Chess Piece Identifier

In this project I will build a Deep Learning Model, more specifically an Image recognition model. My plan is to use a convolutional neural network.

My Model will be able to identify chess pieces from a picture. The chess pieces are Pawn, Knight, Bishop, Rook, Queen and King. The dataset I will use is from Kaggle (https://www.kaggle.com/datasets/anshulmehtakaggl/chess-pieces-detection-images-dataset).

I will be using PyTorch which is the Deep Learning library I feel most at home with. The images I have loaded into a folder. So let's get going.

In [1]:
```
from fastai.vision.all import *
from PIL import ImageFile
import os
import matplotlib.pyplot as plt
import pandas as pd
```

Let's analyze our dataset.

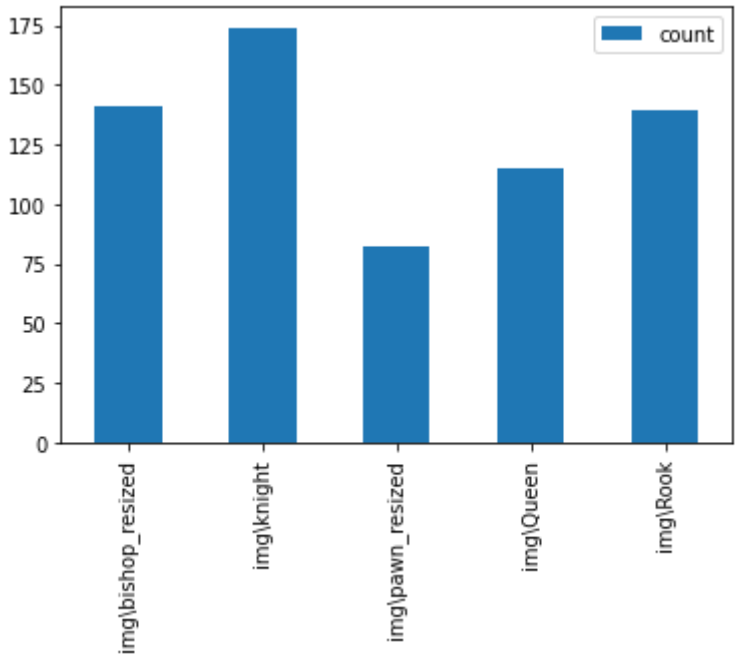
In [2]:
```
path = "img"
sub_dir = [folder.path for folder in os.scandir(path) if folder.is_dir()]
plot_dict = {}
for sub in sub_dir:
    files = os.listdir(sub)
    plot_dict[sub.split("-")[0]]= len(files)

df = pd.DataFrame.from_dict(plot_dict,orient='index', columns=["count"])
df.head()
```

Out[2]:

	count
img\bishop_resized	141
img\knight	174
img\pawn_resized	82
img\Queen	115
img\Rook	139

In [3]:
```
df.plot(kind='bar')
```

Out[3]:
```
<AxesSubplot:>
```



The distribution is not perfectly even, but it will do for the problems.

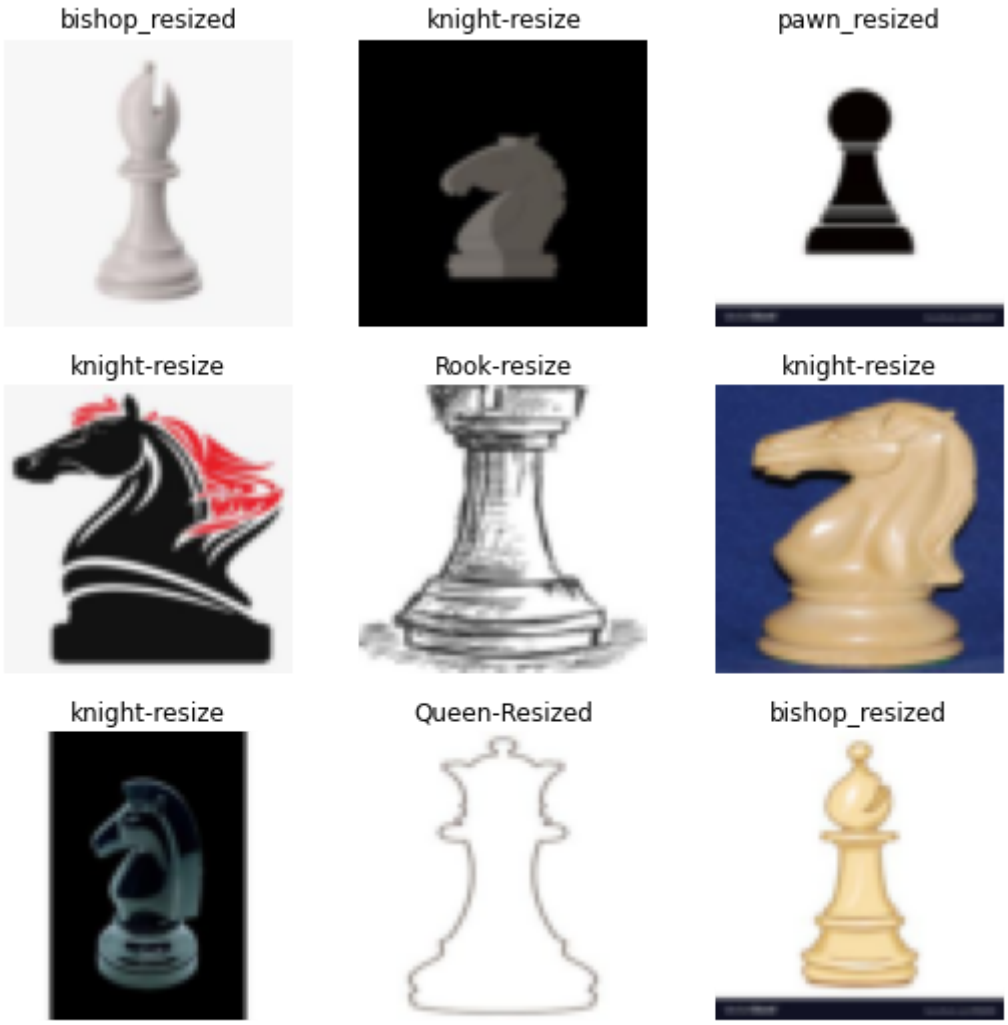
Let's load it into PyTorches ImageDataLoader. I will use 20% for Testing. For the first test to sped up the learning I am reducing the the image size to 64x64 pixels, and I will use the squish method if the dimensions are different.

In [4]:
```
dls64 = ImageDataLoaders.from_folder(path, valid_pct = 0.2, item_tfms=Resize(64, Res
```

```
Due to IPython and Windows limitation, python multiprocessing isn't available now.
So `number_workers` is changed to 0 to avoid getting stuck
```

Let's look at some images.

In [5]:
```
dls64.show_batch()
```

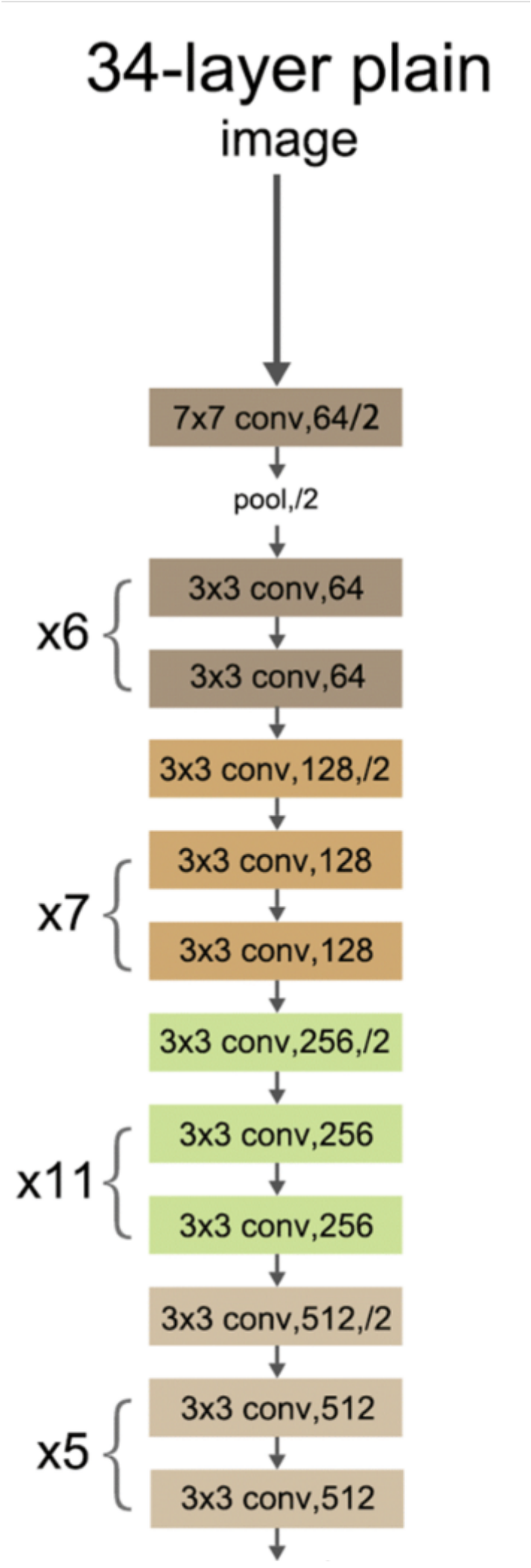


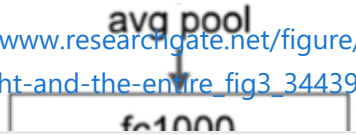
The data comes pre cleaned so we don't need to remove any outliers.

In [6]:
```
ImageFile.LOAD_TRUNCATED_IMAGES = True
```

Model Learning

Now let's do some learning. I will be using resnet34 as the pretrained CNN. The metrics I chose for the initial learning is accuracy and precision.


34-layer plain
image
7x7 conv,64/2
pool,/2
x6
3x3 conv,64
3x3 conv,64
3x3 conv,128,/2
x7
3x3 conv,128
3x3 conv,128
3x3 conv,256,/2
x11
3x3 conv,256
3x3 conv,256
3x3 conv,512,/2
x5
3x3 conv,512
3x3 conv,512



Source: https://www.researchgate.net/figure/Two-structures-are-for-ResNet-34-left-and-ResNet-50-101-152-right-and-the-entire_fig3_344392249

In [7]:
```
learn34 = vision_learner(dls64, resnet34,  metrics=[accuracy,
              Precision(average='macro')])
```

In [8]:
```
learn34.fit_one_cycle(10)
```

epoch	train_loss	valid_loss	accuracy	precision_score	time
0	2.816140	2.238589	0.169231	0.155591	00:06
1	2.535103	1.562980	0.415385	0.396918	00:04
2	2.167478	1.477924	0.492308	0.485291	00:05
3	1.866319	1.505184	0.492308	0.477600	00:04
4	1.617962	1.541731	0.523077	0.507031	00:04
5	1.427121	1.491035	0.546154	0.536689	00:04
6	1.260936	1.469057	0.553846	0.544837	00:04
7	1.129825	1.456585	0.569231	0.566069	00:05
8	1.027869	1.457525	0.569231	0.559299	00:05
9	0.952400	1.444691	0.576923	0.581978	00:05

That accuracy is too low, we will switch to resnet50, which has more layers.

In [38]:
```
learn64 = vision_learner(dls64, resnet50,  metrics=[accuracy,
              Precision(average='macro')])
```

In [39]:
```
learn64.fit_one_cycle(10)
```

epoch	train_loss	valid_loss	accuracy	precision_score	time
0	2.719618	1.767218	0.369231	0.442651	00:08
1	2.184647	1.268401	0.607692	0.591374	00:08
2	1.727865	1.271961	0.661538	0.641767	00:08
3	1.406288	1.370152	0.600000	0.570584	00:08
4	1.161977	1.446343	0.638462	0.611659	00:08
5	0.948633	1.406641	0.669231	0.645702	00:08
6	0.800073	1.411143	0.669231	0.644377	00:08
7	0.695056	1.419425	0.653846	0.628936	00:08
8	0.611299	1.415756	0.653846	0.625329	00:08
9	0.534207	1.395704	0.653846	0.626741	00:08

PROBLEM OVERFITTING!!

We heavily overfit here, we can see that after the 2nd epoch we aren't improving anymore. This is an issue. So let's add some early stopping if our valid_loss stops improving.

So let's try again with the early stopping.

In [40]:
```
learn64 = vision_learner(dls64, resnet50, metrics=[accuracy,
                Precision(average='macro'),
                Recall(average='macro')], cbs=EarlyStoppingCallback(monitor='valid_lo
```

In [41]:
```
learn64.fit_one_cycle(10)
```

epoch	train_loss	valid_loss	accuracy	precision_score	recall_score	time
0	2.529222	1.531807	0.438462	0.418992	0.409454	00:08
1	2.070783	1.314914	0.592308	0.584372	0.572108	00:08
2	1.649625	1.384400	0.638462	0.619478	0.629462	00:08
3	1.343987	1.406980	0.669231	0.645442	0.656259	00:08

```
No improvement since epoch 1: early stopping
```

Success Early stopping

Now we are stopping early which is great, however the accuracy is quite low at 67%. We will however still save this initial model.

In [46]:
```
learn64.export(os.path.abspath('./chess_piecer64.pkl'))
```

Now how to remedy this? We will now load in the pictures at full resolution. This will greatly increase the learning time, but that is the price to pay for accuracy.

In [43]:
```
dls = ImageDataLoaders.from_folder(path, valid_pct = 0.2)
```

```
Due to IPython and Windows limitation, python multiprocessing isn't available now.
So `number_workers` is changed to 0 to avoid getting stuck
```

In [44]:
```
learn = vision_learner(dls, resnet50, metrics=[accuracy,
                Precision(average='macro'),
                Recall(average='macro')], cbs=EarlyStoppingCallback(monitor='valid_lo
```

In [45]:
```
learn.fit_one_cycle(10)
```

epoch	train_loss	valid_loss	accuracy	precision_score	recall_score	time
0	2.485065	1.416551	0.423077	0.403333	0.384524	01:16
1	1.764271	0.839820	0.715385	0.703280	0.700397	01:17
2	1.247062	0.754533	0.792308	0.778386	0.780556	01:15
3	0.938946	0.833941	0.792308	0.776173	0.784524	01:16

```
No improvement since epoch 1: early stopping
```

Let's try adding learning rate to our learning, if it improves through that.

In [47]:
```
learn.fit_one_cycle(10,  lr_max=1e-3)
```

epoch	train_loss	valid_loss	accuracy	precision_score	recall_score	time
0	0.125519	0.813416	0.784615	0.769411	0.774603	01:16
1	0.123621	0.805340	0.776923	0.760216	0.769841	01:16
2	0.110958	0.859037	0.800000	0.790072	0.794048	01:16

```
No improvement since epoch 0: early stopping
```

In [51]:
```
learn.export(os.path.abspath('./chess_piecer.pkl'))
```

Learning rate addition doesn't help.

I will now try adding a weight decay and completely retraining.

In [49]:
```
learnwd = vision_learner(dls, resnet50, metrics=[accuracy,
               Precision(average='macro'),
               Recall(average='macro')], cbs=EarlyStoppingCallback(monitor='valid_lo
```

In [50]:
```
learnwd.fit_one_cycle(10)
```

epoch	train_loss	valid_loss	accuracy	precision_score	recall_score	time
0	2.533559	1.450784	0.361538	0.422650	0.354762	01:16
1	1.823200	0.947915	0.692308	0.675598	0.681746	01:16
2	1.300039	0.781054	0.776923	0.766175	0.761111	01:15
3	0.968728	0.891904	0.776923	0.762635	0.756746	01:16
4	0.740654	0.830121	0.784615	0.772734	0.767460	01:16

```
No improvement since epoch 2: early stopping
```

In [52]:
```
learnwd.export(os.path.abspath('./chess_piecerwd.pkl'))
```

Now let's compare all these models.

In [81]:
```
acc = [["Validation loss", "Accuracy", "Precision", "Recall"],learn.validate(), lear
```

In [80]:
```
acc
```

Out[80]:
```
[(#4) [0.859037458896637,0.800000011920929,0.7900724637681159,0.7940476190476191],
 (#4) [0.8301212191581726,0.7846153974533081,0.772734422262553,0.7674603174603175],
 (#4) [1.4069799184799194,0.6692307591438293,0.6454421671812975,0.6562585999312006]]
```

In [85]:
```
df_acc = pd.DataFrame(np.array(acc[1:]), columns=acc[0], index = [ "learn", "learnwd
```

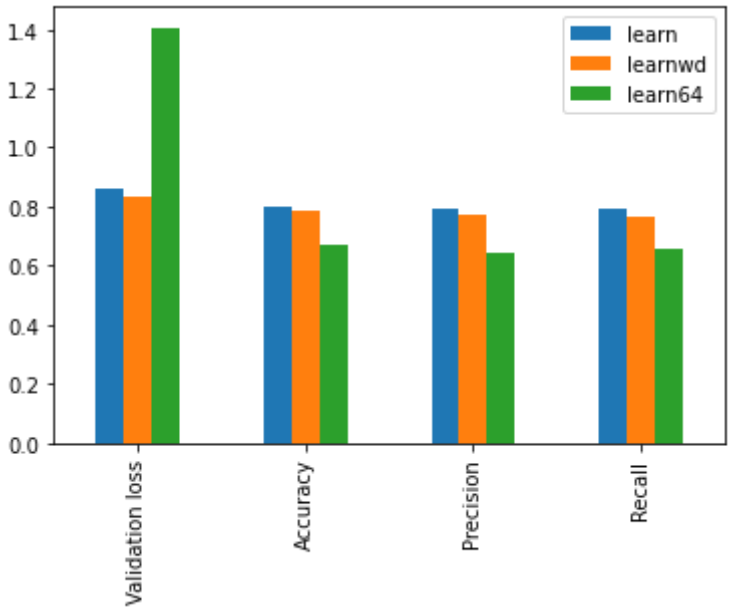
In [86]:
```
df_acc
```

Out[86]:

	Validation loss	Accuracy	Precision	Recall
learn	0.859037	0.800000	0.790072	0.794048
learnwd	0.830121	0.784615	0.772734	0.767460
learn64	1.406980	0.669231	0.645442	0.656259

In [91]:
```
df_acc.T.plot(kind='bar')
```

Out[91]:
```
<AxesSubplot:>
```



We can see our learn model is the best one. It beats the other models in Accuracy, Precision and Recall which are the most important metrics. There is no reason not to prefer it over other models here.

Let's see and example

In [98]:
```
out = learn.predict("img/bishop_resized/00000025_resized.jpg")
```

In [96]:
```
out
```

Out[96]:
```
('bishop_resized',
 TensorBase(2),
 TensorBase([1.6576e-01, 2.3826e-07, 8.3398e-01, 8.4896e-07, 2.5550e-04]))
```

The following code is heavily inspired from an old project I did. It simply makes it possible to upload pictures and have the model do inference on them interactively in the jupyter notebook.

In [100…
```
from fastai.vision.all import *
from fastai.vision.widgets import *
```

In [109…

```
btn_upload = widgets.FileUpload()
out_pl = widgets.Output()
lbl_pred = widgets.Label()


def on_data_change(change):
    lbl_pred.value = ""

    img = PILImage.create(btn_upload.data[-1])
    out_pl.clear_output()
    with out_pl:
        display(img.to_thumb(224,244))

    pred, pred_idx, probs = learn.predict(img)

    lbl_pred.value = f'Prediction: {pred}; Probability: {probs[pred_idx]:.04f}'
```

In [106…

```
btn_upload.observe(on_data_change, names=['data'])

# Display Predictions
display(VBox([widgets.Label('Upload Chess piece'), btn_upload, out_pl, lbl_pred]))
```

Disclaimer: This code for the prediction button is inspired from a project I did years ago.

In [ ]: