Multi-Camera Object Detection on Nvidia Jetson Orin Nano using Zed 2i

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AIM OF THIS PROJECT

- ➢ Real time Object Detection System
- ➢ Using ZED Camera
- ➢ On Jetson Orin Nano
- ➢ YOLOv8 algorithm
- ➢ Do performance evaluation
- ➢ Performance Comparison

WHAT IS **OBJECT DETECTION**?

- Object detection is a computer vision task that involves identifying and locating objects in images or videos.
- Earlier approach was to use R-CNN for object detection.
- We are using YOLO, which is also a neural network.
- It is an important part of many applications, such as surveillance, self-driving cars, or robotics.

HARDWARE USED

1) NVIDIA Jetson Orin Nano

- ➢ AI Performance: 40 TOPS
- ➢ GPU max frequency: 625MHz
- ➢ CPU max frequency: 1.5GHz
- ➢ GPU : 1024-core NVIDIA Ampere architecture GPU with 32 Tensor Cores
- ➢ CPU : 6-core Arm® Cortex®-A78AE v8.2 64-bit CPU
- ➢ 1.5MB L2 + 4MB L3

HARDWARE USED

2) ZED 2i Camera

- ➢ Neural Depth Sensing
- ➢ Spatial Object Detection
- ➢ Built-in Next-Gen IMU, Barometer & Magnetometer
- ➢ 120° Wide-Angle FOV
- ➢ All-Aluminium Frame with Thermal Control
- ➢ Built-in 1.5m USB 3.0 Cable

SOFTWARE USED

Software	**Versions**
Operating System	Ubuntu 20.04
Programming language	Python 3.8
NVIDIA SDK	Jetpack 5.1.2
ZED SDK	4.0.
CUDA	11.4.19
YOLO (Neural Network)	Version 8
PyTorch	2.1.2

NVIDIA JetPack SDK 5.1.2

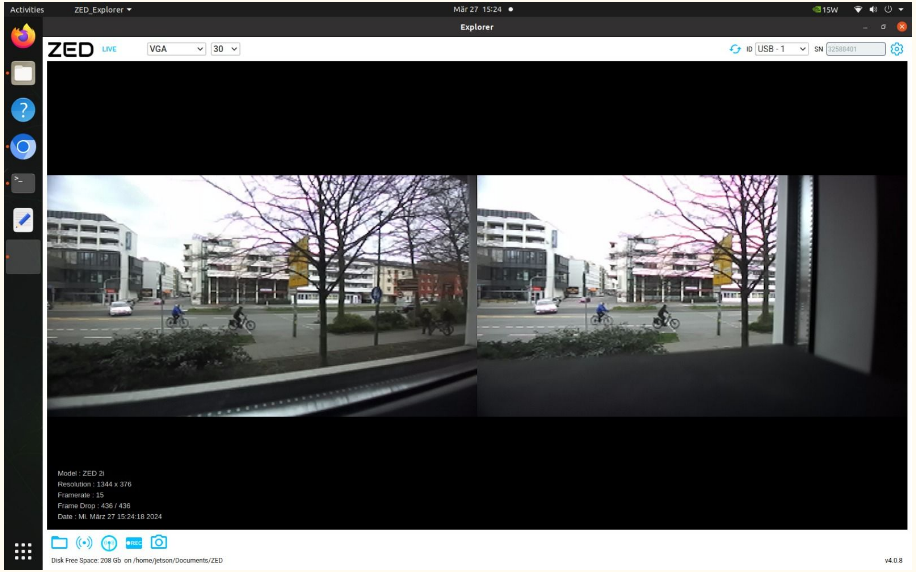
- TensorRT is a high performance deep learning inference runtime for image classification, segmentation, and object detection neural networks
  - JetPack 5.1.2 includes **TensorRT 8.5.2**
- NVIDIA DLA hardware is a fixed-function accelerator engine targeted for deep learning operations.
  - JetPack 5.1.2 includes **DLA 3.12.1**
- CUDA Deep Neural Network library provides high-performance primitives for deep learning frameworks.
  - JetPack 5.1.2 includes **cuDNN 8.6.0**
- CUDA Toolkit provides a comprehensive development environment for C and C++ developers building GPU-accelerated applications.
  - JetPack 5.1.2 includes **CUDA 11.4.19**
- OpenCV is an open source library for computer vision, image processing and machine learning.
  - JetPack 5.1.2 includes **OpenCV 4.5.4**

What is Ultralytics **YOLOv8**?

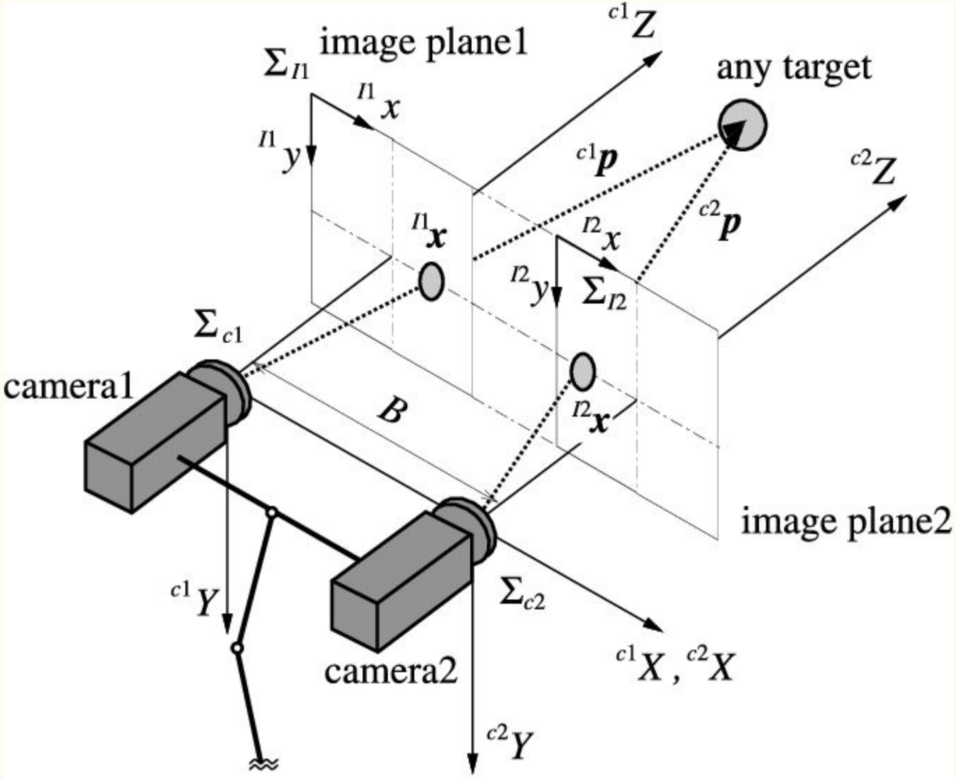
- ➢ YOLOv8 is a deep learning-based object detection model developed by UltraLytics
- ➢ It stands for "You Only Look Once version 8," which is the eighth iteration of the YOLO model series.
- ➢ It typically uses a more advanced backbone architecture, such as CSPDarknet53, to extract features from input images effectively.
- ➢ It offers compatibility with different frameworks like PyTorch or TensorFlow.

ZED SDK

- ➢ Stereo 2K cameras with dual 4MP RGB sensors.
- ➢ UVC-compliant USB 3.0 camera
- ➢ Compatible with USB 2.0
- ➢ Left and right video frames are synchronized and streamed as a single uncompressed video frame in the side-by-side format.
- ➢ Camera has a compact structure and reduced size
- ➢ It relatively simple to incorporate into robotic systems or drones.

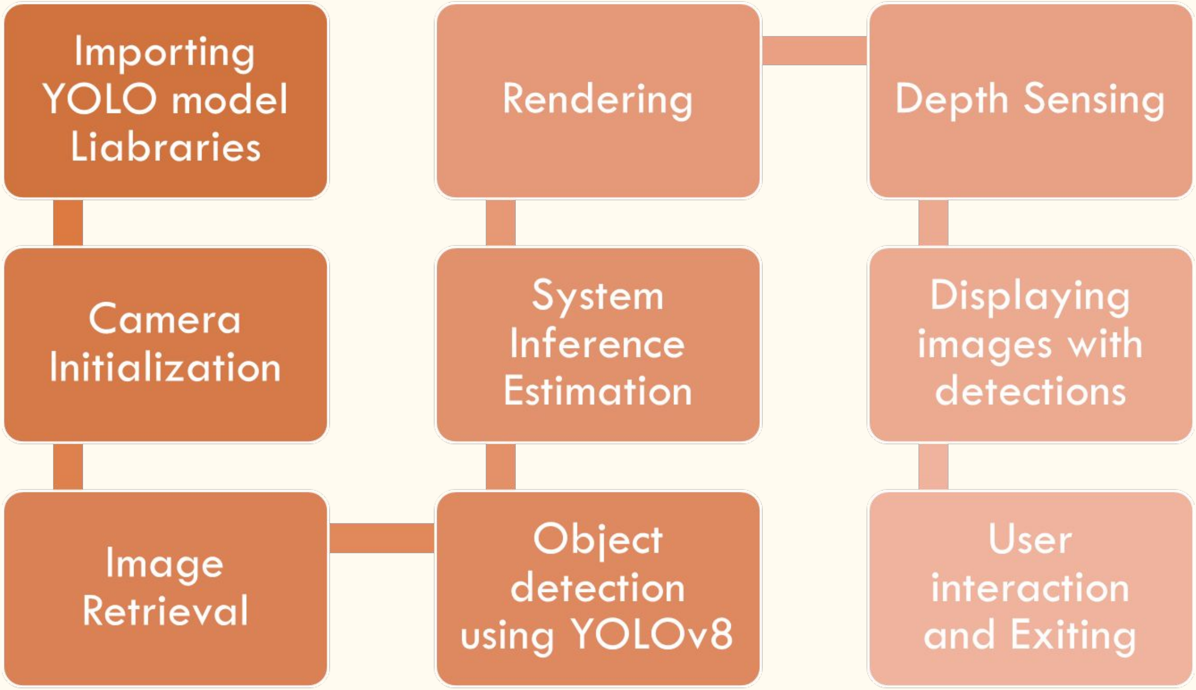


What is **depth sensing?**



- ➢ A technology that allows a device to measure the distance of an object from the sensor.
- ➢ The system in the image works by using two cameras that are slightly offset from each other.
- ➢ Each camera captures a slightly different image of the scene. By comparing the two images, the disparity is calculated.
- ➢ This disparity is used to calculate the distance of the object from the camera.

Process Flow Diagram



IMPLEMENTATION

Camera Instantiation and Initialising Parameters

```
zed = [[] ,[]]

for i in range(2):
    zed[i] = sl.Camera()

init_params = sl.InitParameters()
init_params.camera_resolution = sl.RESOLUTION.VGA
init_params.camera_fps = 100
init_params.coordinate_units = sl.UNIT.METER
init_params.depth_mode = sl.DEPTH_MODE.ULTRA
init_params.coordinate_system = sl.COORDINATE_SYSTEM.RIGHT_HANDED_Y_UP
init_params.depth_maximum_distance = 50
```

Argument Parser and Loading the YOLO models

```
if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('--weights', nargs='+', type=str, default=['yolov8n.pt', 'yolov8l.pt'], help='model.pt paths for each camera')
    parser.add_argument('--svo', type=str, default=None, help='optional svo file')
    parser.add_argument('--img_size', type=int, default=416, help='inference size (pixels)')
    parser.add_argument('--conf_thres', type=float, default=0.4, help='object confidence threshold')
    opt = parser.parse_args()
```

Threaded model inference initialization

```
capture_threads = [
    Thread(target=torch_thread, args=(opt.weights[i], opt.img_size, i + 1, opt.conf_thres)) for i in range(2)
]
for thread in capture_threads:
    thread.start()
```

What happens in the **torch_thread** function?

```
def torch_thread(weights, img_size, camera_id, conf_thres=0.2, iou_thres=0.45):
    global image_nets, exit_signal, run_signals, detections

    print("Intializing Network for Camera", camera_id)

    model = YOLO(weights)

    while not exit_signal:
        start_time = time.time()  # Start time for measuring inference time
        if run_signals[camera_id - 1]:
            lock[camera_id - 1].acquire()
            img = cv2.cvtColor(image_nets[camera_id - 1], cv2.COLOR_BGRA2RGB)
            det = model.predict(img, save=False, imgsz=img_size, conf=conf_thres, iou=iou_thres)[0].cpu().numpy().boxes
            detections[camera_id - 1] = detections_to_custom_box(det, image_nets[camera_id - 1])
            lock[camera_id - 1].release()
            end_time = time.time()  # End time for measuring inference time
            inference_time = end_time - start_time  # Calculate inference time for the current frame
            fps = 1.0 / inference_time  # Calculate frames per second
            print(f"Inference FPS for Camera {camera_id}: {fps:.2f}")
            run_signals[camera_id - 1] = False

        sleep(0.01)

```

Converting detections to Custom Box Objects

```python
def detections_to_custom_box(detections, im0):
    output = []
    for i, det in enumerate(detections):
        xywh = det.xywh[0]

        # Creating ingestable objects for the ZED SDK
        obj = sl.CustomBoxObjectData()
        obj.bounding_box_2d = xywh2abcd(xywh, im0.shape)
        obj.label = det.cls
        obj.probability = det.conf
        obj.is_grounded = False
        output.append(obj)
    return output
```

Image Acquisition and Object Retrieval

```
lock[i].acquire()
zed[i].retrieve_image(image_left_tmp[i], sl.VIEW.LEFT, sl.MEM.CPU, display_resolutions[i])
image_nets[i] = image_left_tmp[i].get_data()

lock[i].release()
run_signals[i] = True

while run_signals[i]:
    sleep(0.001)

lock[i].acquire()
# Ingest detections from respective camera image net
zed[i].ingest_custom_box_objects(detections[i])
det_list = detections[i]

lock[i].release()
zed[i].retrieve_objects(objects[i], obj_runtime_param)
```

Depth Sensing

```
# Retrieve display data
zed[i].retrieve_measure(depth_map[i], sl.MEASURE.DEPTH)
```

```
bbox = det.bounding_box_2d
```

```
center = np.mean(bbox, axis=0)
x = round(center[0])
y = round(center[1])


err, depth_value = depth_map[i].get_value(x,y)
```

The code is scalable. Implementing the project with more than two cameras is also possible.

```python
# Create OpenGL viewer
viewer = gl.GLViewer()

point_cloud_res1 = sl.Resolution(min(camera_res1.width, 720), min(camera_res1.height, 404))
point_cloud_res2 = sl.Resolution(min(camera_res2.width, 720), min(camera_res2.height, 404))

point_cloud_render1 = sl.Mat()
point_cloud_render2 = sl.Mat()
viewer.init(camera_infos1.camera_model, point_cloud_res1, obj_param.enable_tracking)
viewer.init(camera_infos2.camera_model, point_cloud_res2, obj_param.enable_tracking)

point_cloud1 = sl.Mat(point_cloud_res1.width, point_cloud_res1.height, sl.MAT_TYPE.F32_C4, sl.MEM.CPU)
point_cloud2 = sl.Mat(point_cloud_res2.width, point_cloud_res2.height, sl.MAT_TYPE.F32_C4, sl.MEM.CPU)

display_resolution1 = sl.Resolution(min(camera_res1.width, 1280), min(camera_res1.height, 720))
display_resolution2 = sl.Resolution(min(camera_res2.width, 1280), min(camera_res2.height, 720))

image_scale1 = [display_resolution1.width / camera_res1.width, display_resolution1.height / camera_res1.height]
image_scale2 = [display_resolution2.width / camera_res2.width, display_resolution2.height / camera_res2.height]

image_left_ocv1 = np.full((display_resolution1.height, display_resolution1.width, 4), [245, 239, 239, 255], np.uint8)
image_left_ocv2 = np.full((display_resolution2.height, display_resolution2.width, 4), [245, 239, 239, 255], np.uint8)

camera_config1 = camera_infos1.camera_configuration
camera_config2 = camera_infos2.camera_configuration

tracks_resolution1 = sl.Resolution(400, display_resolution1.height)
tracks_resolution2 = sl.Resolution(400, display_resolution2.height)

track_view_generator1 = cv_viewer.TrackingViewer(tracks_resolution1, camera_config1.fps, init_params.depth_maximum_distance)
track_view_generator2 = cv_viewer.TrackingViewer(tracks_resolution2, camera_config2.fps, init_params.depth_maximum_distance)

track_view_generator1.set_camera_calibration(camera_config1.calibration_parameters)
track_view_generator2.set_camera_calibration(camera_config2.calibration_parameters)

image_track_ocv1 = np.zeros((tracks_resolution1.height, tracks_resolution1.width, 4), np.uint8)
image_track_ocv2 = np.zeros((tracks_resolution2.height, tracks_resolution2.width, 4), np.uint8)
```

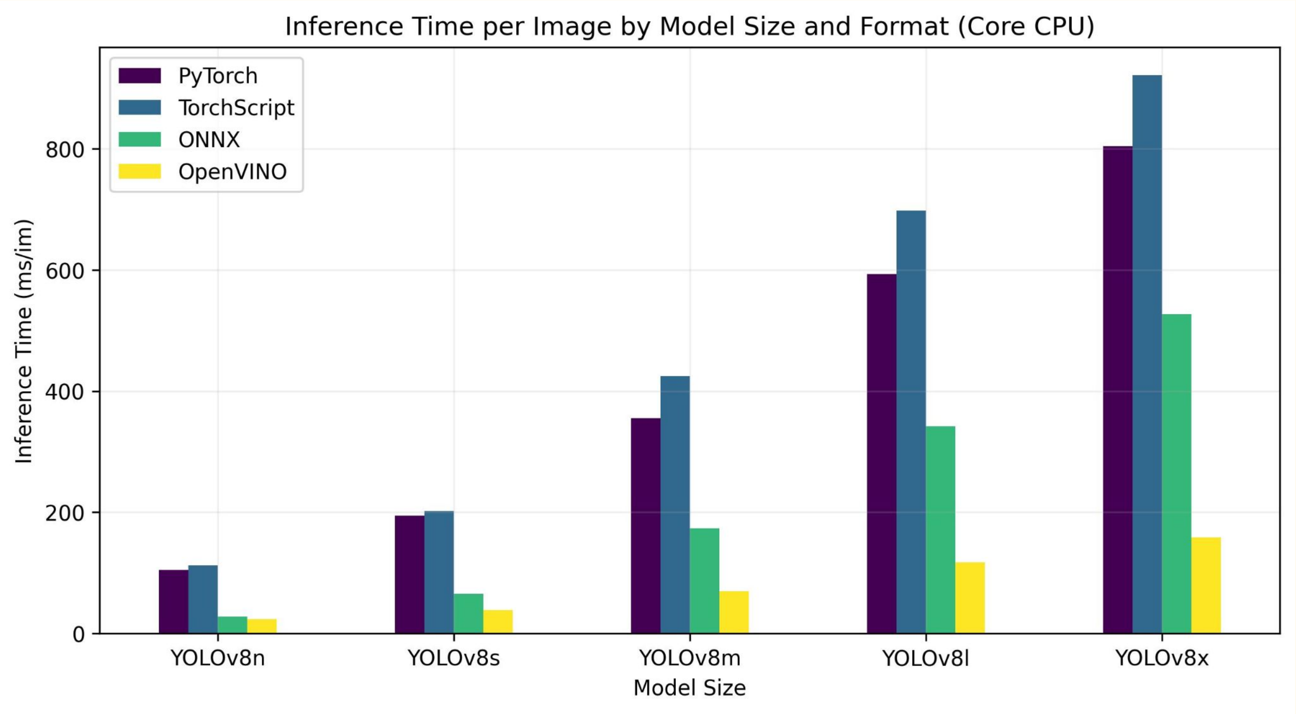
```python
for i in range(2):

    point_cloud_resolutions.append(sl.Resolution(min(camera_resolutions[i].width, 720), min(camera_resolutions[i].height, 404)))
    point_clouds.append(sl.Mat(point_cloud_resolutions[i].width, point_cloud_resolutions[i].height, sl.MAT_TYPE.F32_C4, sl.MEM.CPU))
    viewer.init(camera_infos[i].camera_model, point_cloud_resolutions[i], obj_param.enable_tracking)
    display_resolutions.append(sl.Resolution(min(camera_resolutions[i].width, 1280), min(camera_resolutions[i].height, 720)))
    image_scales.append([display_resolutions[i].width / camera_resolutions[i].width, display_resolutions[i].height / camera_resolutions[i].height])
    image_left_ocvs.append(np.full((display_resolutions[i].height, display_resolutions[i].width, 4), [245, 239, 239, 255], np.uint8))
    camera_configs.append(camera_infos[i].camera_configuration)
    tracks_resolutions.append(sl.Resolution(400, display_resolutions[i].height))
    track_view_generators.append(cv_viewer.TrackingViewer(tracks_resolutions[i], camera_configs[i].fps, init_params.depth_maximum_distance))
    track_view_generators[i].set_camera_calibration(camera_configs[i].calibration_parameters)
    image_track_ocvs.append(np.zeros((tracks_resolutions[i].height, tracks_resolutions[i].width, 4), np.uint8))
```

Concept of **FPS** and **Inference**

- Frames per Second (FPS) in object detection refers to the number of frames or images processed by the detection system in one second.
- In object detection using neural networks like YOLO, "inference" refers to applying a trained model to input data to make predictions or detections.
- Higher inference time, more computational resources.

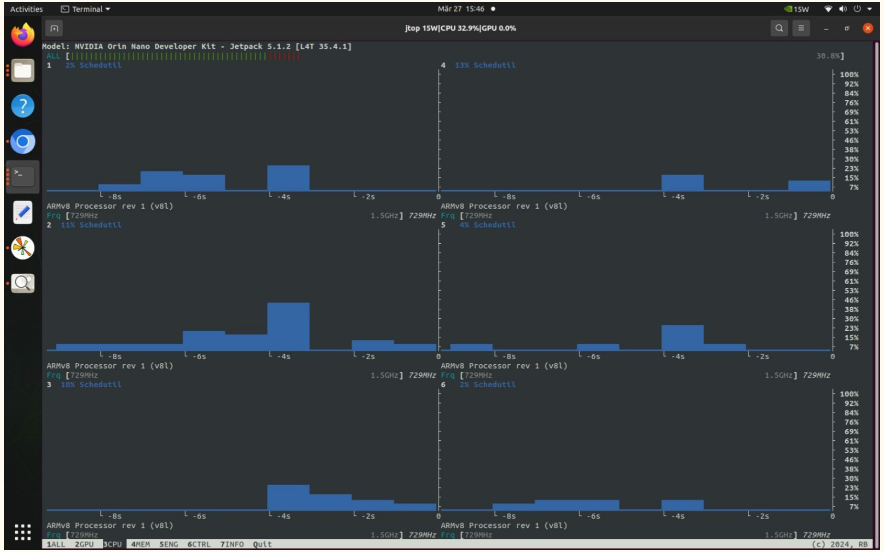
PERFORMANCE COMPARISON

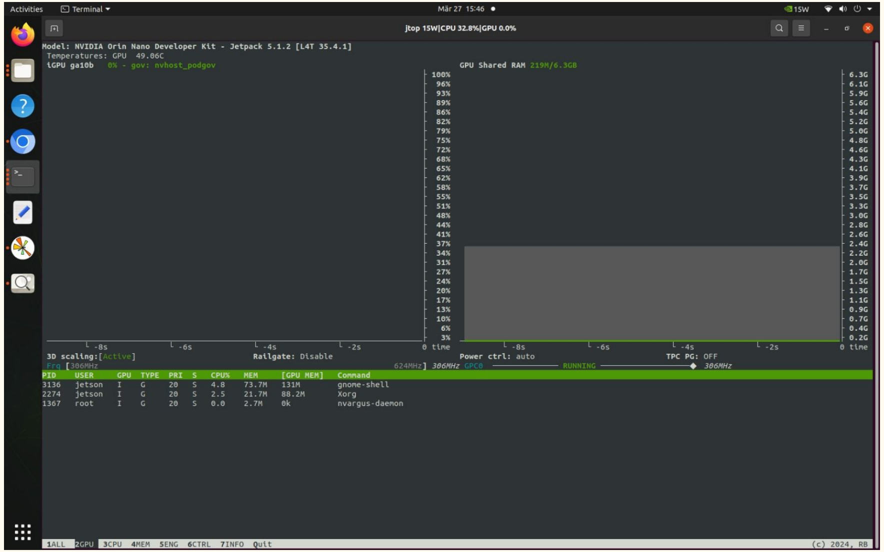


YOLOv8 models vs inference time bar graph

https://rb.gy/wtq56e

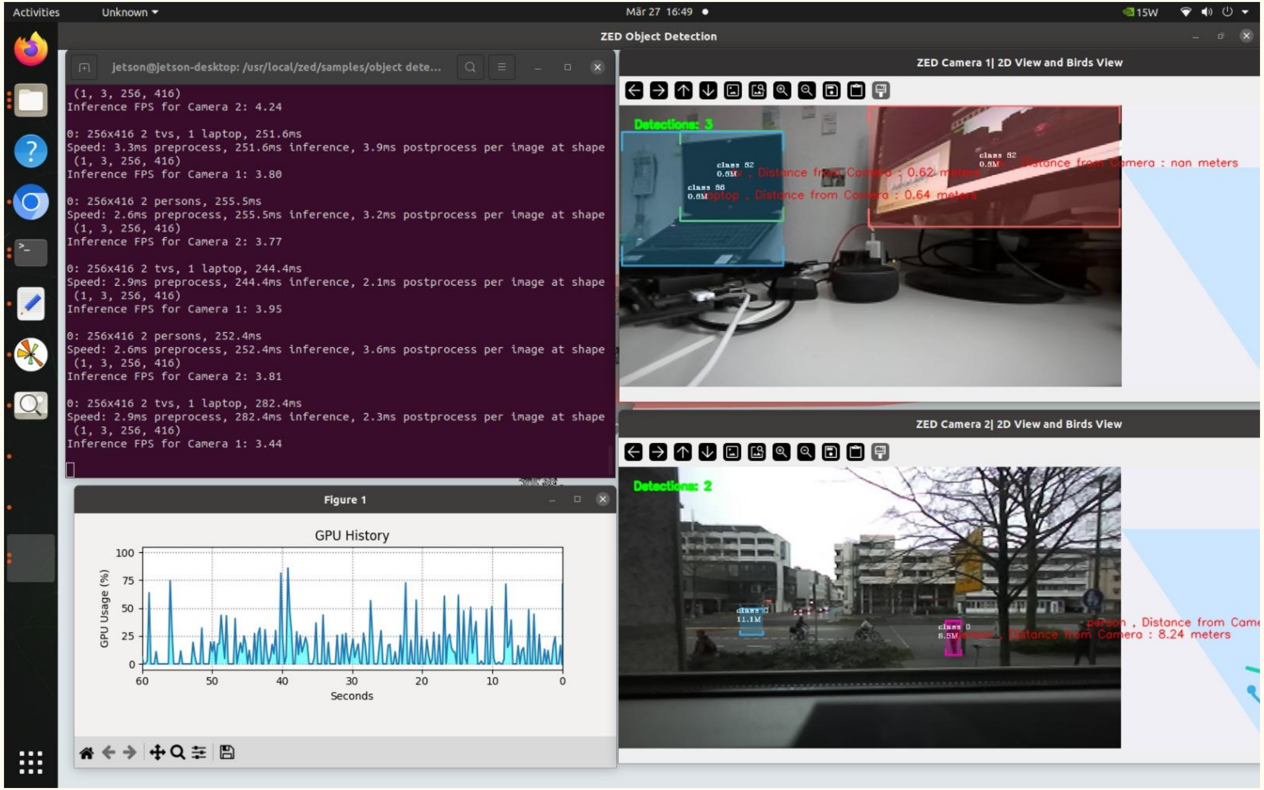
CPU and GPU status without object detection



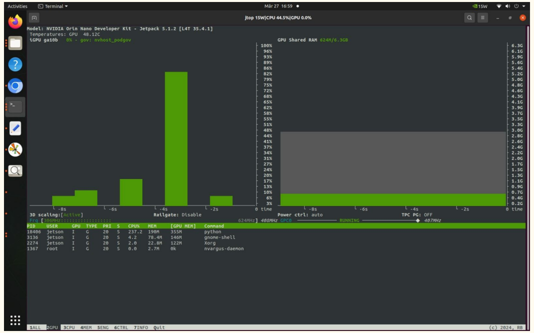


RESULTS

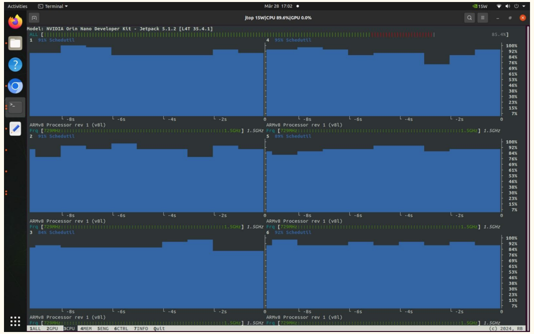
- **Using same models on both the cameras (YOLOv8n)**



GPU status

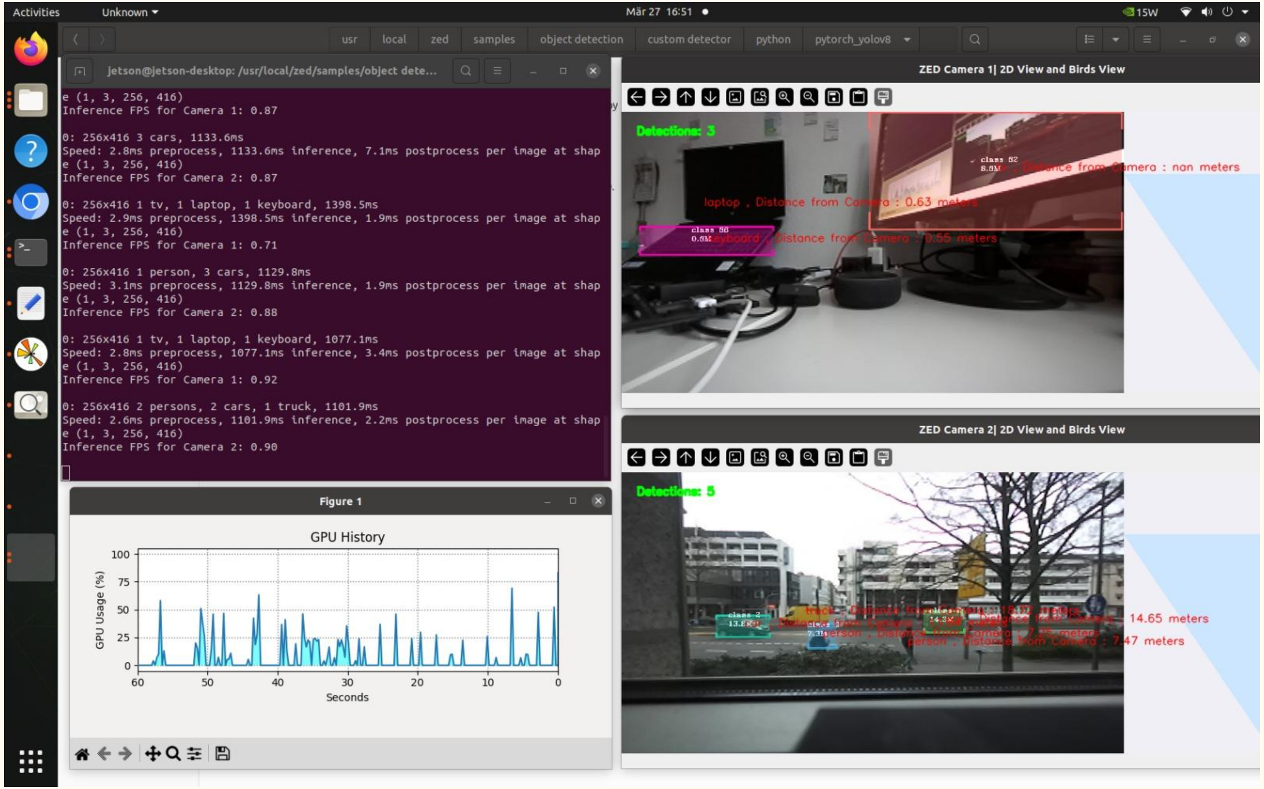


CPU status

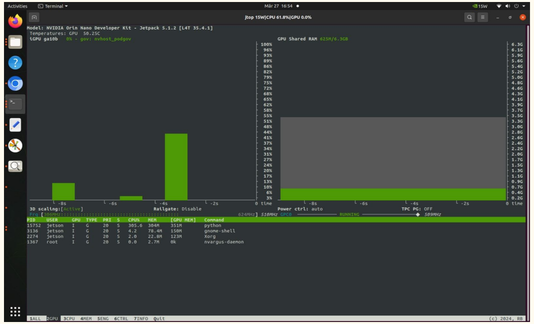


RESULTS

- Using same models on both the cameras (YOLOv8l)



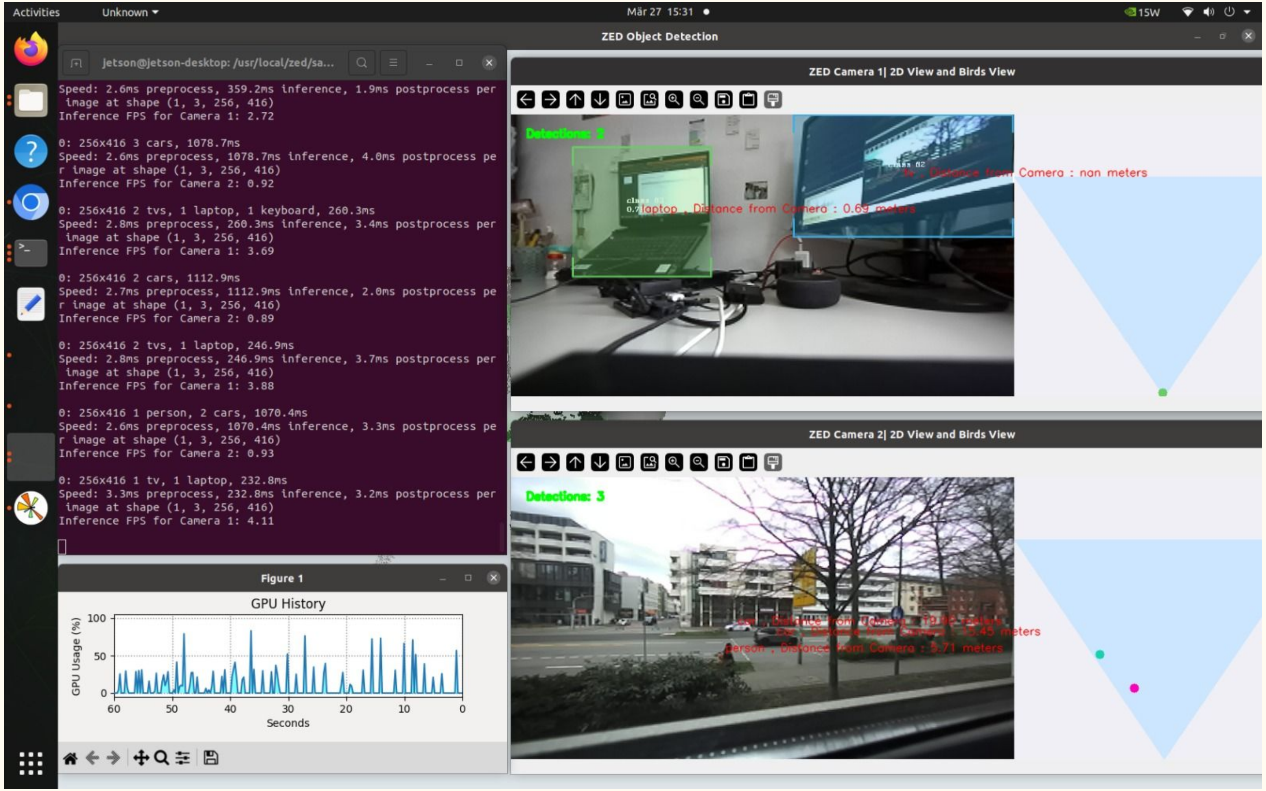
GPU status



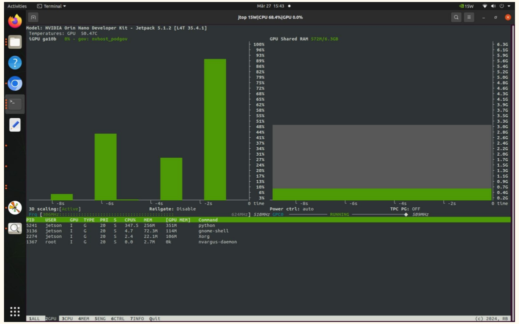
CPU status

RESULTS

- Using different models on both the cameras (Yolov8n and YOLOv8l)

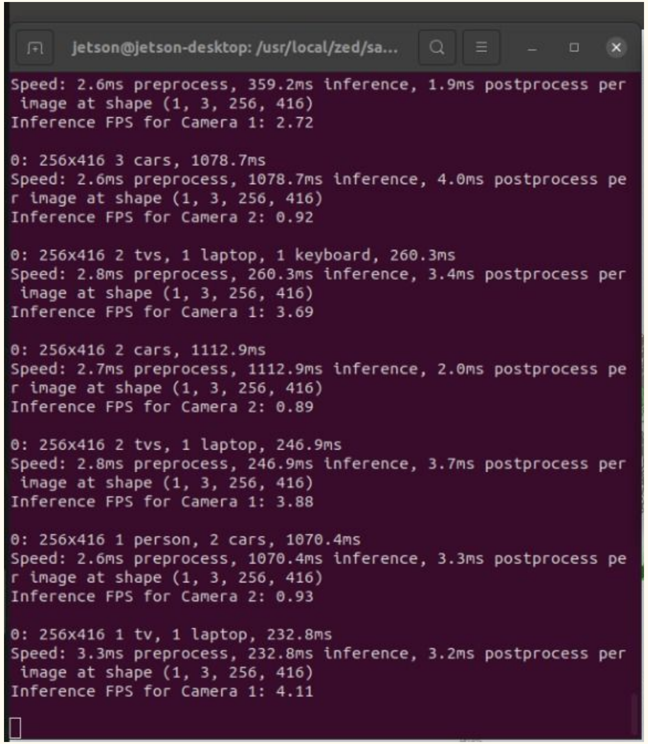


GPU status



CPU status

Observations based on the previous output




```
Speed: 2.6ms preprocess, 359.2ms inference, 1.9ms postprocess per
 image at shape (1, 3, 256, 416)
Inference FPS for Camera 1: 2.72

0: 256x416 3 cars, 1078.7ms
Speed: 2.6ms preprocess, 1078.7ms inference, 4.0ms postprocess pe
r image at shape (1, 3, 256, 416)
Inference FPS for Camera 2: 0.92

0: 256x416 2 tvs, 1 laptop, 1 keyboard, 260.3ms
Speed: 2.8ms preprocess, 260.3ms inference, 3.4ms postprocess per
 image at shape (1, 3, 256, 416)
Inference FPS for Camera 1: 3.69

0: 256x416 2 cars, 1112.9ms
Speed: 2.7ms preprocess, 1112.9ms inference, 2.0ms postprocess pe
r image at shape (1, 3, 256, 416)
Inference FPS for Camera 2: 0.89

0: 256x416 2 tvs, 1 laptop, 246.9ms
Speed: 2.8ms preprocess, 246.9ms inference, 3.7ms postprocess per
 image at shape (1, 3, 256, 416)
Inference FPS for Camera 1: 3.88

0: 256x416 1 person, 2 cars, 1070.4ms
Speed: 2.6ms preprocess, 1070.4ms inference, 3.3ms postprocess pe
r image at shape (1, 3, 256, 416)
Inference FPS for Camera 2: 0.93

0: 256x416 1 tv, 1 laptop, 232.8ms
Speed: 3.3ms preprocess, 232.8ms inference, 3.2ms postprocess per
 image at shape (1, 3, 256, 416)
Inference FPS for Camera 1: 4.11
```

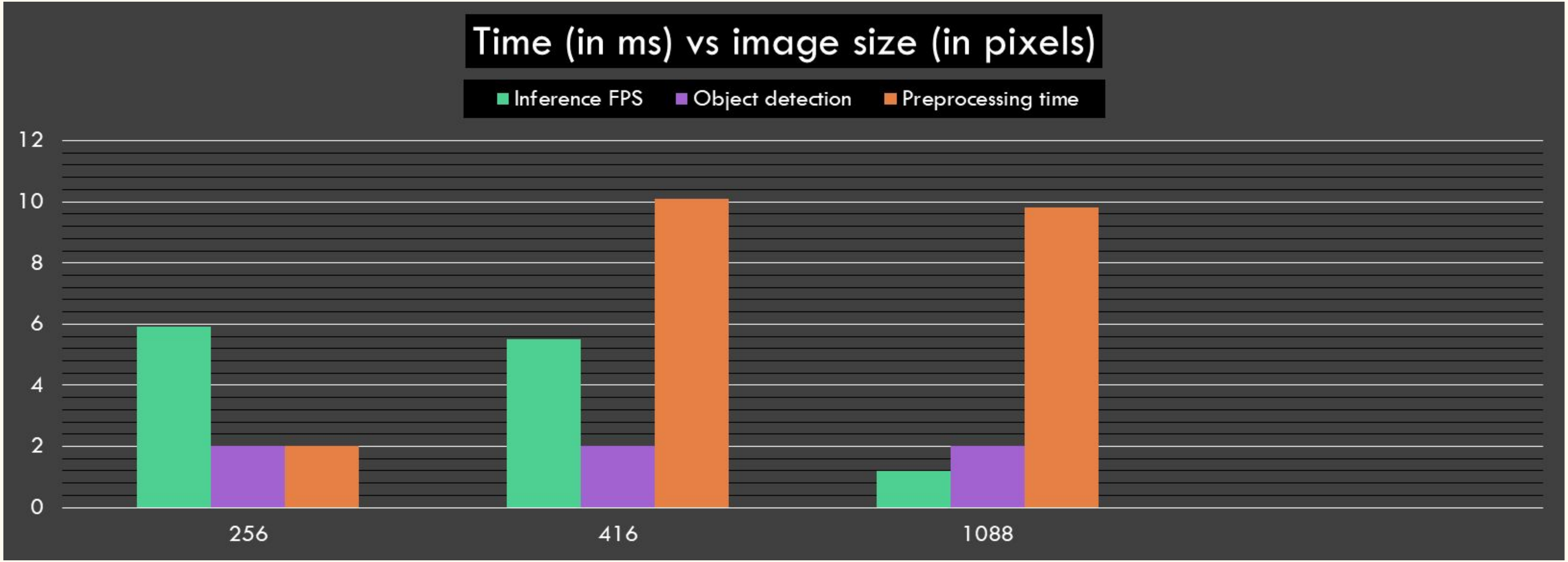
➢ Inference Time: YOLOv8l model requires more computational resources and time for inference due to its larger size and complexity.

➢ Detected Objects: the models are detecting different objects based on their respective features and capabilities.

➢ Inference FPS: the YOLOv8n model performs faster on Camera 1. This could be due to the smaller size and complexity of the YOLOv8n model compared to YOLOv8l.

➢ Model Size: The difference in model size and complexity can affect the performance and accuracy of object detection, as well as the computational resources required for inference.

Observations based on **variation of image size**



CONCLUSION

- Successfully implemented Object Detecting using two ZED 2i cameras.
- With the help of version 8 of YOLO algorithm, optimal performance is ensured.
- Flexible code.
- Performance comparison for various scenarios.
- Numerous applications such as smoke detection, autonomous driving, surveillance, and beyond.

GITHUB REPOSITORY: https://github.com/supriyac282/Jetson_Orin_Nano/tree/main

FUTURE WORK / PROJECT PROPOSAL

REAL TIME MULTI-OBJECT TRACKING

- Objective: Develop a real-time object tracking system.
- Application: To track a single object across the screen, e.g. person/car/object on a live feed.
- Object Tracking using Open cv’s built in trackers.
- Multi-Object Tracking using SORT algorithm.
- Explore whether to use Kalman filtering for improved accuracy if implementing in a noisy environment.

THANK YOU