Run VGG16 on 30 classes without tuning

In this part, we loads all qualified data (30 classes) in VGG16 and only add an output layer.

However, based on accuracy and loss curves, we can clearly see that there exists severe overfitting. To address overfitting, adding noises, regularization may help.

Obviously, we need to find out how we add layers can reduce overfitting as much as possible and maintain the accuracy at the same time.

Therefore, we decide to use 3 classes which contains most paintings and 20 epochs for figuring out how we can train a better model. And then, we go back to 30 classes and compare the results with this untuning version.

```
In [1]: import numpy as np
    import os
    from tensorflow.keras import applications
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras import optimizers
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Dropout, Flatten, Dense
    import matplotlib
    import matplotlib.pyplot as plt
%matplotlib inline
```

Validation of using GPU

```
In [2]: from tensorflow.python.client import device lib
        print(device lib.list local devices())
        [name: "/device:CPU:0"
        device type: "CPU"
        memory limit: 268435456
        locality {
        incarnation: 1655678584681517339
        , name: "/device:GPU:0"
        device type: "GPU"
        memory limit: 2264907776
        locality {
          bus id: 1
          links {
          }
        incarnation: 15477623663351877341
        physical device desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
```

Loading the pre-trained VGG16

In [3]: import tensorflow.keras.backend as K

```
In [4]: nrow = 200
ncol = 200
base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,3 model = Sequential()

for layer in base_model.layers:
    model.add(layer)
for layer in model.layers:
    layer.trainable = False
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating: Colocations handled automatically by placer.

Now, we only add a final fully-connected layer. Since this is a multiple classification, there should be 30 output and softmax activation.

```
In [5]: model.add(Flatten())
  model.add(Dense(30, activation = 'softmax'))
  model.summary()
```

Layer (type)	Output Shape	Param #
block1_conv1 (Conv2D)	(None, 200, 200, 64)	1792
block1_conv2 (Conv2D)	(None, 200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None, 100, 100, 64)	0
block2_conv1 (Conv2D)	(None, 100, 100, 128) 73856
block2_conv2 (Conv2D)	(None, 100, 100, 128) 147584
block2_pool (MaxPooling2D)	(None, 50, 50, 128)	0
block3_conv1 (Conv2D)	(None, 50, 50, 256)	295168
block3_conv2 (Conv2D)	(None, 50, 50, 256)	590080
block3_conv3 (Conv2D)	(None, 50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None, 25, 25, 256)	0
block4_conv1 (Conv2D)	(None, 25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None, 25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None, 25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None, 12, 12, 512)	0
block5_conv1 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 30)	552990

Total params: 15,267,678
Trainable params: 552,990

Non-trainable params: 14,714,688

Using Generators to Load Data

Found 5687 images belonging to 30 classes.

Found 1404 images belonging to 30 classes.

Train the model

Compile the model. we are performing multiple classification, so we use 'categorical_crossentropy' loss function.

```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

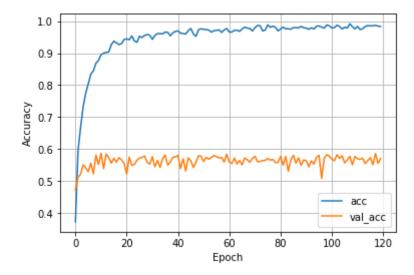
Now, we run the fit. Since we run 120 epochs, even with GPU, it will take hours (about 4 hours in our case).

```
WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten
sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op
s.math ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/120
acc: 0.4715
acc: 0.3726 - val_loss: 1.8798 - val_acc: 0.4715
Epoch 2/120
acc: 0.5121
- acc: 0.5936 - val loss: 1.8880 - val acc: 0.5121
Epoch 3/120
acc: 0.5214
```

Plot the accuracy curve

```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

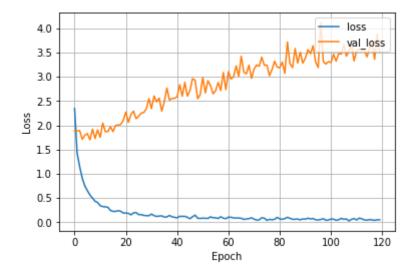
Out[10]: <matplotlib.legend.Legend at 0x2d9317ccb00>



Plot the loss curve

```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x2d916831358>



In [12]: print(loss)
 print(val_loss)
 print(acc)

print(val_acc)

[2.3461001035050724, 1.4235979016874845, 1.1430863561457525, 0.9086284632 525168, 0.7497734822894895, 0.6507400545521362, 0.5618185450956527, 0.497 515937167688, 0.4333582236034413, 0.4072008218772805, 0.3403918516956609, $0.32332254938371197, \ 0.3169648504349434, \ 0.30803932771492826, \ 0.242359506$ 10026422, 0.22409920513116352, 0.22299199451120705, 0.2381320928285825, $0.22565900431023933,\ 0.1895868973198938,\ 0.18879720360218838,\ 0.182640925$ 18734307, 0.15306884070741433, 0.19240670959727718, 0.19870258597465482, 0.15718773798697733, 0.15746098371291067, 0.14063597524793126, 0.13533142 471598555, 0.13465000178611863, 0.16852534865377153, 0.13479207398729207, 0.11998056702503153, 0.12652170437751514, 0.1314194848541847, 0.1068851044963235, 0.10811103968444641, 0.13935735310389033, 0.11262571445435511, 0.09994827654374512, 0.09156880270822702, 0.12170841077027221, 0.11986629047051284, 0.12042203829077608, 0.10257396470124522, 0.07141154148305237, 0.11286345072888482, 0.14545853183142474, 0.08261463096709563, 0.07816871711160547, 0.0834815292300649, 0.08061120286518395, 0.07870132581194748, 0.1100104708078458, 0.09237889285474958, 0.09098280840773605, 0.0775859790803553, 0.11242035616805647, 0.08350875193663551, 0.07306732858002385, 0.10495222422125806, 0.10121314234917625, 0.09041668099852507, 0.085021389281652, 0.08709571150535855, 0.08119573050985286, 0.05720834045503724, 0.06752291287102116, 0.07401366609014232, 0.09078182027614128, 0.06360876 416197629, 0.04408281449970701, 0.04912982641352288, 0.09239701398996975, 0.08397759706717353, 0.03846376826959649, 0.05900241308116014, 0.05116836 12821664, 0.06045130762034617, 0.09908614304464973, 0.06853826708419579, 0.06010749900452524, 0.0750001804639163, 0.10037270990330205, 0.08117188401919835, 0.05964600242207134, 0.06097916190592559, 0.06448622915978296, 0.049291680894329615, 0.06723989536866208, 0.06261745889440076, 0.0828949253097588, 0.06829598370735772, 0.07648963783003805, 0.05037049173159812 6, 0.04628097680067349, 0.05635536908192869, 0.07244983570611244, 0.03961 103102834645, 0.04535775429545275, 0.06595275171501659, 0.062991343934500 97, 0.0404003969792762, 0.0501003786742999, 0.08006950906923796, 0.060235 21859767723, 0.06697451766250852, 0.028666988472729863, 0.058501245508568 85, 0.07587163815681296, 0.04663811410420758, 0.08466476121967642, 0.0710 8294285135548, 0.04754935567612289, 0.04140392171914331, 0.05381673431490 354, 0.04729886747521981, 0.03891590693035378, 0.049779767958332374, 0.05 0056391059340271 [1.8798491602594203, 1.8879662372849204, 1.8866435939615422, 1.7108222733 84441, 1.794157469814474, 1.8281896331093528, 1.7015701694922014, 1.92040 62115062366, 1.7281528440388767, 1.9042668640613556, 1.750350003892725, 2.0468101501464844, 1.8679933900182897, 1.871904801238667, 1.969529035416 5165, 1.8692320016297428, 1.9964542416009037, 2.0064142779870466, 2.01484 8356897181, 2.101751360026273, 2.273027856241573, 2.0610892826860603, 2.2 239972949028015, 2.2918768660588698, 2.136060793291439, 2.18583698435263 2, 2.25144502249631, 2.263073284517635, 2.3427226055752146, 2.54858815399 0832, 2.344073311849074, 2.6048515899614855, 2.4827307760715485, 2.561436 5718581458, 2.291786703196439, 2.488292637196454, 2.7692495503208856, 2.5 21276568824595, 2.5499190959063442, 2.5560632808641954, 2.58809532902457 5, 2.838707988912409, 2.600795794617046, 2.884335707534443, 2.60051744363 5247, 2.7178437899459493, 2.9621128141880035, 2.932340982285413, 2.548693 830316717, 2.631456044587222, 2.986494557424025, 2.6665902733802795, 2.92 00825582851064, 2.821283047849482, 2.6478641114451666, 2.710980046879161 6, 2.8821339241482993, 2.7162570005113427, 3.0881751017137007, 2.73587841 3373774, 3.1072994470596313, 2.9527191438458185, 3.0017079412937164, 3.22 37656604159963, 3.0099908736619083, 3.4242454875599253, 3.09478339011018 9, 3.062528184869073, 3.2398743548176507, 2.968336186625741, 3.1587945737 622003, 3.2433025484735314, 3.218614635142413, 3.4046757139942865, 3.2372 12760881944, 3.2428165620023552, 3.021511275659908, 3.1484800306233494, 3.3216919844800774, 3.2022319463166324, 3.184491596438668, 3.305086414922 3673, 3.0715756795623084, 3.7181684239344164, 3.2697226892818105, 3.18903 4489068118, 3.5838129466230217, 3.282617674632506, 3.5069586146961558, 3. 2830505316907708, 3.3833330761302602, 3.559149671684612, 3.47740050879391 75, 3.6409821293570777, 3.3053645572879096, 3.1910788254304365, 4.1142676 31010576, 3.3127417726950212, 3.2631784812970595, 3.313422804529017, 3.29 3671580878171, 3.4643251408230173, 3.3222834400155326, 3.479178431359204 5, 3.4695660200985996, 3.667523671280254, 3.4244197715412485, 3.535086276 856336, 3.6762977242469788, 3.326822979883714, 3.5333000042221765, 3.5777 104551141914, 3.538788849657232, 3.5542741905559194, 3.4110266024416145, 3.5744017741896887, 3.7527989582581953, 3.361420116641305, 3.878032784570 347, 3.5141435455192221 [0.3726042, 0.5936346, 0.66731143, 0.73184454, 0.77474946, 0.803763, 0.83]40074, 0.8447336, 0.86882365, 0.87726396, 0.8951996, 0.8999472, 0.9025848 5, 0.903464, 0.92667484, 0.9374011, 0.93195003, 0.92685074, 0.92983997, 0.94285214, 0.9444347, 0.9419729, 0.9537542, 0.93810445, 0.93406016, 0.95 26991, 0.94883066, 0.9555126, 0.95815015, 0.9556884, 0.9432038, 0.955512 6, 0.96113944, 0.9609636, 0.9600844, 0.9658871, 0.9650079, 0.95393, 0.963 6012, 0.96782136, 0.96957976, 0.96237034, 0.96113944, 0.9597327, 0.970107 26, 0.976965, 0.9600844, 0.95234746, 0.9729207, 0.97590995, 0.9746791, 0. 9734482, 0.9722173, 0.9655354, 0.97010726, 0.97133815, 0.9727449, 0.96465 623, 0.9727449, 0.9767892, 0.9658871, 0.96606296, 0.97133815, 0.9716898, 0.9679972, 0.97538245, 0.98118514, 0.97837174, 0.97714084, 0.9692281, 0.9 796026, 0.9864603, 0.985757, 0.96957976, 0.97186565, 0.98839456, 0.980657 64, 0.9845261, 0.98065764, 0.9694039, 0.9757341, 0.9810093, 0.97590995, 0.9762617, 0.9746791, 0.9799543, 0.9796026, 0.97889924, 0.9836469, 0.9794 2674, 0.9781959, 0.9745033, 0.9790751, 0.9757341, 0.98417443, 0.98487777, 0.981361, 0.9780201, 0.98786706, 0.9854053, 0.97889924, 0.9796026, 0.9873 3956, 0.9834711, 0.97538245, 0.98118514, 0.9781959, 0.9917355, 0.9829435 3, 0.9757341, 0.9836469, 0.97362405, 0.9762617, 0.9834711, 0.98610866, 0. 98505366, 0.985757, 0.98663616, 0.98470193, 0.983295261 5562678, 0.52279204, 0.5811966, 0.5519943, 0.5868946, 0.5391738, 0.584757 86, 0.5733618, 0.5562678, 0.57122505, 0.5591168, 0.5733618, 0.5662393, 0. 5555556, 0.52207977, 0.5747863, 0.5491453, 0.5519943, 0.5655271, 0.571937 3, 0.5740741, 0.57834756, 0.55840456, 0.5534188, 0.5762108, 0.5448718, 0. 5648148, 0.54273504, 0.57051283, 0.5811966, 0.54985756, 0.5591168, 0.5747 863, 0.5754986, 0.58048433, 0.5391738, 0.56980056, 0.53205127, 0.5726496, 0.5633903, 0.54273504, 0.5591168, 0.57905984, 0.57763535, 0.56125355, 0.5 740741, 0.56837606, 0.5740741, 0.57977206, 0.5769231, 0.5719373, 0.574074 1, 0.55982906, 0.5840456, 0.55982906, 0.5548433, 0.5719373, 0.5534188, 0. 5641026, 0.5505698, 0.5719373, 0.5669516, 0.5591168, 0.57051283, 0.577635 35, 0.56054133, 0.56125355, 0.5641026, 0.5648148, 0.57051283, 0.5655271, 0.5676638, 0.5576923, 0.55840456, 0.5769231, 0.54985756, 0.5769231, 0.530 6268, 0.5676638, 0.58048433, 0.5562678, 0.5726496, 0.5491453, 0.5662393, 0.5633903, 0.5448718, 0.5633903, 0.55270654, 0.5747863, 0.58048433, 0.508 547, 0.57122505, 0.5826211, 0.57763535, 0.56837606, 0.5633903, 0.5826211, 0.57122505, 0.57905984, 0.5569801, 0.5655271, 0.57763535, 0.5505698, 0.57 69231, 0.56980056, 0.5676638, 0.57122505, 0.5548433, 0.5641026, 0.573361 8, 0.55128205, 0.58618236, 0.5548433, 0.57051283]

Summary

Based on above accuracy and loss curves, we can clearly see that there exists severe overfitting. Obviously, we need to find out how we add layers can reduce overfitting as much as possible and maintain the accuracy at the same time.

So we decide to use 3 classes which contains most paintings and 20 epochs as the starting point. To address overfiting, adding noises, regularization may help.

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T11 •	

Run VGG16 on selected 3 classes without tuning

In this part, we only loads 3 classes with most paintings in VGG16 and still without tuning, because we need to compare it with the other tuned versions.

Though this time we only run 20 epochs, we can still tell there exists severe overfitting.

```
In [1]: import numpy as np
        import os
        from tensorflow.keras import applications
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras import optimizers
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Dropout, Flatten, Dense
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
In [2]: from tensorflow.python.client import device_lib
        print(device_lib.list_local_devices())
        [name: "/device:CPU:0"
        device_type: "CPU"
        memory limit: 268435456
        locality {
        incarnation: 8866674015826737595
        , name: "/device:GPU:0"
        device type: "GPU"
        memory limit: 2264907776
        locality {
          bus id: 1
          links {
          }
        incarnation: 10400245706179158261
        physical device desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
        ]
```

In [3]: import tensorflow.keras.backend as K
K.clear_session()

```
In [4]: nrow = 200
    ncol = 200
    base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,3 model = Sequential()

for layer in base_model.layers:
    model.add(layer)
for layer in model.layers:
    layer.trainable = False
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

```
In [5]: model.add(Flatten())
  model.add(Dense(3, activation = 'softmax'))
  model.summary()
```

Layer (type)	Output Shape	Param #
block1_conv1 (Conv2D)	(None, 200, 200, 64)	1792
block1_conv2 (Conv2D)	(None, 200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None, 100, 100, 64)	0
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block2_conv2 (Conv2D)	(None, 100, 100, 128) 147584
block2_pool (MaxPooling2D)	(None, 50, 50, 128)	0
block3_conv1 (Conv2D)	(None, 50, 50, 256)	295168
block3_conv2 (Conv2D)	(None, 50, 50, 256)	590080
block3_conv3 (Conv2D)	(None, 50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None, 25, 25, 256)	0
block4_conv1 (Conv2D)	(None, 25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None, 25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None, 25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None, 12, 12, 512)	0
block5_conv1 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 3)	55299

Total params: 14,769,987 Trainable params: 55,299

Non-trainable params: 14,714,688

Found 1616 images belonging to 3 classes.

Found 402 images belonging to 3 classes.

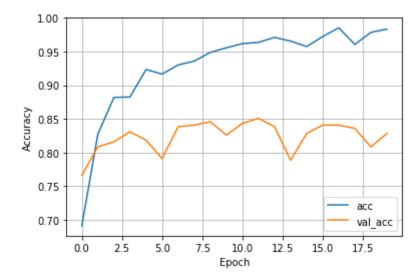
```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op s.math ops) is deprecated and will be removed in a future version. Instructions for updating: Use tf.cast instead. Epoch 1/20 acc: 0.7662 51/51 [============] - 48s 951ms/step - loss: 0.7488 acc: 0.6912 - val_loss: 0.5347 - val_acc: 0.7662 Epoch 2/20 13/13 [============] - 11s 884ms/step - loss: 0.4963 acc: 0.8085 acc: 0.8274 - val loss: 0.4963 - val acc: 0.8085 Epoch 3/20 acc: 0.8159 acc: 0.8818 - val_loss: 0.5242 - val_acc: 0.8159 Epoch 4/20 c: 0.8308 acc: 0.8824 - val loss: 0.4377 - val acc: 0.8308 Epoch 5/20 c: 0.8184 acc: 0.9233 - val_loss: 0.4771 - val_acc: 0.8184 Epoch 6/20 acc: 0.7910 acc: 0.9165 - val loss: 0.5297 - val acc: 0.7910 Epoch 7/20 acc: 0.8383 acc: 0.9301 - val loss: 0.4441 - val acc: 0.8383 Epoch 8/20 acc: 0.8408 acc: 0.9356 - val loss: 0.4205 - val acc: 0.8408 Epoch 9/20

```
acc: 0.8458
51/51 [============ ] - 38s 745ms/step - loss: 0.1703 -
acc: 0.9486 - val_loss: 0.4478 - val_acc: 0.8458
Epoch 10/20
acc: 0.8259
acc: 0.9554 - val loss: 0.4054 - val acc: 0.8259
Epoch 11/20
13/13 [============= ] - 11s 827ms/step - loss: 0.4796 -
acc: 0.8433
acc: 0.9616 - val loss: 0.4796 - val acc: 0.8433
Epoch 12/20
acc: 0.8507
acc: 0.9635 - val_loss: 0.3918 - val_acc: 0.8507
Epoch 13/20
acc: 0.8383
acc: 0.9709 - val loss: 0.4435 - val acc: 0.8383
Epoch 14/20
acc: 0.7886
acc: 0.9653 - val_loss: 0.5926 - val_acc: 0.7886
Epoch 15/20
acc: 0.8284
acc: 0.9573 - val loss: 0.4586 - val acc: 0.8284
Epoch 16/20
c: 0.8408
acc: 0.9722 - val loss: 0.4632 - val_acc: 0.8408
Epoch 17/20
acc: 0.8408
acc: 0.9851 - val loss: 0.4997 - val acc: 0.8408
Epoch 18/20
acc: 0.8358
acc: 0.9604 - val loss: 0.4993 - val acc: 0.8358
Epoch 19/20
acc: 0.8085
51/51 [============ ] - 42s 823ms/step - loss: 0.0796 -
acc: 0.9783 - val loss: 0.5603 - val acc: 0.8085
Epoch 20/20
acc: 0.8284
```

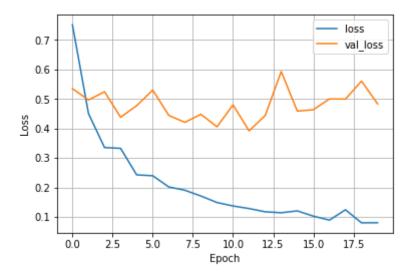
```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x1445d9b44e0>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x14476bee470>



```
In [12]: print(loss)
    print(val_loss)
    print(acc)
    print(val_acc)
```

[0.7509350723559314, 0.4501491076875441, 0.33513500932419654, 0.332461600 8465833, 0.24263272545125225, 0.23967051196216357, 0.20171235774708265, 0.19057435534968234, 0.1708688954315563, 0.14899897678653792, 0.13720300022770862, 0.12850487748585124, 0.11753369001026201, 0.11433112636060998, 0.12057178120801945, 0.10282738853504161, 0.08929582699985787, 0.12433314500468792, 0.08017670243314587, 0.08062718273832066] [0.5346578520077926, 0.49634360120846677, 0.5241671640139359, 0.437715965]96791196, 0.47711492157899416, 0.529675291134761, 0.44406301700151884, 0. 4204594859710106, 0.4477960444413699, 0.4053718986419531, 0.4796006221037 645, 0.3917713027734023, 0.44345738566838777, 0.5926056137451758, 0.45863 019273831296, 0.46321375782673174, 0.4996836426166388, 0.499333129479334 9, 0.5602593078063085, 0.4830422126329862] [0.6912129, 0.8273515, 0.8818069, 0.8824257, 0.9232673, 0.9164604, 0.9300 743, 0.93564355, 0.9486386, 0.9554455, 0.9616337, 0.9634901, 0.97091585, 0.9653465, 0.957302, 0.9721535, 0.9851485, 0.96039605, 0.9783416, 0.98329 [0.76616913, 0.80845773, 0.8159204, 0.8308458, 0.81840795, 0.7910448, 0.8 3830845, 0.840796, 0.84577113, 0.82587063, 0.8432836, 0.8507463, 0.838308 45, 0.78855723, 0.82835823, 0.840796, 0.840796, 0.8358209, 0.80845773, 0. 82835823]

```
In [ ]:
```

Run VGG16 on 3 classes test1

For this part, we loads 3 classes with most paintings in VGG16 and adds several layers to test the performance. Still, run 20 epochs.

Before adding layers, we let the $base_model.output$ load into variable x. Then, we just operate on the x. The operations are as following:

- A Flatten()(x) layer which reshapes the outputs to a single channel.
- A fully-connected layer with 2304 output units and relu activation.
- A GaussianNoise(0.1)(x) layer.
- A Dropout(0.5)(x) layer.
- A fully-connected layer with 288 output units and relu activation.
- A BatchNormalization()(x) layer.
- A Dropout(0.5)(x) layer.
- A final fully-connected layer. Since this is a multiple classification, there should be three output and softmax activation. To mitigate overfitting, we add several arguments:

```
kernel\_initializer='random\_uniform'\,,\,\,bias\_initializer='random\_uniform'\,,\,\,and\,\,bias\_regularizer=regularizers.12(0.01)\,.
```

However, at the end of this test1, we can still clearly see overfitting.

```
In [1]: import numpy as np
    import os
    from tensorflow.keras import applications
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras import optimizers, regularizers
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
    import matplotlib
    import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: from tensorflow.python.client import device lib
        print(device lib.list local devices())
        [name: "/device:CPU:0"
        device type: "CPU"
        memory_limit: 268435456
        locality {
        }
        incarnation: 13973592982641359775
        , name: "/device:XLA GPU:0"
        device_type: "XLA_GPU"
        memory limit: 17179869184
        locality {
        }
        incarnation: 15866717560866743607
        physical_device_desc: "device: XLA_GPU device"
        , name: "/device:XLA CPU:0"
        device_type: "XLA_CPU"
        memory limit: 17179869184
        locality {
        }
        incarnation: 17454529404844390179
        physical device desc: "device: XLA CPU device"
        , name: "/device:GPU:0"
        device type: "GPU"
        memory_limit: 15856546612
        locality {
          bus id: 1
          links {
          }
        incarnation: 11389401770462418927
        physical device desc: "device: 0, name: Tesla P100-PCIE-16GB, pci bus id:
        0000:00:04.0, compute capability: 6.0"
In [3]:
        import tensorflow.keras.backend as K
        K.clear session()
```

Before adding layers, we let the base_model.output load into variable x. Then, we just operate on the x. The operations are as following:

- A Flatten()(x) layer which reshapes the outputs to a single channel.
- A fully-connected layer with 2304 output units and relu activation.
- A GaussianNoise(0.1)(x) layer.
- A Dropout(0.5)(x) layer.
- A fully-connected layer with 288 output units and relu activation.
- A BatchNormalization()(x) layer.
- A Dropout(0.5)(x) layer.
- A final fully-connected layer. Since this is a multiple classification, there should be three output and softmax activation. To mitigate overfitting, we add several arguments:

```
kernel_initializer='random_uniform', bias_initializer='random_uniform', and bias regularizer=regularizers.12(0.01).
```

```
In [1]: nrow = 200
        ncol = 200
        nclass = 3
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base_model.layers:
            layer.trainable = False
        x = base_model.output
        x = Flatten()(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias_initializer='random_uniform',
                     bias regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base_model.input, outputs=pred)
```

NameError: name 'applications' is not defined

In [5]: model.summary()

Layor (type)	011+211+	Chano	 Param #
Layer (type)	Output 	======================================	========
<pre>input_1 (InputLayer)</pre>	(None,	200, 200, 3)	0
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise (GaussianNois	(None,	2304)	0
dropout (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840
batch_normalization_v1 (Batc	(None,	288)	1152
dropout_1 (Dropout)	(None,	288)	0

Found 1616 images belonging to 3 classes.

Found 402 images belonging to 3 classes.

```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
    steps_per_epoch = train_generator.n // batch_size
    validation_steps = test_generator.n // batch_size
```

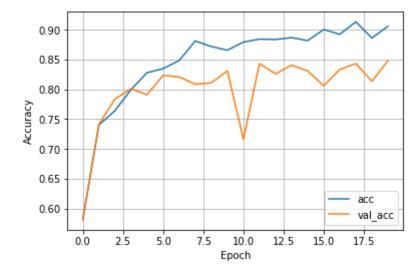
```
WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflo
w/python/ops/math ops.py:3066: to int32 (from tensorflow.python.ops.math_
ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/20
c: 0.5821
c: 0.5811 - val_loss: 1.2578 - val_acc: 0.5821
Epoch 2/20
c: 0.7413
c: 0.7401 - val loss: 0.6700 - val acc: 0.7413
Epoch 3/20
c: 0.7836
c: 0.7642 - val_loss: 0.5407 - val_acc: 0.7836
Epoch 4/20
c: 0.8010
c: 0.7995 - val loss: 0.5485 - val acc: 0.8010
Epoch 5/20
c: 0.7910
c: 0.8280 - val_loss: 0.5116 - val_acc: 0.7910
Epoch 6/20
c: 0.8234
c: 0.8348 - val loss: 0.4602 - val acc: 0.8234
Epoch 7/20
c: 0.8209
c: 0.8484 - val loss: 0.4421 - val acc: 0.8209
Epoch 8/20
c: 0.8085
c: 0.8812 - val loss: 0.4749 - val acc: 0.8085
Epoch 9/20
```

```
c: 0.8109
51/51 [============ ] - 84s 2s/step - loss: 0.3398 - ac
c: 0.8719 - val_loss: 0.4725 - val_acc: 0.8109
Epoch 10/20
c: 0.8308
c: 0.8657 - val_loss: 0.4336 - val_acc: 0.8308
Epoch 11/20
c: 0.7164
51/51 [=============== ] - 85s 2s/step - loss: 0.3140 - ac
c: 0.8793 - val loss: 0.8778 - val acc: 0.7164
Epoch 12/20
c: 0.8433
51/51 [============== ] - 86s 2s/step - loss: 0.3292 - ac
c: 0.8843 - val_loss: 0.4288 - val_acc: 0.8433
Epoch 13/20
c: 0.8259
c: 0.8837 - val_loss: 0.4722 - val_acc: 0.8259
Epoch 14/20
c: 0.8868 - val_loss: 0.4710 - val_acc: 0.8408
Epoch 15/20
c: 0.8308
c: 0.8818 - val loss: 0.4941 - val acc: 0.8308
Epoch 16/20
c: 0.8060
c: 0.9004 - val loss: 0.6483 - val acc: 0.8060
Epoch 17/20
c: 0.8333
c: 0.8923 - val_loss: 0.4420 - val_acc: 0.8333
Epoch 18/20
c: 0.8433
c: 0.9134 - val loss: 0.4617 - val acc: 0.8433
Epoch 19/20
c: 0.8134
51/51 [============ ] - 83s 2s/step - loss: 0.2808 - ac
c: 0.8861 - val_loss: 0.5188 - val_acc: 0.8134
Epoch 20/20
c: 0.8483
```

```
51/51 [=============] - 84s 2s/step - loss: 0.2513 - ac c: 0.9059 - val_loss: 0.4446 - val_acc: 0.8483
```

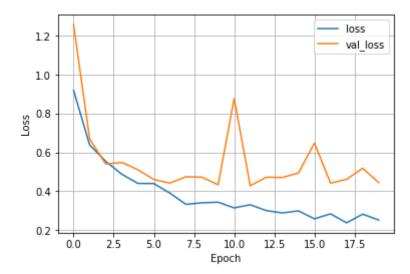
```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x7ff13c577828>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x7ff13c481518>



```
In [12]: print(loss)
    print(val_loss)
    print(acc)
    print(val_acc)
```

[0.9197668498105341, 0.6389658262233923, 0.5544988536598658, 0.4881614077 799391, 0.44060463657473575, 0.43979209454933016, 0.3903113628673081, 0.3 3251514175150654, 0.34068196362788133, 0.3435912899451681, 0.314347134663 3269, 0.3304667539230668, 0.3004123606894276, 0.2883142184207935, 0.29904 315701805717, 0.2581148448556957, 0.283596468001309, 0.23742855900880133, 0.28195172607308566, 0.251845593499665231 [1.2577795065366304, 0.6699514022240272, 0.5406953211014087, 0.5484803112 653586, 0.5115789484519225, 0.4601581853169661, 0.44214536593510556, 0.47 486457228660583, 0.4725213853212503, 0.43356338372597325, 0.8777518776746 897, 0.42876676240792644, 0.47224560150733363, 0.47098710445257336, 0.494 0937597018022, 0.6483332835710965, 0.44195979833602905, 0.461708098649978 64, 0.5188222928689077, 0.444645609993201] [0.58106434, 0.740099, 0.7642327, 0.79950494, 0.8279703, 0.83477724, 0.84 83911, 0.8811881, 0.8719059, 0.8657178, 0.8793317, 0.8842822, 0.88366336, 0.88675743, 0.8818069, 0.9003713, 0.8923267, 0.9133663, 0.8861386, 0.9059 [0.58208954, 0.74129355, 0.7835821, 0.80099505, 0.7910448, 0.8233831, 0.8 208955, 0.80845773, 0.8109453, 0.8308458, 0.7164179, 0.8432836, 0.8258706 3, 0.840796, 0.8308458, 0.80597013, 0.83333333, 0.8432836, 0.8134328, 0.84 825873]

```
In [ ]:
```

Run VGG16 on 3 classes test2

For this part, we still loads 3 classes with most paintings in VGG16 while adds two more layers than test1. Still, run 20 epochs.

Before adding layers, we let the $base_model.output$ load into variable x. Then, we just operate on the x. The operations are as following:

- A Flatten()(x) layer which reshapes the outputs to a single channel.
- (new) A GaussianNoise(0.1)(x) layer.
- (new) A Dropout(0.5)(x) layer.
- A fully-connected layer with 2304 output units and relu activation.
- A GaussianNoise(0.1)(x) layer.
- A Dropout(0.5)(x) layer.
- A fully-connected layer with 288 output units and relu activation.
- A BatchNormalization()(x) layer.
- A Dropout(0.5)(x) layer.
- A final fully-connected layer. Since this is a multiple classification, there should be three output and softmax activation. To mitigate overfitting, we add several arguments:

```
kernel_initializer='random_uniform', bias_initializer='random_uniform', and bias_regularizer=regularizers.12(0.01).
```

Fortunately, at the end of this test2, we got nicer loss curves which reflects no obvious overfitting.

```
In [1]: import numpy as np
    import os
    from tensorflow.keras import applications
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras import optimizers, regularizers
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
    import matplotlib
    import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: from tensorflow.python.client import device lib
        print(device_lib.list_local_devices())
        [name: "/device:CPU:0"
        device_type: "CPU"
        memory_limit: 268435456
        locality {
        }
        incarnation: 16256100486386227842
        , name: "/device:GPU:0"
        device_type: "GPU"
        memory_limit: 2264907776
        locality {
          bus_id: 1
          links {
          }
        }
        incarnation: 2620730678667875277
        physical_device_desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
        ]
In [3]: import tensorflow.keras.backend as K
        K.clear_session()
```

```
localhost:8892/notebooks/Desktop/NYU-S2/ML_2/Project/code/4_Vgg16_3class_test2 (best fitting).ipynb
```

```
In [3]:
        nrow = 200
        ncol = 200
        nclass = 3
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base model.layers:
            layer.trainable = False
        x = base model.output
        x = Flatten()(x)
        x = GaussianNoise(0.1)(x)
        x = Dropout(0.5)(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias initializer='random uniform',
                     bias regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base_model.input, outputs=pred)
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten sorflow\python\keras\layers\core.py:143: calling dropout (from tensorflo w.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep prob`.

In [4]: model.summary()

Layer (type)	Output	Shape	Param #
<pre>input_1 (InputLayer)</pre>	(None.		0
			-
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
gaussian_noise (GaussianNois	(None,	18432)	0
dropout (Dropout)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise_1 (GaussianNo	(None,	2304)	0
dropout_1 (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840

Found 1616 images belonging to 3 classes.

Found 402 images belonging to 3 classes.

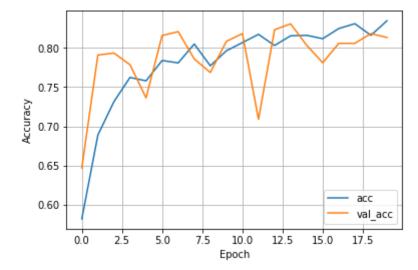
```
In [7]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

```
WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten
sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op
s.math ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/20
acc: 0.6468
162/162 [============= ] - 51s 314ms/step - loss: 0.9062
- acc: 0.5817 - val_loss: 0.8014 - val_acc: 0.6468
Epoch 2/20
acc: 0.7910
- acc: 0.6887 - val loss: 0.5261 - val acc: 0.7910
Epoch 3/20
acc: 0.7935
- acc: 0.7314 - val loss: 0.4968 - val acc: 0.7935
Epoch 4/20
41/41 [============= ] - 9s 230ms/step - loss: 0.5469 - a
cc: 0.7786
- acc: 0.7624 - val loss: 0.5469 - val acc: 0.7786
Epoch 5/20
acc: 0.7363
- acc: 0.7580 - val_loss: 0.6292 - val_acc: 0.7363
Epoch 6/20
cc: 0.8159
- acc: 0.7840 - val loss: 0.4780 - val acc: 0.8159
Epoch 7/20
cc: 0.8209
162/162 [================ ] - 46s 287ms/step - loss: 0.5742
- acc: 0.7809 - val_loss: 0.4713 - val_acc: 0.8209
Epoch 8/20
acc: 0.7861
- acc: 0.8051 - val loss: 0.5374 - val acc: 0.7861
Epoch 9/20
```

```
cc: 0.7687
162/162 [============== ] - 46s 286ms/step - loss: 0.5573
- acc: 0.7772 - val_loss: 0.5552 - val_acc: 0.7687
Epoch 10/20
acc: 0.8085
- acc: 0.7964 - val_loss: 0.4952 - val_acc: 0.8085
Epoch 11/20
cc: 0.8184
- acc: 0.8069 - val loss: 0.4551 - val acc: 0.8184
Epoch 12/20
acc: 0.7090
- acc: 0.8175 - val_loss: 0.7736 - val_acc: 0.7090
Epoch 13/20
cc: 0.8234
162/162 [=============] - 46s 282ms/step - loss: 0.4993
- acc: 0.8032 - val loss: 0.4404 - val acc: 0.8234
Epoch 14/20
acc: 0.8308
- acc: 0.8156 - val loss: 0.4481 - val acc: 0.8308
Epoch 15/20
cc: 0.8035
- acc: 0.8162 - val loss: 0.5458 - val acc: 0.8035
Epoch 16/20
cc: 0.7811
162/162 [=============== ] - 47s 290ms/step - loss: 0.4841
- acc: 0.8119 - val_loss: 0.5927 - val_acc: 0.7811
Epoch 17/20
acc: 0.8060
- acc: 0.8249 - val loss: 0.4682 - val acc: 0.8060
Epoch 18/20
acc: 0.8060
- acc: 0.8311 - val loss: 0.4739 - val acc: 0.8060
Epoch 19/20
acc: 0.8184
162/162 [============== ] - 49s 302ms/step - loss: 0.4780
- acc: 0.8162 - val loss: 0.4896 - val acc: 0.8184
Epoch 20/20
acc: 0.8134
```

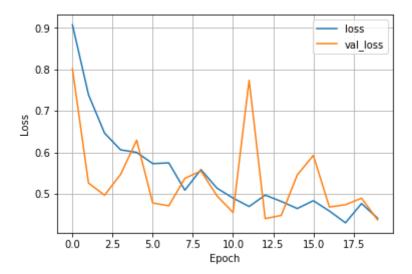
```
In [9]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[9]: <matplotlib.legend.Legend at 0x1b6acc61898>



```
In [10]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[10]: <matplotlib.legend.Legend at 0x1b6c6575f98>



```
In [11]: print(loss)
    print(val_loss)
    print(acc)
    print(val_acc)
```

[0.9074013190030461, 0.7389471186970425, 0.6464045981295629, 0.6060428023 246107, 0.5999550910131766, 0.5728324980539555, 0.5746590845047099, 0.508 8578708617404, 0.558343212138677, 0.5137309753658748, 0.4898616761743727, 0.4695385329628197, 0.4970195085861453, 0.48181152163018093, 0.46463041681575007, 0.483507089943874, 0.4586440159911566, 0.43021603463457364, 0.47 66368215331937, 0.44136604086708021 [0.8013866336607351, 0.5260722466358324, 0.49675964255158495, 0.546905299 8757944, 0.6292213034339067, 0.47799311978061026, 0.471272920599071, 0.53 74162589631429, 0.5552048854893301, 0.49515536618305417, 0.45510127018319 396, 0.7736208001833137, 0.44041226286350227, 0.4480742525036742, 0.54579 53320043843, 0.5926764856387929, 0.468191360918487, 0.4738691456434203, 0.48956028026778525, 0.43735222977290794[0.58168316, 0.68873763, 0.73143566, 0.76237625, 0.75804454, 0.78403467, 0.7809406, 0.8050743, 0.7772277, 0.7964109, 0.8069307, 0.8174505, 0.80321 78, 0.8155941, 0.8162129, 0.8118812, 0.82487625, 0.83106434, 0.8162129, 0.834777241 [0.6467662, 0.7910448, 0.7935323, 0.77860695, 0.7363184, 0.8159204, 0.820 8955, 0.78606963, 0.76865673, 0.80845773, 0.81840795, 0.7089552, 0.823383 1, 0.8308458, 0.8034826, 0.78109455, 0.80597013, 0.80597013, 0.81840795, 0.8134328]

```
In [ ]:
```

Run VGG16 on 3 classes test3

For this part, we still loads 3 classes with most paintings in VGG16 while adds two more layers than test2. Still, run 20 epochs.

Before adding layers, we let the $base_model.output$ load into variable x. Then, we just operate on the x. The operations are as following:

- A Flatten()(x) layer which reshapes the outputs to a single channel.
- A GaussianNoise(0.1)(x) layer.
- A Dropout(0.5)(x) layer.
- A fully-connected layer with 2304 output units and relu activation.
- A GaussianNoise(0.1)(x) layer.
- A Dropout(0.5)(x) layer.
- A fully-connected layer with 288 output units and relu activation.
- A BatchNormalization()(x) layer.
- A Dropout(0.5)(x) layer.
- (new) A fully-connected layer with 288 output units and relu activation.
- (new) A Dropout(0.5)(x) layer.
- A final fully-connected layer. Since this is a multiple classification, there should be three output and softmax activation. To mitigate overfitting, we add several arguments:

```
kernel_initializer='random_uniform', bias_initializer='random_uniform', and bias_regularizer=regularizers.12(0.01).
```

However, at the end of test3, we end up to an obvious underfitting.

```
In [1]: import numpy as np
    import os
    from tensorflow.keras import applications
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras import optimizers, regularizers
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
    import matplotlib
    import matplotlib.pyplot as plt
    %matplotlib inline
```

```
In [2]: from tensorflow.python.client import device lib
        print(device_lib.list_local_devices())
        [name: "/device:CPU:0"
        device_type: "CPU"
        memory_limit: 268435456
        locality {
        }
        incarnation: 2638700649349130033
        , name: "/device:GPU:0"
        device_type: "GPU"
        memory_limit: 2264907776
        locality {
          bus_id: 1
          links {
          }
        }
        incarnation: 14776539995965970595
        physical_device_desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
        ]
In [3]: import tensorflow.keras.backend as K
        K.clear_session()
```

```
In [4]:
        nrow = 200
        ncol = 200
        nclass = 3
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base model.layers:
            layer.trainable = False
        x = base model.output
        x = Flatten()(x)
        x = GaussianNoise(0.1)(x)
        x = Dropout(0.5)(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias_initializer='random_uniform',
                     bias_regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base model.input, outputs=pred)
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\keras\layers\core.py:143: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep prob`.

In [5]: model.summary()

Layer (type)	Output	Shape	
=======================================	======	=======================================	=========
<pre>input_1 (InputLayer)</pre>	(None,	200, 200, 3)	0
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
gaussian_noise (GaussianNois	(None,	18432)	0
dropout (Dropout)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise_1 (GaussianNo	(None,	2304)	0
dropout_1 (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840

```
batch normalization v1 (Batc (None, 288)
                                               1152
dropout 2 (Dropout)
                                               0
                         (None, 288)
dense 2 (Dense)
                         (None, 288)
                                               83232
dropout 3 (Dropout)
                         (None, 288)
predictions (Dense)
                         (None, 3)
                                               867
______
Total params: 57,933,411
Trainable params: 43,218,147
Non-trainable params: 14,715,264
```

Found 1616 images belonging to 3 classes.

Found 402 images belonging to 3 classes.

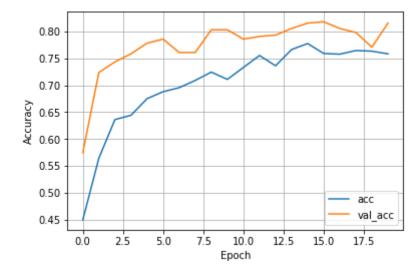
```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

```
WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten
sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op
s.math ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/20
acc: 0.5746
324/324 [============== ] - 58s 178ms/step - loss: 1.0749
- acc: 0.4493 - val_loss: 0.8665 - val_acc: 0.5746
Epoch 2/20
acc: 0.7239
- acc: 0.5644 - val loss: 0.6374 - val acc: 0.7239
Epoch 3/20
acc: 0.7438
- acc: 0.6361 - val_loss: 0.6223 - val_acc: 0.7438
Epoch 4/20
81/81 [============ ] - 11s 136ms/step - loss: 0.6065 -
acc: 0.7587
324/324 [=============== ] - 56s 173ms/step - loss: 0.8256
- acc: 0.6442 - val loss: 0.6065 - val acc: 0.7587
Epoch 5/20
cc: 0.7786
324/324 [================ ] - 55s 170ms/step - loss: 0.7670
- acc: 0.6751 - val_loss: 0.5289 - val_acc: 0.7786
Epoch 6/20
acc: 0.7861
324/324 [=============== ] - 56s 173ms/step - loss: 0.7464
- acc: 0.6881 - val loss: 0.5223 - val acc: 0.7861
Epoch 7/20
acc: 0.7612
324/324 [=============== ] - 56s 172ms/step - loss: 0.7299
- acc: 0.6955 - val_loss: 0.5701 - val_acc: 0.7612
Epoch 8/20
acc: 0.7612
- acc: 0.7092 - val loss: 0.5727 - val acc: 0.7612
Epoch 9/20
```

```
acc: 0.8035
324/324 [============== ] - 56s 173ms/step - loss: 0.6799
- acc: 0.7246 - val_loss: 0.5174 - val_acc: 0.8035
Epoch 10/20
acc: 0.8035
- acc: 0.7110 - val_loss: 0.4813 - val_acc: 0.8035
Epoch 11/20
acc: 0.7861
324/324 [============== ] - 57s 176ms/step - loss: 0.6640
- acc: 0.7333 - val loss: 0.5021 - val acc: 0.7861
Epoch 12/20
acc: 0.7910
- acc: 0.7556 - val_loss: 0.5168 - val_acc: 0.7910
Epoch 13/20
acc: 0.7935
324/324 [============== ] - 56s 173ms/step - loss: 0.6604
- acc: 0.7364 - val loss: 0.5120 - val acc: 0.7935
Epoch 14/20
acc: 0.8060
324/324 [============== ] - 54s 168ms/step - loss: 0.6215
- acc: 0.7667 - val loss: 0.5025 - val acc: 0.8060
Epoch 15/20
acc: 0.8159
- acc: 0.7778 - val loss: 0.4450 - val acc: 0.8159
Epoch 16/20
acc: 0.8184
324/324 [============== ] - 55s 169ms/step - loss: 0.6520
- acc: 0.7593 - val_loss: 0.4971 - val_acc: 0.8184
Epoch 17/20
acc: 0.8060
324/324 [=============== ] - 55s 171ms/step - loss: 0.6010
- acc: 0.7580 - val loss: 0.5052 - val acc: 0.8060
Epoch 18/20
acc: 0.7985
324/324 [=============== ] - 54s 167ms/step - loss: 0.6009
- acc: 0.7649 - val loss: 0.5317 - val acc: 0.7985
Epoch 19/20
acc: 0.7711
324/324 [============== ] - 55s 170ms/step - loss: 0.6075
- acc: 0.7636 - val loss: 0.5673 - val acc: 0.7711
Epoch 20/20
acc: 0.8159
```

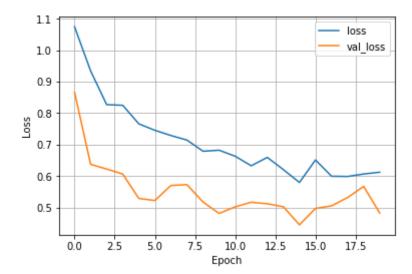
```
In [10]: hist_his = hist.history
acc = hist_his['acc']
val_acc = hist_his['val_acc']
plt.plot(acc)
plt.plot(val_acc)
plt.grid()
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x1d2c6043630>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x1d2dfacfef0>



```
In [12]: print(loss)
    print(val_loss)
    print(acc)
    print(val_acc)
```

[1.0747226900651607, 0.9344037247286869, 0.8271783235953143, 0.8250294966 0146, 0.7661922124795394, 0.7455206539131479, 0.7290131777091561, 0.71442 07797557263, 0.6789925487131102, 0.6822495735204308, 0.6631154680191217, 0.6327936213860048, 0.6593814821070115, 0.6206221104424336, 0.5797280672635643, 0.651208940951043, 0.5995261630119461, 0.5987160129813791, 0.60664 43066546084, 0.6123226203789731] [0.8664734724127217, 0.6373515651549821, 0.6223491394409427, 0.6064664299 289385, 0.5288627569874128, 0.5222727093431685, 0.5701493821854209, 0.572 7167229777501, 0.5173582800744493, 0.48125729663872424, 0.502123031351301 4, 0.5168457585789356, 0.5119663116142705, 0.5025214562422515, 0.44499328 03112416, 0.49711152147731663, 0.5052004380174625, 0.5317020053503874, 0. 5672682631059469, 0.482544251016260641 69554454, 0.7091584, 0.7246287, 0.71101487, 0.7332921, 0.7555693, 0.73638 61, 0.7667079, 0.7778465, 0.7592822, 0.75804454, 0.7648515, 0.7636139, 0. 758663361 [0.57462686, 0.7238806, 0.7437811, 0.75870645, 0.77860695, 0.78606963, 0.76119405, 0.76119405, 0.8034826, 0.8034826, 0.78606963, 0.7910448, 0.7935 323, 0.80597013, 0.8159204, 0.81840795, 0.80597013, 0.79850745, 0.771144 3, 0.8159204]

```
In [ ]:
```

First validation of test2

Based on all three tests' results, the test2 has the best performance. Thus, we decide to repeat the test2's model two more times which verify the modle may work well on 30 classes.

The results of this repeat goes well.

```
In [1]: import numpy as np
        import os
        from tensorflow.keras import applications
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras import optimizers, regularizers
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
In [2]: from tensorflow.python.client import device_lib
        print(device_lib.list_local_devices())
        [name: "/device:CPU:0"
        device type: "CPU"
        memory limit: 268435456
        locality {
        incarnation: 14699118327036049130
        , name: "/device:GPU:0"
        device type: "GPU"
        memory limit: 2264907776
        locality {
          bus id: 1
          links {
          }
        }
        incarnation: 10900450880824840497
        physical_device_desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
        ]
In [3]: import tensorflow.keras.backend as K
        K.clear session()
```

```
In [4]:
        nrow = 200
        ncol = 200
        nclass = 3
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base model.layers:
            layer.trainable = False
        x = base model.output
        x = Flatten()(x)
        x = GaussianNoise(0.1)(x)
        x = Dropout(0.5)(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias initializer='random uniform',
                     bias regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base_model.input, outputs=pred)
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten sorflow\python\keras\layers\core.py:143: calling dropout (from tensorflo w.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep prob`.

In [5]: model.summary()

Layer (type)	Output	Shape	Param #
<pre>input_1 (InputLayer)</pre>	(None.		0
			-
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
gaussian_noise (GaussianNois	(None,	18432)	0
dropout (Dropout)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise_1 (GaussianNo	(None,	2304)	0
dropout_1 (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840

```
batch_normalization_v1 (Batc (None, 288) 1152

dropout_2 (Dropout) (None, 288) 0

predictions (Dense) (None, 3) 867

Total params: 57,850,179

Trainable params: 43,134,915

Non-trainable params: 14,715,264
```

Found 1616 images belonging to 3 classes.

Found 402 images belonging to 3 classes.

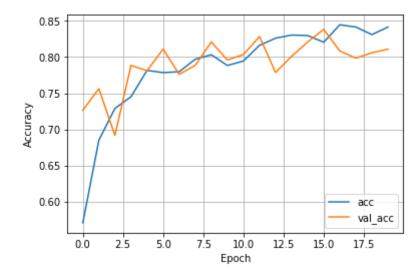
```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

```
WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten
sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op
s.math ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/20
acc: 0.7264
- acc: 0.5705 - val_loss: 0.7035 - val_acc: 0.7264
Epoch 2/20
acc: 0.7562
- acc: 0.6850 - val loss: 0.5645 - val acc: 0.7562
Epoch 3/20
acc: 0.6915
- acc: 0.7290 - val_loss: 0.7018 - val_acc: 0.6915
Epoch 4/20
acc: 0.7886
162/162 [=============== ] - 48s 299ms/step - loss: 0.6296
- acc: 0.7450 - val loss: 0.5393 - val acc: 0.7886
Epoch 5/20
41/41 [============] - 11s 268ms/step - loss: 0.5456 -
acc: 0.7811
162/162 [================ ] - 51s 315ms/step - loss: 0.5613
- acc: 0.7816 - val_loss: 0.5456 - val_acc: 0.7811
Epoch 6/20
acc: 0.8109
- acc: 0.7785 - val loss: 0.4797 - val acc: 0.8109
Epoch 7/20
acc: 0.7761
162/162 [=============== ] - 50s 309ms/step - loss: 0.5580
- acc: 0.7797 - val_loss: 0.5121 - val_acc: 0.7761
Epoch 8/20
acc: 0.7886
- acc: 0.7970 - val loss: 0.6488 - val acc: 0.7886
Epoch 9/20
```

```
acc: 0.8209
162/162 [============= ] - 51s 313ms/step - loss: 0.5074
- acc: 0.8032 - val_loss: 0.4694 - val_acc: 0.8209
Epoch 10/20
cc: 0.7960
- acc: 0.7884 - val_loss: 0.4876 - val_acc: 0.7960
Epoch 11/20
cc: 0.8035
162/162 [=============== ] - 51s 312ms/step - loss: 0.5444
- acc: 0.7946 - val loss: 0.4746 - val acc: 0.8035
Epoch 12/20
acc: 0.8284
- acc: 0.8162 - val_loss: 0.4461 - val_acc: 0.8284
Epoch 13/20
acc: 0.7786
162/162 [============= ] - 56s 346ms/step - loss: 0.4607
- acc: 0.8261 - val_loss: 0.5734 - val_acc: 0.7786
Epoch 14/20
acc: 0.8010
- acc: 0.8304 - val loss: 0.4948 - val acc: 0.8010
Epoch 15/20
acc: 0.8209
- acc: 0.8298 - val loss: 0.4757 - val acc: 0.8209
Epoch 16/20
acc: 0.8383
- acc: 0.8205 - val loss: 0.4391 - val acc: 0.8383
Epoch 17/20
acc: 0.8085
- acc: 0.8447 - val loss: 0.4942 - val acc: 0.8085
Epoch 18/20
acc: 0.7985
- acc: 0.8416 - val loss: 0.5018 - val acc: 0.7985
Epoch 19/20
acc: 0.8060
162/162 [============= ] - 50s 310ms/step - loss: 0.4563
- acc: 0.8311 - val loss: 0.5036 - val acc: 0.8060
Epoch 20/20
acc: 0.8109
```

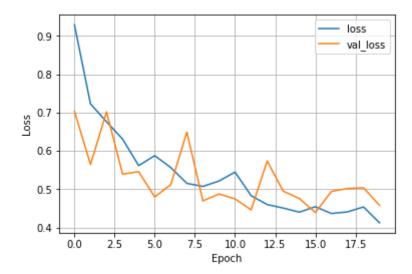
```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x1a406a05940>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x1a41f41f8d0>



```
In [12]: print(loss)
    print(val_loss)
    print(acc)
    print(val_acc)
```

[0.9289161065353615, 0.7224967200677879, 0.6759471297264099, 0.6306312879 418382, 0.5615544472959372, 0.5874900020161035, 0.556419783779005, 0.5151 083443018765, 0.5072679424308019, 0.5212524245944944, 0.5445805789423314, 0.4830270196947426, 0.45990993905960037, 0.45074576311883063, 0.44000948075721463, 0.45428610602301533, 0.43651072863526275, 0.4407050690088089, 0.45363716278594024, 0.41222541288260631[0.7035112217432116, 0.5645308351007904, 0.7017756362513798, 0.5393307526]118871, 0.5456454886532411, 0.4796854878616769, 0.5120801929293609, 0.648 7705882911275, 0.469417158241679, 0.4875728570651717, 0.4746148335497553 7, 0.44605547989287025, 0.5734203847624907, 0.49476630040785163, 0.475654 5166416866, 0.43909876557385047, 0.4941506394889297, 0.5017719225185674, 0.5036047856982161, 0.45769268665008431 [0.57054454, 0.68502474, 0.7289604, 0.7450495, 0.7815594, 0.77846533, 0.7 7970296, 0.7970297, 0.8032178, 0.7883663, 0.7945545, 0.8162129, 0.826113 9, 0.8304455, 0.8298267, 0.82054454, 0.8446782, 0.84158415, 0.83106434, 0.841584151 [0.7263682, 0.7562189, 0.69154227, 0.78855723, 0.78109455, 0.8109453, 0.7 761194, 0.78855723, 0.8208955, 0.7960199, 0.8034826, 0.82835823, 0.778606 95, 0.80099505, 0.8208955, 0.83830845, 0.80845773, 0.79850745, 0.8059701 3, 0.8109453]

```
In [ ]:
```

Second validation of test2

Still, this part repeat the test2 model second time to verify the modle may work well on 30 classes.

The results of this repeat goes well. Thus, we finally confirm using this model for classifying the whole 30 classes by 120 epochs.

```
In [1]: import numpy as np
    import os
    from tensorflow.keras import applications
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras import optimizers, regularizers
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
    import matplotlib
    import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [2]: from tensorflow.python.client import device_lib
        print(device lib.list local devices())
        [name: "/device:CPU:0"
        device_type: "CPU"
        memory_limit: 268435456
        locality {
        }
        incarnation: 4375126007341548165
        , name: "/device:XLA_GPU:0"
        device_type: "XLA_GPU"
        memory_limit: 17179869184
        locality {
        }
        incarnation: 12474301033500099600
        physical_device_desc: "device: XLA_GPU device"
        , name: "/device:XLA_CPU:0"
        device_type: "XLA_CPU"
        memory limit: 17179869184
        locality {
        }
        incarnation: 13806675105940690515
        physical_device_desc: "device: XLA_CPU device"
        , name: "/device:GPU:0"
        device_type: "GPU"
        memory_limit: 15856484352
        locality {
          bus id: 1
          links {
          }
        incarnation: 9834537617546067114
        physical device desc: "device: 0, name: Tesla P100-PCIE-16GB, pci bus id:
        0000:00:04.0, compute capability: 6.0"
        import tensorflow.keras.backend as K
In [3]:
        K.clear_session()
```

```
In [4]:
        nrow = 200
        ncol = 200
        nclass = 3
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base model.layers:
            layer.trainable = False
        x = base model.output
        x = Flatten()(x)
        x = GaussianNoise(0.1)(x)
        x = Dropout(0.5)(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias initializer='random uniform',
                     bias regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base_model.input, outputs=pred)
```

WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow/python/ops/resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflow/python/keras/layers/core.py:143: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep prob`.

In [5]: model.summary()

Layer (type)	Output	Shape	
=======================================	======	=======================================	=========
<pre>input_1 (InputLayer)</pre>	(None,	200, 200, 3)	0
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
gaussian_noise (GaussianNois	(None,	18432)	0
dropout (Dropout)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise_1 (GaussianNo	(None,	2304)	0
dropout_1 (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840

Found 1616 images belonging to 3 classes.

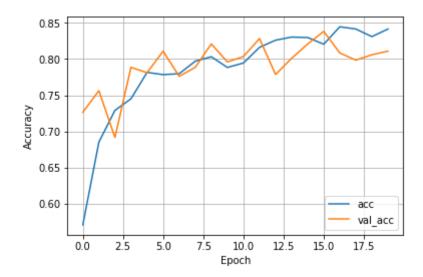
Found 402 images belonging to 3 classes.

```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

WARNING:tensorflow:From /usr/local/lib/python3.5/dist-packages/tensorflo w/python/ops/math ops.py:3066: to int32 (from tensorflow.python.ops.math_ ops) is deprecated and will be removed in a future version. Instructions for updating: Use tf.cast instead. Epoch 1/120 c: 0.7488 51/51 [=============] - 103s 2s/step - loss: 0.8890 - ac c: 0.5928 - val_loss: 0.7350 - val_acc: 0.7488 Epoch 2/120 c: 0.7488 c: 0.7116 - val loss: 0.6261 - val acc: 0.7488 Epoch 3/120 15/51 [======>.....] - ETA: 15s - loss: 0.5960 - acc: 0.7563

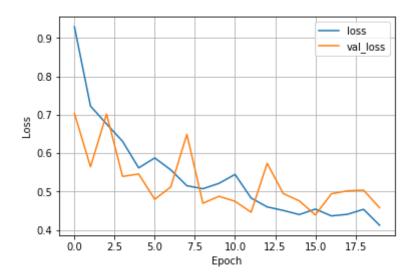
```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x1a406a05940>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x1a41f41f8d0>



In [12]: print(loss)
 print(val_loss)
 print(acc)
 print(val_acc)

[0.9289161065353615, 0.7224967200677879, 0.6759471297264099, 0.6306312879 418382, 0.5615544472959372, 0.5874900020161035, 0.556419783779005, 0.5151 083443018765, 0.5072679424308019, 0.5212524245944944, 0.5445805789423314, $0.4830270196947426,\ 0.45990993905960037,\ 0.45074576311883063,\ 0.440009480$ 75721463, 0.45428610602301533, 0.43651072863526275, 0.4407050690088089, 0.45363716278594024, 0.4122254128826063] $\lceil 0.7035112217432116,\ 0.5645308351007904,\ 0.7017756362513798,\ 0.5393307526$ 118871, 0.5456454886532411, 0.4796854878616769, 0.5120801929293609, 0.648 7705882911275, 0.469417158241679, 0.4875728570651717, 0.4746148335497553 7, 0.44605547989287025, 0.5734203847624907, 0.49476630040785163, 0.475654 5166416866, 0.43909876557385047, 0.4941506394889297, 0.5017719225185674, 0.5036047856982161, 0.45769268665008431 [0.57054454, 0.68502474, 0.7289604, 0.7450495, 0.7815594, 0.77846533, 0.7 7970296, 0.7970297, 0.8032178, 0.7883663, 0.7945545, 0.8162129, 0.826113 9, 0.8304455, 0.8298267, 0.82054454, 0.8446782, 0.84158415, 0.83106434, 0.84158415] [0.7263682, 0.7562189, 0.69154227, 0.78855723, 0.78109455, 0.8109453, 0.7 761194, 0.78855723, 0.8208955, 0.7960199, 0.8034826, 0.82835823, 0.778606 95, 0.80099505, 0.8208955, 0.83830845, 0.80845773, 0.79850745, 0.8059701 3, 0.8109453]

In []:

Test (3 classes) results summary

For this part, we compare the results of all test models for 3 classes: untuned, test1, test2, and test3. We will use the loss, val loss, acc, and val acc from former tests.

For these models,

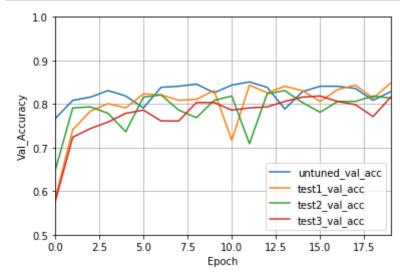
- untuned and test1 are overfitting.
- test2 is the best fitting.
- test3 is underfitting.

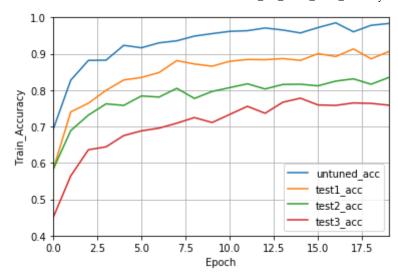
Thus, we will use the model from test2 to classify the 30 classes.

```
In [1]: untuned_loss = [0.7509350723559314, 0.4501491076875441, 0.33513500932419654,
    untuned_val_loss = [0.5346578520077926, 0.49634360120846677, 0.5241671640139
    untuned_acc = [0.6912129, 0.8273515, 0.8818069, 0.8824257, 0.9232673, 0.9164
    untuned_val_acc = [0.76616913, 0.80845773, 0.8159204, 0.8308458, 0.81840795,
```

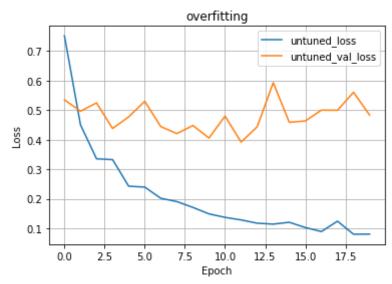
- In [2]: test1_loss = [0.9197668498105341, 0.6389658262233923, 0.5544988536598658, 0.
 test1_val_loss = [1.2577795065366304, 0.6699514022240272, 0.5406953211014087
 test1_acc = [0.58106434, 0.740099, 0.7642327, 0.79950494, 0.8279703, 0.83477
 test1_val_acc = [0.58208954, 0.74129355, 0.7835821, 0.80099505, 0.7910448, 0.80099505]
- In [3]: test2_loss = [0.9074013190030461, 0.7389471186970425, 0.6464045981295629, 0.
 test2_val_loss = [0.8013866336607351, 0.5260722466358324, 0.4967596425515849
 test2_acc = [0.58168316, 0.68873763, 0.73143566, 0.76237625, 0.75804454, 0.7
 test2_val_acc = [0.6467662, 0.7910448, 0.7935323, 0.77860695, 0.7363184, 0.8
- In [4]: test3_loss = [1.0747226900651607, 0.9344037247286869, 0.8271783235953143, 0.
 test3_val_loss = [0.8664734724127217, 0.6373515651549821, 0.6223491394409427
 test3_acc = [0.44925743, 0.56435645, 0.6361386, 0.64418316, 0.67512375, 0.68
 test3_val_acc = [0.57462686, 0.7238806, 0.7437811, 0.75870645, 0.77860695, 0.7238806]

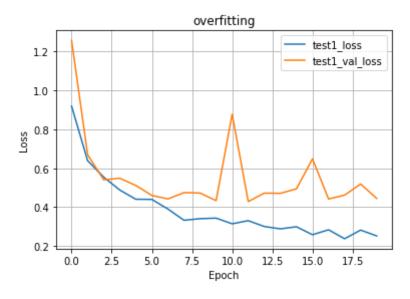
```
In [7]:
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
        plt.plot(untuned_val_acc)
        plt.plot(test1_val_acc)
        plt.plot(test2_val_acc)
        plt.plot(test3_val_acc)
        plt.grid()
        plt.axis([0,19,0.5,1])
        plt.xlabel('Epoch')
        plt.ylabel('Val_Accuracy')
        plt.legend(['untuned_val_acc','test1_val_acc','test2_val_acc','test3_val_acc'
        plt.show()
        plt.plot(untuned_acc)
        plt.plot(test1_acc)
        plt.plot(test2_acc)
        plt.plot(test3_acc)
        plt.grid()
        plt.axis([0,19,0.4,1])
        plt.xlabel('Epoch')
        plt.ylabel('Train_Accuracy')
        plt.legend(['untuned_acc','test1_acc','test2_acc','test3_acc'], loc = 4)
        plt.show()
```

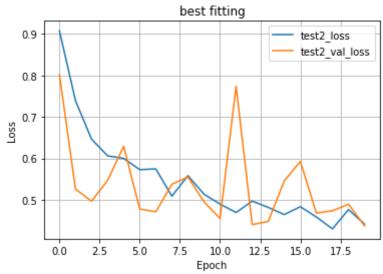


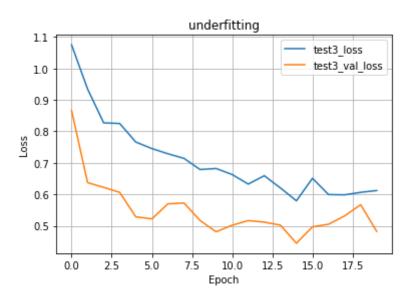


```
In [13]:
         plt.plot(untuned_loss)
         plt.plot(untuned val loss)
         plt.title('overfitting')
         plt.grid()
         plt.xlabel('Epoch')
         plt.ylabel('Loss')
         plt.legend(['untuned_loss','untuned_val_loss'], loc = 1)
         plt.show()
         plt.plot(test1_loss)
         plt.plot(test1_val_loss)
         plt.title('overfitting')
         plt.grid()
         plt.xlabel('Epoch')
         plt.ylabel('Loss')
         plt.legend(['test1_loss','test1_val_loss'], loc = 1)
         plt.show()
         plt.plot(test2_loss)
         plt.plot(test2 val loss)
         plt.title('best fitting')
         plt.grid()
         plt.xlabel('Epoch')
         plt.ylabel('Loss')
         plt.legend(['test2 loss','test2 val loss'], loc = 1)
         plt.show()
         plt.plot(test3_loss)
         plt.plot(test3 val loss)
         plt.title('underfitting')
         plt.grid()
         plt.xlabel('Epoch')
         plt.ylabel('Loss')
         plt.legend(['test3_loss','test3_val_loss'], loc = 1)
         plt.show()
```









Tn []•	
[]•	

Run VGG16 on 30 classes with 120 epochs

Finally, we use the model from test2 to classify 30 artists' paintings with 120 epochs.

Obviously, the validation accuraccy is stable at more than %60, and the validation loss keep decreasing during the 120 epochs while keep reasonable difference between the training loss.

Given that there are 30 classes and some of the artists have similar art style, the accuracy of 60% is an acceptable result.

```
In [1]: import numpy as np
        import os
        from tensorflow.keras import applications
        from tensorflow.keras.preprocessing.image import ImageDataGenerator
        from tensorflow.keras import optimizers, regularizers
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Dropout, Flatten, Dense, GaussianNoise,
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
In [2]: from tensorflow.python.client import device lib
        print(device lib.list local devices())
        [name: "/device:CPU:0"
        device_type: "CPU"
        memory limit: 268435456
        locality {
        incarnation: 17738829143079950615
        , name: "/device:GPU:0"
        device type: "GPU"
        memory limit: 2264907776
        locality {
          bus id: 1
          links {
          }
        incarnation: 18079149120323357725
        physical device desc: "device: 0, name: GeForce GTX 970M, pci bus id: 000
        0:01:00.0, compute capability: 5.2"
In [3]: import tensorflow.keras.backend as K
        K.clear session()
```

```
In [4]:
        nrow = 200
        ncol = 200
        nclass = 30
        base_model = applications.VGG16(weights='imagenet', input_shape=(nrow,ncol,
        for layer in base model.layers:
            layer.trainable = False
        x = base model.output
        x = Flatten()(x)
        x = GaussianNoise(0.1)(x)
        x = Dropout(0.5)(x)
        x = Dense(2304, activation = 'relu')(x) # 18432/4
        x = GaussianNoise(0.1)(x) # add noise to mitigate overfitting (regularization)
        x = Dropout(0.5)(x)
        x = Dense(288, activation='relu')(x)
        x = BatchNormalization()(x)
        x = Dropout(0.5)(x)
        pred = Dense(nclass, activation='softmax',
                     kernel_initializer='random_uniform',
                     bias initializer='random uniform',
                     bias regularizer=regularizers.12(0.01),
                     name='predictions')(x)
        model = Model(inputs=base_model.input, outputs=pred)
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten sorflow\python\keras\layers\core.py:143: calling dropout (from tensorflo w.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep prob`.

In [5]: model.summary()

Layer (type)	Output	Shape	Param #
input_1 (InputLayer)	(None,	200, 200, 3)	0
block1_conv1 (Conv2D)	(None,	200, 200, 64)	1792
block1_conv2 (Conv2D)	(None,	200, 200, 64)	36928
block1_pool (MaxPooling2D)	(None,	100, 100, 64)	0
block2_conv1 (Conv2D)	(None,	100, 100, 128)	73856
block2_conv2 (Conv2D)	(None,	100, 100, 128)	147584
block2_pool (MaxPooling2D)	(None,	50, 50, 128)	0
block3_conv1 (Conv2D)	(None,	50, 50, 256)	295168
block3_conv2 (Conv2D)	(None,	50, 50, 256)	590080
block3_conv3 (Conv2D)	(None,	50, 50, 256)	590080
block3_pool (MaxPooling2D)	(None,	25, 25, 256)	0
block4_conv1 (Conv2D)	(None,	25, 25, 512)	1180160
block4_conv2 (Conv2D)	(None,	25, 25, 512)	2359808
block4_conv3 (Conv2D)	(None,	25, 25, 512)	2359808
block4_pool (MaxPooling2D)	(None,	12, 12, 512)	0
block5_conv1 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv2 (Conv2D)	(None,	12, 12, 512)	2359808
block5_conv3 (Conv2D)	(None,	12, 12, 512)	2359808
block5_pool (MaxPooling2D)	(None,	6, 6, 512)	0
flatten (Flatten)	(None,	18432)	0
gaussian_noise (GaussianNois	(None,	18432)	0
dropout (Dropout)	(None,	18432)	0
dense (Dense)	(None,	2304)	42469632
gaussian_noise_1 (GaussianNo	(None,	2304)	0
dropout_1 (Dropout)	(None,	2304)	0
dense_1 (Dense)	(None,	288)	663840

Found 5687 images belonging to 30 classes.

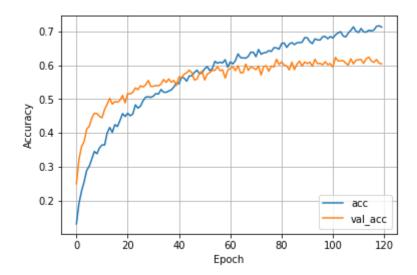
Found 1404 images belonging to 30 classes.

```
In [8]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['a
steps_per_epoch = train_generator.n // batch_size
validation_steps = test_generator.n // batch_size
```

WARNING:tensorflow:From D:\Anaconda\envs\tensorflow\lib\site-packages\ten sorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.python.op s.math ops) is deprecated and will be removed in a future version. Instructions for updating: Use tf.cast instead. Epoch 1/120 - acc: 0.2493 91 - acc: 0.1310 - val_loss: 2.5986 - val_acc: 0.2493 Epoch 2/120 - acc: 0.3219 32 - acc: 0.1918 - val loss: 2.4152 - val acc: 0.3219 Epoch 3/120 - acc: 0.3597

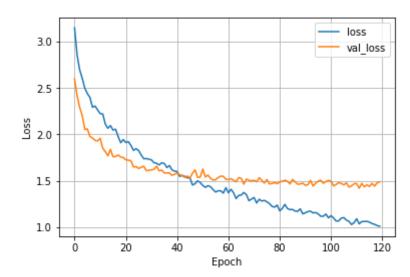
```
In [10]: hist_his = hist.history
    acc = hist_his['acc']
    val_acc = hist_his['val_acc']
    plt.plot(acc)
    plt.plot(val_acc)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.legend(['acc','val_acc'], loc = 4)
```

Out[10]: <matplotlib.legend.Legend at 0x24bb18c3748>



```
In [11]: loss = hist_his['loss']
    val_loss = hist_his['val_loss']
    plt.plot(loss)
    plt.plot(val_loss)
    plt.grid()
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend(['loss','val_loss'], loc = 1)
```

Out[11]: <matplotlib.legend.Legend at 0x24bb1909ba8>



In [12]: print(loss)
 print(val_loss)

print(acc)
print(val_acc)

[3.14887666830137, 2.8532378607524054, 2.6948824729885055, 2.603927112807 9124, 2.4979331421164566, 2.440019819100083, 2.399272446737613, 2.2927422 82639536, 2.30581997699429, 2.2634986593640707, 2.2238892891274116, 2.220 4405017470945, 2.110854354446794, 2.0661793674560305, 2.0953340293737712, 2.047150615105546, 2.0561495057272956, 1.9780113589623198, 1.910356094107 9305, 1.9441882107470394, 1.9133827449442402, 1.921118175116662, 1.881087 851315784, 1.8279229860241224, 1.8463588798163497, 1.825864585407677, 1.7 781568921490631, 1.7375602504637742, 1.7402194728693268, 1.73256280559719 56, 1.7249106890065862, 1.69454954486751, 1.6893229365626559, 1.671006831 0514494, 1.694082800954638, 1.687026359556177, 1.642625775837366, 1.66534 71243717937, 1.6179302782737373, 1.6038959688491135, 1.5998659210237989, 1.547910915263533, 1.5579253501190502, 1.5476253076022677, 1.5329002478466693, 1.5308413288705227, 1.4540808080568326, 1.4685977000107093, 1.50013 6630329596, 1.481121332802734, 1.4495783738067454, 1.429472905664415, 1.4 4756361214483, 1.4370123727857302, 1.406100361045769, 1.3790945432122508, 1.392482722140436, 1.3928008942883012, 1.3669300967664004, 1.426529755423 8139, 1.3708891403490093, 1.409018208908976, 1.3711955135172986, 1.308138 2734742633, 1.3428455541588016, 1.346025437286937, 1.3744070033800084, 1. 3512422148448124, 1.2855672028039522, 1.302735023932862, 1.32019892789021 26, 1.2604598219240981, 1.3012864021746517, 1.2816157268115596, 1.2891119 165122982, 1.2739969535231463, 1.253721626086679, 1.2249442387456757, 1.2 151649425905744, 1.2389106319423655, 1.1761944099647603, 1.20193574727315 24, 1.2460170154629597, 1.2017211732416113, 1.1896493020401135, 1.1911034 554587645, 1.173888971134614, 1.1710680727395752, 1.1973944686435742, 1.1 431129749884648, 1.1558843259851124, 1.168114076966411, 1.173178361045238 9, 1.1538946076419256, 1.1581114742473222, 1.1429505718009574, 1.11822127 09685542, 1.1175019128334236, 1.1415150390097164, 1.1008182604233347, 1.1 248400598477506, 1.0991875380395544, 1.0664902638233917, 1.06784067309230 8, 1.097637352785343, 1.1032167018122783, 1.0760066149307927, 1.063404732 6620217, 1.0284685007055279, 1.0486837283565518, 1.0912402716370475, 1.03 56118842272908, 1.0608548783499525, 1.0607053105070392, 1.064400925454134 2, 1.0540254852266635, 1.0391940124246437, 1.0307174821649383, 1.01709449 79791328, 1.01050656522257861 [2.5986390673817263, 2.4152131207897147, 2.2908821453827555, 2.2023981801 13144, 2.0528401929712805, 2.0596567402955053, 1.9760068330476293, 1.9615 514961425944, 1.936446952438015, 1.9301648468733683, 1.9580832193754747, 1.851916514999926, 1.8150155751094275, 1.7698578359393462, 1.838367413371 4831, 1.7600538260253722, 1.7621840319175313, 1.7785802632570267, 1.75639 4695556885, 1.7512089908653308, 1.7272833022570695, 1.7224288245537103, 1.716591116796609, 1.6486663927599203, 1.6531337413181189, 1.632963371658 6647, 1.6471444270788986, 1.6565643461997823, 1.6086759656879825, 1.61392 50046895068, 1.6181251450683722, 1.6238818162276651, 1.6580979210122413, 1.6068940174325081, 1.6154659823166517, 1.584228739460592, 1.585238944460 701, 1.5855607588202079, 1.5594624436834954, 1.5699501504253237, 1.582968 9502716064, 1.5645903365361733, 1.55543631887945, 1.536528892205279, 1.55 11978027341204, 1.5310094711301165, 1.581782923182771, 1.617809724500170 8, 1.5361509071497306, 1.5404548884180518, 1.6265546720859418, 1.54115970 09734963, 1.5621406999930367, 1.5277147977563197, 1.5086268228064441, 1.5 118827614601822, 1.5350136824243859, 1.5507322604373575, 1.54830767573570 02, 1.5157892402539899, 1.5139411654044936, 1.522371015594311, 1.50671618 14346115, 1.4893123643121473, 1.5346368134843709, 1.5262638342125985, 1.4 637971964276983, 1.5183051515940669, 1.5058256992241665, 1.49980634092966 43, 1.5059065040369979, 1.4899178577911811, 1.5330901763922273, 1.5056956 097536665, 1.4753895334342622, 1.5136543880233349, 1.4666676466681354, 1. 4709212028046943, 1.480322968705269, 1.4692638841228978, 1.48668276256089 54, 1.495926550884476, 1.5064830970933853, 1.4961913378107166, 1.46541278 42749989, 1.5147791323500597, 1.488247580905826, 1.4624823325999692, 1.46 66374412454743, 1.474243866982356, 1.4511621594429016, 1.458440694706083 5, 1.5042794497279297, 1.4436638161964264, 1.474070118972203, 1.496235860 1205714, 1.5070647389969367, 1.4736667002064052, 1.4920057622828518, 1.50 3540256428549, 1.4964379253548659, 1.4452120655637195, 1.460496266276386 7, 1.4804624406309315, 1.4719022546639646, 1.4560790446676393, 1.47778608 70100956, 1.432703056488703, 1.444938014781772, 1.4677913017650517, 1.470 7328780584064, 1.4194630855343096, 1.4723218056601985, 1.436070863939689, 1.4563526885047078, 1.439350330294027, 1.4723250337634435, 1.442419101520 5774, 1.4782642004116575, 1.4890809308843576] [0.13100053, 0.19184104, 0.228064, 0.25531915, 0.28890452, 0.30138913, 0. 32266572, 0.34499738, 0.33831546, 0.3553719, 0.3643397, 0.36416388, 0.399 85934, 0.41586074, 0.40144187, 0.42430103, 0.41867417, 0.4369615, 0.45683 137, 0.44839108, 0.4578864, 0.45050114, 0.45595217, 0.48285565, 0.473008 6, 0.47933885, 0.49516442, 0.50553894, 0.50676984, 0.5048356, 0.50870407, 0.51626515, 0.5146826, 0.528222226, 0.5201336, 0.5199578, 0.5236504, 0.52699137, 0.5356075, 0.5473888, 0.54545456, 0.5646211, 0.56180763, 0.552839 8, 0.5681379, 0.5683137, 0.57868826, 0.5853701, 0.57481974, 0.5776332, 0. 5894145, 0.5959205, 0.58396345, 0.58976614, 0.6113944, 0.6059434, 0.60875 684, 0.60682255, 0.6163179, 0.5939863, 0.60981184, 0.6038333, 0.6136803, 0.63337433, 0.62229645, 0.6215931, 0.6207139, 0.6259891, 0.6384737, 0.638 29786, 0.62528574, 0.6463865, 0.63249516, 0.6363636, 0.63777035, 0.643045 54, 0.64075965, 0.6516617, 0.65131, 0.6472657, 0.66379464, 0.66572887, 0. 6527167, 0.6623879, 0.66678387, 0.6609812, 0.6664322, 0.66660804, 0.66801 476, 0.6813786, 0.6810269, 0.6694215, 0.66379464, 0.6778618, 0.6748725, 0.6741692, 0.68401617, 0.68507123, 0.6782135, 0.6848954, 0.6801477, 0.689 643, 0.6954458, 0.6991384, 0.68647796, 0.68348867, 0.6947424, 0.70300686, 0.7133814, 0.7008968, 0.6965008, 0.7086337, 0.698435, 0.6977317, 0.703358 53, 0.7014243, 0.70388603, 0.71478814, 0.71654654, 0.712678] [0.24928775, 0.32193732, 0.3596866, 0.37393162, 0.41096866, 0.41951567, 0.4437322, 0.4579772, 0.45726496, 0.44871795, 0.44444445, 0.46937323, 0.4 8504272, 0.50213677, 0.48504272, 0.49216524, 0.49074075, 0.49643874, 0.51 06838, 0.48860398, 0.51638174, 0.51495725, 0.519943, 0.53276354, 0.527777 8, 0.5391738, 0.5356125, 0.54202276, 0.5548433, 0.537037, 0.5377493, 0.53 988606, 0.5391738, 0.54415953, 0.5576923, 0.5491453, 0.5591168, 0.5498575 6, 0.5548433, 0.53988606, 0.5655271, 0.56267804, 0.5733618, 0.57763535, 0.5854701, 0.57763535, 0.5562678, 0.5591168, 0.5762108, 0.5826211, 0.5562 678, 0.5733618, 0.57834756, 0.58475786, 0.58475786, 0.5954416, 0.5840456, 0.58618236, 0.5619658, 0.58475786, 0.59045583, 0.5954416, 0.5840456, 0.5982906, 0.57763535, 0.57763535, 0.6032764, 0.58475786, 0.59472936, 0.59188 03, 0.5868946, 0.59757835, 0.57122505, 0.59615386, 0.5982906, 0.5819088, 0.59757835, 0.59472936, 0.61752135, 0.6018519, 0.6096866, 0.6004273, 0.59 757835, 0.58618236, 0.60897434, 0.5868946, 0.6032764, 0.6118234, 0.597578 35, 0.6096866, 0.60470086, 0.60897434, 0.5968661, 0.61752135, 0.60470086, 0.6054131, 0.6011396, 0.6103989, 0.6018519, 0.60470086, 0.59472936, 0.6232194, 0.6125356, 0.6125356, 0.6139601, 0.60612535, 0.6004273, 0.6189459, 0.6039886, 0.61467236, 0.61609685, 0.6168091, 0.6054131, 0.6189459, 0.623 93165, 0.6125356, 0.6082621, 0.6168091, 0.60612535, 0.6039886]

In []:

30 classes results summary

For this part, we compare the results two models for 3 classes: untuned, and the model from test2. We will use the loss, val_loss, acc, and val_acc from the former tests.

In conclusion,

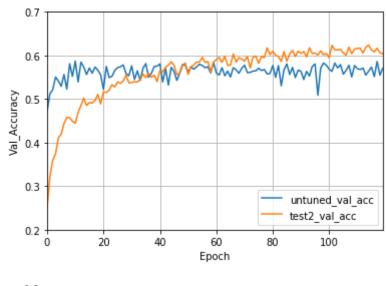
- untuned is overfitting.
- test2 for 30 classes mitigate the severe overfitting from untuned model. However, since
 the resource limitation, we only run 120 epochs. From the curves, val_acc does not seem to
 fully converge. Thus, the accuracy may get higher if adding more epochs.

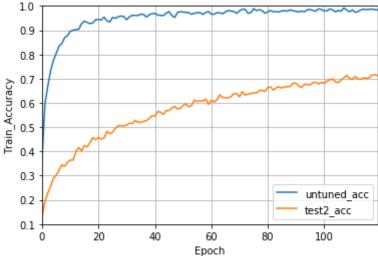
From the untuned_loss_curve, the val_loss keep increasing during all 120 epoch, which reflects severe overfitting; By comparison, from the test2_loss_curve, the val_loss keep decreasing during the 120 epochs which is what we expect.

```
In [1]: untuned_loss = [2.3461001035050724, 1.4235979016874845, 1.1430863561457525,
    untuned_val_loss = [1.8798491602594203, 1.8879662372849204, 1.88664359396154
    untuned_acc = [0.3726042, 0.5936346, 0.66731143, 0.73184454, 0.77474946, 0.8
    untuned_val_acc = [0.47150996, 0.51210827, 0.52136755, 0.5505698, 0.54131055]
```

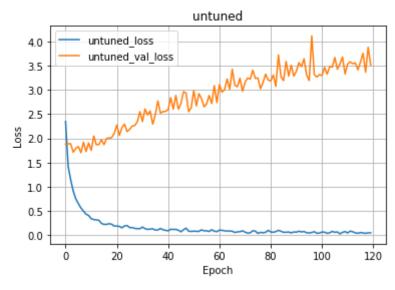
```
In [2]: test2_loss = [3.14887666830137, 2.8532378607524054, 2.6948824729885055, 2.60
    test2_val_loss = [2.5986390673817263, 2.4152131207897147, 2.2908821453827555
    test2_acc = [0.13100053, 0.19184104, 0.228064, 0.25531915, 0.28890452, 0.301
    test2_val_acc = [0.24928775, 0.32193732, 0.3596866, 0.37393162, 0.41096866,
```

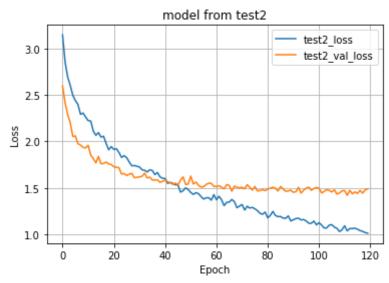
```
import matplotlib
In [6]:
        import matplotlib.pyplot as plt
        %matplotlib inline
        plt.plot(untuned_val_acc)
        plt.plot(test2_val_acc)
        plt.grid()
        plt.axis([0,119,0.2,0.7])
        plt.xlabel('Epoch')
        plt.ylabel('Val_Accuracy')
        plt.legend(['untuned_val_acc','test2_val_acc'], loc = 4)
        plt.show()
        plt.plot(untuned acc)
        plt.plot(test2_acc)
        plt.grid()
        plt.axis([0,119,0.1,1])
        plt.xlabel('Epoch')
        plt.ylabel('Train_Accuracy')
        plt.legend(['untuned acc','test2 acc'], loc = 4)
        plt.show()
```





```
plt.plot(untuned_loss)
plt.plot(untuned_val_loss)
plt.title('untuned')
plt.grid()
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['untuned_loss', 'untuned_val_loss'], loc = 2)
plt.show()
plt.plot(test2_loss)
plt.plot(test2_val_loss)
plt.title('model from test2')
plt.grid()
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['test2_loss','test2_val_loss'], loc = 1)
plt.show()
```





In [1:	
T11 [] •	