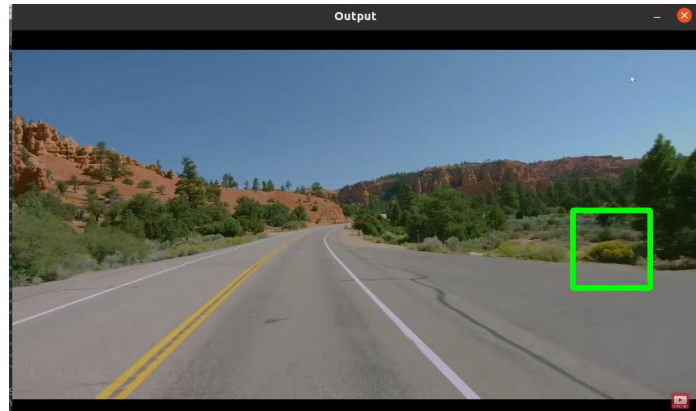


Figure 10 : Haar Cascade false positive

```

mohit@mohit-desktop: ~/ECV/final
PTHREAD SCOPE SYSTEM
rt_max_prio=99
rt_min_prio=1
mohit@mohit-desktop:~/ECV/final$ make
g++ -O0 -g -I/usr/local/include/opencv4 -c lane_haar.cpp
g++ -O0 -g -I/usr/local/include/opencv4 -o lane_haar.o `pkg-config --li
bs opencv4` -L/usr/lib -lopencv_core -lopencv_flann -lopencv_video -lrt -lopencv_cu
daarithm -lopencv_cudafilters -lopencv_cudaimgproc -lopencv_imgproc -lopencv_highgu
l -lpthread
mohit@mohit-desktop:~/ECV/final$ sudo ./lane_haar cars_roadway.mp4 -s
SCHED FIFO
PTHREAD SCOPE SYSTEM
rt_max_prio=99
rt_min_prio=1
mohit@mohit-desktop:~/ECV/final$ sudo ./lane_haar cars_roadway.mp4 -s
SCHED FIFO
PTHREAD SCOPE SYSTEM
rt_max_prio=99
rt_min_prio=1
mohit@mohit-desktop:~/ECV/final$ sudo ./lane_haar cars_roadway.mp4
SCHED FIFO
PTHREAD SCOPE SYSTEM
rt_max_prio=99
rt_min_prio=1

and lookup manager.
Aug 7 21:29:03 mohit-desktop Logs[14590]: #012time elapsed:2.108878 fps: 0.474186
Aug 7 21:29:04 mohit-desktop Logs[14590]: #012time elapsed:2.150315 fps: 24.259945
Aug 7 21:29:04 mohit-desktop tracker-store[14557]: OK
Aug 7 21:29:04 mohit-desktop systemd[1586]: tracker-store.service: Succeeded.
Aug 7 21:29:04 mohit-desktop Logs[14590]: #012time elapsed:3.004851 fps: 21.066720
Aug 7 21:29:05 mohit-desktop Logs[14590]: #012time elapsed:4.043943 fps: 21.175821
Aug 7 21:29:06 mohit-desktop Logs[14590]: #012time elapsed:5.035492 fps: 21.182113
Aug 7 21:29:07 mohit-desktop Logs[14590]: #012time elapsed:6.022061 fps: 21.289411
Aug 7 21:29:08 mohit-desktop Logs[14590]: #012time elapsed:7.010460 fps: 21.249926
Aug 7 21:29:09 mohit-desktop Logs[14590]: #012time elapsed:8.046644 fps: 21.234634
Aug 7 21:29:10 mohit-desktop Logs[14590]: #012time elapsed:9.036940 fps: 21.209296
Aug 7 21:29:11 mohit-desktop Logs[14590]: #012time elapsed:10.025674 fps: 21.242885
Aug 7 21:29:12 mohit-desktop Logs[14590]: #012time elapsed:11.014754 fps: 21.234962
Aug 7 21:29:13 mohit-desktop Logs[14590]: #012time elapsed:12.002580 fps: 21.261938
Aug 7 21:29:14 mohit-desktop Logs[14590]: #012time elapsed:13.042580 fps: 21.158528
Aug 7 21:29:15 mohit-desktop Logs[14590]: #012time elapsed:14.035268 fps: 21.156271
Aug 7 21:29:16 mohit-desktop Logs[14590]: #012time elapsed:15.017607 fps: 21.381400
Aug 7 21:29:17 mohit-desktop Logs[14590]: #012time elapsed:16.008322 fps: 21.200256
Aug 7 21:29:18 mohit-desktop Logs[14590]: #012time elapsed:17.002135 fps: 21.134190
Aug 7 21:29:19 mohit-desktop Logs[14590]: #012time elapsed:18.033611 fps: 21.331961
Aug 7 21:29:20 mohit-desktop Logs[14590]: #012time elapsed:19.022157 fps: 21.246940
Aug 7 21:29:21 mohit-desktop Logs[14590]: #012time elapsed:20.010412 fps: 21.253144
Aug 7 21:29:22 mohit-desktop Logs[14590]: #012time elapsed:21.045424 fps: 21.259146

```

Figure 11 : Haar Cascade fps without imshow

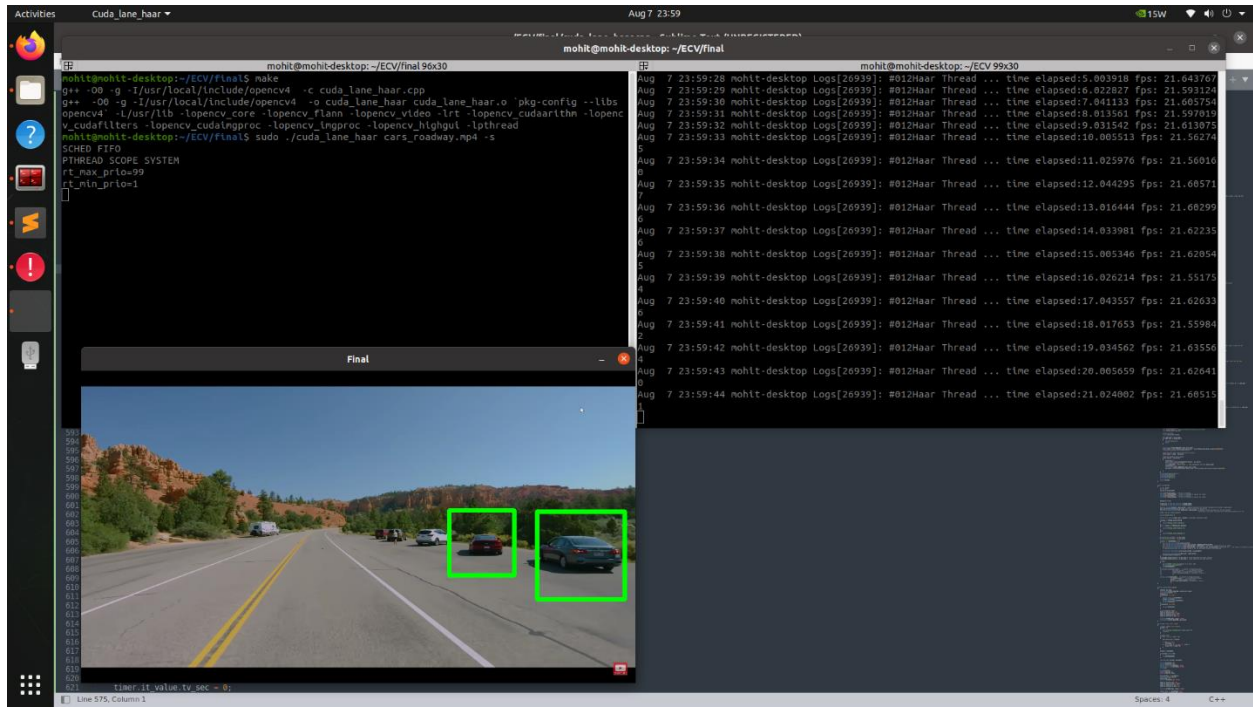


Figure 12 : CUDA Haar Cascade imshow and fps

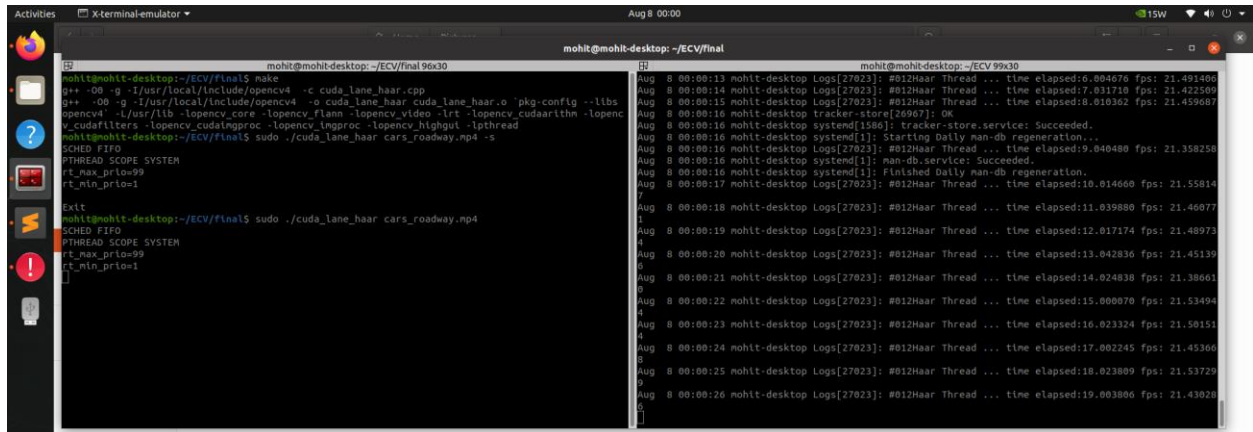


Figure 13 : CUDA Haar Cascade fps without imshow

	OpenCV (approx. fps)	OpenCV's CUDA (approx. fps)
1. Lane Detection	25.9	25.6
2. Haar Cascade	21.2	21.5

As we can see from the results above OpenCV's CUDA has similar processing speed when it comes to traditional algorithms like Canny edge detection, Hough-Line Probabilistic, BGR to grayscale conversion, Haar Cascade, etc. And is actually a bit slower in some cases, this might be because of couple of reasons, the limited parallelism nature of the traditional algorithms itself or because of slow uploads/downloads to the GPU device.

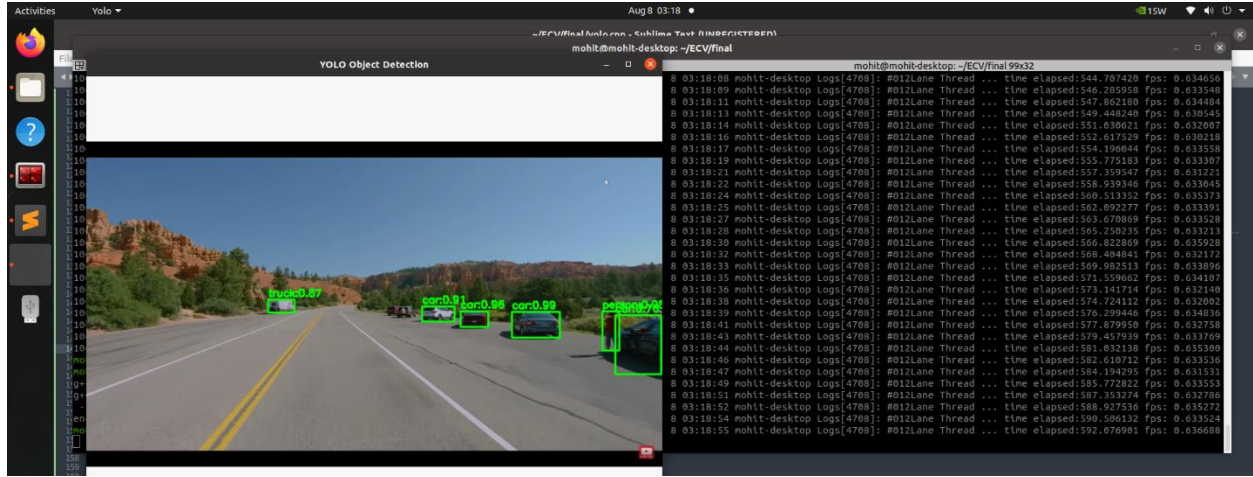
Yolo:

Figure 14 : Yolo v4 fps

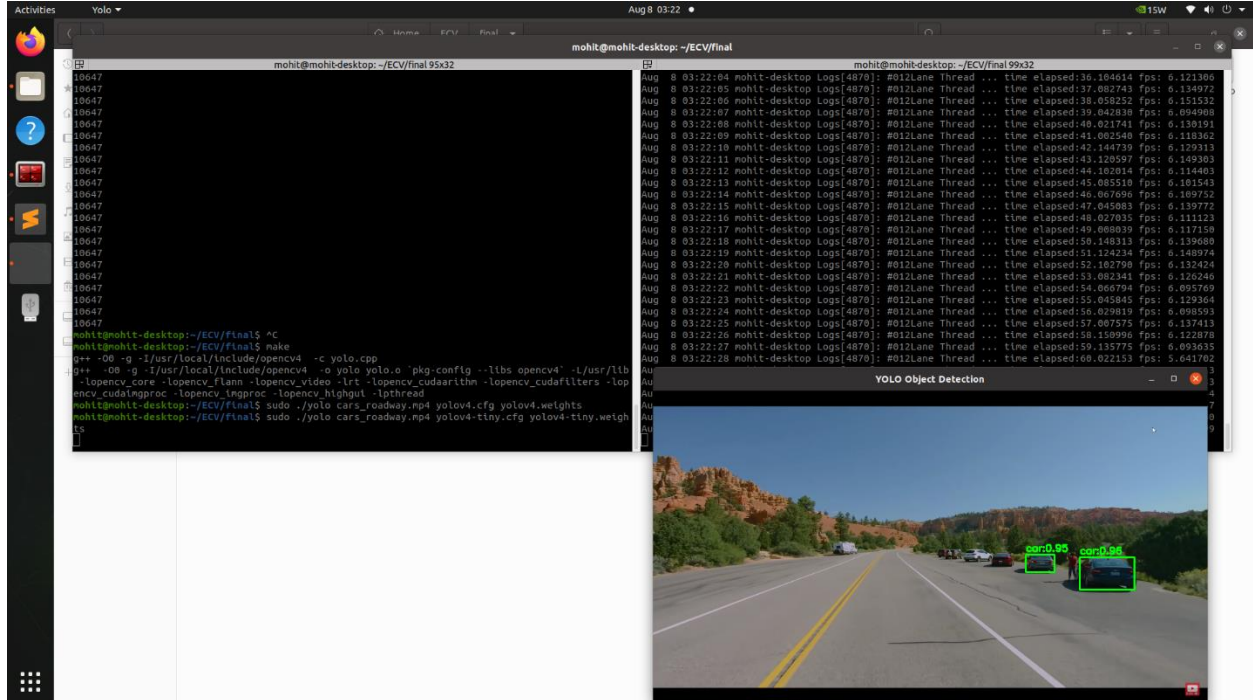


Figure 15 : yolov4-tiny fps

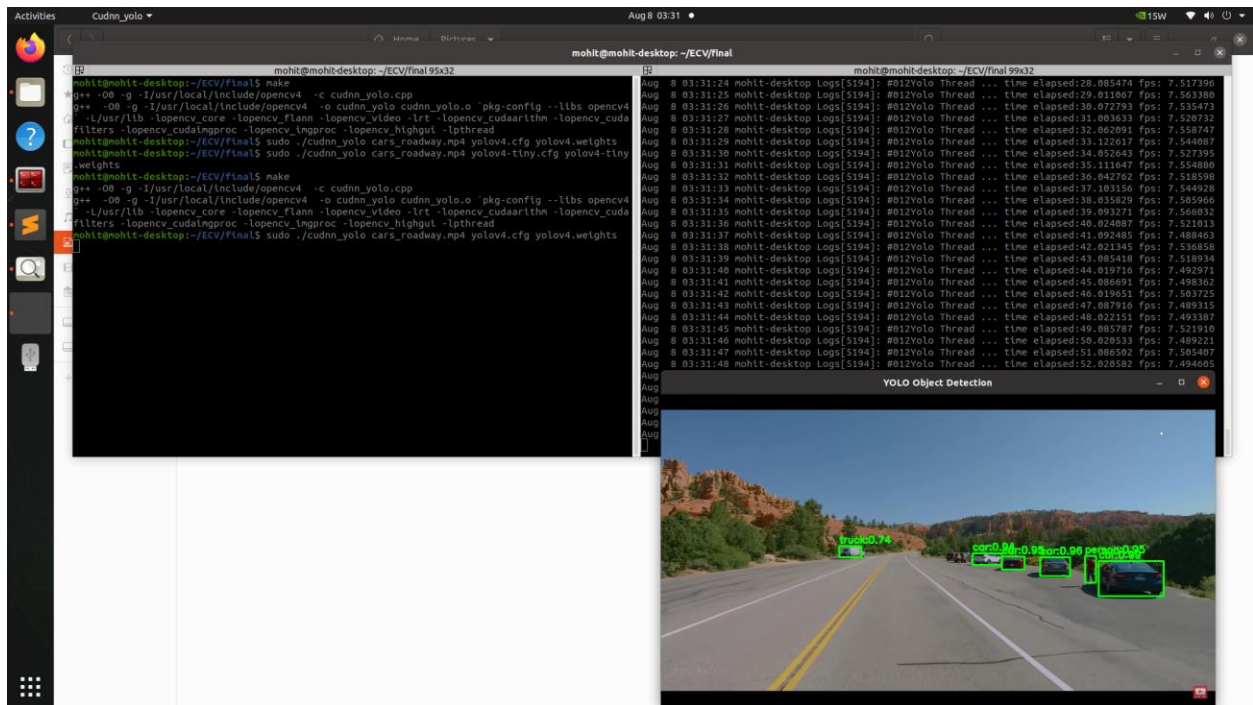


Figure 16 : CUDNN yolov4 fps

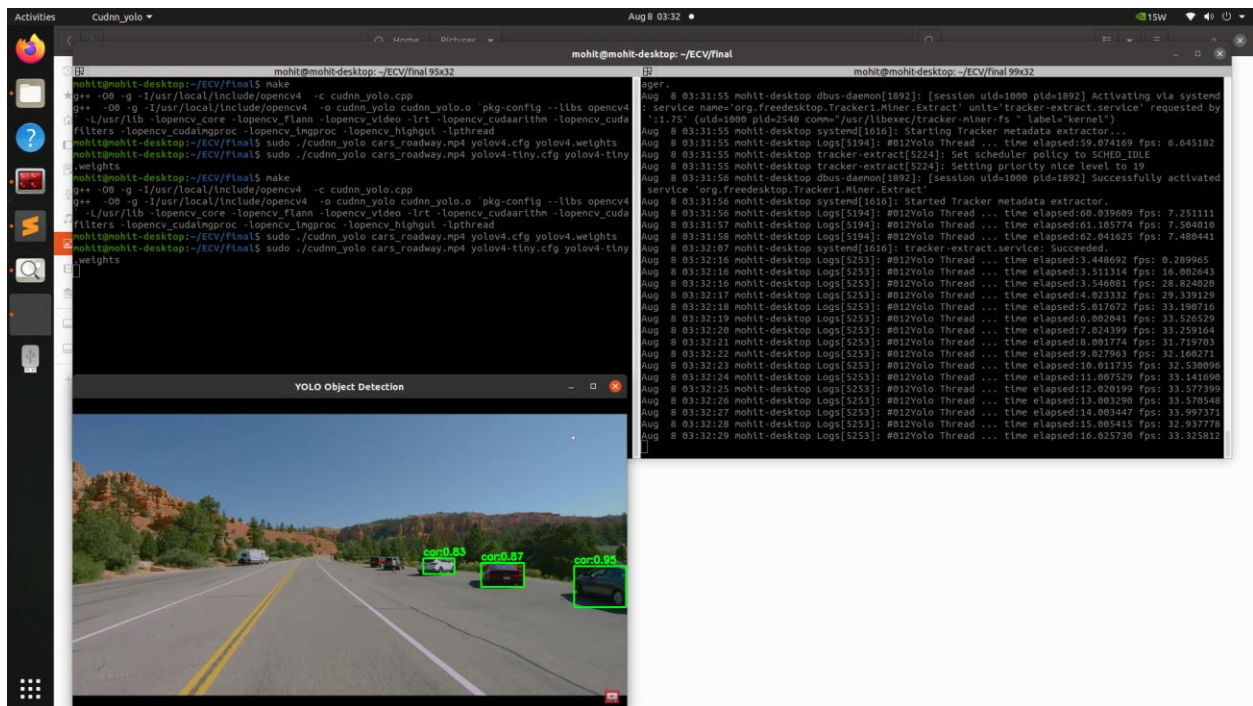


Figure 17 : CUDNN yolov4-tiny fps

	Yolov4 (approx. fps)	Yolov4-tiny (approx. fps)
1. CPU Backend	0.63	6.1
2. GPU Backend (CUDNN)	7.5	33.5

As we can see from the results above, in case of yolo we get much better performance when using GPU in the backend. This is also more accurate when compared to Haar-Cascade which had a high false positive rate. The only draw back is that yolov4-tiny has limited capability while detecting vehicles which are far away.

Combined Versions Comparisons:

	Lane Detection (approx Fps)	Car Detection (approx. fps)
1. Lane detection & Haar Cascade	19.9	19.9
2. CUDA lane detect & CUDA Haar	24.9	19.9
3. Lane detection & CUDNN yolov4-tiny	24.9	24.9

As we can see from the implementation, the third program which is combination of CPU based lane detection and GPU based car detection gives the best results when it comes to performance. Also, Haar-cascade pretrained models had around 5% false positive rate for this dataset and more tuning and preprocessing might be required for better results.

Haar Cascade:

True Positive rate: 96%

False Positive rate: 5.3%

Yolov4-Tiny:

True Positive rate: 92%

False Positive rate: 0%

Note that the false and true positive rates are approximate and were calculated by seeing the frames manually.

Thus, Yolov4-tiny with lane detection on CPU was used which gave the best performance, which was highly accurate and reliable.

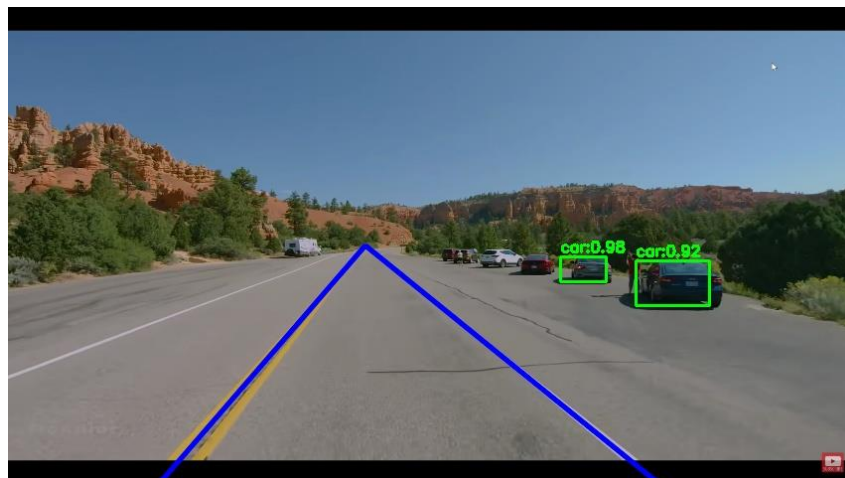


Figure 18 : Lane detection & CUDNN Yolov4-tiny Output

Using this program further steering and vehicle warnings were developed. Note that the data set selected didn't have cars coming right in front of the car. So to demonstrate that the warnings are working, once a car/truck comes within some range, "vehicle Nearby" warning pops up on the left top of the window. This feature was developed by adding threshold to the width of the object detected as the width will be directly proportional to the distance of the object.

The Turn Value is proportional to the steering angle, negative values signify left direction and positive value signify right direction, which can be seen on the right top of the window. This feature was developed by averaging the left and right lines and turn value is basically tilt of this new line. With this the optimal objective was successfully achieved.

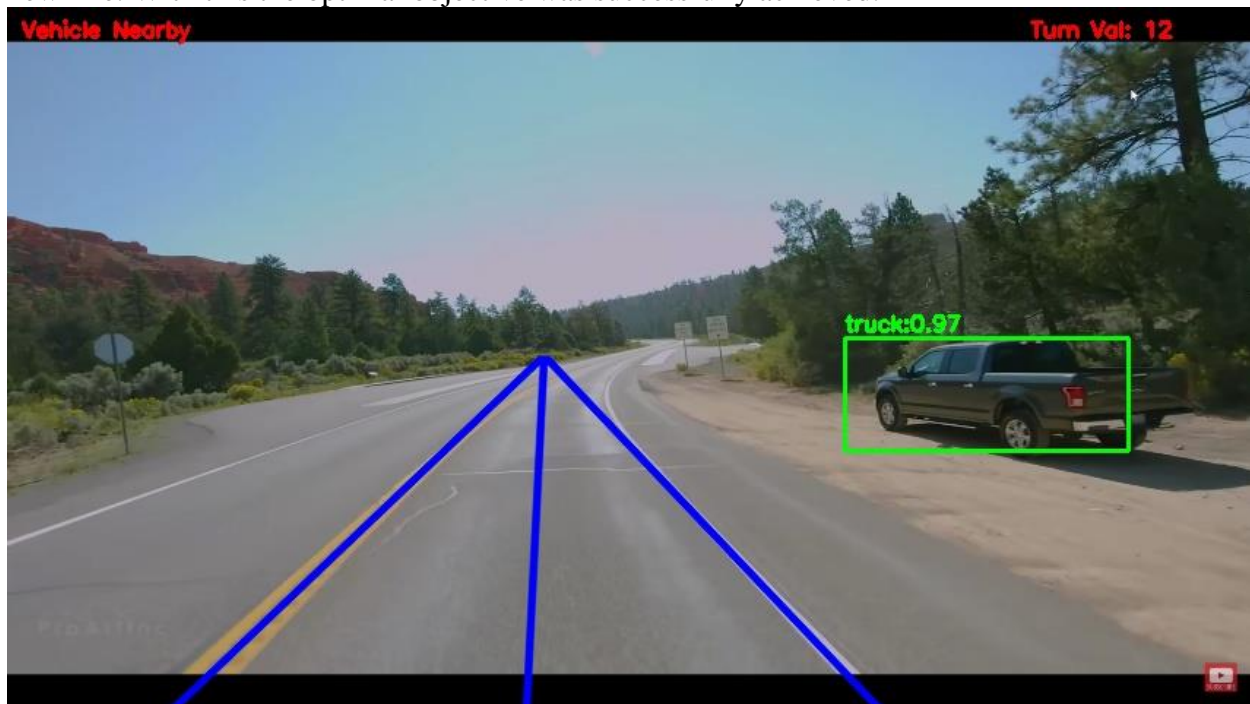


Figure 19 : Final Output

Conclusion

This project successfully developed an Advanced Driver Assistance System (ADAS) by progressing through three stages: minimum, target, and optimal. Beginning with basic lane detection using Canny edge detection and the Probabilistic Hough Transform, the system achieved reliable real-time processing, establishing a solid foundation.

Through this project, an exhaustive analysis of different algorithms provided by OpenCV and their comparison which OpenCV's CUDA extension has been provided. The developed lane detection application is highly reliable and can be developed further for higher performance. Overall, the study offered insightful information on real-time processing and system integration while showcasing how embedded computer vision may improve vehicle safety and further autonomous driving.

References

1. https://github.com/siewertsmooc/ECV-ECEE-5763/tree/main/computer_vision_cv4_tested
2. <https://docs.opencv.org/4.5.4/index.html>
3. https://o365coloradoedu-my.sharepoint.com/personal/siewerts_colorado_edu/_layouts/15/onedrive.aspx?id=%2Fpersonal%2Fsiewerts%5Fcolorado%5Fedu%2FDocuments%2FESEE%2DWeb%2DResources%2FECV%2D5763%2DCU%2Fcode
4. <https://github.com/siewertsmooc/ECV-ECEE-5763/tree/main/simple-capture>
5. https://docs.opencv.org/4.x/da/d22/tutorial_py_canny.html
6. https://docs.opencv.org/3.4/d9/db0/tutorial_hough_lines.html
7. <https://learnopencv.com/object-detection-using-yolov5-and-opencv-dnn-in-c-and-python/>
8. <https://gist.github.com/YashasSamaga/e2b19a6807a13046e399f4bc3cca3a49>
9. <https://opencv.org/platforms/cuda/>
10. <https://www.youtube.com/watch?v=ZOZOqbK86t0>
11. <https://github.com/AlexeyAB/darknet>
12. <https://www.geeksforgeeks.org/opencv-real-time-road-lane-detection/>

Appendices

In the outputs folder, all the three implementations:

1. Lane detection and Haar cascade: lane_haar.mp4
2. CUDA lane detection and CUDA Haar Cascade: cuda_lane_haar.mp4
3. Lane detection and CUDNN yolov4 tiny: cudnn_yolo_lane.mp4

In the Screenshots folder, the ffmpeg command screenshot, output of all the programs is present. The input video has been uploaded to google drive.

Link: <https://drive.google.com/file/d/1JLknG1IgN9M-hGOQ4gJ0QyYbNvsk9rDy/view?usp=sharing>

[The instructions for running the programs can be found in the readme.txt file in the codes folder](#)