Capstone Project
License Plate Detection

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1. Introduction

In this project, we'll be developing a web-based application that will be applying Computer Vision and use one of the applications of Computer Vision which is object detection by detecting the plate number for cars. These detected objects will be using the trained model and that will be developed and deployed throughout the project. In addition, it will be able to use optical character recognition to extract the characters and compare the detected license plate numbers of cars and the database that will be used for registering or adding information related to the license plate number, so for instance, determining if the given vehicle has access to the place it's entering, or maybe some other tasks. Finally, this project could be extendable by adding more features to the database that will be adding more values to the project and that would make the model able to do more tasks that help the user of the web-based application.

2. Proposed Approach and Tools

The Approach of this project is that we do an Automatic license plate number recognition project. And in this project has the following features:

- Detecting the license plate number of cars.
- Applying Analysis to the detected license plate numbers if the license plate number either expired or not.
- Applying Analysis to Know the type of the car by detecting the license plate number.
- Applying Analysis if the detected license plate number of the car is already registered to a specific company or the compound building.
- Applying Analysis to the detected license plate number and knowing the person who's driving the car.

2.1. Tools

The tool that will be used are as follows:

- **Google Colab:** is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser and is especially well suited to machine learning, data analysis, and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing access free of charge to computing resources including GPUs.
- **GitHub:** is an Internet hosting service for software development and version control using Git.
- **Yolo7:** it's a tool that will help us for real-time detection of an object.
- **DataSpell:** is an IDE for data science and Machine learning with intelligent Jupyter notebooks, interactive Python scripts, and lots of other built-in tools.
- **Wandb:** the tool used to track, compare, and visualize machine learning models.
- **Heroku:** it's used for deploying and hosting the website with continuous integration and version control.
- **VScode:** Visual Studio Code is a code editor redefined and optimized for building and debugging modern web and cloud applications.

3. The Dataset available

For our project, we are going to use an external existing license plate number of images dataset for cars to shorten our development time and increase the accuracy of our project, most of our datasets will be taken from the **Roboflow** website.

4. Dataset Specification

The Dataset: https://universe.roboflow.com/augmented-startups/vehicle-registration-plates-trudk/dataset/2.

Dataset Description: The following dataset contains the images of cars and the coordinates of the license plate number within the images or the labeled license plate number of the car.

The shape of the Dataset:

- **Rows:** 21959
- **Columns:** 8

Features:

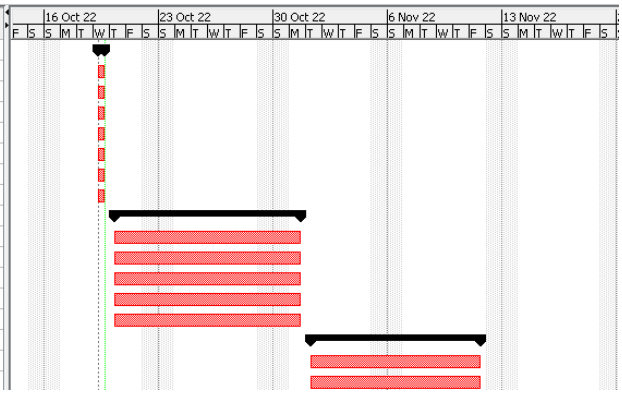
- **(Filename)** file path that contains many files that contain the images.
- **(width)** the width of the image frame.
- **(height)** the height of the image frame.
- **(xmin)** x-axis start-point coordinate in the image frame of the license plate number from the image.
- **(xmax)** x-axis endpoint coordinate in the image frame of the license plate number from the image.
- **(ymin)** y-axis start-point coordinate in the image frame of the license plate number from the image.
- **(ymax)** y-axis endpoint coordinate in the image frame of the license plate number from the image.

Dataset benefit:

- It contains huge amounts of images, so that would lead to high accuracy and promising results.
- The dataset is already labeled, so would save us a lot of time.

5. Work Plan

Name	Duration	Start	Finish
Proposal	1 day?	**10/19/22 8:00 AM**	**10/19/22 5:00 PM**
Introduction	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
Objectives	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
The Dataset avaliable	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
Dataset Specification	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
Tools to be Used	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
Work Plan	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
References	1 day?	10/19/22 8:00 AM	10/19/22 5:00 PM
Progress Report	8 days?	**10/20/22 8:00 AM**	**10/31/22 5:00 PM**
Problem definition	8 days?	10/20/22 8:00 AM	10/31/22 5:00 PM
Model used	8 days?	10/20/22 8:00 AM	10/31/22 5:00 PM
EDA	8 days?	10/20/22 8:00 AM	10/31/22 5:00 PM
Model Matrices	8 days?	10/20/22 8:00 AM	10/31/22 5:00 PM
Evaluating the Model	8 days?	10/20/22 8:00 AM	10/31/22 5:00 PM
Final Report	9 days?	**11/1/22 8:00 AM**	**11/11/22 5:00 PM**
Presentation	9 days?	11/1/22 8:00 AM	11/11/22 5:00 PM
Report	9 days?	11/1/22 8:00 AM	11/11/22 5:00 PM



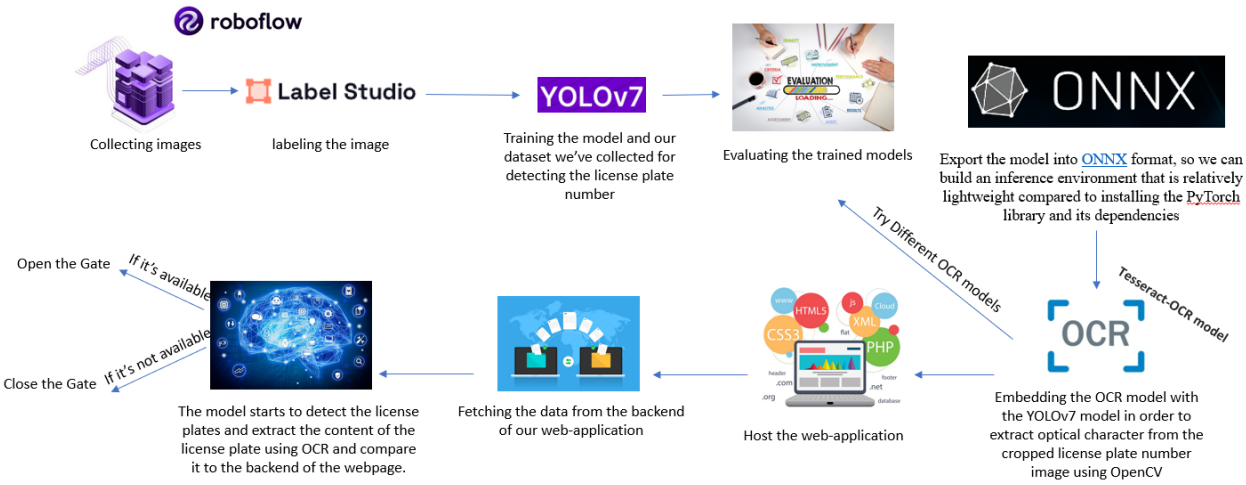
6. The Problem

The problem that we are trying to solve is that we want to apply multiple trained models that will be detecting multiple objects in real-time, and these are the following:

- Detecting multiple license plate number objects.
- Detecting the license plate number of the car.
- Extracting the optical character to extract the characters from the license plate number.

These detection models require a lot of datasets for training, so in that case, it would take a lot of time and effort for collecting a dataset and label each one of them. And These results that we've to find a solution to shorten our time consumption for training the model, so in that case, we're going to use pre-trained models to detect the optical characters of the license plate number while detecting the license plate number of the car, we're going to use the provided dataset as mentioned above and train it.

7. Project Architecture



8. Applied Tool & Models

The following tools and models that we're going to use as follows:

- **Google colab** for visualization purposes.
- **DataSpell** to train the model on the GPU offline without getting interrupted or disconnected while training the model.

- **Yolov7** will be used to train the datasets for detecting multiple classes which are the following:
    - Cars
    - license plate number
    - Optical character recognition.
- **GitHub** will be used for gathering useful code resources.
- **Roboflow** will be used to import the datasets that will be already labeled and Split into train and testing datasets.
- **VScode:** it'll be used for web development purposes.
- **Heroku:** it will be used for hosting the website and the backend of the website.
- **Wandb:** a tool used to track, compare, and visualize machine learning models.
- **OCR Model** will be used for extracting the characters of the license plate number using optical characters recognition from the images. And has multiple pre-trained models as follows:
    - Paddle OCR model
    - Keras OCR model
    - Tesseract model.
    - **Easy OCR model we will be using this one.**

9. Tool & Model Comparison

In this section, we'll be comparing different models and tools and we will explain why we would choose that specific tool and model based on the related projects of other people who had experience with these tools and models.

Tool comparison 1:

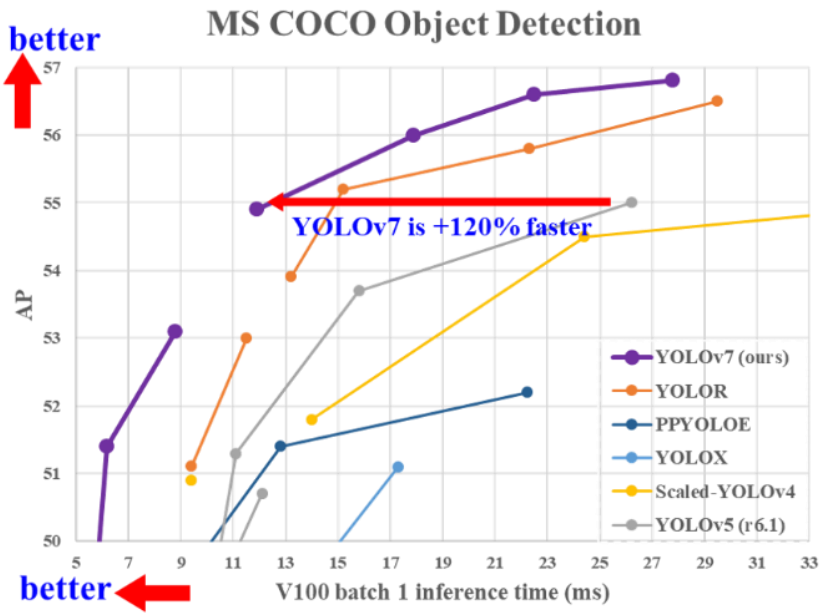
These two tools will be used since **Google colab** cannot handle the training process because of high GPU memory usage and it requires **12GB** to train on **YOLOv7** and it might crash during the training process, so to solve this problem we will be using an offline tool that works for training and doing the other visualization part on the **Google colab**.

Model Comparison 2:

The following model could be applied for real-time object detection to our project are the following:

- YOLO (2016).
- SSD (2016).
- RetinaNet (2017).
- YOLOv3 (2018).
- YOLOv4 (2020).
- YOLOR (2021).
- **YOLOv7 (2022).**

The model that we're going to use is **YOLOv7** which is the most recent version and algorithm used for real-time object detection model that has been established until now. And based on the performance that has been tested compared to other different versions of **YOLO's** it's performing 120% faster than other versions as shown in the figures below.



According to the resources, the mean average precision (**MAP**) of **RetinaNet** reached 82.89%, but the frames per second (**FPS**) is only one-third of **YOLOv3**, which makes it difficult to achieve real-time performance. **SSD** does not perform as well on the indicators of MAP and FPS. Although the **MAP** of **YOLOv3** is slightly lower than the others (80.69%). And these results that the **YOLOv3** is having better performance than **SSD** and **RetinaNet** algorithms. Finally, **YOLOv7** is having the leading accuracy with higher **FPS** and real-time performance compared to other versions of **YOLO's**.

Model Comparison 3:

The following model could be applied to the optical character recognition of our project are the following:

- Tesseract
- Keras-OCR
- **Easy-OCR**
- Paddle-OCR

The best OCR model is **Paddle-OCR model** since it works both for detecting the optical character in either high-quality or low-quality images while other models for instance **Easy-OCR** it does the same as the **Keras-ORC model** in either high-quality or low-quality images, but with lower accuracy. Finally, the last model is the **Tesseract model** which can only extract optical characters in high-quality images while in low-quality images it cannot extract optical characters, but it can achieve very high accuracy as shown in below the 2 figures.

	Actual Value	Tesseract Prediction	Keras-OCR Prediction	EasyOCR Prediction
Number Plate High Quality	HR26DK8337	HR260K8337	HR26DK8337	HRZ6DK8337
Number Plate Low Quality	MH14GN9239	Spaces	MHL4GH9239	9239
Handwritten Low Quality	AMIT ASHISH	Spaces	ADIT ASHISH	AdIT ASHISH
Handwritten High Quality	LAKSHMINIVAS TOURIST HOME	LAKSHMINIVAS TOURIST HOME	LAKSHMINIVAS TOURIST HOM	LAKSHMINIVAS TOURIST HOME
Image with text High Quality	Albert Einstein	Albert Einstein	Albert Einstein	A|ber t Einsteim
Image with text Low Quality	Kotak Mahindra Bank	Kotak Mahindra Bank	Kotak Mahindra Bank	Kotak Mahindra Bank
Reciept High Quality	Order #19866	Order #19866	Order #119666	Order #19866
Reciept Low Quality	Amoxicillin 500mg	Spaces	Amoxicillin 500mg	Amoxicillin 500mg

	Tesseract	PaddleOCR	PaddleOCR (Puntucation fixed)	PaddleOCR (White-spaces fixed)
Number of Errors	95	387	274	164
Accuracy	0.98	0.92	0.96	0.97

	Tesseract	PaddleOCR CPU	PaddleOCR GPU
Speed	3.83 s	4.12 s	2.07 s
English Model Size	23 MB	2 MB	2 MB

And based on the resources the model **Paddle-OCR model** performs 46% in a fast manner in 2.07 seconds while the **Tesseract** model spends 3.83 seconds. And in addition to that, the difference in the size of the English model is very high in the **Tesseract model** compared to the **Paddle-OCR model.** And based on the comparison and the use case we've had. We've made a decision to use the **Tesseract-OCR** model.

Why we're going to use Tesseract -OCR?

Since other **OCR models** requires a lot of time to set up for instance **Keras**, and **Paddle OCR models**. And in addition to that, the **YOLOv7 model** is already heavy model, and embedding with these **OCR models** would give great and more accurate results. And because of the time limit will take to embed these other **OCR models** as we've mentioned above. Finally, the main advantage of the **Tesseract-OCR model** is that very light model and gives good accuracy for extracting the optical characters.

10. Experiment

10.1 Visualization:

In this section, we'll visualize the dataset that we have and apply some analysis on the dataset as follows:

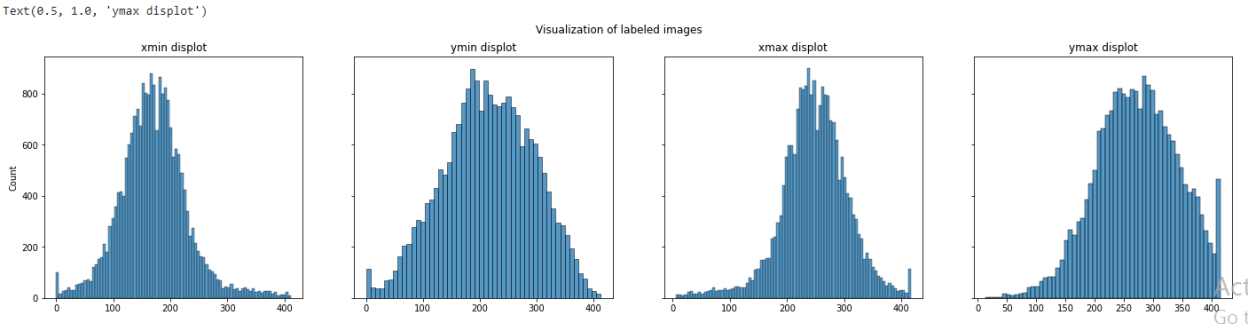
Google Colab Notebook Link:

1. **Getting details about our dataset and knowing the number of rows and columns of our dataset.**

```
[7]  1 df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 21959 entries, 0 to 1839
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   filename  21941 non-null  object
 1   width     21941 non-null  float64
 2   height    21941 non-null  float64
 3   class     21941 non-null  object
 4   xmin      21941 non-null  float64
 5   ymin      21941 non-null  float64
 6   xmax      21941 non-null  float64
 7   ymax      21941 non-null  float64
dtypes: float64(6), object(2)
memory usage: 1.5+ MB
```

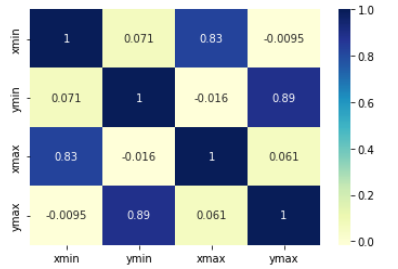
```
[8]  1 print("- The Following Dataset contains:",df.shape[0],"Images with",df.shape[1],"Features")

- The Following Dataset contains: 21959 Images with 8 Features
```

2. **Visualizing the distribution of data of the bounding box of plate numbers values that are (xmin, xmax, ymin, ymax) or labeled images as shown below:**



3. **Visualizing the correlation of data of the bounding box of plate numbers values that are (xmin, xmax, ymin, ymax) or labeled images as shown below:**

```
            xmin      ymin      xmax      ymax
xmin    1.000000  0.070865  0.828156 -0.009510
ymin    0.070865  1.000000 -0.015842  0.892064
xmax    0.828156 -0.015842  1.000000  0.060578
ymax   -0.009510  0.892064  0.060578  1.000000
```

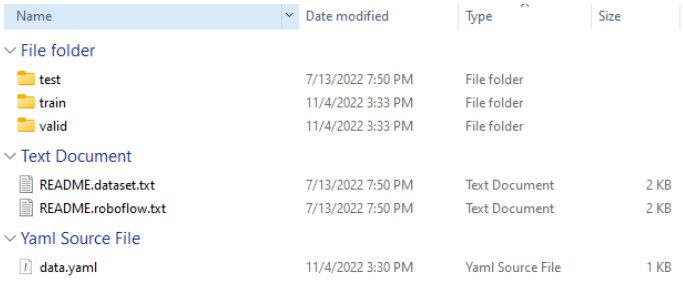


10.2 Training

In this section, we'll show the complete step for training our model on our dataset to achieve one of the approaches by detecting the license plate number in real time.
Script Code: Google Colab Notebook Link:

The following step for training our dataset as follows:

1. **The first step is that convert our dataset format into YOLO format to be able to train our dataset.**



2. **Making sure that we are using an appropriate GPU since it requires a high Graphics memory card of approximately more than 12GB memory card for training the YOLOv7 model since it's a heavy model, so we have to make sure that we have selected an appropriate GPU card and make sure that it works fine as shown below in the figure**

```
!nvidia-smi
✓ 0.2s
Fri Nov  4 23:51:25 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 526.47       Driver Version: 526.47       CUDA Version: 12.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name            TCC/WDDM | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA GeForce ... WDDM  | 00000000:01:00.0  On |                  N/A |
| N/A   66C    P3    27W /  N/A |   2371MiB /  6144MiB |     34%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A      8224    C+G   ...ser\Application\brave.exe    N/A      |
|    0   N/A  N/A     13940      C   ...les\LGHUB\lghub_agent.exe    N/A      |
|    0   N/A  N/A     16404      C   ...thon\Python310\python.exe    N/A      |
|    0   N/A  N/A     21656    C+G   ...root\Office16\WINWORD.EXE    N/A      |
+-----------------------------------------------------------------------------+
```

```
torch.cuda.is_available()
✓ 0.1s
True

torch.cuda.device_count(), torch.cuda.current_device()
✓ 0.1s
(1, 0)

torch.cuda.get_device_name(0)
✓ 0.9s
'NVIDIA GeForce RTX 2060'

torch.backends.cudnn.enabled
✓ 0.5s
True

torch.backends.cudnn.version()
✓ 0.1s
8302
```

3. **Download the [YOLOv7] model from GitHub and its dependencies.**

Model	Test Size	AP^{test}	AP_{50}^{test}	AP_{75}^{test}	batch 1 fps	batch 32 average time
YOLOv7	640	51.4%	69.7%	55.9%	161 *fps*	2.8 *ms*
YOLOv7-X	640	53.1%	71.2%	57.8%	114 *fps*	4.3 *ms*
YOLOv7-W6	1280	54.9%	72.6%	60.1%	84 *fps*	7.6 *ms*
YOLOv7-E6	1280	56.0%	73.5%	61.2%	56 *fps*	12.3 *ms*
YOLOv7-D6	1280	56.6%	74.0%	61.8%	44 *fps*	15.0 *ms*
YOLOv7-E6E	1280	56.8%	74.4%	62.1%	36 *fps*	18.7 *ms*

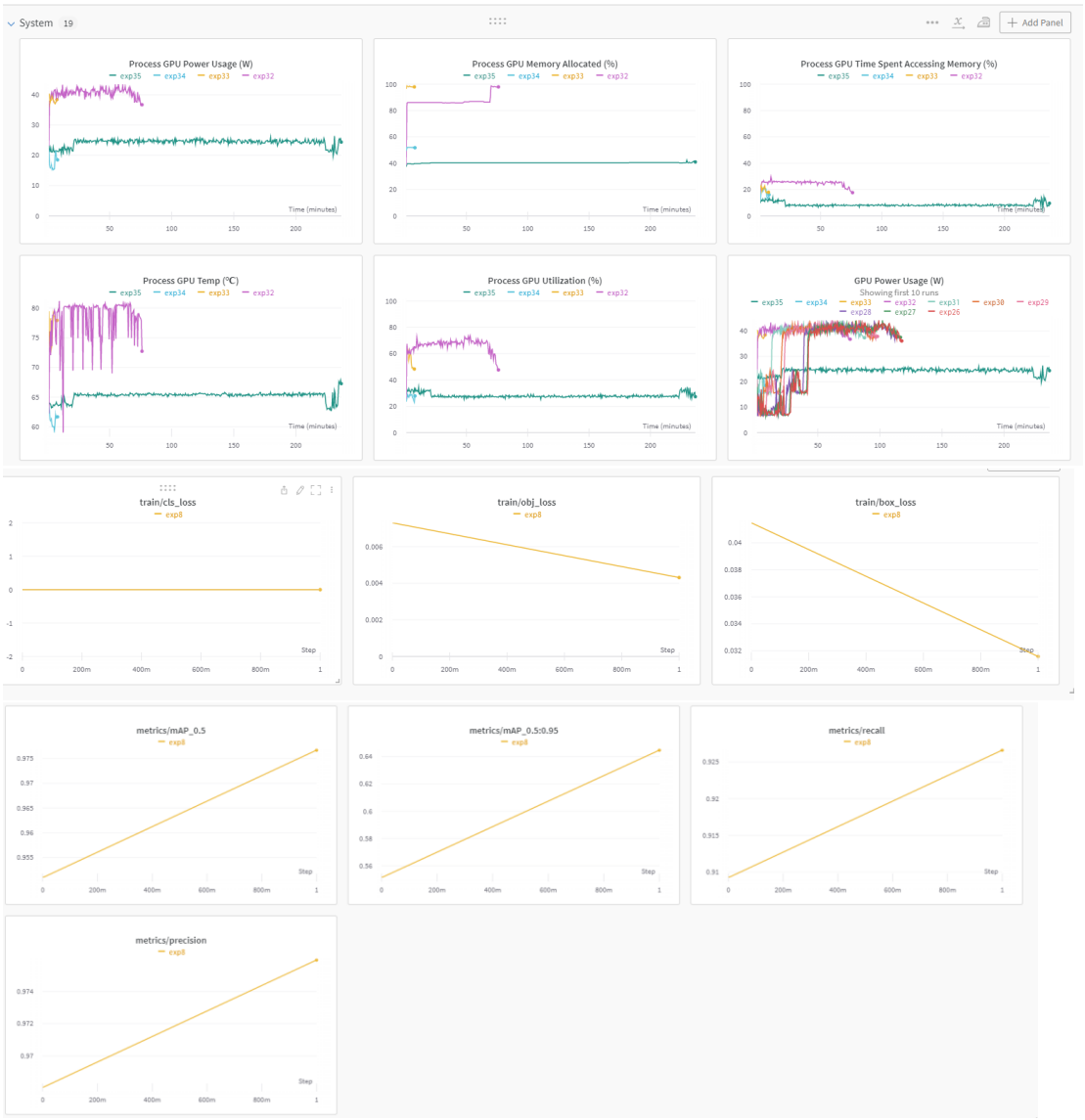
```
# Download YOLOv7 repository and install requirements
%cd /Users/fouad/Work/Courses/ZAKA_ML_Track/Capstone_Project/LP
!git clone https://github.com/augmentedstartups/yolov7.git
%cd yolov7
!pip install -r requirements.txt
✓
```

4. **After that, we Download the yolov7x.pt model that will be used for training our model as shown below in the figure:**

```
%%bash
wget https://github.com/WongKinYiu/yolov7/releases/download/v0.1/yolov7x.pt
```

5. **Use the Wandb tool for visualizing how the training process is going on during the training based on the given dataset we are training on it and ensuring that our model is training in the right path. After that, we start training the YOLO7 model by defining the batch size, the weight of the specified model that we have downloaded (yolov7x.pt), and defining the GPU we're using for training the model as shown below in the figure:**

6. **Using the Wandb tool.**



7. **Training the model.**

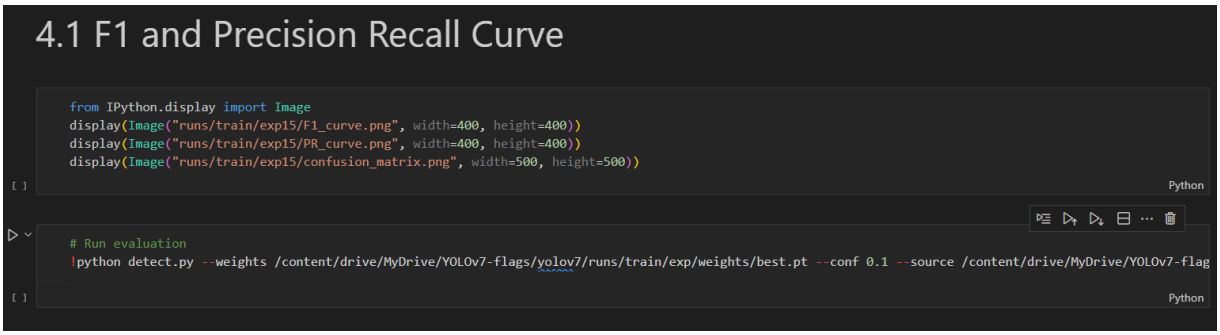
```
!python train.py --batch 8 --cfg cfg/training/yolov7.yaml --epochs 5 --data {dataset.location}/data.yaml --weights 'yolov7x.pt' --device 0
```

```
Namespace(adam=False, artifact_alias='latest', batch_size=16, bbox_interval=-1, bucket='', cache_images=False, cfg='cfg/training/yolov7.yaml', data='/content/Vehicle-Registration-Plates-2/data.yaml', device='0', entity=None, epochs=5, evolve=False, exi
tensorboard: Start with 'tensorboard --logdir runs/train', view at http://localhost:6006/
hyperparameters: lr0=0.01, lrf=0.1, momentum=0.937, weight_decay=0.0005, warmup_epochs=3.0, warmup_momentum=0.8, warmup_bias_lr=0.1, box=0.05, cls=0.3, cls_pw=1.0, obj=0.7, obj_pw=1.0, iou_t=0.2, anchor_t=4.0, fl_gamma=0.0, hsv_h=0.015, hsv_s=0.7, hsv_
wandb: Currently logged in as: fouad_alkadri. Use `wandb login --relogin` to force relogin
wandb: Tracking run with wandb version 0.13.4
wandb: Run data is saved locally in /content/yolov7/wandb/run-20221102_210602-3vm740r6
wandb: Run `wandb offline` to turn off syncing.
wandb: Syncing run exp3
wandb: ⭐️ View project at https://wandb.ai/fouad_alkadri/YOLOR
wandb: 🚀 View run at https://wandb.ai/fouad_alkadri/YOLOR/runs/3vm740r6
Overriding model.yaml nc=80 with nc=1

                 from  n    params  module                                  arguments
  0                -1  1       928  models.common.Conv                      [3, 32, 3, 1]
  1                -1  1     18560  models.common.Conv                      [32, 64, 3, 2]
  2                -1  1     36992  models.common.Conv                      [64, 64, 3, 1]
  3                -1  1     73984  models.common.Conv                      [64, 128, 3, 2]
  4                -1  1      8320  models.common.Conv                      [128, 64, 1, 1]
  5                -2  1      8320  models.common.Conv                      [128, 64, 1, 1]
  6                -1  1     36992  models.common.Conv                      [64, 64, 3, 1]
  7                -1  1     36992  models.common.Conv                      [64, 64, 3, 1]
  8                -1  1     36992  models.common.Conv                      [64, 64, 3, 1]
  9                -1  1     36992  models.common.Conv                      [64, 64, 3, 1]
 10  [-1, -3, -5, -6]  1         0  models.common.Concat                    [1]
 11                -1  1     66048  models.common.Conv                      [256, 256, 1, 1]
 12                -1  1         0  models.common.MP                        []
 13                -1  1     33024  models.common.Conv                      [256, 128, 1, 1]
 14                -3  1     33024  models.common.Conv                      [256, 128, 1, 1]
 15                -1  1    147712  models.common.Conv                      [128, 128, 3, 2]
 16        [-1, -3]  1         0  models.common.Concat                    [1]
 17                -1  1     33024  models.common.Conv                      [256, 128, 1, 1]
 18                -2  1     33024  models.common.Conv                      [256, 128, 1, 1]
 19                -1  1    147712  models.common.Conv                      [128, 128, 3, 1]
 20                -1  1    147712  models.common.Conv                      [128, 128, 3, 1]
 21                -1  1    147712  models.common.Conv                      [128, 128, 3, 1]
 22                -1  1    147712  models.common.Conv                      [128, 128, 3, 1]
 23  [-1, -3, -5, -6]  1         0  models.common.Concat                    [1]
```

8. **Keep tracking the training process and monitoring the performance of our training by using the Wandb tool.**

10.3 Evaluation:

1. **Evaluating our trained model after we have finished our training process.**



10.4 Model format:

Explanation:

After we've got the trained model we export the model into **ONNX** format, so we can build an inference environment that is relatively lightweight compared to installing the **PyTorch** library and its dependencies, so the main component of the inference environment are **Cuda** toolkit, **cuDNN**, and **DONNX** functions/libraries to let **ONNX** communicate to the GPU. In the next step, we'll use the **NumPy** library for math purposes, fetching the data from our backend web-application, and **OpenCV** for processing the images.

Why do we use fetch the data from our backend?
It'll help us fetch the data into the backend of the website-application we've developed so that I'll add the detected license plate number to the license plate database table.

Script Demonstration:

In this part, we'll explain the writing script of the inference, so basically, we wrote it using **OpenCV** and it gets the frames of the video and passes the frames one by one to the model and get the prediction of the model of the license plate then we compare the area of all the detected license plates. And gets the best license plate the one that has the largest area. Next, we crop the license plate box from the image and apply the **Tesseract-OCR model** to it to extract the optical character of the license plate number/box then we compare the detected content of the license plates box with the list of allowed license plates in our backend of the website, so if the license is available in the table we throw a condition of opening the gate of the compound building. And if not, we throw a condition that we don't open the gate of the compound building.

10.5 Hosting the web application

In this section, we'll be using the **Heroku** tool to host our website application in public or private with continuous integration, version control, and followed by the backend of the website.

So, it has been done the following steps:

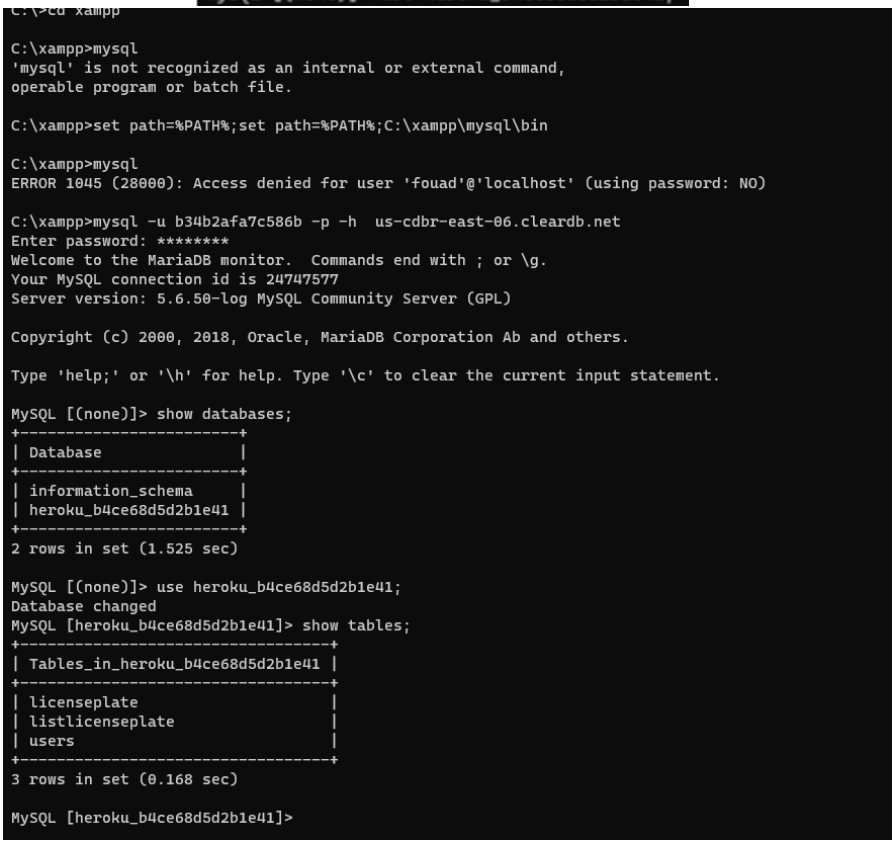
- Create a Heroku account to use for hosting.
- Having a GitHub repository that contains our website application to connect the Heroku.
- Selecting the repository that you want to host.
- Make sure that we install a build-pack of PHP, so it can detect the pages of the website application for instance **index.php** as a home page.
- Let the Heroku website make a continuous integration with GitHub, so whenever the website is updated, the hosted website will also be updated through the changes of the **commits in GitHub.**
- Click on the host button to start hosting the web application.
- The website is deployed/hosted.

After that, we 'll add the backend of the hosted page, so we do the following steps:

- Go to the resources section on the Heroku website.
- Click on the add-ons option.
- Select **ClearDB MySQL.**
- Get the username and Password of the website and the name of the database.
- Connect to the database.

```
$serverName = "us-cdbr-east-06.cleardb.net";
$DBusername = "b34b2afa7c586b";
$DBpassword = "0[redacted]";
$DBname = "heroku_b4ce68d5d2b1e41";
```

- Do the following command to make sure that the database is connected to the web application.
  - Change the directory to xampp
    - cd ..
    - cd ..
    - cd xampp
  - Set the MySQL path if it's not working
    - `C:\xampp>set path=%PATH%;set path=%PATH%;C:\xampp\mysql\bin`
  - Connect to the database
    - `>mysql -u b34b2afa7c586b -p -h  us-cdbr-east-06.cleardb.net`
    - mysql -u username -p -h link
  - put the password of the database.
  - use the database.
    - `MySQL [(none)]> use heroku_b4ce68d5d2b1e41;`



- Finally, the website is hosted successfully.

10.4 Issues Related:

Throughout these processes and steps that we have done we had some related issues as follows:

- Limit Resources
    - Not enough GPU memory since we had of range (8 GB - 10 GB).
    - Sometimes it crashes because it gets over the limit of what we had, and the training got interrupted.
    - Time-consuming since the model takes days to train the model.
    - Embedding the **OCR** got us some difficulty since the model is already huge and requires a lot of time to embed it.

10.5 Features could be added

The features that could be added in the future are the following:

- We could use a better ORC model.
- We could train the YOLOv7 model more.
- We could have more features in the backend table in the website application, so we could not only for opening the gate or close it we could use as follows:
    - Check the expiration date of the license plate number.
    - Knowing the type of car.
    - The time that he/she went outside and inside the compound building
    - And more features could be added.

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