

Q2. Train a deep learning classification model for chess piece dataset.

Steps Involved :

- Find dataset
- Select a model to train the images on
- Train the model with training data
- Test with model with testing data
- Evaluation of the model

I tried a few datasets available online, but they were not suitable for real-time detection or classification tasks. Either they had a high dimensions or random images that are irrelevant to chess pieces in real life.

I even tried to train YOLOv5 on the above datasets for detection task, but they did not perform well.

So, I decided to collect my own dataset from the chess pieces I had.

Also thought it would be fun to do it.

Why YOLOV5?

YOLOv5 is **fast, easy to use, and capable of achieving state-of-the-art results for object detection tasks**. It is also more accurate and easier to train than its predecessors. It requires less data and give better results with it.

Collecting dataset :

I took 25 images of each chess piece and then resized them to 640*640 .

Then annotated them and stored the labels.

Split them into train and test datasets.

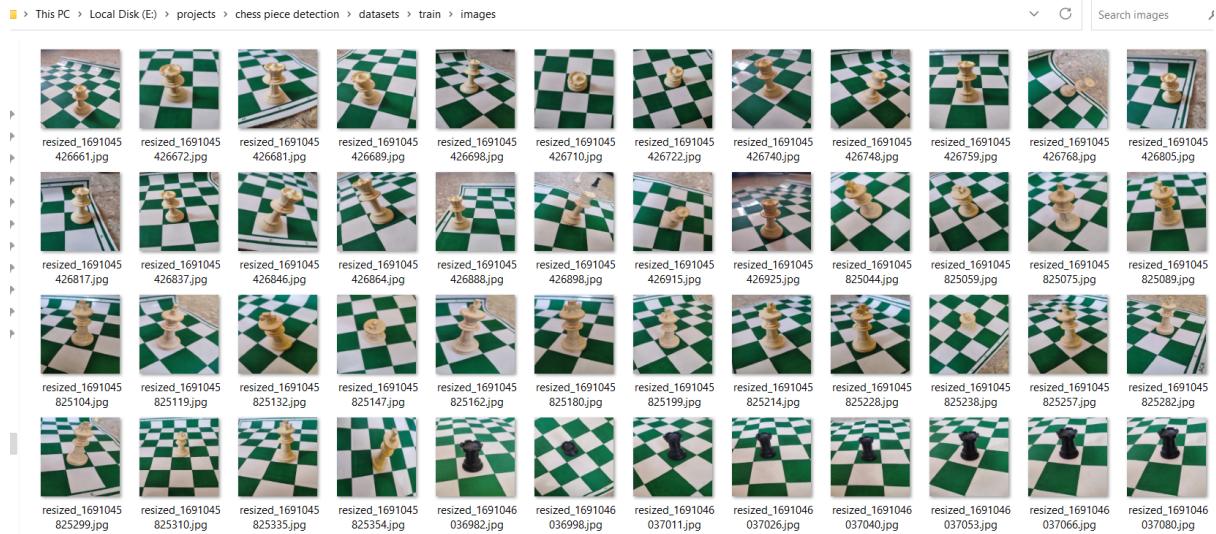
The classes include - White king, White queen, White rook, White bishop, White pawn, White knight, Black king, Black queen, Black rook, Black bishop, Black pawn, Black knight. Total of 12 classes.

So, $12 \times 25 = 300$

Did a train-test split as : train - 20 images of each class , test - 5 images of each class. Then annotated each image using labelimg

Name	Date modified	Type	Size
📁 all_resized_640	03-08-2023 05:36 PM	File folder	
📁 Black bishop	03-08-2023 04:23 PM	File folder	
📁 Black king	03-08-2023 04:23 PM	File folder	
📁 Black knight	03-08-2023 04:27 PM	File folder	
📁 Black pawn	03-08-2023 04:23 PM	File folder	
📁 Black queen	03-08-2023 04:23 PM	File folder	
📁 Black rook	03-08-2023 12:32 PM	File folder	
📁 datasets	03-08-2023 01:30 PM	File folder	
📁 White bishop	03-08-2023 04:23 PM	File folder	
📁 White king	03-08-2023 12:32 PM	File folder	
📁 White knight	03-08-2023 04:23 PM	File folder	
📁 White pawn	03-08-2023 04:23 PM	File folder	
📁 White queen	03-08-2023 12:32 PM	File folder	
📁 White rook	03-08-2023 04:23 PM	File folder	
📄 resized_test_multiple.jpeg	03-08-2023 07:45 PM	JPEG File	120 KB
📄 resizer.ipynb	03-08-2023 05:39 PM	IPYNB File	4 KB

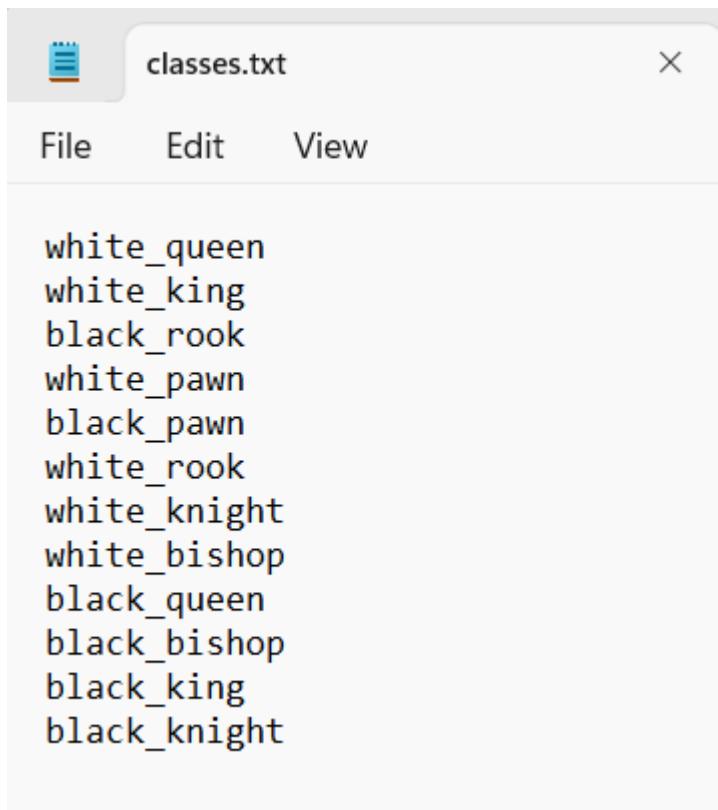
Then dumped them it into a single folder as YOLOv5 takes dataset in such format. Now, we have both images and labels for each image into corresponding folders.



> This PC > Local Disk (E:) > projects > chess piece detection > datasets > train > labels

Name	Date modified	Type	Size
resized_1691045426672.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426681.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426689.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426698.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426710.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426722.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426740.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426748.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426759.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426768.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426805.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426817.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426837.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426846.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426864.txt	03-08-2023 01:30 PM	Text Document	1 KB
resized_1691045426888.txt	03-08-2023 01:30 PM	Text Document	1 KB

classes.txt file - defines the classes and labels for the images depends on their index of the class



```
white_king
white_knight
white_bishop
white_rook
white_pawn
black_king
black_knight
black_bishop
black_rook
black_pawn
black_queen
```

I cloned the YOLOv5 repository from ultralytics and continue to train it using the dataset we just created. Used the YOLOv5 Large model for better results.

Directory setup

📁	datasets	03-08-2023 05:34 PM
📁	yolov5	03-08-2023 01:00 AM
📄	chess piece detection.ipynb	03-08-2023 01:39 PM
📄	yolov5l.pt	03-08-2023 12:56 AM
📄	yolov5s.pt	02-08-2023 08:09 PM

Before training the model, We need to define the classes and dataset paths in dataset.yaml file within yolov5 folder



A screenshot of a code editor window titled "dataset.yaml". The file contains the following YAML configuration:

```
path: ../../datasets
train: train/images
val: test/images

nc: 12
names: ['white_queen', 'white_king', 'black_rook', 'white_pawn', 'black_pawn', 'white_rook', 'white_knight', 'white_bishop', 'black_queen', 'black_bishop', 'black_king', 'black_knight']
```

Install and import the requirements for yolov5.

```
!cd yolov5 & pip install -r requirements.txt

import torch
import numpy as np
import cv2
from matplotlib import pyplot as plt

model = torch.hub.load('ultralytics/yolov5', 'yolov5l')
```

We use the command prompt to train the model using the following command. cd into the project folder and run :

```
!cd yolov5 && python train.py --img 640 --batch 8 --epochs 300 --data dataset.yaml
--weights yolov5l.pt
--name yolov5l_results
--cache
```

We run the train.py file with following parameters.

'img' parameter denotes the smaller side of the image for kernel size setting as YOLO uses variable kernel size for first kernel. It is 640 in our case, as the image is of dimensions 640*640.

'batch' size is set 8 for minimal RAM usage.

'epoch' is set 300

'data' parameter denotes the location where the dataset is located and the number of classes involved in training.

'weights' denotes the initial weights, we use the pretrained weights of yolov5l model.

'cache' is used to cache the results, so we can continue training later.

Fusing layers

```

train: weights=yolov5l.pt, cfg=../models/yolov5l.yaml, data=dataset.yaml, hyp=data/hyps/hyp.scratch-low.yaml, epochs=300, batch_size=8, imgsz=640, rect=False, resume=False, noval=False, noautoanc
hor=False, noplots=False, evolve=None, bucket+, cache=ram, image_weights=False, device=cpu, multi_scale=False, optimizer=SGD, sync_bn=False, workers=8, project=runs\\train, name=yolov5l_results,
exist_ok=False, quad=False, cos_lr=False, label_smoothing=0.0, patience=100, freeze=[0], save_periods=1, seed=0, local_rank=-1, entity=None, upload_dataset=False, bbox_interval=1, artifact_alias=latest
github: YOLOv5 is out of date by 1 commit. Use 'git pull' or 'git clone https://github.com/ultralytics/yolov5' to update.

YOLOv5 v7.0-002-gf9f02a Python-3.8.17 torch-2.0.1 CUDA-10.2.240 (NVIDIA GeForce RTX 3060 Laptop GPU, 8GB)

hyperparameters: lr=0.01, lr_f=0.01, momentum=0.937, weight_decay=0.0005, warmup_epochs=3.0, warmup_momentum=0.8, warmup_bias_lr=0.1, box=0.85, cls=0.5,cls_pw=1.0, obj=1.0, 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_v=0.4, degree=0.0, translate=0.1, scale=0.5, shear=0.0, perspective=0.0, flipud=0.0, filpLR=0.5, mosaic=1.0, mixup=0.0, copy_paste=0.0

Comet: run 'pip install comet_ml' to automatically track and visualize YOLOv5 runs in Comet
TensorBoard: Start with 'tensorboard --logdir runs\\train', view at http://localhost:6006

Overriding model.yaml nc=12 with nc=12

from n    params module           arguments
0      -1  1    7040 models.common.Conv   [3, 64, 6, 2, 2]
1      -1  1    73984 models.common.Conv  [64, 128, 3, 2]
2      -1  1    156928 models.common.C3   [128, 128, 3]
3      -1  1    295424 models.common.Conv  [128, 256, 3, 2]
4      -1  1    590848 models.common.Conv  [256, 256, 3, 2]
5      -1  1    1180672 models.common.Conv  [256, 256, 3, 2]
6      -1  1    6433792 models.common.C3   [512, 512, 3]
7      -1  1    4720640 models.common.Conv  [512, 1024, 3, 2]
8      -1  1    9971712 models.common.C3   [1024, 1024, 3]
9      -1  1    2624512 models.common.SPPF  [1024, 1024, 5]
10     -1  1    525312 models.common.Conv  [1024, 512, 1, 1]
11     -1  1    0    torch.nn.modules.upsampling.Upsample [None, 2, 'nearest']
12     [-1, 1] 0    models.common.Concat  [1]
13     -1  1    2757632 models.common.Conv  [1024, 512, 3, False]
14     -1  1    1315840 models.common.Conv  [512, 256, 1, 1]
15     -1  1    0    torch.nn.modules.upsampling.Upsample [None, 2, 'nearest']
16     [-1, 1] 0    models.common.Concat  [1]
17     -1  1    6996880 models.common.C3   [512, 256, 3, False]
18     -1  1    5983360 models.common.Conv  [256, 256, 3, 2]
19     [-1, 1] 0    models.common.Concat  [1]
20     -1  1    2095080 models.common.C3   [512, 512, 3, False]
21     -1  1    2360320 models.common.Conv  [512, 512, 3, 2]
22     [-1, 10] 1    0    models.common.Concat [1]
23     -1  3    9971712 models.common.C3   [1024, 1024, 3, False]
24     [17, 20, 23] 1    91545 models.yolo.Detect [12, [[10, 13, 16, 30, 33, 23], [30, 61, 62, 45, 59, 119], [116, 98, 156, 198, 373, 326]], [256, 512, 1024]]

YOLOv5 summary: 368 layers, 46197529 parameters, 46197529 gradients, 108.4 GFLOPs

```

Epoch start

```

Transferred 606/613 items from yolov5l.pt
AMP: checks passed
optimizer: SGD(lr=0.01) with parameter group 101 weight(decay=0.0), 104 weight(decay=0.0005), 104 bias
train: Scanning C:\Myfiles\Project\Kritihiik\yolo\datasets\train\labels...  train: Scanning C:\Myfiles\Project\Kritihiik\yolo\datasets\train\labels... 1 train: Scanning C:\Myfiles\Project\Kritihiik\yolo\dataset
s\train\labels...  train: Cache directory C:\Myfiles\Project\Kritihiik\yolo\datasets\train is not writable: [WinError 183] Cannot create a file when that file already exists: 'C:\\Myfiles\\Project\\Kritihiik\\yolo\\data
sets\\train\\labels.cache.npy' -> 'C:\\Myfiles\\Project\\Kritihiik\\yolo\\datasets\\train\\labels.cache'
train: Caching Images (0.3GB ram): 100%|██████████| 201/201 [00:00:00:00:00:00]
val: Scanning C:\Myfiles\Project\Kritihiik\yolo\datasets\test\labels... 60 i
val: WARNING Cache directory C:\Myfiles\Project\Kritihiik\yolo\datasets\test is not writable: [WinError 183] Cannot create a file when that file already exists: 'C:\\Myfiles\\Project\\Kritihiik\\yolo\\dataset
s\\test\\labels.cache.npy' -> 'C:\\Myfiles\\Project\\Kritihiik\\yolo\\datasets\\test\\labels.cache'
Val: Caching Images (0.1GB ram): 100%|██████████| 60/60 [00:00:00:00, 1243]

AutAnchor: 3.55 anchors/target, 1.000 Best Possible Recall (BPR). Current anchors are a good fit to dataset
Plotting labels to runs\\train\\yolov5l_results2\\labels.jpg...
Image sizes 640 train, 640 val
Using 8 dataloader workers
Logging results to runs\\train\\yolov5l_results2
Starting training for 300 epochs...

```

Epoch	GPU_mem	box loss	obj loss	cls loss	Instances	Size
0/299	5.15G	0.0797	0.03204	0.05948	1	6
	Class	Images	Instances	P	R	mAP50
	all	60	60	0.987	0.983	0.986
						0.798
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size
298/299	5.71G	0.01173	0.004966	0.003887	1	640: 100% ████
	Class	Images	Instances	P	R	mAP50
	all	60	60	0.988	0.983	0.988
						0.798
Epoch	GPU_mem	box_loss	obj_loss	cls_loss	Instances	Size
299/299	5.71G	0.01014	0.004964	0.002496	1	640: 100% ████
	Class	Images	Instances	P	R	mAP50
	all	60	60	0.988	0.983	0.99
						0.798

Epoch end

```

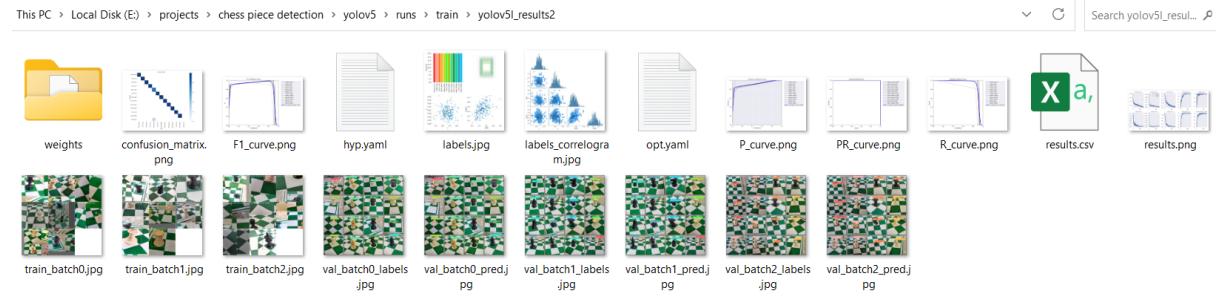
300 epochs completed in 1.155 hours.
Optimizer stripped from runs\\train\\yolov5l_results2\\weights\\last.pt, 93.0MB
Optimizer stripped from runs\\train\\yolov5l_results2\\weights\\best.pt, 93.0MB

Validating runs\\train\\yolov5l_results2\\weights\\best.pt...
Fusing layers...
YOLOv5 summary: 267 layers, 46167513 parameters, 0 gradients, 107.8 GFLOPs
          Class   Images Instances   P   R   mAP50   mAP50-9
          all       60       60   0.983   0.986   0.995   0.823   white_king      60      5   0.976      1
          0.995   0.797   white_king      60      5   0.979      1   0.995   0.852   black_rook     60      5
          0.978   1     0.995   0.825   white_pawn     60      5   0.98     1   0.995   0.797   black_pawn     60      5
          60      5     1     0.831   0.995   0.872   white_rook     60      5   0.981   0.995   0.797   black_bishop   60      5
          white_knight  60      5   0.981      1   0.995   0.801   white_bishop   60      5   0.974   0.995   0.896
          5     0.766   black_queen    60      5   0.999      1   0.995   0.846   black_bishop   60      5   0.974   0.995   0.896
          1     0.995   0.813   black_king     60      5   0.991      1   0.995   0.873   black_knight   60
          5     0.985      1   0.995   0.801 Results saved to runs\\train\\yolov5l_results2

```

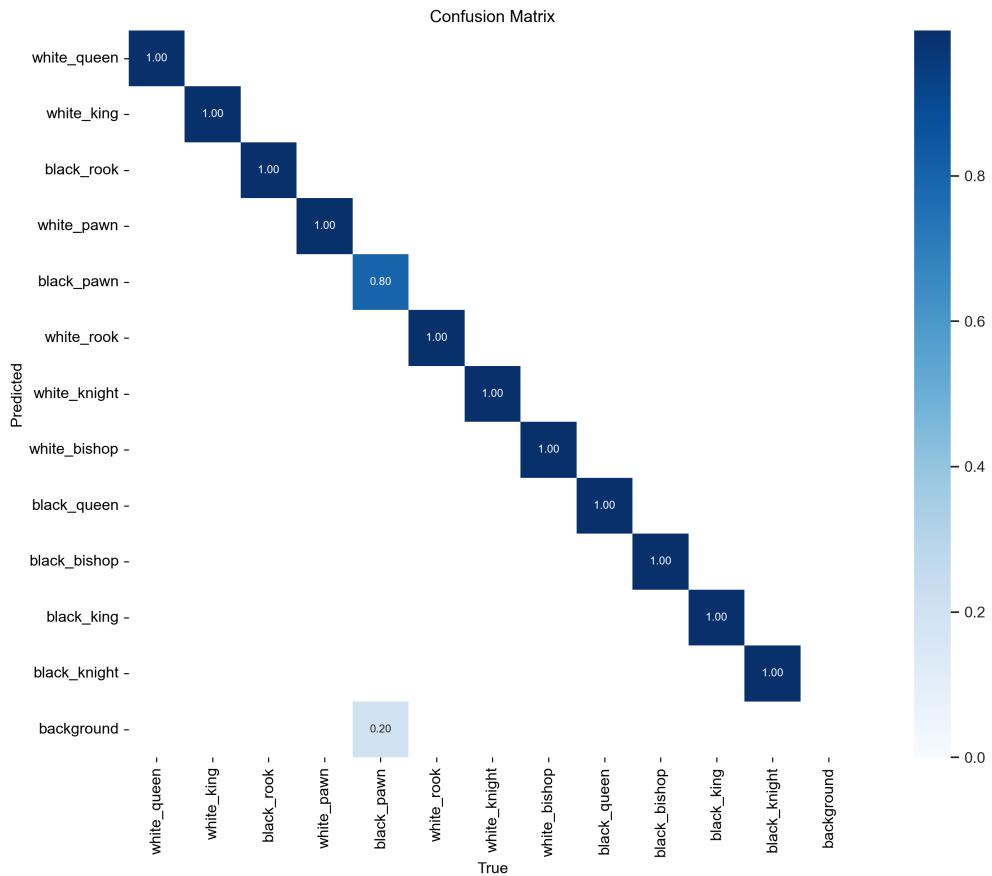
After the model is trained, we will have the results in the runs folder.

It has several evaluation metrics executed.



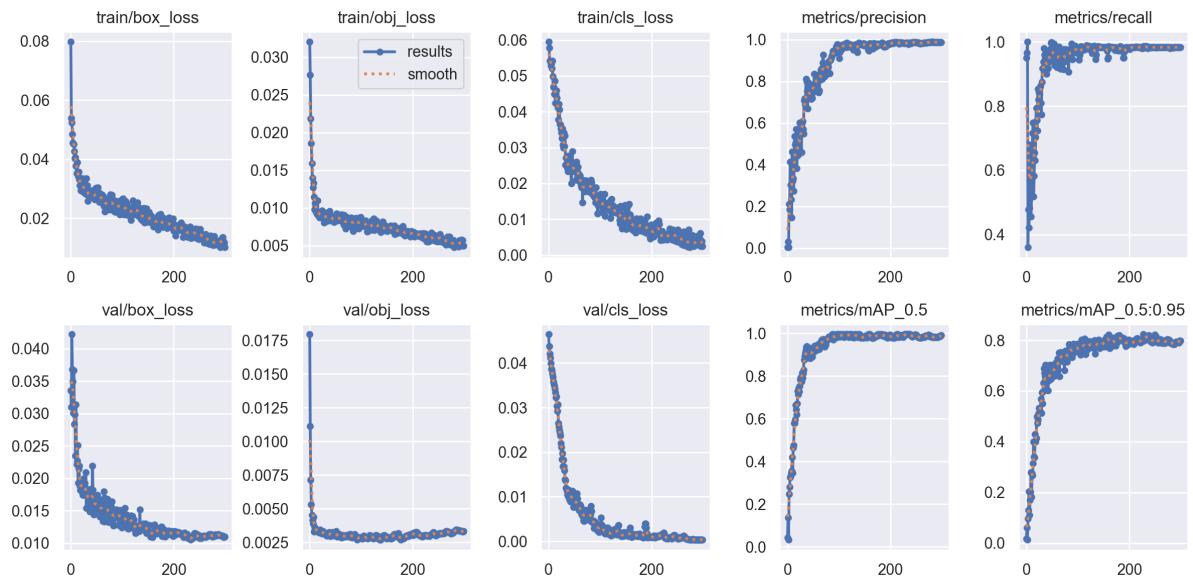
results.csv has the progress of the model on over 300 epochs.

Confusion matrix



We can notice that the model performs really good on the given task.

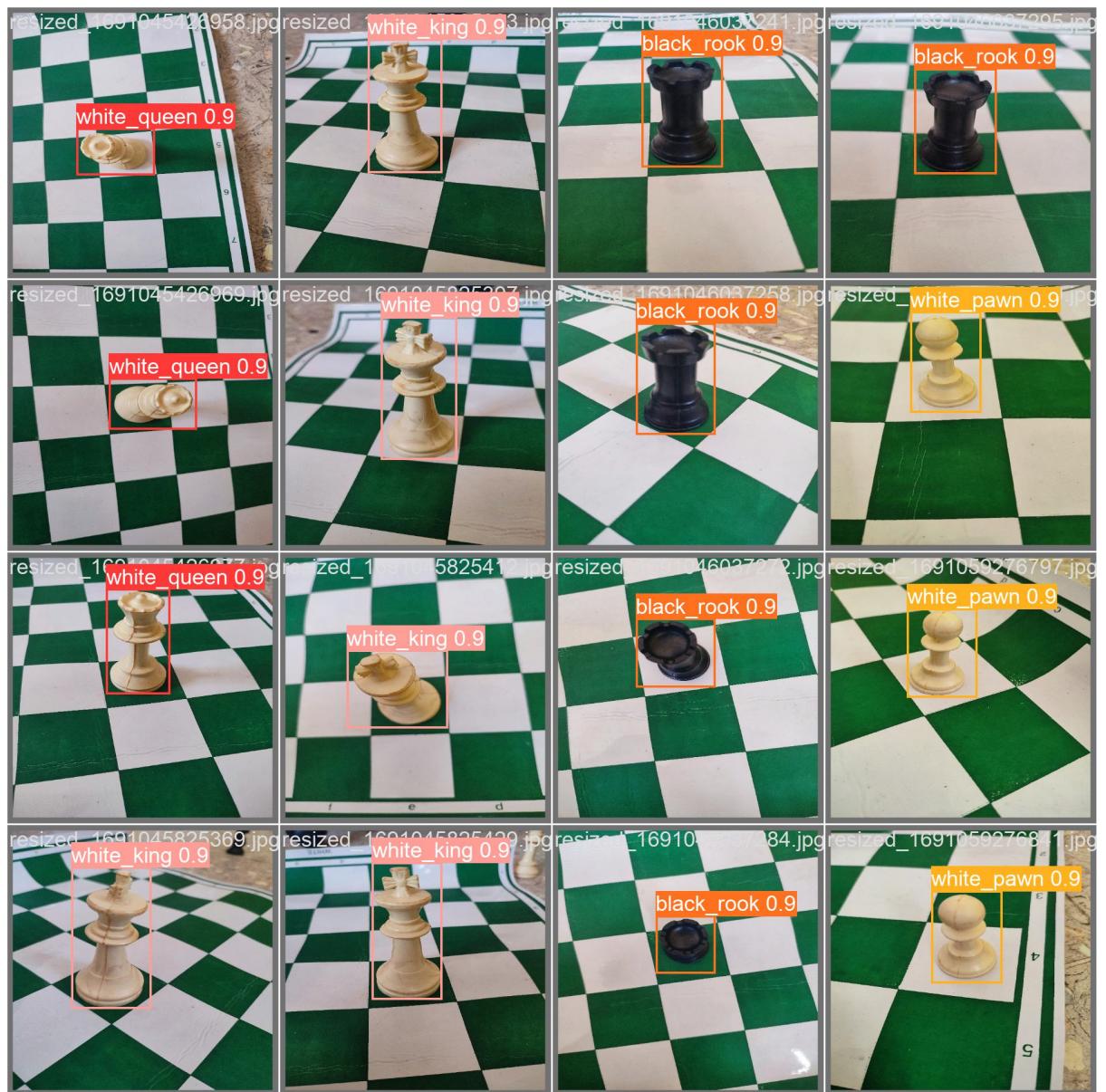
We can also have a look at the results.png



We can notice that the model achieved better precision and recall on training.

To be precise the *precision is - 0.988 and recall is 0.983*, which can be seen in results.csv or at the end of training session.

Detection:



```
!python detect.py --weights runs/train/yolov5l_results/weights/best.pt  
--img 640 --conf 0.5 --source ../test/images
```

we run the detect.py to test our model on the test images.

'weights' parameter is set to our best weights ie. best.pt achieved during training.

'conf' is the threshold on confidence metric for detection.

'source' denotes the file path for test images or '0' for live camera detection.

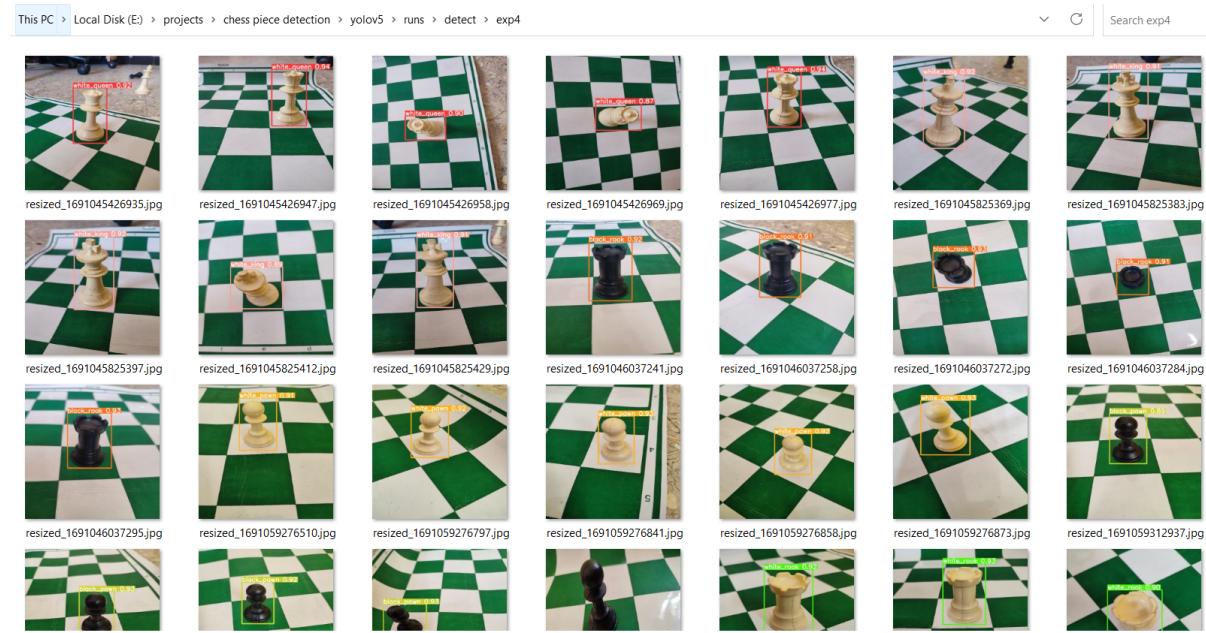
```

detect: weights=['runs/train/yolov5l_results2/weights/best.pt'], source=..../datasets/test/images, data=data\coco128.yaml, imgsz=[640, 640], conf_thres=0.45, iou_thres=0.45, max_det=1000, device=, view_img=False
, save_txt=False, save_conf=False, save_crop=False, nosave=False, classes=None, agnostic_nms=False, augment=False, visualize=False, update=False, project=runs\detect, name=exp, exist_ok=False, line_thickness=3, hide_labels=False, hide_conf=False, half=False, dnn=False, vid_stride=1
YOLOv5 v7.0-202-gf9fe23a Python-3.8.17 torch-2.0.1 CUDA-0 (NVIDIA GeForce RTX 3060 Laptop GPU, 6144MiB)

Fusing layers...
YOLOv5 Summary: 267 layers, 46167513 parameters, 0 gradients, 187.8 GFLOPs
image 1/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045426935.jpg: 640x640 1 white_queen, 22.9ms
image 2/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045426947.jpg: 640x640 1 white_queen, 23.3ms
image 3/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045426958.jpg: 640x640 1 white_queen, 23.0ms
image 4/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045426969.jpg: 640x640 1 white_queen, 22.2ms
image 5/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045426977.jpg: 640x640 1 white_queen, 22.4ms
image 6/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045425369.jpg: 640x640 1 white_king, 22.1ms
image 7/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045425377.jpg: 640x640 1 white_king, 22.0ms
image 8/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045425429.jpg: 640x640 1 white_king, 22.6ms
image 9/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045425412.jpg: 640x640 1 white_king, 22.1ms
image 10/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691045425429.jpg: 640x640 1 white_king, 22.4ms
image 11/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691046037241.jpg: 640x640 1 black_rook, 22.1ms
image 12/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691046037258.jpg: 640x640 1 black_rook, 22.0ms
image 13/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691046037272.jpg: 640x640 1 black_rook, 22.3ms
image 14/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691046037284.jpg: 640x640 1 black_rook, 22.5ms
image 15/60 C:\MyFiles\Project\Kritihik\yolo\datasets\test\images\resized_1691046037295.jpg: 640x640 1 black_rook, 21.9ms

```

It can be seen that the detection on images occur within milli-seconds. That is the advantage of using YOLO models. They are relatively small and provide better results , faster.



Utility functions

resizes the image into a 640*640 dimensions by crawling through defined sub folders of images.

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
import os
import glob
import pickle
import xml.etree.ElementTree as ET
from os import listdir, getcwd
from os.path import join

def getImagesInDir(dir_path):
    image_list = []
    for filename in glob.glob(dir_path + '/*.jpg'):
        image_list.append(filename)

    return image_list

dirs = [ 'Black rook', 'White king', 'White queen','White rook', 'White pawn',
'White bishop', 'White knight', 'Black king', 'Black queen','Black pawn',
'Black bishop', 'Black knight'  ]

cwd = getcwd()

for dir_path in dirs:
    full_dir_path = cwd + '/' + dir_path
    output_path = cwd +'/resized/' + dir_path + '/'
    if not os.path.exists(output_path):
        os.makedirs(output_path)

    image_paths = getImagesInDir(full_dir_path)
    for image_path in image_paths:
        image = cv2.imread(r''+image_path)
        new_image = cv2.resize(image, (640, 640))

        filename = 'resized_' + os.path.basename(image_path).split('/')[-1]
        cv2.imwrite(filename, new_image)
```

Q1. Chess piece classification - inception

An inception network is a deep neural network with an architectural design that consists of repeating components referred to as Inception modules.

It is widely used for image classification tasks.

It has following advantages over other network such as VGG:

- It can provide improved accuracy
- Deep architecture with reduced parameters
- Multi-scale feature extraction
- Dimensionality reduction
- Transfer learning capabilities

Model summary

Model: "model"			
Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[None, 224, 224, 3 0)]	0	[]
conv2d_94 (Conv2D)	(None, 111, 111, 32 864)	864	['input_2[0][0]']
batch_normalization_94 (BatchN ormalization)	(None, 111, 111, 32 96)	96	['conv2d_94[0][0]']
activation_94 (Activation)	(None, 111, 111, 32 0)	0	['batch_normalization_94[0][0]']
conv2d_95 (Conv2D)	(None, 109, 109, 32 9216)	9216	['activation_94[0][0]']
batch_normalization_95 (BatchN ormalization)	(None, 109, 109, 32 96)	96	['conv2d_95[0][0]']
activation_95 (Activation)	(None, 109, 109, 32 0)	0	['batch_normalization_95[0][0]']
...			
Total params:	22,417,196		
Trainable params:	614,412		
Non-trainable params:	21,802,784		

We use transfer learning method by initializing the weights for ' imagenet '.

We modify the input and output layers according to the dataset. Here we need to add the input layer according to the image size. We resized our images of chess pieces to 224 * 224 for this purpose.

Then, we add the output layer depending on the number of classes that we want our model to predict. In our case it is 12 (number of distinct chess pieces).

Preprocessing :

We preprocess the image data for training the network.

→ rescale - scale down the values with a certain range.

1./255 is the scaling value we choose. It reduces the model complexity.

→ we use sheer range and zoom range parameters as well.

Fit:

While training, we define the training set and validation set. The number of epochs is 10. It takes sometime to train as it is a complex model. So, we run the model for less epochs only.

The train and validation loss get reduced and the accuracy increases as the training steps increase. This can be seen in the graph in the ipynb file.

Predict:

Load the model with trained weights stored in h5 format. Inorder to predict an image, the image should be in numpy array format. We scale down the image in the same ratio as we used while training.

Format - (1,224,224,3)

Then, we call the .predict() method and call argmax function that returns the prediction category of the given image.

```
model.predict(img_data)
```

```
1/1 [=====] - 1s 1s/step  
array([[3.9231088e-02, 4.2647470e-02, 5.4844004e-01, 8.4745284e-04,  
       1.2884967e-04, 7.1436830e-06, 3.0903568e-02, 4.0902891e-05,  
       2.9366493e-01, 3.9114268e-04, 1.3219624e-02, 3.0477740e-02]],  
      dtype=float32)
```

```
a=np.argmax(model.predict(img_data), axis=1)
```

```
1/1 [=====] - 0s 29ms/step
```

```
a
```

```
array([2], dtype=int64)
```