CS440 Class Challenge

Blake Abel, Richard Chen

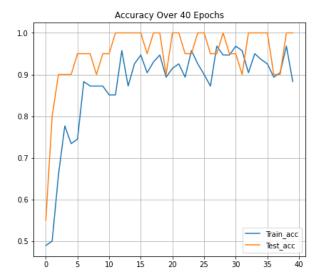
Task 1:

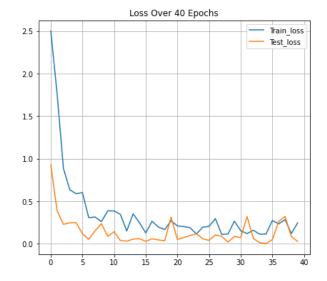
Architecture Used:

For this task, we are using a model with the following layers: VGG16 layer with input shape 224 by 224 by 3, flatten layer, dense layers with 1000, 500, and 125 neurons each, a dropout layer with 0.2 dropout rate after each of these dense layers, and finally, an output layer with sigmoid activation. We initialized the model parameters with ImageNet weights. For the loss function, we are using binary cross entropy with the Adam optimizer and a learning rate of 0.0005.

Layer (type)	Output Shape	Param #	
vgg16 (Functional)	(None, 7, 7, 512)	14714688	
flatten_5 (Flatten)	(None, 25088)	0	
dense_8 (Dense)	(None, 1000)	25089000	
dropout_6 (Dropout)	(None, 1000)	0	
dense_9 (Dense)	(None, 500)	500500	
dropout_7 (Dropout)	(None, 500)	0	
dense_10 (Dense)	(None, 125)	62625	
dropout_8 (Dropout)	(None, 125)	0	
dense_11 (Dense)	(None, 1)	126	

Architecture Performance:



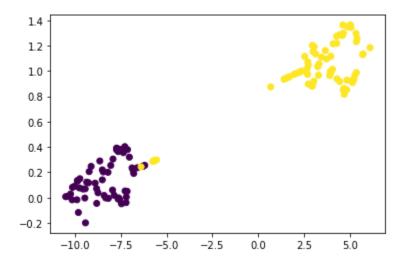


Test loss: 0.03205887973308563

Test accuracy: 1.0

The accuracy and loss of our model was very good! In the first few epochs, it quickly jumps from 0.6 up to 0.9, and then effectively stays there, many times getting every single test case correct in the training set. The loss similarly has a sharp decline, and then stays very close to 0 for many epochs. We were very happy with the performance of our model, especially given that the model doesn't have a ton of data to train on.

t-SNE Visualization:



Our t-SNE visualization was slightly different than the example provided, but showed just as good, distinct clustering even when reduced to just two features instead of the whole set. To perform the t-SNE visualization, we used the penultimate layer of our

model, with 125 features in the dense layer. From there, we used sklearn to generate the t-SNE visualization with these parameters: <code>n_components=2</code>, <code>perplexity=48</code>, <code>learning_rate='auto'</code>, <code>init='pca'</code>, <code>square_distances=True</code>. We know how many components there should be so that was simple, but finding the right perplexity was a little more tricky. The output graph is very very sensitive to this parameter, which from what we could tell, helped define how tightly our data is clustered, with values too low not being clustered enough, and values too high attempted to be clustered too much, resulting in dispersed ring or donut shapes. After trial and error, it seems that 48 was a great pick. While the shape isn't triangular like the sample, and there are a few outliers in the bottom left cluster, we are quite happy with how clean and distinct the clusters it has found are in just two dimensions.

Task 2:

Architecture Used:

We started with a pre-trained VGG system, and just added one layer to flatten it, taking it from a 3 dimensional tensor of shape 7x7x512, to just a single dimensional layer of size 25088. Then, we applied a fully-connected layer, reducing the shape to 128, and finally an output fully connected layer, giving us our 4 categories. For the loss, we used a categorical cross entropy with the Adam optimizer and a learning rate of 0.0005, similar to task 1 but with a different cross entropy function to suit categorical classification instead of binary classification.

Layer (type)	Output Shape	Param #	
vgg16 (Functional)	(None, 7, 7, 512)	14714688	
flatten_1 (Flatten)	(None, 25088)	0	
dense_2 (Dense)	(None, 128)	3211392	
dense_3 (Dense)	(None, 4)	516	

Architecture Investigation and Comparison:

VGG16 Improvement with more layers and dropout:

Layer (type)	Output Shape	Param #	
vgg16 (Functional)	(None, 7, 7, 512)	14714688	
flatten_25 (Flatten)	(None, 25088)	0	
dense_76 (Dense)	(None, 500)	12544500	
dropout_49 (Dropout)	(None, 500)	0	
dense_77 (Dense)	(None, 125)	62625	
dropout_50 (Dropout)	(None, 125)	0	
dense_78 (Dense)	(None, 4)	504	

To improve our accuracy from our simple model, we decided to try out a more complicated model that adds in additional dropout layers, which should reduce

overfitting and give us higher accuracy. To be more clear, we added a fully connected layer before our first fully-connected layer of size 500, with a dropout layer of the same size after it. Then, we also added a dropout layer after our initial fully connected layer. However, in our testing, the accuracy actually decreased by 0.05%, so we looked elsewhere for improvements.

Extra data augmentation:

Layer (type)	Output Shape	Param #	
vgg16 (Functional)	(None, 7, 7, 512)	14714688	
flatten_34 (Flatten)	(None, 25088)	0	
dense_98 (Dense)	(None, 128)	3211392	
dense_99 (Dense)	(None, 4)	516	

Next we tried to use extra data augmentation. From what we could tell, this meant that we had to increase how many epochs we ran it with, as each one perturbed our input images slightly and gave the rest a larger dataset to work with. Besides that, it has the same parameters as our initial model. The accuracy still leveled out at the same spot, although with so many more epochs, it was much more gradual getting there.

AlexNet:

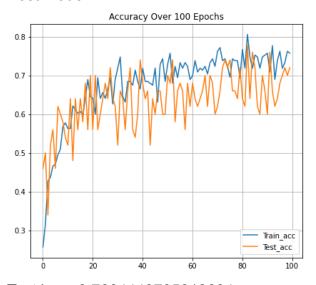
Layer (type)	Output Shape P	Param #
conv2d_60 (Conv2D)	(None, 54, 54, 96)	34944
batch_normalization_	60 (Batc (None, 54, 54, 9	96) 384
max_pooling2d_36 (N	MaxPooling (None, 26, 26	6, 96) 0
conv2d_61 (Conv2D)	(None, 26, 26, 256	6) 614656
batch_normalization_	61 (Batc (None, 26, 26, 2	256) 1024
max_pooling2d_37 (N	MaxPooling (None, 12, 12	2, 256) 0
conv2d_62 (Conv2D)	(None, 12, 12, 384	4) 885120
batch_normalization_	62 (Batc (None, 12, 12, 3	384) 1536
conv2d_63 (Conv2D)	(None, 12, 12, 384	4) 1327488

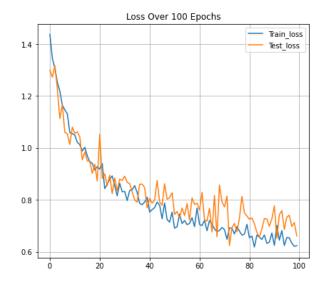
batch_normalization_6	3 (Batc (None, 12, 1	2, 384) 1536	
conv2d_64 (Conv2D)	(None, 12, 12,	256) 884992	
batch_normalization_6	4 (Batc (None, 12, 1	2, 256) 1024	
max_pooling2d_38 (Ma	axPooling (None, 5,	5, 256) 0	
flatten_32 (Flatten)	(None, 6400)	0	
dense_93 (Dense)	(None, 4096)	26218496	
dropout_55 (Dropout)	(None, 4096)	0	
dense_94 (Dense)	(None, 4096)	16781312	
dropout_56 (Dropout)	(None, 4096)	0	
dense_95 (Dense)	(None, 4)	16388	

We then tried a very different approach, using the AlexNet image classifier, which was almost completely different from our model. We thought that by using more Conv2D layers for the image, our performance would improve, but this accuracy was much lower than our first. However, it does give us a good idea of how some standard models perform on this dataset!

Architecture Performance:

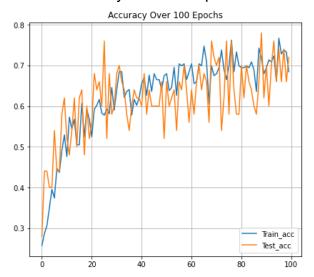
Best model:

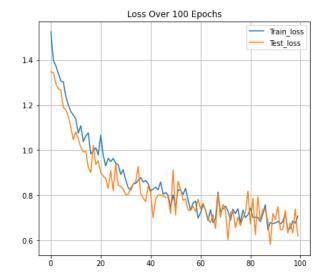




Test loss: 0.7604448795318604 Test accuracy: 0.6944444179534912 Our simplest model turned out to have the highest accuracy we could achieve, around 0.69. It has a steady even rise until capping out at that level. The loss also steadily decreases, but never drops below 0.6. We think that the small size of the input dataset may have been the reason behind the much smaller accuracy, as with categorical classification, especially with similar classes, it is harder to tell apart the distinct differences for all the classes.

VGC16 More layers and dropout:

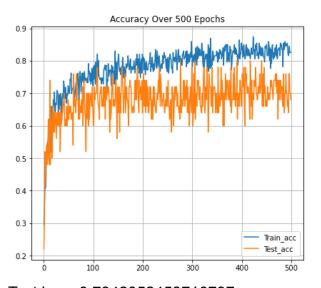


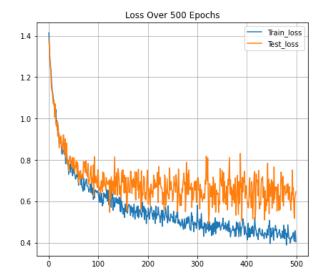


Test loss: 0.8460082411766052 Test accuracy: 0.6388888955116272

Adding more layers did very little to change the accuracy of the model at all, but managed to have slightly lower accuracy than our simpler first model! We were disappointed but given our first model can find more complicated weights and is already building off of the VGG16 model, it is not entirely surprising in retrospect either.

Extra data augmentation:

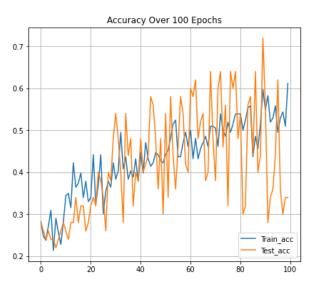


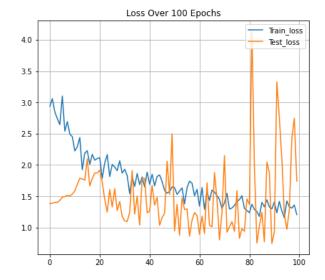


Test loss: 0.7342052459716797 Test accuracy: 0.6944444179534912

Adding many more epochs and augmenting the data did not seem to help much. After a certain point, much like our first one, it leveled out around the same spot. This was also slightly disappointing, since we had figured that more data would be the limiting factor that could make our model improve, but with the extra data augmentation, while our training set could improve, our testing set still didn't. Perhaps we needed truly novel new data to help perform better, instead of label preserving transformations which can only do so much.

AlexNet:





Test loss: 1.9850109815597534

Test accuracy: 0.5277777910232544

Alexnet's performance left a lot to be desired. It bounced all over the place, was very inconsistent, and the most complicated of our models, so it seemed clear to us not to spend too much time pursuing this route. Although it does

Our best attempt turned out to be with our first and most simple model. While we are somewhat happy with the accuracy, and feel good having thoroughly exhausted other options, it does feel a bit strange having these additional tools not work very well on this particular task!

t-SNE Visualization:

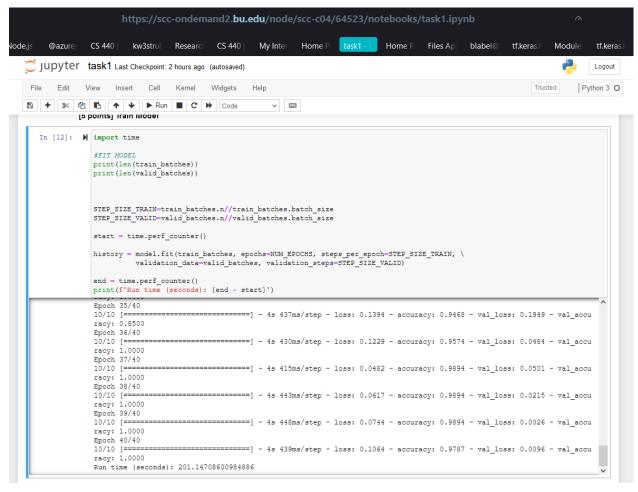
We could not successfully use t-SNE to visualize our categorical data, but we will leave the code for that section and our changes to it here.

```
from sklearn.manifold import TSNE
intermediate layer model = tf.keras.models.Model(inputs=model.input,
outputs=model.get layer('dense 2').output)
tsne data generator =
test_datagen.flow_from_directory(DATASET_PATH, target size=IMAGE SIZE,
batch size=1, shuffle=False, seed=42, class mode="binary")
intermediate layer model.compile(optimizer='adam',
                loss='categorical crossentropy',
                metrics=['accuracy'])
predictions = intermediate layer model.predict(tsne data generator)
tsne model = TSNE(n components=4, perplexity=48, learning rate='auto',
init='pca', square distances=True).fit transform(predictions)
tsne_data_generator.reset
print(tsne_model.shape)
plt.scatter(tsne_model[:, 0], tsne_model[:, 1],
c=tsne data generator.labels)
```

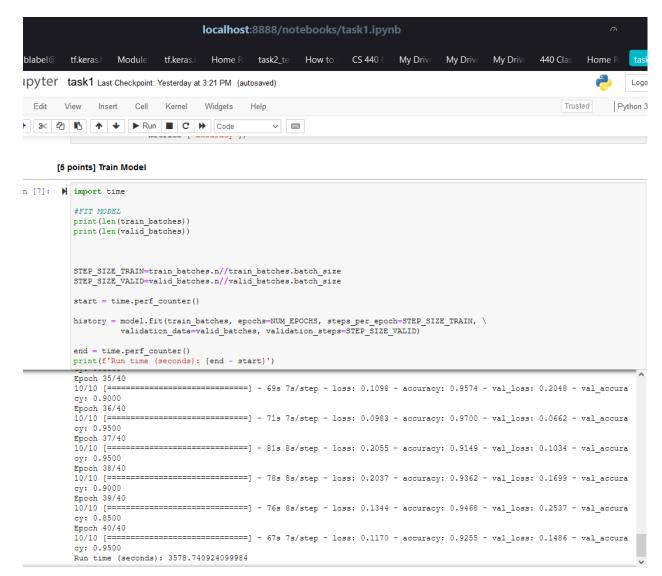
plt.show()

Bonus:

We set up our notebook to run using the GPUs in the SCC cluster. Doing so led to a massive boost in performance! We asked for 2 hours with 4 CPU cores, and 4 GPU cores (using the 3.5 setting so that any available GPU cards would be considered. Here is the time it took to train the first model in the SCC cluster:



201.147 seconds! Now, for running it locally on my laptop without a GPU:



3578 seconds! More than 10x slower! It is clear that having a GPU that can do these calculations using hardware suited for the job is a great enabler for deep learning tasks.

[30 points] Report

- o [5 points] Describe the architectures used in detail: layers, layer dimensions, dropout layers, etc. for both tasks. List the optimizer, loss function, parameters, and any regularization used in both tasks
- [10 points] Comparison of the performance of different architectures for the second task and relating this to the architecture and parameter settings used

- [10 points] Plot and comment on the accuracy and the loss for both tasks
- o [5 points] Plot and comment on the t-SNE visualizations
- o [Bonus: 5 points] Run the training on a GPU on the SCC cluster and include a CPU
- vs. GPU training time comparison by taking snapshots from your terminal

Task 1 Code

Jupyter Notebook printout, ran in Google Colab

Class Challenge: Image Classification of COVID-19 X-rays Task 1 [Total points: 30]

Setup

- This assignment involves the following packages: 'matplotlib', 'numpy', and 'sklearn'.
- If you are using conda, use the following commands to install the above packages:

```
conda install matplotlib
conda install numpy
conda install -c anaconda scikit-learn
```

• If you are using pip, use use the following commands to install the above packages:

```
pip install matplotlib
pip install numpy
pip install sklearn
```

Google Colab moment

```
Cloning into 'CS440-Class-Challenge'...
remote: Enumerating objects: 336, done.
remote: Counting objects: 100% (336/336), done.
remote: Compressing objects: 100% (331/331), done.
remote: Total 336 (delta 3), reused 333 (delta 3), pack-reused 0
Receiving objects: 100% (336/336), 83.51 MiB | 30.81 MiB/s, done.
Resolving deltas: 100% (3/3), done.
```

!git clone https://github.com/RichardChen123/CS440-Class-Challenge.git

Data

Please download the data using the following link: <u>COVID-19</u>.

Checking out files: 100% (465/465), done.

• After downloading 'Covid_Data_GradientCrescent.zip', unzip the file and you should see the

|----train

|----test

• Put the 'all' folder, the 'two' folder and this python notebook in the **same directory** so that the following code can correctly locate the data.

[20 points] Binary Classification: COVID-19 vs. Normal

```
import os
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
os.environ['OMP_NUM_THREADS'] = '1'
os.environ['CUDA_VISIBLE_DEVICES'] = '-1'
tf.__version__
'2.7.0'
```

Load Image Data

```
DATA_LIST -= ·os.listdir('_/content/CS440-Class-Challenge/two/train')

DATASET_PATH · · = · ' /content/CS440-Class-Challenge/two/train'

TEST_DIR · = · · ' /content/CS440-Class-Challenge/two/test'

IMAGE_SIZE = (224, 224)

NUM_CLASSES = len(DATA_LIST)

BATCH_SIZE = 10  # try reducing batch size or freeze more layers if your GPU run

NUM_EPOCHS = 40

LEARNING_RATE = 0.0005  # start off with high rate first 0.001 and experiment with 1
```

Generate Training and Validation Batches

```
train_datagen = ImageDataGenerator(rescale=1./255,rotation_range=50,featurewise_cerfeaturewise_std_normalization = True,width_shift
```

```
class_mode="binary")
/usr/local/lib/python3.7/dist-packages/keras_preprocessing/image/image_data_granings.warn('This ImageDataGenerator specifies '
Found 104 images belonging to 2 classes.
Found 26 images belonging to 2 classes.
```

subset = "validation", seed=42,

[10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

```
vgg16 = tf.keras.applications.VGG16(weights='imagenet', include top=False, input sl
vgg16.trainable = False
model = tf.keras.models.Sequential([
   vaa16,
   tf.keras.layers.Flatten(),
   tf.keras.layers.Dense(1000, activation='relu'),
   tf.keras.layers.Dropout(rate=0.2),
   tf.keras.layers.Dense(500, activation='relu'),
   tf.keras.layers.Dropout(rate=0.2),
   tf.keras.layers.Dense(125, activation='relu'),
   tf.keras.layers.Dropout(rate=0.2),
   tf.keras.layers.Dense(1, activation='sigmoid')
])
   Downloading data from https://storage.googleapis.com/tensorflow/keras-applica
   58892288/58889256 [==============] - 0s Ous/step
    model.summary()
   Model: "sequential"
                                                 Param #
    Layer (type)
                           Output Shape
```

```
Trainable params: 25,652,251
Non-trainable params: 14,714,688
```

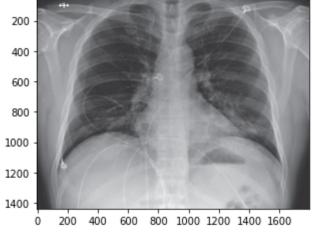
[5 points] Train Model

```
Epoch 16/40
Epoch 17/40
Epoch 18/40
Epoch 19/40
Epoch 20/40
Epoch 21/40
Epoch 22/40
Epoch 23/40
Epoch 24/40
Epoch 25/40
Epoch 26/40
```

[5 points] Plot Accuracy and Loss During Training

OF CC OC C2 OF C2

Plot Test Results



covid/nejmoa2001191_f5-PA.jpeg

validation_data=valid_batches, validation_steps=STEP_SIZE_VALID)

tsne_model = TSNE(n_components=2, perplexity=48, learning_rate='auto', init='pca',
tsne_data_generator.reset

Found 130 images belonging to 2 classes.

Task 2 Code

Jupyter Notebook printout, ran in Google Colab

Class Challenge: Image Classification of COVID-19 X-rays

Task 2 [Total points: 30]

Setup

- This assignment involves the following packages: 'matplotlib', 'numpy', and 'sklearn'.
- If you are using conda, use the following commands to install the above packages:

```
conda install matplotlib
conda install numpy
conda install -c anaconda scikit-learn
```

• If you are using pip, use use the following commands to install the above packages:

```
pip install matplotlib
pip install numpy
pip install sklearn
```

Data

Please download the data using the following link: COVID-19.

 After downloading 'Covid_Data_GradientCrescent.zip', unzip the file and you should see the following data structure:

```
|--all
|-----train
|-----test
|--two
|-----train
|-----test
```

• Put the 'all' folder, the 'two' folder and this python notebook in the **same directory** so that the following code can correctly locate the data.

[20 points] Multi-class Classification

```
import os

import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
os.environ['OMP_NUM_THREADS'] = '1'
os.environ['CUDA_VISIBLE_DEVICES'] = '-1'
tf.__version__

Out[2]:
```

Load Image Data

```
In [20]: DATA_LIST = os.listdir('all/train')
    DATASET_PATH = 'all/train'
    TEST_DIR = 'all/test'
    IMAGE_SIZE = (224, 224)
    NUM_CLASSES = len(DATA_LIST)
    BATCH_SIZE = 10 # try reducing batch size or freeze more layers if your GPU runs ou
    NUM_EPOCHS = 100
    LEARNING_RATE = 0.0005 # start off with high rate first 0.001 and experiment with reduc
```

Generate Training and Validation Batches

Found 216 images belonging to 4 classes. Found 54 images belonging to 4 classes.

C:\ProgramData\Anaconda3\lib\site-packages\keras_preprocessing\image\image_data_generato r.py:342: UserWarning: This ImageDataGenerator specifies `zca_whitening` which overrides setting of`featurewise_std_normalization`.

warnings.warn('This ImageDataGenerator specifies '

Model 1: VGG16

[10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

```
vgg16 = tf.keras.applications.VGG16(weights='imagenet', include_top=False, input_shape=
vgg16.trainable = False
```

```
model = tf.keras.Sequential([
    vgg16,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(4, activation='softmax')
])
model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['categorical_crossentropy', metrics = ['categorical_crossentropy']]
```

In [6]:

In [8]:

model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 128)	3211392
dense_1 (Dense)	(None, 4)	516
=======================================	=======================================	========

Total params: 17,926,596 Trainable params: 3,211,908 Non-trainable params: 14,714,688

[5 points] Train Model

#FIT MODEL

```
print(len(train batches))
print(len(valid batches))
STEP SIZE TRAIN=train batches.n//train batches.batch size
STEP SIZE VALID=valid batches.n//valid batches.batch size
res = model.fit(train batches, epochs=NUM EPOCHS, steps per epoch=STEP SIZE TRAIN, \
         validation data=valid batches, validation steps=STEP SIZE VALID)
22
C:\ProgramData\Anaconda3\lib\site-packages\keras preprocessing\image\image data generato
r.py:720: UserWarning: This ImageDataGenerator specifies `featurewise_center`, but it ha
sn't been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
 warnings.warn('This ImageDataGenerator specifies '
C:\ProgramData\Anaconda3\lib\site-packages\keras preprocessing\image\image data generato
r.py:739: UserWarning: This ImageDataGenerator specifies `zca whitening`, but it hasn't
been fit on any training data. Fit it first by calling `.fit(numpy data)`.
 warnings.warn('This ImageDataGenerator specifies '
Epoch 1/100
uracy: 0.3641 - val_loss: 1.0474 - val_categorical_accuracy: 0.5200
Epoch 2/100
```

```
uracy: 0.5049 - val_loss: 0.9806 - val_categorical_accuracy: 0.6400
Epoch 3/100
uracy: 0.5388 - val_loss: 1.4163 - val_categorical_accuracy: 0.5600
Epoch 4/100
uracy: 0.5485 - val loss: 1.2122 - val categorical accuracy: 0.5800
Epoch 5/100
uracy: 0.5922 - val loss: 1.0407 - val categorical accuracy: 0.4800
Epoch 6/100
uracy: 0.5922 - val_loss: 0.9112 - val_categorical_accuracy: 0.6400
Epoch 7/100
uracy: 0.6796 - val_loss: 0.8962 - val_categorical_accuracy: 0.7200
Epoch 8/100
uracy: 0.6019 - val loss: 0.7324 - val categorical accuracy: 0.6600
Epoch 9/100
uracy: 0.6359 - val_loss: 0.8045 - val_categorical_accuracy: 0.6200
Epoch 10/100
uracy: 0.6748 - val_loss: 0.8133 - val_categorical_accuracy: 0.7000
Epoch 11/100
uracy: 0.6602 - val_loss: 0.8591 - val_categorical_accuracy: 0.6000
Epoch 12/100
uracy: 0.6796 - val_loss: 0.8321 - val_categorical_accuracy: 0.6400
Epoch 13/100
uracy: 0.7039 - val_loss: 0.8407 - val_categorical_accuracy: 0.6600
Epoch 14/100
uracy: 0.7233 - val_loss: 1.0960 - val_categorical_accuracy: 0.5200
Epoch 15/100
uracy: 0.6748 - val_loss: 0.6260 - val_categorical_accuracy: 0.7000
uracy: 0.6165 - val_loss: 1.0902 - val_categorical_accuracy: 0.5800
Epoch 17/100
uracy: 0.6117 - val_loss: 1.3743 - val_categorical_accuracy: 0.4600
Epoch 18/100
uracy: 0.6748 - val_loss: 0.6242 - val_categorical_accuracy: 0.7200
Epoch 19/100
uracy: 0.6505 - val loss: 0.7225 - val categorical accuracy: 0.7000
Epoch 20/100
uracy: 0.6990 - val_loss: 0.8855 - val_categorical_accuracy: 0.5000
Epoch 21/100
uracy: 0.7087 - val_loss: 0.5505 - val_categorical_accuracy: 0.8000
Epoch 22/100
```

```
uracy: 0.6796 - val_loss: 0.7556 - val_categorical_accuracy: 0.5600
Epoch 23/100
uracy: 0.6893 - val_loss: 0.7624 - val_categorical_accuracy: 0.6400
Epoch 24/100
uracy: 0.6845 - val loss: 0.5872 - val categorical accuracy: 0.8200
Epoch 25/100
uracy: 0.6990 - val loss: 0.6140 - val categorical accuracy: 0.7200
Epoch 26/100
uracy: 0.6650 - val_loss: 0.7307 - val_categorical_accuracy: 0.6400
Epoch 27/100
uracy: 0.6505 - val_loss: 0.6007 - val_categorical_accuracy: 0.6800
Epoch 28/100
uracy: 0.6650 - val loss: 0.6771 - val categorical accuracy: 0.6600
uracy: 0.7476 - val_loss: 0.5150 - val_categorical_accuracy: 0.7400
Epoch 30/100
uracy: 0.7282 - val_loss: 0.8201 - val_categorical_accuracy: 0.7000
Epoch 31/100
uracy: 0.7427 - val loss: 0.6378 - val categorical accuracy: 0.7200
Epoch 32/100
uracy: 0.7330 - val_loss: 0.5242 - val_categorical_accuracy: 0.7800
Epoch 33/100
uracy: 0.7573 - val_loss: 0.5628 - val_categorical_accuracy: 0.7400
Epoch 34/100
uracy: 0.6796 - val_loss: 0.6085 - val_categorical_accuracy: 0.6400
Epoch 35/100
uracy: 0.7573 - val_loss: 1.3283 - val_categorical_accuracy: 0.6000
uracy: 0.6602 - val_loss: 0.7400 - val_categorical_accuracy: 0.6400
Epoch 37/100
uracy: 0.6408 - val_loss: 0.6764 - val_categorical_accuracy: 0.6600
Epoch 38/100
uracy: 0.6990 - val_loss: 1.0589 - val_categorical_accuracy: 0.5600
Epoch 39/100
uracy: 0.7087 - val loss: 0.6743 - val categorical accuracy: 0.6200
Epoch 40/100
uracy: 0.7621 - val_loss: 0.7640 - val_categorical_accuracy: 0.6400
Epoch 41/100
uracy: 0.7233 - val_loss: 0.9113 - val_categorical_accuracy: 0.6000
Epoch 42/100
```

```
uracy: 0.7039 - val_loss: 0.7954 - val_categorical_accuracy: 0.6800
Epoch 43/100
uracy: 0.7476 - val_loss: 0.5490 - val_categorical_accuracy: 0.6800
Epoch 44/100
uracy: 0.7621 - val loss: 0.6132 - val categorical accuracy: 0.7200
Epoch 45/100
uracy: 0.7718 - val loss: 0.7525 - val categorical accuracy: 0.6600
Epoch 46/100
uracy: 0.7573 - val_loss: 0.5611 - val_categorical_accuracy: 0.7000
Epoch 47/100
uracy: 0.7524 - val_loss: 0.5471 - val_categorical_accuracy: 0.7800
Epoch 48/100
uracy: 0.7816 - val loss: 0.6566 - val categorical accuracy: 0.6600
Epoch 49/100
uracy: 0.7767 - val_loss: 0.5557 - val_categorical_accuracy: 0.7400
Epoch 50/100
uracy: 0.7913 - val_loss: 0.7965 - val_categorical_accuracy: 0.6400
Epoch 51/100
uracy: 0.7330 - val loss: 0.8610 - val categorical accuracy: 0.6400
Epoch 52/100
uracy: 0.7718 - val_loss: 0.9379 - val_categorical_accuracy: 0.6200
Epoch 53/100
uracy: 0.7476 - val_loss: 0.8440 - val_categorical_accuracy: 0.6000
Epoch 54/100
uracy: 0.7476 - val_loss: 0.6495 - val_categorical_accuracy: 0.7600
Epoch 55/100
uracy: 0.7864 - val_loss: 0.6188 - val_categorical_accuracy: 0.7000
uracy: 0.7427 - val_loss: 0.5679 - val_categorical_accuracy: 0.7400
Epoch 57/100
uracy: 0.7476 - val_loss: 0.6813 - val_categorical_accuracy: 0.6000
Epoch 58/100
uracy: 0.7476 - val_loss: 0.5886 - val_categorical_accuracy: 0.7200
Epoch 59/100
uracy: 0.7524 - val loss: 0.6768 - val categorical accuracy: 0.7200
Epoch 60/100
uracy: 0.8010 - val_loss: 0.6979 - val_categorical_accuracy: 0.7200
Epoch 61/100
uracy: 0.7233 - val_loss: 0.6975 - val_categorical_accuracy: 0.6000
Epoch 62/100
```

```
uracy: 0.7233 - val_loss: 0.7930 - val_categorical_accuracy: 0.6600
Epoch 63/100
uracy: 0.7767 - val_loss: 0.7554 - val_categorical_accuracy: 0.5800
Epoch 64/100
uracy: 0.7282 - val loss: 0.4864 - val categorical accuracy: 0.7800
Epoch 65/100
uracy: 0.7233 - val loss: 0.7780 - val categorical accuracy: 0.6200
Epoch 66/100
uracy: 0.7621 - val_loss: 0.9396 - val_categorical_accuracy: 0.5600
Epoch 67/100
uracy: 0.7282 - val_loss: 0.8330 - val_categorical_accuracy: 0.6200
Epoch 68/100
uracy: 0.7621 - val loss: 0.7627 - val categorical accuracy: 0.6400
Epoch 69/100
uracy: 0.8058 - val_loss: 0.8683 - val_categorical_accuracy: 0.6000
Epoch 70/100
uracy: 0.7184 - val_loss: 1.2533 - val_categorical_accuracy: 0.5400
Epoch 71/100
uracy: 0.6748 - val loss: 0.7456 - val categorical accuracy: 0.6400
Epoch 72/100
uracy: 0.7816 - val_loss: 0.8743 - val_categorical_accuracy: 0.6600
Epoch 73/100
uracy: 0.7427 - val_loss: 0.5851 - val_categorical_accuracy: 0.7000
Epoch 74/100
uracy: 0.7621 - val_loss: 0.5795 - val_categorical_accuracy: 0.7200
Epoch 75/100
uracy: 0.7961 - val_loss: 0.6762 - val_categorical_accuracy: 0.7000
uracy: 0.8107 - val_loss: 0.6786 - val_categorical_accuracy: 0.7200
Epoch 77/100
uracy: 0.7767 - val_loss: 0.8066 - val_categorical_accuracy: 0.6400
Epoch 78/100
uracy: 0.7864 - val loss: 1.1145 - val categorical accuracy: 0.6200
Epoch 79/100
uracy: 0.7621 - val loss: 0.4777 - val categorical accuracy: 0.8400
Epoch 80/100
uracy: 0.7864 - val_loss: 0.5568 - val_categorical_accuracy: 0.7600
Epoch 81/100
uracy: 0.7816 - val_loss: 0.6957 - val_categorical_accuracy: 0.6600
Epoch 82/100
```

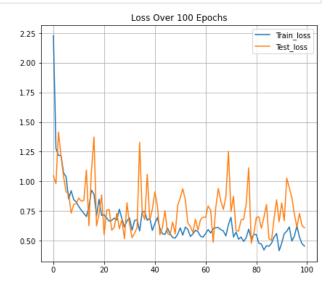
```
uracy: 0.8107 - val_loss: 0.7011 - val_categorical_accuracy: 0.6800
Epoch 83/100
uracy: 0.8155 - val_loss: 0.6044 - val_categorical_accuracy: 0.6800
Epoch 84/100
uracy: 0.8155 - val loss: 0.6969 - val categorical accuracy: 0.6600
Epoch 85/100
uracy: 0.7864 - val loss: 0.8051 - val categorical accuracy: 0.7000
Epoch 86/100
uracy: 0.8252 - val_loss: 0.5153 - val_categorical_accuracy: 0.7000
Epoch 87/100
uracy: 0.7961 - val_loss: 0.5039 - val_categorical_accuracy: 0.7400
Epoch 88/100
uracy: 0.7767 - val loss: 0.6858 - val categorical accuracy: 0.6600
uracy: 0.7913 - val_loss: 0.8444 - val_categorical_accuracy: 0.7000
Epoch 90/100
uracy: 0.8252 - val_loss: 0.6589 - val_categorical_accuracy: 0.7400
Epoch 91/100
uracy: 0.7816 - val_loss: 0.8178 - val_categorical_accuracy: 0.6000
Epoch 92/100
uracy: 0.7573 - val_loss: 0.6674 - val_categorical_accuracy: 0.6800
Epoch 93/100
uracy: 0.7379 - val_loss: 1.0272 - val_categorical_accuracy: 0.6600
Epoch 94/100
uracy: 0.7184 - val_loss: 0.9452 - val_categorical_accuracy: 0.6000
Epoch 95/100
uracy: 0.7670 - val_loss: 0.8646 - val_categorical_accuracy: 0.6200
uracy: 0.7864 - val_loss: 0.7234 - val_categorical_accuracy: 0.6400
Epoch 97/100
uracy: 0.7136 - val_loss: 0.6121 - val_categorical_accuracy: 0.6400
Epoch 98/100
uracy: 0.7573 - val_loss: 0.7294 - val_categorical_accuracy: 0.6000
Epoch 99/100
uracy: 0.8058 - val loss: 0.6275 - val categorical accuracy: 0.6800
Epoch 100/100
uracy: 0.8252 - val_loss: 0.6081 - val_categorical_accuracy: 0.7000
```

[5 points] Plot Accuracy and Loss During Training

```
In [9]: import matplotlib.pyplot as plt
```

```
fig, (ax1, ax2) = plt.subplots(1, 2)
fig.set_figheight(6)
fig.set_figwidth(15)
ax1.plot(res.history['categorical_accuracy'])
ax1.plot(res.history['val_categorical_accuracy'])
ax1.set_title('Accuracy Over ' + str(NUM_EPOCHS) + ' Epochs')
ax1.legend(['Train_acc', 'Test_acc'], loc='lower right')
ax1.grid(True)
ax2.set_title('Loss Over ' + str(NUM_EPOCHS) + ' Epochs')
ax2.plot(res.history['loss'])
ax2.plot(res.history['val_loss'])
ax2.legend(['Train_loss', 'Test_loss'], loc='upper right')
ax2.grid(True)
plt.show()
```





Testing Model

[10 points] TSNE Plot

t-Distributed Stochastic Neighbor Embedding (t-SNE) is a widely used technique for dimensionality reduction that is particularly well suited for the visualization of high-dimensional datasets. After training is complete, extract features from a specific deep layer of your choice, use t-SNE to reduce the dimensionality of your extracted features to 2 dimensions and plot the resulting 2D features.

```
In [15]:
          from sklearn.manifold import TSNE
          intermediate layer model = models.Model(inputs=model.input,
                                                   outputs=model.get layer('feature dense').output
          tsne eval generator = test datagen.flow from directory(DATASET PATH,target size=IMAGE S
                                                             batch size=1, shuffle=True, seed=42, cla
          raise NotImplementedError("Extract features from the tsne data generator and fit a t-SN
                                     "and plot the resulting 2D features of the four classes.")
         Found 270 images belonging to 4 classes.
         {'covid': 0, 'normal': 1, 'pneumonia bac': 2, 'pneumonia vir': 3}
         Extracting features for 270 images.
         270/270 [=========== ] - 71s 265ms/step
         Training TSNE model.
           15
           10
            5
                                                 COVID-19
                                                 Normal
            0
                                                 Pneumonia bac
                                                 Pneumonia vir
          -10
```

Attempt 2: Revising the vgg16 model with additional layers

10

[10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

15

20

```
vgg16 = tf.keras.applications.VGG16(weights='imagenet', include_top=False, input_shape=
vgg16.trainable = False
model = tf.keras.Sequential([
    vgg16,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(500, activation='relu'),
```

-15

-15

```
tf.keras.layers.Dropout(rate=0.2),
    tf.keras.layers.Dense(125, activation='relu'),
    tf.keras.layers.Dropout(rate=0.2),
    tf.keras.layers.Dense(4, activation='softmax')
])
model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate=1e-5), loss = 'categor'
    metrics = ['categorical_accuracy'])
```

In [107...

model.summary()

Model: "sequential_25"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten_25 (Flatten)	(None, 25088)	0
dense_76 (Dense)	(None, 500)	12544500
dropout_49 (Dropout)	(None, 500)	0
dense_77 (Dense)	(None, 125)	62625
dropout_50 (Dropout)	(None, 125)	0
dense_78 (Dense)	(None, 4)	504 ======

Total params: 27,322,317 Trainable params: 12,607,629 Non-trainable params: 14,714,688

[5 points] Train Model

```
uracy: 0.3058 - val_loss: 1.2964 - val_categorical_accuracy: 0.4400
Epoch 4/100
uracy: 0.3495 - val_loss: 1.2727 - val_categorical_accuracy: 0.4000
Epoch 5/100
uracy: 0.3952 - val loss: 1.2660 - val categorical accuracy: 0.4000
Epoch 6/100
uracy: 0.3738 - val loss: 1.1904 - val categorical accuracy: 0.5400
Epoch 7/100
uracy: 0.4466 - val_loss: 1.1790 - val_categorical_accuracy: 0.4400
Epoch 8/100
uracy: 0.4369 - val_loss: 1.1511 - val_categorical_accuracy: 0.4400
Epoch 9/100
uracy: 0.4903 - val loss: 1.1022 - val categorical accuracy: 0.5800
uracy: 0.5291 - val_loss: 1.0469 - val_categorical_accuracy: 0.6200
Epoch 11/100
uracy: 0.4757 - val_loss: 1.0814 - val_categorical_accuracy: 0.5200
Epoch 12/100
uracy: 0.5728 - val loss: 1.0509 - val categorical accuracy: 0.4800
Epoch 13/100
uracy: 0.5437 - val_loss: 1.0136 - val_categorical_accuracy: 0.5400
Epoch 14/100
uracy: 0.5680 - val_loss: 0.9926 - val_categorical_accuracy: 0.6200
Epoch 15/100
uracy: 0.5049 - val_loss: 0.9945 - val_categorical_accuracy: 0.5000
Epoch 16/100
uracy: 0.5049 - val_loss: 0.9241 - val_categorical_accuracy: 0.6200
uracy: 0.6068 - val_loss: 0.9012 - val_categorical_accuracy: 0.6400
Epoch 18/100
uracy: 0.5243 - val_loss: 1.0218 - val_categorical_accuracy: 0.4800
Epoch 19/100
uracy: 0.5922 - val_loss: 0.9368 - val_categorical_accuracy: 0.6000
Epoch 20/100
uracy: 0.5680 - val loss: 0.9529 - val categorical accuracy: 0.5200
Epoch 21/100
uracy: 0.5243 - val_loss: 0.9011 - val_categorical_accuracy: 0.5600
Epoch 22/100
uracy: 0.5922 - val_loss: 0.8851 - val_categorical_accuracy: 0.6800
Epoch 23/100
```

```
uracy: 0.6019 - val_loss: 0.8752 - val_categorical_accuracy: 0.6400
Epoch 24/100
uracy: 0.6165 - val_loss: 0.8295 - val_categorical_accuracy: 0.6600
Epoch 25/100
uracy: 0.5825 - val loss: 0.9095 - val categorical accuracy: 0.6000
Epoch 26/100
uracy: 0.5777 - val loss: 0.8205 - val categorical accuracy: 0.7600
Epoch 27/100
uracy: 0.5922 - val_loss: 0.9387 - val_categorical_accuracy: 0.5200
Epoch 28/100
uracy: 0.5810 - val_loss: 0.8439 - val_categorical_accuracy: 0.6800
Epoch 29/100
uracy: 0.6456 - val loss: 0.8396 - val categorical accuracy: 0.5800
Epoch 30/100
uracy: 0.5905 - val_loss: 0.8276 - val_categorical_accuracy: 0.6000
Epoch 31/100
uracy: 0.6408 - val_loss: 0.8018 - val_categorical_accuracy: 0.6800
Epoch 32/100
uracy: 0.6845 - val loss: 0.8046 - val categorical accuracy: 0.7000
Epoch 33/100
uracy: 0.6845 - val_loss: 0.8323 - val_categorical_accuracy: 0.6600
Epoch 34/100
uracy: 0.6214 - val_loss: 0.8489 - val_categorical_accuracy: 0.6400
Epoch 35/100
uracy: 0.6359 - val_loss: 0.8607 - val_categorical_accuracy: 0.5800
Epoch 36/100
uracy: 0.6408 - val_loss: 0.9271 - val_categorical_accuracy: 0.5400
uracy: 0.5777 - val_loss: 0.8072 - val_categorical_accuracy: 0.6000
Epoch 38/100
uracy: 0.6165 - val_loss: 0.7877 - val_categorical_accuracy: 0.6400
Epoch 39/100
uracy: 0.6019 - val_loss: 0.7711 - val_categorical_accuracy: 0.6200
Epoch 40/100
uracy: 0.6214 - val loss: 0.8392 - val categorical accuracy: 0.6200
Epoch 41/100
uracy: 0.6553 - val_loss: 0.8123 - val_categorical_accuracy: 0.6000
Epoch 42/100
uracy: 0.6699 - val_loss: 0.7008 - val_categorical_accuracy: 0.6800
Epoch 43/100
```

```
uracy: 0.6262 - val_loss: 0.7835 - val_categorical_accuracy: 0.5800
Epoch 44/100
uracy: 0.6762 - val_loss: 0.8003 - val_categorical_accuracy: 0.6400
Epoch 45/100
uracy: 0.6359 - val loss: 0.8018 - val categorical accuracy: 0.6000
Epoch 46/100
uracy: 0.6796 - val loss: 0.7967 - val categorical accuracy: 0.6000
Epoch 47/100
uracy: 0.6650 - val_loss: 0.7897 - val_categorical_accuracy: 0.6000
Epoch 48/100
uracy: 0.6650 - val_loss: 0.7925 - val_categorical_accuracy: 0.6000
Epoch 49/100
uracy: 0.6408 - val loss: 0.7188 - val categorical accuracy: 0.6600
Epoch 50/100
uracy: 0.6748 - val_loss: 0.9118 - val_categorical_accuracy: 0.5200
Epoch 51/100
uracy: 0.6796 - val_loss: 0.7118 - val_categorical_accuracy: 0.6600
Epoch 52/100
uracy: 0.6381 - val loss: 0.8619 - val categorical accuracy: 0.6000
Epoch 53/100
uracy: 0.6456 - val_loss: 0.8276 - val_categorical_accuracy: 0.6200
Epoch 54/100
uracy: 0.6952 - val_loss: 0.7786 - val_categorical_accuracy: 0.6400
Epoch 55/100
uracy: 0.6262 - val_loss: 0.7834 - val_categorical_accuracy: 0.5400
Epoch 56/100
uracy: 0.7039 - val_loss: 0.7350 - val_categorical_accuracy: 0.6600
uracy: 0.6990 - val_loss: 0.7322 - val_categorical_accuracy: 0.6400
Epoch 58/100
uracy: 0.7039 - val_loss: 0.7506 - val_categorical_accuracy: 0.7000
Epoch 59/100
uracy: 0.6650 - val_loss: 0.7285 - val_categorical_accuracy: 0.6400
Epoch 60/100
uracy: 0.6845 - val loss: 0.7820 - val categorical accuracy: 0.5600
Epoch 61/100
uracy: 0.7039 - val_loss: 0.7406 - val_categorical_accuracy: 0.6400
Epoch 62/100
uracy: 0.6553 - val_loss: 0.7649 - val_categorical_accuracy: 0.5800
Epoch 63/100
```

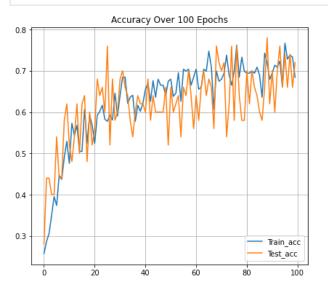
```
uracy: 0.6602 - val_loss: 0.7345 - val_categorical_accuracy: 0.6600
Epoch 64/100
uracy: 0.7039 - val_loss: 0.6959 - val_categorical_accuracy: 0.7000
Epoch 65/100
uracy: 0.6990 - val loss: 0.6780 - val categorical accuracy: 0.6400
Epoch 66/100
uracy: 0.7476 - val loss: 0.7135 - val categorical accuracy: 0.6800
Epoch 67/100
uracy: 0.7087 - val_loss: 0.6518 - val_categorical_accuracy: 0.6600
Epoch 68/100
uracy: 0.6068 - val_loss: 0.8039 - val_categorical_accuracy: 0.5600
Epoch 69/100
uracy: 0.6990 - val loss: 0.7028 - val categorical accuracy: 0.7600
uracy: 0.6748 - val_loss: 0.7585 - val_categorical_accuracy: 0.7200
Epoch 71/100
uracy: 0.6796 - val_loss: 0.7324 - val_categorical_accuracy: 0.7000
Epoch 72/100
uracy: 0.6942 - val_loss: 0.6031 - val_categorical_accuracy: 0.7200
Epoch 73/100
uracy: 0.7379 - val_loss: 0.7213 - val_categorical_accuracy: 0.5400
Epoch 74/100
uracy: 0.6893 - val_loss: 0.7330 - val_categorical_accuracy: 0.6200
Epoch 75/100
uracy: 0.6650 - val_loss: 0.6559 - val_categorical_accuracy: 0.7600
Epoch 76/100
uracy: 0.6990 - val_loss: 0.7027 - val_categorical_accuracy: 0.5800
uracy: 0.7621 - val_loss: 0.6649 - val_categorical_accuracy: 0.7600
Epoch 78/100
uracy: 0.6845 - val_loss: 0.6997 - val_categorical_accuracy: 0.6400
Epoch 79/100
uracy: 0.7330 - val_loss: 0.7243 - val_categorical_accuracy: 0.5800
Epoch 80/100
uracy: 0.6990 - val loss: 0.8181 - val categorical accuracy: 0.5800
Epoch 81/100
uracy: 0.6942 - val_loss: 0.6730 - val_categorical_accuracy: 0.7000
Epoch 82/100
uracy: 0.6942 - val_loss: 0.7864 - val_categorical_accuracy: 0.6200
Epoch 83/100
```

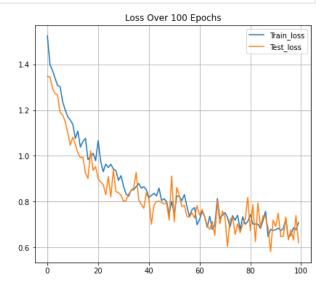
```
uracy: 0.6990 - val_loss: 0.6251 - val_categorical_accuracy: 0.7000
Epoch 84/100
uracy: 0.6942 - val_loss: 0.7933 - val_categorical_accuracy: 0.6600
Epoch 85/100
uracy: 0.7087 - val loss: 0.6870 - val categorical accuracy: 0.6400
Epoch 86/100
uracy: 0.6893 - val loss: 0.7381 - val categorical accuracy: 0.6000
Epoch 87/100
uracy: 0.6359 - val_loss: 0.7317 - val_categorical_accuracy: 0.5800
Epoch 88/100
uracy: 0.7427 - val_loss: 0.6850 - val_categorical_accuracy: 0.6600
Epoch 89/100
uracy: 0.7184 - val loss: 0.5812 - val categorical accuracy: 0.7800
Epoch 90/100
uracy: 0.6796 - val_loss: 0.7188 - val_categorical_accuracy: 0.6200
Epoch 91/100
uracy: 0.6942 - val_loss: 0.6916 - val_categorical_accuracy: 0.7000
Epoch 92/100
uracy: 0.7136 - val loss: 0.7494 - val categorical accuracy: 0.6000
Epoch 93/100
uracy: 0.7087 - val_loss: 0.6472 - val_categorical_accuracy: 0.7000
Epoch 94/100
uracy: 0.7233 - val_loss: 0.6472 - val_categorical_accuracy: 0.7600
Epoch 95/100
uracy: 0.6619 - val_loss: 0.7326 - val_categorical_accuracy: 0.6600
Epoch 96/100
uracy: 0.7670 - val_loss: 0.6320 - val_categorical_accuracy: 0.7400
uracy: 0.7282 - val_loss: 0.6764 - val_categorical_accuracy: 0.6600
Epoch 98/100
uracy: 0.7379 - val_loss: 0.6319 - val_categorical_accuracy: 0.7400
Epoch 99/100
uracy: 0.7330 - val loss: 0.7390 - val categorical accuracy: 0.6600
Epoch 100/100
uracy: 0.6845 - val loss: 0.6197 - val categorical accuracy: 0.7200
```

[5 points] Plot Accuracy and Loss During Training

```
import matplotlib.pyplot as plt
fig, (ax1, ax2) = plt.subplots(1, 2)
fig.set_figheight(6)
```

```
fig.set_figwidth(15)
ax1.plot(res.history['categorical_accuracy'])
ax1.plot(res.history['val_categorical_accuracy'])
ax1.set_title('Accuracy Over ' + str(NUM_EPOCHS) + ' Epochs')
ax1.legend(['Train_acc', 'Test_acc'], loc='lower right')
ax1.grid(True)
ax2.set_title('Loss Over ' + str(NUM_EPOCHS) + ' Epochs')
ax2.plot(res.history['loss'])
ax2.plot(res.history['val_loss'])
ax2.legend(['Train_loss', 'Test_loss'], loc='upper right')
ax2.grid(True)
plt.show()
```





Testing Model

Attempt 3: Try generating more fake data with data augmentation

Generate Training and Validation Batches

```
In [115... train_datagen = ImageDataGenerator(rescale=1./255,rotation_range=50,featurewise_center
```

Found 216 images belonging to 4 classes. Found 54 images belonging to 4 classes.

[10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

```
vgg16 = tf.keras.applications.VGG16(weights='imagenet', include_top=False, input_shape=
vgg16.trainable = False
model = tf.keras.Sequential([
    vgg16,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(4, activation='softmax')
])
model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate=1e-5),
    loss = 'categorical_crossentropy', metrics = ['categorical_accuracy'])
```

In [124...

model.summary()

Model: "sequential 29"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten_29 (Flatten)	(None, 25088)	0
dense_85 (Dense)	(None, 128)	3211392
dense_86 (Dense)	(None, 4)	516
Total params: 17,926,596 Trainable params: 3,211,908		

[5 points] Train Model

Non-trainable params: 14,714,688

```
In [125... | #FIT MODEL
```

```
Epoch 1/500
uracy: 0.2961 - val_loss: 1.3821 - val_categorical_accuracy: 0.2200
Epoch 2/500
uracy: 0.3398 - val_loss: 1.3469 - val_categorical_accuracy: 0.3000
Epoch 3/500
uracy: 0.4029 - val_loss: 1.2987 - val_categorical_accuracy: 0.5200
Epoch 4/500
uracy: 0.4078 - val_loss: 1.2541 - val_categorical_accuracy: 0.4200
Epoch 5/500
uracy: 0.4126 - val_loss: 1.2271 - val_categorical_accuracy: 0.4800
uracy: 0.5291 - val_loss: 1.1538 - val_categorical_accuracy: 0.5400
Epoch 7/500
uracy: 0.5146 - val_loss: 1.1344 - val_categorical_accuracy: 0.5400
Epoch 8/500
uracy: 0.5485 - val_loss: 1.1357 - val_categorical_accuracy: 0.4800
Epoch 9/500
uracy: 0.5485 - val loss: 1.0950 - val categorical accuracy: 0.5400
Epoch 10/500
uracy: 0.5631 - val loss: 1.0731 - val categorical accuracy: 0.6200
Epoch 11/500
uracy: 0.5194 - val_loss: 1.0887 - val_categorical_accuracy: 0.5000
Epoch 12/500
uracy: 0.5485 - val_loss: 1.0651 - val_categorical_accuracy: 0.4800
Epoch 13/500
uracy: 0.6262 - val_loss: 1.0061 - val_categorical_accuracy: 0.7400
uracy: 0.5825 - val_loss: 1.0708 - val_categorical_accuracy: 0.4800
Epoch 15/500
uracy: 0.5194 - val_loss: 0.9748 - val_categorical_accuracy: 0.6600
Epoch 16/500
uracy: 0.6359 - val loss: 0.9666 - val categorical accuracy: 0.6200
Epoch 17/500
```

```
uracy: 0.6019 - val loss: 0.9611 - val categorical accuracy: 0.6000
Epoch 18/500
uracy: 0.6602 - val loss: 0.9859 - val categorical accuracy: 0.5000
Epoch 19/500
uracy: 0.5922 - val_loss: 0.9143 - val_categorical_accuracy: 0.6600
Epoch 20/500
uracy: 0.6796 - val loss: 0.9621 - val categorical accuracy: 0.5800
Epoch 21/500
uracy: 0.6650 - val loss: 0.9041 - val categorical accuracy: 0.6400
uracy: 0.7039 - val_loss: 0.8591 - val_categorical_accuracy: 0.5800
Epoch 23/500
uracy: 0.6408 - val loss: 0.9096 - val categorical accuracy: 0.6200
Epoch 24/500
uracy: 0.6429 - val loss: 0.8812 - val categorical accuracy: 0.6400
Epoch 25/500
uracy: 0.6699 - val_loss: 0.9165 - val_categorical_accuracy: 0.6000
uracy: 0.6650 - val_loss: 0.8861 - val_categorical_accuracy: 0.5600
Epoch 27/500
uracy: 0.6942 - val_loss: 0.8626 - val_categorical_accuracy: 0.6400
Epoch 28/500
uracy: 0.7087 - val_loss: 0.8623 - val_categorical_accuracy: 0.6000
uracy: 0.6990 - val_loss: 0.8460 - val_categorical_accuracy: 0.6400
Epoch 30/500
uracy: 0.6408 - val_loss: 0.9214 - val_categorical_accuracy: 0.6400
Epoch 31/500
uracy: 0.6650 - val_loss: 0.9201 - val_categorical_accuracy: 0.6000
Epoch 32/500
uracy: 0.6952 - val loss: 0.8307 - val categorical accuracy: 0.6400
uracy: 0.6796 - val_loss: 0.8540 - val_categorical_accuracy: 0.6400
Epoch 34/500
uracy: 0.6505 - val_loss: 0.9021 - val_categorical_accuracy: 0.5200
Epoch 35/500
uracy: 0.6990 - val_loss: 0.8136 - val_categorical_accuracy: 0.6600
Epoch 36/500
uracy: 0.6748 - val_loss: 0.8104 - val_categorical_accuracy: 0.6000
Epoch 37/500
```

```
uracy: 0.6165 - val loss: 0.8809 - val categorical accuracy: 0.6200
Epoch 38/500
uracy: 0.6845 - val loss: 0.7799 - val categorical accuracy: 0.6400
Epoch 39/500
uracy: 0.6990 - val_loss: 0.7913 - val_categorical_accuracy: 0.6400
Epoch 40/500
uracy: 0.6845 - val loss: 0.7951 - val categorical accuracy: 0.6600
Epoch 41/500
uracy: 0.7379 - val_loss: 0.7460 - val_categorical_accuracy: 0.6800
uracy: 0.7233 - val_loss: 0.7928 - val_categorical_accuracy: 0.7000
Epoch 43/500
uracy: 0.6893 - val loss: 0.8132 - val categorical accuracy: 0.6000
Epoch 44/500
uracy: 0.6845 - val loss: 0.8192 - val categorical accuracy: 0.6200
Epoch 45/500
uracy: 0.7184 - val_loss: 0.7871 - val_categorical_accuracy: 0.6000
Epoch 46/500
uracy: 0.6699 - val_loss: 0.7937 - val_categorical_accuracy: 0.6000
Epoch 47/500
uracy: 0.6699 - val_loss: 0.7656 - val_categorical_accuracy: 0.6600
Epoch 48/500
uracy: 0.6990 - val_loss: 0.8123 - val_categorical_accuracy: 0.6000
uracy: 0.6942 - val_loss: 0.8031 - val_categorical_accuracy: 0.6200
uracy: 0.7233 - val_loss: 0.7603 - val_categorical_accuracy: 0.6800
Epoch 51/500
uracy: 0.7136 - val_loss: 0.7727 - val_categorical_accuracy: 0.6200
Epoch 52/500
uracy: 0.6990 - val loss: 0.8109 - val categorical accuracy: 0.6400
uracy: 0.7087 - val_loss: 0.7407 - val_categorical_accuracy: 0.6600
Epoch 54/500
uracy: 0.7427 - val_loss: 0.7707 - val_categorical_accuracy: 0.6400
Epoch 55/500
uracy: 0.7379 - val_loss: 0.7603 - val_categorical_accuracy: 0.6600
Epoch 56/500
uracy: 0.7621 - val_loss: 0.7937 - val_categorical_accuracy: 0.6200
Epoch 57/500
```

```
uracy: 0.6990 - val loss: 0.7928 - val categorical accuracy: 0.6200
Epoch 58/500
uracy: 0.7136 - val loss: 0.7332 - val categorical accuracy: 0.6400
Epoch 59/500
uracy: 0.7136 - val_loss: 0.7883 - val_categorical_accuracy: 0.6200
Epoch 60/500
uracy: 0.7136 - val loss: 0.7645 - val categorical accuracy: 0.5400
Epoch 61/500
uracy: 0.7330 - val_loss: 0.6944 - val_categorical_accuracy: 0.7600
uracy: 0.7039 - val_loss: 0.6878 - val_categorical_accuracy: 0.7000
Epoch 63/500
uracy: 0.6845 - val loss: 0.7436 - val categorical accuracy: 0.6600
Epoch 64/500
uracy: 0.6990 - val loss: 0.7091 - val categorical accuracy: 0.6800
Epoch 65/500
uracy: 0.7190 - val_loss: 0.7491 - val_categorical_accuracy: 0.6400
uracy: 0.7330 - val_loss: 0.7089 - val_categorical_accuracy: 0.6600
Epoch 67/500
uracy: 0.6893 - val_loss: 0.7178 - val_categorical_accuracy: 0.7600
Epoch 68/500
uracy: 0.7330 - val_loss: 0.7202 - val_categorical_accuracy: 0.6800
uracy: 0.7524 - val_loss: 0.7328 - val_categorical_accuracy: 0.6800
Epoch 70/500
uracy: 0.7621 - val_loss: 0.7090 - val_categorical_accuracy: 0.6800
Epoch 71/500
uracy: 0.7039 - val_loss: 0.7922 - val_categorical_accuracy: 0.6200
Epoch 72/500
uracy: 0.6699 - val loss: 0.7654 - val categorical accuracy: 0.6800
Epoch 73/500
uracy: 0.7476 - val_loss: 0.7910 - val_categorical_accuracy: 0.6200
Epoch 74/500
uracy: 0.7670 - val_loss: 0.7384 - val_categorical_accuracy: 0.6600
Epoch 75/500
uracy: 0.7524 - val_loss: 0.7511 - val_categorical_accuracy: 0.6400
Epoch 76/500
uracy: 0.7039 - val_loss: 0.7950 - val_categorical_accuracy: 0.6600
Epoch 77/500
```

```
uracy: 0.7330 - val loss: 0.7377 - val categorical accuracy: 0.6800
Epoch 78/500
uracy: 0.7621 - val loss: 0.7289 - val categorical accuracy: 0.6400
Epoch 79/500
uracy: 0.7379 - val_loss: 0.7194 - val_categorical_accuracy: 0.7200
Epoch 80/500
uracy: 0.7621 - val loss: 0.7827 - val categorical accuracy: 0.6000
Epoch 81/500
uracy: 0.7330 - val_loss: 0.6818 - val_categorical_accuracy: 0.7000
uracy: 0.7427 - val_loss: 0.6890 - val_categorical_accuracy: 0.7400
Epoch 83/500
uracy: 0.7670 - val loss: 0.7012 - val categorical accuracy: 0.6800
Epoch 84/500
uracy: 0.7379 - val loss: 0.7140 - val categorical accuracy: 0.6400
Epoch 85/500
uracy: 0.7476 - val_loss: 0.7522 - val_categorical_accuracy: 0.6200
uracy: 0.7427 - val_loss: 0.7710 - val_categorical_accuracy: 0.5200
Epoch 87/500
uracy: 0.7427 - val_loss: 0.6979 - val_categorical_accuracy: 0.7000
Epoch 88/500
uracy: 0.7330 - val_loss: 0.6852 - val_categorical_accuracy: 0.6600
uracy: 0.7476 - val_loss: 0.7164 - val_categorical_accuracy: 0.6200
Epoch 90/500
uracy: 0.7330 - val_loss: 0.6902 - val_categorical_accuracy: 0.7000
Epoch 91/500
uracy: 0.7913 - val_loss: 0.7757 - val_categorical_accuracy: 0.6000
Epoch 92/500
uracy: 0.7621 - val loss: 0.6256 - val categorical accuracy: 0.7000
uracy: 0.7670 - val_loss: 0.8152 - val_categorical_accuracy: 0.6200
Epoch 94/500
uracy: 0.7379 - val_loss: 0.6905 - val_categorical_accuracy: 0.6800
Epoch 95/500
uracy: 0.7619 - val_loss: 0.6883 - val_categorical_accuracy: 0.6800
Epoch 96/500
uracy: 0.7282 - val_loss: 0.7228 - val_categorical_accuracy: 0.7000
Epoch 97/500
```

```
uracy: 0.7476 - val loss: 0.7072 - val categorical accuracy: 0.6600
Epoch 98/500
uracy: 0.7767 - val loss: 0.6805 - val categorical accuracy: 0.6600
Epoch 99/500
uracy: 0.7330 - val_loss: 0.6660 - val_categorical_accuracy: 0.7200
Epoch 100/500
uracy: 0.7233 - val_loss: 0.7528 - val_categorical_accuracy: 0.6400
Epoch 101/500
uracy: 0.7816 - val_loss: 0.7405 - val_categorical_accuracy: 0.6000
uracy: 0.7427 - val_loss: 0.6523 - val_categorical_accuracy: 0.6200
Epoch 103/500
uracy: 0.7864 - val loss: 0.6699 - val categorical accuracy: 0.7200
Epoch 104/500
uracy: 0.7816 - val loss: 0.6656 - val categorical accuracy: 0.6800
Epoch 105/500
uracy: 0.7282 - val_loss: 0.6369 - val_categorical_accuracy: 0.7000
uracy: 0.7961 - val_loss: 0.6747 - val_categorical_accuracy: 0.7000
Epoch 107/500
uracy: 0.7379 - val_loss: 0.6994 - val_categorical_accuracy: 0.7000
Epoch 108/500
uracy: 0.7379 - val_loss: 0.6638 - val_categorical_accuracy: 0.7600
uracy: 0.8204 - val_loss: 0.6461 - val_categorical_accuracy: 0.7800
Epoch 110/500
uracy: 0.7524 - val_loss: 0.7418 - val_categorical_accuracy: 0.6800
Epoch 111/500
uracy: 0.8010 - val_loss: 0.6703 - val_categorical_accuracy: 0.6600
Epoch 112/500
uracy: 0.7573 - val loss: 0.7378 - val categorical accuracy: 0.6600
Epoch 113/500
uracy: 0.7476 - val_loss: 0.7194 - val_categorical_accuracy: 0.6200
Epoch 114/500
uracy: 0.7427 - val_loss: 0.6743 - val_categorical_accuracy: 0.7000
Epoch 115/500
uracy: 0.7427 - val_loss: 0.6859 - val_categorical_accuracy: 0.7000
Epoch 116/500
uracy: 0.7476 - val_loss: 0.6546 - val_categorical_accuracy: 0.7200
Epoch 117/500
```

```
uracy: 0.7286 - val_loss: 0.7151 - val_categorical_accuracy: 0.7200
Epoch 118/500
uracy: 0.7427 - val loss: 0.6916 - val categorical accuracy: 0.6600
Epoch 119/500
uracy: 0.7476 - val_loss: 0.6935 - val_categorical_accuracy: 0.6800
Epoch 120/500
uracy: 0.7379 - val_loss: 0.6806 - val_categorical_accuracy: 0.6600
Epoch 121/500
uracy: 0.7282 - val_loss: 0.6946 - val_categorical_accuracy: 0.7200
uracy: 0.7718 - val_loss: 0.6838 - val_categorical_accuracy: 0.7000
Epoch 123/500
uracy: 0.7767 - val loss: 0.7039 - val categorical accuracy: 0.6600
Epoch 124/500
uracy: 0.7864 - val loss: 0.5464 - val categorical accuracy: 0.7200
Epoch 125/500
uracy: 0.7718 - val_loss: 0.7020 - val_categorical_accuracy: 0.6200
Epoch 126/500
uracy: 0.7767 - val_loss: 0.6127 - val_categorical_accuracy: 0.7200
Epoch 127/500
uracy: 0.7864 - val_loss: 0.7186 - val_categorical_accuracy: 0.6800
Epoch 128/500
uracy: 0.6942 - val_loss: 0.6821 - val_categorical_accuracy: 0.7200
uracy: 0.7427 - val_loss: 0.6464 - val_categorical_accuracy: 0.7000
Epoch 130/500
uracy: 0.7379 - val_loss: 0.6983 - val_categorical_accuracy: 0.7000
Epoch 131/500
uracy: 0.7913 - val_loss: 0.6611 - val_categorical_accuracy: 0.7200
Epoch 132/500
uracy: 0.7524 - val loss: 0.6338 - val categorical accuracy: 0.7200
Epoch 133/500
uracy: 0.7621 - val_loss: 0.7271 - val_categorical_accuracy: 0.6600
Epoch 134/500
uracy: 0.7718 - val_loss: 0.8153 - val_categorical_accuracy: 0.5800
Epoch 135/500
uracy: 0.7718 - val_loss: 0.6326 - val_categorical_accuracy: 0.6800
Epoch 136/500
uracy: 0.7670 - val_loss: 0.7190 - val_categorical_accuracy: 0.6200
Epoch 137/500
```

```
uracy: 0.7233 - val loss: 0.6729 - val categorical accuracy: 0.6400
Epoch 138/500
uracy: 0.7864 - val loss: 0.7383 - val categorical accuracy: 0.7000
Epoch 139/500
uracy: 0.7427 - val_loss: 0.6269 - val_categorical_accuracy: 0.7600
Epoch 140/500
uracy: 0.7816 - val loss: 0.6510 - val categorical accuracy: 0.7400
Epoch 141/500
uracy: 0.7670 - val_loss: 0.7577 - val_categorical_accuracy: 0.6600
uracy: 0.7670 - val_loss: 0.7339 - val_categorical_accuracy: 0.6800
Epoch 143/500
uracy: 0.7282 - val loss: 0.6982 - val categorical accuracy: 0.6800
Epoch 144/500
uracy: 0.7718 - val loss: 0.6339 - val categorical accuracy: 0.6600
Epoch 145/500
uracy: 0.8301 - val_loss: 0.6749 - val_categorical_accuracy: 0.6800
uracy: 0.7282 - val_loss: 0.6150 - val_categorical_accuracy: 0.7400
Epoch 147/500
uracy: 0.7961 - val_loss: 0.6319 - val_categorical_accuracy: 0.7400
Epoch 148/500
uracy: 0.7767 - val_loss: 0.7328 - val_categorical_accuracy: 0.6400
uracy: 0.7427 - val_loss: 0.7503 - val_categorical_accuracy: 0.5600
Epoch 150/500
uracy: 0.7864 - val_loss: 0.6920 - val_categorical_accuracy: 0.7200
Epoch 151/500
uracy: 0.8058 - val_loss: 0.7519 - val_categorical_accuracy: 0.6400
Epoch 152/500
uracy: 0.8204 - val loss: 0.7105 - val categorical accuracy: 0.6600
Epoch 153/500
uracy: 0.7767 - val_loss: 0.6403 - val_categorical_accuracy: 0.7200
Epoch 154/500
uracy: 0.7670 - val_loss: 0.7253 - val_categorical_accuracy: 0.5800
Epoch 155/500
uracy: 0.7767 - val_loss: 0.6426 - val_categorical_accuracy: 0.7000
Epoch 156/500
uracy: 0.7573 - val_loss: 0.6474 - val_categorical_accuracy: 0.6400
Epoch 157/500
```

```
uracy: 0.7816 - val loss: 0.7152 - val categorical accuracy: 0.7000
Epoch 158/500
uracy: 0.7621 - val_loss: 0.5751 - val_categorical_accuracy: 0.7600
Epoch 159/500
uracy: 0.7621 - val_loss: 0.5522 - val_categorical_accuracy: 0.7800
Epoch 160/500
uracy: 0.8107 - val_loss: 0.6632 - val_categorical_accuracy: 0.7400
Epoch 161/500
uracy: 0.7913 - val_loss: 0.7154 - val_categorical_accuracy: 0.7000
uracy: 0.7476 - val_loss: 0.6978 - val_categorical_accuracy: 0.6400
Epoch 163/500
uracy: 0.7816 - val loss: 0.6426 - val categorical accuracy: 0.6800
Epoch 164/500
uracy: 0.7524 - val loss: 0.6600 - val categorical accuracy: 0.7000
Epoch 165/500
uracy: 0.7718 - val_loss: 0.6410 - val_categorical_accuracy: 0.7600
uracy: 0.7524 - val_loss: 0.7462 - val_categorical_accuracy: 0.6400
Epoch 167/500
uracy: 0.7913 - val_loss: 0.7427 - val_categorical_accuracy: 0.6800
Epoch 168/500
uracy: 0.7767 - val_loss: 0.6857 - val_categorical_accuracy: 0.7200
uracy: 0.7816 - val_loss: 0.6365 - val_categorical_accuracy: 0.6800
Epoch 170/500
uracy: 0.7864 - val_loss: 0.7030 - val_categorical_accuracy: 0.6800
Epoch 171/500
uracy: 0.8155 - val_loss: 0.6679 - val_categorical_accuracy: 0.6600
Epoch 172/500
uracy: 0.7864 - val loss: 0.7113 - val categorical accuracy: 0.6000
Epoch 173/500
uracy: 0.7816 - val_loss: 0.6886 - val_categorical_accuracy: 0.7200
Epoch 174/500
uracy: 0.7718 - val_loss: 0.6664 - val_categorical_accuracy: 0.7200
Epoch 175/500
uracy: 0.8010 - val_loss: 0.7428 - val_categorical_accuracy: 0.7400
Epoch 176/500
uracy: 0.8058 - val_loss: 0.6113 - val_categorical_accuracy: 0.7200
Epoch 177/500
```

```
uracy: 0.7621 - val_loss: 0.6056 - val_categorical_accuracy: 0.7200
Epoch 178/500
uracy: 0.7816 - val loss: 0.7411 - val categorical accuracy: 0.6600
Epoch 179/500
uracy: 0.7767 - val_loss: 0.7093 - val_categorical_accuracy: 0.6400
Epoch 180/500
uracy: 0.7816 - val_loss: 0.7101 - val_categorical_accuracy: 0.6400
Epoch 181/500
uracy: 0.7718 - val_loss: 0.6531 - val_categorical_accuracy: 0.6600
uracy: 0.7767 - val_loss: 0.7552 - val_categorical_accuracy: 0.6600
Epoch 183/500
uracy: 0.8000 - val loss: 0.6147 - val categorical accuracy: 0.6400
Epoch 184/500
uracy: 0.7816 - val loss: 0.6806 - val categorical accuracy: 0.6800
Epoch 185/500
uracy: 0.7621 - val_loss: 0.6649 - val_categorical_accuracy: 0.7400
Epoch 186/500
uracy: 0.7816 - val_loss: 0.6958 - val_categorical_accuracy: 0.6800
Epoch 187/500
uracy: 0.8058 - val_loss: 0.5609 - val_categorical_accuracy: 0.7400
Epoch 188/500
uracy: 0.7864 - val_loss: 0.7479 - val_categorical_accuracy: 0.6800
uracy: 0.8204 - val_loss: 0.5969 - val_categorical_accuracy: 0.7400
Epoch 190/500
uracy: 0.8010 - val_loss: 0.6383 - val_categorical_accuracy: 0.7800
Epoch 191/500
uracy: 0.7767 - val_loss: 0.6310 - val_categorical_accuracy: 0.7200
Epoch 192/500
uracy: 0.8058 - val loss: 0.6838 - val categorical accuracy: 0.6600
Epoch 193/500
uracy: 0.7621 - val_loss: 0.7220 - val_categorical_accuracy: 0.6400
Epoch 194/500
uracy: 0.8204 - val_loss: 0.7089 - val_categorical_accuracy: 0.7400
Epoch 195/500
uracy: 0.7864 - val_loss: 0.6131 - val_categorical_accuracy: 0.7000
Epoch 196/500
uracy: 0.7476 - val_loss: 0.6436 - val_categorical_accuracy: 0.7200
Epoch 197/500
```

```
uracy: 0.7913 - val loss: 0.6058 - val categorical accuracy: 0.6800
Epoch 198/500
uracy: 0.8058 - val loss: 0.6343 - val categorical accuracy: 0.6800
Epoch 199/500
uracy: 0.7621 - val_loss: 0.6927 - val_categorical_accuracy: 0.7400
Epoch 200/500
uracy: 0.8204 - val loss: 0.7500 - val categorical accuracy: 0.6400
Epoch 201/500
uracy: 0.8010 - val_loss: 0.7077 - val_categorical_accuracy: 0.6400
uracy: 0.8107 - val_loss: 0.5865 - val_categorical_accuracy: 0.7600
Epoch 203/500
uracy: 0.7718 - val loss: 0.6647 - val categorical accuracy: 0.6800
Epoch 204/500
uracy: 0.8058 - val loss: 0.6556 - val categorical accuracy: 0.6600
Epoch 205/500
uracy: 0.7913 - val_loss: 0.6152 - val_categorical_accuracy: 0.7400
uracy: 0.7573 - val_loss: 0.5776 - val_categorical_accuracy: 0.7000
Epoch 207/500
uracy: 0.7905 - val_loss: 0.6833 - val_categorical_accuracy: 0.6400
Epoch 208/500
uracy: 0.7961 - val_loss: 0.6793 - val_categorical_accuracy: 0.7400
uracy: 0.7718 - val_loss: 0.6374 - val_categorical_accuracy: 0.7200
Epoch 210/500
uracy: 0.7767 - val_loss: 0.6513 - val_categorical_accuracy: 0.6600
Epoch 211/500
uracy: 0.7718 - val_loss: 0.6194 - val_categorical_accuracy: 0.7200
Epoch 212/500
uracy: 0.7913 - val loss: 0.6653 - val categorical accuracy: 0.6400
Epoch 213/500
uracy: 0.7913 - val_loss: 0.7259 - val_categorical_accuracy: 0.6400
Epoch 214/500
uracy: 0.7913 - val_loss: 0.6607 - val_categorical_accuracy: 0.6800
Epoch 215/500
uracy: 0.8058 - val_loss: 0.7039 - val_categorical_accuracy: 0.7200
Epoch 216/500
uracy: 0.8252 - val_loss: 0.6685 - val_categorical_accuracy: 0.6800
Epoch 217/500
```

```
uracy: 0.7670 - val_loss: 0.6666 - val_categorical_accuracy: 0.7200
Epoch 218/500
uracy: 0.7913 - val loss: 0.6870 - val categorical accuracy: 0.6200
Epoch 219/500
uracy: 0.7816 - val_loss: 0.6686 - val_categorical_accuracy: 0.6800
Epoch 220/500
uracy: 0.8107 - val loss: 0.7399 - val categorical accuracy: 0.6400
Epoch 221/500
uracy: 0.7767 - val_loss: 0.6956 - val_categorical_accuracy: 0.6200
uracy: 0.7670 - val_loss: 0.5932 - val_categorical_accuracy: 0.7200
Epoch 223/500
uracy: 0.7913 - val loss: 0.7676 - val categorical accuracy: 0.6600
Epoch 224/500
uracy: 0.7718 - val loss: 0.6810 - val categorical accuracy: 0.7200
Epoch 225/500
uracy: 0.7864 - val_loss: 0.6906 - val_categorical_accuracy: 0.6800
Epoch 226/500
uracy: 0.8204 - val_loss: 0.7155 - val_categorical_accuracy: 0.6600
Epoch 227/500
uracy: 0.8350 - val_loss: 0.6732 - val_categorical_accuracy: 0.6400
Epoch 228/500
uracy: 0.7864 - val_loss: 0.6643 - val_categorical_accuracy: 0.6400
uracy: 0.7767 - val_loss: 0.6669 - val_categorical_accuracy: 0.6800
Epoch 230/500
uracy: 0.8301 - val_loss: 0.6519 - val_categorical_accuracy: 0.7000
Epoch 231/500
uracy: 0.8058 - val_loss: 0.5853 - val_categorical_accuracy: 0.6800
Epoch 232/500
uracy: 0.7816 - val loss: 0.6421 - val categorical accuracy: 0.7400
Epoch 233/500
uracy: 0.8107 - val_loss: 0.6296 - val_categorical_accuracy: 0.7000
Epoch 234/500
uracy: 0.8155 - val_loss: 0.5566 - val_categorical_accuracy: 0.7800
Epoch 235/500
uracy: 0.7864 - val_loss: 0.7274 - val_categorical_accuracy: 0.7200
Epoch 236/500
uracy: 0.7670 - val_loss: 0.7166 - val_categorical_accuracy: 0.6600
Epoch 237/500
```

```
uracy: 0.7816 - val loss: 0.5799 - val categorical accuracy: 0.7600
Epoch 238/500
uracy: 0.7913 - val loss: 0.5992 - val categorical accuracy: 0.7200
Epoch 239/500
uracy: 0.7816 - val_loss: 0.6527 - val_categorical_accuracy: 0.6800
Epoch 240/500
uracy: 0.7767 - val_loss: 0.7102 - val_categorical_accuracy: 0.6600
Epoch 241/500
uracy: 0.8155 - val_loss: 0.6402 - val_categorical_accuracy: 0.6800
uracy: 0.7913 - val_loss: 0.6338 - val_categorical_accuracy: 0.6800
Epoch 243/500
uracy: 0.8155 - val loss: 0.6196 - val categorical accuracy: 0.7000
Epoch 244/500
uracy: 0.8252 - val loss: 0.6101 - val categorical accuracy: 0.6600
Epoch 245/500
uracy: 0.8095 - val_loss: 0.7619 - val_categorical_accuracy: 0.6400
uracy: 0.8155 - val_loss: 0.6658 - val_categorical_accuracy: 0.6600
Epoch 247/500
uracy: 0.8010 - val_loss: 0.6548 - val_categorical_accuracy: 0.6800
Epoch 248/500
uracy: 0.7767 - val_loss: 0.6949 - val_categorical_accuracy: 0.6600
uracy: 0.8048 - val_loss: 0.6564 - val_categorical_accuracy: 0.7200
Epoch 250/500
uracy: 0.7670 - val_loss: 0.6543 - val_categorical_accuracy: 0.6600
Epoch 251/500
uracy: 0.8058 - val_loss: 0.6005 - val_categorical_accuracy: 0.7000
Epoch 252/500
uracy: 0.8107 - val loss: 0.6071 - val categorical accuracy: 0.7400
Epoch 253/500
uracy: 0.7621 - val_loss: 0.6627 - val_categorical_accuracy: 0.6600
Epoch 254/500
uracy: 0.7816 - val_loss: 0.7201 - val_categorical_accuracy: 0.6600
Epoch 255/500
uracy: 0.8107 - val_loss: 0.6810 - val_categorical_accuracy: 0.6200
Epoch 256/500
uracy: 0.8204 - val_loss: 0.6815 - val_categorical_accuracy: 0.6600
Epoch 257/500
```

```
uracy: 0.8058 - val loss: 0.6437 - val categorical accuracy: 0.6800
Epoch 258/500
uracy: 0.8058 - val_loss: 0.7287 - val_categorical_accuracy: 0.6000
Epoch 259/500
uracy: 0.7767 - val_loss: 0.6999 - val_categorical_accuracy: 0.5800
Epoch 260/500
uracy: 0.7816 - val_loss: 0.6622 - val_categorical_accuracy: 0.7200
Epoch 261/500
uracy: 0.7621 - val_loss: 0.5491 - val_categorical_accuracy: 0.7000
uracy: 0.8252 - val_loss: 0.6330 - val_categorical_accuracy: 0.7000
Epoch 263/500
uracy: 0.8010 - val loss: 0.7563 - val categorical accuracy: 0.6000
Epoch 264/500
uracy: 0.8058 - val loss: 0.6686 - val categorical accuracy: 0.6400
Epoch 265/500
uracy: 0.8107 - val_loss: 0.5992 - val_categorical_accuracy: 0.7200
uracy: 0.7961 - val_loss: 0.5786 - val_categorical_accuracy: 0.6800
Epoch 267/500
uracy: 0.8058 - val_loss: 0.6344 - val_categorical_accuracy: 0.7200
Epoch 268/500
uracy: 0.8333 - val_loss: 0.5789 - val_categorical_accuracy: 0.7000
uracy: 0.8058 - val_loss: 0.5819 - val_categorical_accuracy: 0.7200
Epoch 270/500
uracy: 0.7718 - val_loss: 0.6629 - val_categorical_accuracy: 0.6600
Epoch 271/500
uracy: 0.7961 - val_loss: 0.6421 - val_categorical_accuracy: 0.7000
Epoch 272/500
uracy: 0.8252 - val loss: 0.6905 - val categorical accuracy: 0.6600
Epoch 273/500
uracy: 0.8350 - val_loss: 0.7072 - val_categorical_accuracy: 0.6600
Epoch 274/500
uracy: 0.7961 - val_loss: 0.7368 - val_categorical_accuracy: 0.6400
Epoch 275/500
uracy: 0.7961 - val_loss: 0.6804 - val_categorical_accuracy: 0.6600
Epoch 276/500
uracy: 0.8155 - val_loss: 0.6917 - val_categorical_accuracy: 0.6200
Epoch 277/500
```

```
uracy: 0.8010 - val_loss: 0.5501 - val_categorical_accuracy: 0.8000
Epoch 278/500
uracy: 0.7864 - val loss: 0.6174 - val categorical accuracy: 0.7200
Epoch 279/500
uracy: 0.8058 - val_loss: 0.7890 - val_categorical_accuracy: 0.6400
Epoch 280/500
uracy: 0.7864 - val_loss: 0.7243 - val_categorical_accuracy: 0.6800
Epoch 281/500
uracy: 0.8204 - val_loss: 0.6337 - val_categorical_accuracy: 0.6800
uracy: 0.8204 - val_loss: 0.7319 - val_categorical_accuracy: 0.6600
Epoch 283/500
uracy: 0.8301 - val loss: 0.6333 - val categorical accuracy: 0.7400
Epoch 284/500
uracy: 0.8048 - val loss: 0.7514 - val categorical accuracy: 0.6800
Epoch 285/500
uracy: 0.8107 - val_loss: 0.6579 - val_categorical_accuracy: 0.7400
uracy: 0.8107 - val_loss: 0.6662 - val_categorical_accuracy: 0.6600
Epoch 287/500
uracy: 0.8204 - val_loss: 0.6551 - val_categorical_accuracy: 0.7200
Epoch 288/500
uracy: 0.8301 - val_loss: 0.6703 - val_categorical_accuracy: 0.6800
uracy: 0.7816 - val_loss: 0.6878 - val_categorical_accuracy: 0.7200
Epoch 290/500
uracy: 0.8301 - val_loss: 0.5696 - val_categorical_accuracy: 0.7400
Epoch 291/500
uracy: 0.8155 - val_loss: 0.6663 - val_categorical_accuracy: 0.6400
Epoch 292/500
uracy: 0.7913 - val loss: 0.6057 - val categorical accuracy: 0.7200
uracy: 0.8204 - val_loss: 0.6093 - val_categorical_accuracy: 0.6400
Epoch 294/500
uracy: 0.8204 - val_loss: 0.6500 - val_categorical_accuracy: 0.6800
Epoch 295/500
uracy: 0.7961 - val_loss: 0.6964 - val_categorical_accuracy: 0.6000
Epoch 296/500
uracy: 0.8058 - val_loss: 0.6547 - val_categorical_accuracy: 0.6800
Epoch 297/500
```

```
uracy: 0.8252 - val_loss: 0.6655 - val_categorical_accuracy: 0.7200
Epoch 298/500
uracy: 0.8107 - val loss: 0.6973 - val categorical accuracy: 0.6800
Epoch 299/500
uracy: 0.8592 - val_loss: 0.6049 - val_categorical_accuracy: 0.6400
Epoch 300/500
uracy: 0.8238 - val loss: 0.5941 - val categorical accuracy: 0.7800
Epoch 301/500
uracy: 0.7816 - val_loss: 0.7048 - val_categorical_accuracy: 0.7000
uracy: 0.8155 - val_loss: 0.7153 - val_categorical_accuracy: 0.6000
Epoch 303/500
uracy: 0.8058 - val loss: 0.7078 - val categorical accuracy: 0.6400
Epoch 304/500
uracy: 0.7961 - val loss: 0.6536 - val categorical accuracy: 0.7600
Epoch 305/500
uracy: 0.8204 - val_loss: 0.6584 - val_categorical_accuracy: 0.6400
uracy: 0.8058 - val_loss: 0.5631 - val_categorical_accuracy: 0.8000
Epoch 307/500
uracy: 0.7961 - val_loss: 0.6824 - val_categorical_accuracy: 0.6200
Epoch 308/500
uracy: 0.8398 - val_loss: 0.6174 - val_categorical_accuracy: 0.7000
uracy: 0.7961 - val_loss: 0.6556 - val_categorical_accuracy: 0.7000
uracy: 0.7864 - val_loss: 0.6409 - val_categorical_accuracy: 0.6600
Epoch 311/500
uracy: 0.8447 - val_loss: 0.5998 - val_categorical_accuracy: 0.7400
Epoch 312/500
uracy: 0.8058 - val loss: 0.6100 - val categorical accuracy: 0.7200
Epoch 313/500
uracy: 0.8107 - val_loss: 0.6194 - val_categorical_accuracy: 0.7400
Epoch 314/500
uracy: 0.8398 - val_loss: 0.6364 - val_categorical_accuracy: 0.7000
Epoch 315/500
uracy: 0.8155 - val_loss: 0.6138 - val_categorical_accuracy: 0.6800
Epoch 316/500
uracy: 0.8350 - val_loss: 0.6121 - val_categorical_accuracy: 0.7200
Epoch 317/500
```

```
uracy: 0.8204 - val loss: 0.7032 - val categorical accuracy: 0.6600
Epoch 318/500
uracy: 0.8155 - val loss: 0.6822 - val categorical accuracy: 0.6600
Epoch 319/500
uracy: 0.8155 - val_loss: 0.8182 - val_categorical_accuracy: 0.6400
Epoch 320/500
uracy: 0.8544 - val_loss: 0.7251 - val_categorical_accuracy: 0.6400
Epoch 321/500
uracy: 0.8350 - val_loss: 0.6988 - val_categorical_accuracy: 0.7000
uracy: 0.7961 - val_loss: 0.8105 - val_categorical_accuracy: 0.6600
Epoch 323/500
uracy: 0.7816 - val loss: 0.6308 - val categorical accuracy: 0.7200
Epoch 324/500
uracy: 0.8301 - val loss: 0.4931 - val categorical accuracy: 0.7800
Epoch 325/500
uracy: 0.7767 - val_loss: 0.5362 - val_categorical_accuracy: 0.7800
Epoch 326/500
uracy: 0.8010 - val_loss: 0.6861 - val_categorical_accuracy: 0.6400
Epoch 327/500
uracy: 0.8107 - val_loss: 0.6720 - val_categorical_accuracy: 0.6600
Epoch 328/500
uracy: 0.8204 - val_loss: 0.6219 - val_categorical_accuracy: 0.7200
uracy: 0.8058 - val_loss: 0.6314 - val_categorical_accuracy: 0.6800
uracy: 0.8204 - val_loss: 0.6737 - val_categorical_accuracy: 0.7200
Epoch 331/500
uracy: 0.7670 - val_loss: 0.5700 - val_categorical_accuracy: 0.7800
Epoch 332/500
uracy: 0.7961 - val loss: 0.6157 - val categorical accuracy: 0.7200
Epoch 333/500
uracy: 0.8495 - val_loss: 0.7174 - val_categorical_accuracy: 0.5800
Epoch 334/500
uracy: 0.7670 - val_loss: 0.7013 - val_categorical_accuracy: 0.6600
Epoch 335/500
uracy: 0.8398 - val_loss: 0.5837 - val_categorical_accuracy: 0.7600
Epoch 336/500
uracy: 0.8010 - val_loss: 0.6561 - val_categorical_accuracy: 0.7200
Epoch 337/500
```

```
uracy: 0.7762 - val loss: 0.6865 - val categorical accuracy: 0.7200
Epoch 338/500
uracy: 0.8689 - val loss: 0.5472 - val categorical accuracy: 0.7200
Epoch 339/500
uracy: 0.7816 - val_loss: 0.6250 - val_categorical_accuracy: 0.6600
Epoch 340/500
uracy: 0.8010 - val_loss: 0.6550 - val_categorical_accuracy: 0.6600
Epoch 341/500
uracy: 0.7864 - val_loss: 0.6339 - val_categorical_accuracy: 0.7800
uracy: 0.8301 - val_loss: 0.6384 - val_categorical_accuracy: 0.6400
Epoch 343/500
uracy: 0.8252 - val loss: 0.6400 - val categorical accuracy: 0.7000
Epoch 344/500
uracy: 0.8010 - val loss: 0.5456 - val categorical accuracy: 0.7200
Epoch 345/500
uracy: 0.8107 - val_loss: 0.6040 - val_categorical_accuracy: 0.7200
uracy: 0.8155 - val_loss: 0.5854 - val_categorical_accuracy: 0.7200
Epoch 347/500
uracy: 0.8155 - val_loss: 0.7586 - val_categorical_accuracy: 0.7000
Epoch 348/500
uracy: 0.8155 - val_loss: 0.6990 - val_categorical_accuracy: 0.6400
uracy: 0.8155 - val_loss: 0.6990 - val_categorical_accuracy: 0.7000
Epoch 350/500
uracy: 0.8301 - val_loss: 0.6735 - val_categorical_accuracy: 0.6800
Epoch 351/500
uracy: 0.8252 - val_loss: 0.7496 - val_categorical_accuracy: 0.6400
Epoch 352/500
uracy: 0.7961 - val loss: 0.7007 - val categorical accuracy: 0.6400
Epoch 353/500
uracy: 0.7961 - val_loss: 0.6018 - val_categorical_accuracy: 0.7800
Epoch 354/500
uracy: 0.8252 - val_loss: 0.7391 - val_categorical_accuracy: 0.6400
Epoch 355/500
uracy: 0.8058 - val_loss: 0.5911 - val_categorical_accuracy: 0.7000
Epoch 356/500
uracy: 0.8350 - val_loss: 0.6952 - val_categorical_accuracy: 0.6800
Epoch 357/500
```

```
uracy: 0.8204 - val_loss: 0.6151 - val_categorical_accuracy: 0.6600
Epoch 358/500
uracy: 0.8301 - val loss: 0.6386 - val categorical accuracy: 0.6800
Epoch 359/500
uracy: 0.8301 - val_loss: 0.5848 - val_categorical_accuracy: 0.7800
Epoch 360/500
uracy: 0.8058 - val_loss: 0.6743 - val_categorical_accuracy: 0.6800
Epoch 361/500
uracy: 0.8204 - val_loss: 0.6475 - val_categorical_accuracy: 0.7400
uracy: 0.8155 - val_loss: 0.5579 - val_categorical_accuracy: 0.7200
Epoch 363/500
uracy: 0.8398 - val loss: 0.7069 - val categorical accuracy: 0.6000
Epoch 364/500
uracy: 0.7864 - val loss: 0.6783 - val categorical accuracy: 0.7000
Epoch 365/500
uracy: 0.8252 - val_loss: 0.7408 - val_categorical_accuracy: 0.6000
uracy: 0.8447 - val_loss: 0.8126 - val_categorical_accuracy: 0.7000
Epoch 367/500
uracy: 0.8301 - val_loss: 0.6383 - val_categorical_accuracy: 0.6800
Epoch 368/500
uracy: 0.8495 - val_loss: 0.7046 - val_categorical_accuracy: 0.7600
uracy: 0.8495 - val_loss: 0.6310 - val_categorical_accuracy: 0.7200
Epoch 370/500
uracy: 0.8495 - val_loss: 0.6672 - val_categorical_accuracy: 0.6800
Epoch 371/500
uracy: 0.7961 - val_loss: 0.5753 - val_categorical_accuracy: 0.7400
Epoch 372/500
uracy: 0.8495 - val loss: 0.6524 - val categorical accuracy: 0.7400
Epoch 373/500
uracy: 0.8010 - val_loss: 0.6069 - val_categorical_accuracy: 0.7200
Epoch 374/500
uracy: 0.8155 - val_loss: 0.6828 - val_categorical_accuracy: 0.6800
Epoch 375/500
uracy: 0.8252 - val_loss: 0.6710 - val_categorical_accuracy: 0.6800
Epoch 376/500
uracy: 0.7961 - val_loss: 0.5922 - val_categorical_accuracy: 0.7400
Epoch 377/500
```

```
uracy: 0.8447 - val loss: 0.6358 - val categorical accuracy: 0.6800
Epoch 378/500
uracy: 0.8252 - val loss: 0.7140 - val categorical accuracy: 0.6600
Epoch 379/500
uracy: 0.8350 - val_loss: 0.5330 - val_categorical_accuracy: 0.7800
Epoch 380/500
uracy: 0.7718 - val_loss: 0.6027 - val_categorical_accuracy: 0.6400
Epoch 381/500
uracy: 0.7961 - val_loss: 0.6476 - val_categorical_accuracy: 0.6800
uracy: 0.8190 - val_loss: 0.7255 - val_categorical_accuracy: 0.6800
Epoch 383/500
uracy: 0.8301 - val loss: 0.6368 - val categorical accuracy: 0.6800
Epoch 384/500
uracy: 0.8252 - val loss: 0.5372 - val categorical accuracy: 0.7600
Epoch 385/500
uracy: 0.8333 - val_loss: 0.6953 - val_categorical_accuracy: 0.6800
uracy: 0.8495 - val_loss: 0.5890 - val_categorical_accuracy: 0.7800
Epoch 387/500
uracy: 0.8204 - val_loss: 0.6029 - val_categorical_accuracy: 0.7000
Epoch 388/500
uracy: 0.8398 - val_loss: 0.8315 - val_categorical_accuracy: 0.6600
uracy: 0.8204 - val_loss: 0.6658 - val_categorical_accuracy: 0.7000
Epoch 390/500
uracy: 0.8350 - val_loss: 0.6861 - val_categorical_accuracy: 0.6800
Epoch 391/500
uracy: 0.8204 - val_loss: 0.5046 - val_categorical_accuracy: 0.8000
Epoch 392/500
uracy: 0.8107 - val loss: 0.7161 - val categorical accuracy: 0.6200
Epoch 393/500
uracy: 0.7864 - val_loss: 0.6450 - val_categorical_accuracy: 0.7000
Epoch 394/500
uracy: 0.8204 - val_loss: 0.7090 - val_categorical_accuracy: 0.6600
Epoch 395/500
uracy: 0.8107 - val_loss: 0.6905 - val_categorical_accuracy: 0.7000
Epoch 396/500
uracy: 0.8641 - val_loss: 0.7451 - val_categorical_accuracy: 0.6600
Epoch 397/500
```

```
uracy: 0.8058 - val loss: 0.6899 - val categorical accuracy: 0.7400
Epoch 398/500
uracy: 0.8252 - val loss: 0.6134 - val categorical accuracy: 0.7400
Epoch 399/500
uracy: 0.8204 - val_loss: 0.6759 - val_categorical_accuracy: 0.7000
Epoch 400/500
uracy: 0.8544 - val loss: 0.6700 - val categorical accuracy: 0.6600
Epoch 401/500
uracy: 0.8350 - val_loss: 0.6249 - val_categorical_accuracy: 0.6800
uracy: 0.8447 - val_loss: 0.5967 - val_categorical_accuracy: 0.7600
Epoch 403/500
uracy: 0.8107 - val loss: 0.5873 - val categorical accuracy: 0.7200
Epoch 404/500
uracy: 0.8155 - val loss: 0.5678 - val categorical accuracy: 0.7200
Epoch 405/500
uracy: 0.8495 - val_loss: 0.5853 - val_categorical_accuracy: 0.7800
Epoch 406/500
uracy: 0.8204 - val_loss: 0.6781 - val_categorical_accuracy: 0.6600
Epoch 407/500
uracy: 0.8058 - val_loss: 0.7146 - val_categorical_accuracy: 0.6000
Epoch 408/500
uracy: 0.8107 - val_loss: 0.6188 - val_categorical_accuracy: 0.7800
uracy: 0.8447 - val_loss: 0.6158 - val_categorical_accuracy: 0.7400
Epoch 410/500
uracy: 0.8495 - val_loss: 0.5688 - val_categorical_accuracy: 0.7600
Epoch 411/500
uracy: 0.8155 - val_loss: 0.6952 - val_categorical_accuracy: 0.7200
Epoch 412/500
uracy: 0.8398 - val loss: 0.6529 - val categorical accuracy: 0.7000
Epoch 413/500
uracy: 0.8333 - val_loss: 0.5158 - val_categorical_accuracy: 0.7200
Epoch 414/500
uracy: 0.8155 - val_loss: 0.6059 - val_categorical_accuracy: 0.7200
Epoch 415/500
uracy: 0.8350 - val_loss: 0.6844 - val_categorical_accuracy: 0.7000
Epoch 416/500
uracy: 0.8252 - val_loss: 0.7333 - val_categorical_accuracy: 0.6800
Epoch 417/500
```

```
uracy: 0.8155 - val loss: 0.7434 - val categorical accuracy: 0.6200
Epoch 418/500
uracy: 0.8058 - val loss: 0.5129 - val categorical accuracy: 0.8000
Epoch 419/500
uracy: 0.8238 - val_loss: 0.5660 - val_categorical_accuracy: 0.7400
Epoch 420/500
uracy: 0.8398 - val_loss: 0.7318 - val_categorical_accuracy: 0.6600
Epoch 421/500
uracy: 0.8204 - val_loss: 0.6954 - val_categorical_accuracy: 0.7400
uracy: 0.8252 - val_loss: 0.7025 - val_categorical_accuracy: 0.6200
Epoch 423/500
uracy: 0.8204 - val loss: 0.6817 - val categorical accuracy: 0.6800
Epoch 424/500
uracy: 0.8738 - val loss: 0.6261 - val categorical accuracy: 0.7000
Epoch 425/500
uracy: 0.8301 - val_loss: 0.7493 - val_categorical_accuracy: 0.6800
Epoch 426/500
uracy: 0.8350 - val_loss: 0.5859 - val_categorical_accuracy: 0.7400
Epoch 427/500
uracy: 0.8058 - val_loss: 0.5629 - val_categorical_accuracy: 0.7200
Epoch 428/500
uracy: 0.8155 - val_loss: 0.5969 - val_categorical_accuracy: 0.7400
uracy: 0.8495 - val_loss: 0.5839 - val_categorical_accuracy: 0.7800
Epoch 430/500
uracy: 0.8350 - val_loss: 0.6880 - val_categorical_accuracy: 0.7000
Epoch 431/500
uracy: 0.8544 - val_loss: 0.7100 - val_categorical_accuracy: 0.7000
Epoch 432/500
uracy: 0.8155 - val loss: 0.7050 - val categorical accuracy: 0.6800
Epoch 433/500
uracy: 0.8252 - val_loss: 0.7191 - val_categorical_accuracy: 0.6800
Epoch 434/500
uracy: 0.8204 - val_loss: 0.6177 - val_categorical_accuracy: 0.7200
Epoch 435/500
uracy: 0.8058 - val_loss: 0.6694 - val_categorical_accuracy: 0.7000
Epoch 436/500
uracy: 0.8544 - val_loss: 0.6664 - val_categorical_accuracy: 0.7200
Epoch 437/500
```

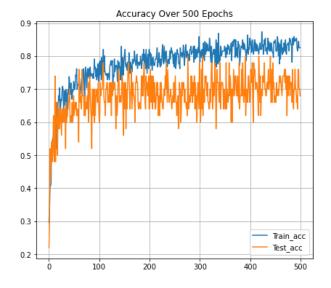
```
uracy: 0.8204 - val loss: 0.5099 - val categorical accuracy: 0.7600
Epoch 438/500
uracy: 0.8447 - val loss: 0.6506 - val categorical accuracy: 0.7000
Epoch 439/500
uracy: 0.8155 - val_loss: 0.5537 - val_categorical_accuracy: 0.7200
Epoch 440/500
uracy: 0.8155 - val_loss: 0.6082 - val_categorical_accuracy: 0.7200
Epoch 441/500
uracy: 0.8398 - val loss: 0.5801 - val categorical accuracy: 0.8000
uracy: 0.8155 - val_loss: 0.6662 - val_categorical_accuracy: 0.6600
Epoch 443/500
uracy: 0.8398 - val loss: 0.7844 - val categorical accuracy: 0.6600
Epoch 444/500
uracy: 0.8252 - val loss: 0.5982 - val categorical accuracy: 0.7600
Epoch 445/500
uracy: 0.8107 - val_loss: 0.7075 - val_categorical_accuracy: 0.6600
Epoch 446/500
uracy: 0.8107 - val_loss: 0.5402 - val_categorical_accuracy: 0.7800
Epoch 447/500
uracy: 0.7961 - val_loss: 0.6846 - val_categorical_accuracy: 0.7000
Epoch 448/500
uracy: 0.8447 - val_loss: 0.6282 - val_categorical_accuracy: 0.7200
uracy: 0.8398 - val_loss: 0.6233 - val_categorical_accuracy: 0.6600
Epoch 450/500
uracy: 0.8398 - val_loss: 0.6921 - val_categorical_accuracy: 0.6800
Epoch 451/500
uracy: 0.8495 - val_loss: 0.7043 - val_categorical_accuracy: 0.6600
Epoch 452/500
uracy: 0.8155 - val loss: 0.5662 - val categorical accuracy: 0.6600
Epoch 453/500
uracy: 0.8155 - val_loss: 0.6938 - val_categorical_accuracy: 0.7200
Epoch 454/500
uracy: 0.8155 - val_loss: 0.6686 - val_categorical_accuracy: 0.6800
Epoch 455/500
uracy: 0.8592 - val_loss: 0.5904 - val_categorical_accuracy: 0.7000
Epoch 456/500
uracy: 0.8447 - val_loss: 0.7660 - val_categorical_accuracy: 0.7000
Epoch 457/500
```

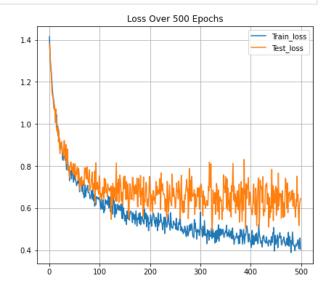
```
uracy: 0.8010 - val loss: 0.6104 - val categorical accuracy: 0.6800
Epoch 458/500
uracy: 0.8398 - val loss: 0.6432 - val categorical accuracy: 0.7000
Epoch 459/500
uracy: 0.7767 - val_loss: 0.6700 - val_categorical_accuracy: 0.7400
Epoch 460/500
uracy: 0.8350 - val_loss: 0.6537 - val_categorical_accuracy: 0.7200
Epoch 461/500
uracy: 0.7913 - val_loss: 0.6684 - val_categorical_accuracy: 0.7400
uracy: 0.8447 - val_loss: 0.5526 - val_categorical_accuracy: 0.7200
Epoch 463/500
uracy: 0.8495 - val loss: 0.6498 - val categorical accuracy: 0.7000
Epoch 464/500
uracy: 0.8107 - val loss: 0.6831 - val categorical accuracy: 0.6800
Epoch 465/500
uracy: 0.8048 - val_loss: 0.5975 - val_categorical_accuracy: 0.7200
Epoch 466/500
uracy: 0.8252 - val_loss: 0.5550 - val_categorical_accuracy: 0.7400
Epoch 467/500
uracy: 0.8107 - val_loss: 0.6268 - val_categorical_accuracy: 0.7400
Epoch 468/500
uracy: 0.8398 - val_loss: 0.5602 - val_categorical_accuracy: 0.7400
uracy: 0.8252 - val_loss: 0.6359 - val_categorical_accuracy: 0.7600
Epoch 470/500
uracy: 0.8155 - val_loss: 0.7417 - val_categorical_accuracy: 0.7200
Epoch 471/500
uracy: 0.8495 - val_loss: 0.7297 - val_categorical_accuracy: 0.7600
Epoch 472/500
uracy: 0.8107 - val loss: 0.6838 - val categorical accuracy: 0.7000
Epoch 473/500
uracy: 0.8058 - val_loss: 0.5992 - val_categorical_accuracy: 0.7400
Epoch 474/500
uracy: 0.8350 - val_loss: 0.7189 - val_categorical_accuracy: 0.6200
Epoch 475/500
uracy: 0.8350 - val_loss: 0.5782 - val_categorical_accuracy: 0.7400
Epoch 476/500
uracy: 0.8398 - val_loss: 0.6689 - val_categorical_accuracy: 0.6800
Epoch 477/500
```

```
uracy: 0.8398 - val loss: 0.6603 - val categorical accuracy: 0.7400
Epoch 478/500
uracy: 0.8155 - val loss: 0.6763 - val categorical accuracy: 0.7000
Epoch 479/500
uracy: 0.8544 - val_loss: 0.6302 - val_categorical_accuracy: 0.7400
Epoch 480/500
uracy: 0.8447 - val loss: 0.6427 - val categorical accuracy: 0.6800
Epoch 481/500
uracy: 0.8495 - val_loss: 0.6396 - val_categorical_accuracy: 0.7200
uracy: 0.8350 - val_loss: 0.6812 - val_categorical_accuracy: 0.7200
Epoch 483/500
uracy: 0.8350 - val loss: 0.6431 - val categorical accuracy: 0.7200
Epoch 484/500
uracy: 0.7816 - val loss: 0.6852 - val categorical accuracy: 0.6600
Epoch 485/500
uracy: 0.8544 - val_loss: 0.6087 - val_categorical_accuracy: 0.7600
Epoch 486/500
uracy: 0.8350 - val_loss: 0.6606 - val_categorical_accuracy: 0.6800
Epoch 487/500
uracy: 0.8350 - val_loss: 0.6702 - val_categorical_accuracy: 0.6400
Epoch 488/500
uracy: 0.8592 - val_loss: 0.5993 - val_categorical_accuracy: 0.7000
uracy: 0.8544 - val_loss: 0.6044 - val_categorical_accuracy: 0.7000
Epoch 490/500
uracy: 0.8447 - val_loss: 0.5570 - val_categorical_accuracy: 0.7600
Epoch 491/500
uracy: 0.8476 - val_loss: 0.6415 - val_categorical_accuracy: 0.7000
Epoch 492/500
uracy: 0.8495 - val loss: 0.6066 - val categorical accuracy: 0.7000
Epoch 493/500
uracy: 0.8544 - val_loss: 0.7514 - val_categorical_accuracy: 0.6600
Epoch 494/500
uracy: 0.8252 - val_loss: 0.6310 - val_categorical_accuracy: 0.6800
Epoch 495/500
uracy: 0.8155 - val_loss: 0.6661 - val_categorical_accuracy: 0.6400
Epoch 496/500
uracy: 0.8252 - val_loss: 0.5709 - val_categorical_accuracy: 0.7600
Epoch 497/500
```

[5 points] Plot Accuracy and Loss During Training

```
In [126...
          import matplotlib.pyplot as plt
          fig, (ax1, ax2) = plt.subplots(1, 2)
          fig.set_figheight(6)
          fig.set figwidth(15)
          ax1.plot(res.history['categorical_accuracy'])
          ax1.plot(res.history['val_categorical_accuracy'])
          ax1.set_title('Accuracy Over ' + str(NUM_EPOCHS) + ' Epochs')
          ax1.legend(['Train_acc', 'Test_acc'], loc='lower right')
          ax1.grid(True)
          ax2.set title('Loss Over ' + str(NUM EPOCHS) + ' Epochs')
          ax2.plot(res.history['loss'])
          ax2.plot(res.history['val loss'])
          ax2.legend(['Train loss', 'Test loss'], loc='upper right')
          ax2.grid(True)
          plt.show()
```





Testing Model

Model 2: AlexNet

[10 points] Build Model

Hint: Starting from a pre-trained model typically helps performance on a new task, e.g. starting with weights obtained by training on ImageNet.

```
In [128...
          # from https://towardsdatascience.com/implementing-alexnet-cnn-architecture-using-tenso
          model = tf.keras.models.Sequential([
              tf.keras.layers.Conv2D(filters=96, kernel_size=(11,11), strides=(4,4), activation='
              tf.keras.layers.BatchNormalization(),
              tf.keras.layers.MaxPool2D(pool size=(3,3), strides=(2,2)),
              tf.keras.layers.Conv2D(filters=256, kernel size=(5,5), strides=(1,1), activation='r
              tf.keras.layers.BatchNormalization(),
              tf.keras.layers.MaxPool2D(pool_size=(3,3), strides=(2,2)),
              tf.keras.layers.Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), activation='r
              tf.keras.layers.BatchNormalization(),
              tf.keras.layers.Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), activation='r
              tf.keras.layers.BatchNormalization(),
              tf.keras.layers.Conv2D(filters=256, kernel_size=(3,3), strides=(1,1), activation='r
              tf.keras.layers.BatchNormalization(),
              tf.keras.layers.MaxPool2D(pool size=(3,3), strides=(2,2)),
              tf.keras.layers.Flatten(),
              tf.keras.layers.Dense(4096, activation='relu'),
              tf.keras.layers.Dropout(0.5),
              tf.keras.layers.Dense(4096, activation='relu'),
              tf.keras.layers.Dropout(0.5),
              tf.keras.layers.Dense(4, activation='softmax')
          ])
          model.compile(loss='categorical crossentropy', optimizer=tf.optimizers.SGD(lr=1e-7), me
```

In [129...

```
model.summary()
```

Model: "sequential_30"

Layer (type)	Output	Shap	oe		Param #
conv2d_50 (Conv2D)	(None,	54,	54,	96)	34944
batch_normalization_50 (Batc	(None,	54,	54,	96)	384
max_pooling2d_30 (MaxPooling	(None,	26,	26,	96)	0
conv2d_51 (Conv2D)	(None,	26,	26,	256)	614656

batch_normalization_51 (Batc	(None,	26, 26, 256)	1024
max_pooling2d_31 (MaxPooling	(None,	12, 12, 256)	0
conv2d_52 (Conv2D)	(None,	12, 12, 384)	885120
batch_normalization_52 (Batc	(None,	12, 12, 384)	1536
conv2d_53 (Conv2D)	(None,	12, 12, 384)	1327488
batch_normalization_53 (Batc	(None,	12, 12, 384)	1536
conv2d_54 (Conv2D)	(None,	12, 12, 256)	884992
batch_normalization_54 (Batc	(None,	12, 12, 256)	1024
max_pooling2d_32 (MaxPooling	(None,	5, 5, 256)	0
flatten_30 (Flatten)	(None,	6400)	0
dense_87 (Dense)	(None,	4096)	26218496
dropout_51 (Dropout)	(None,	4096)	0
dense_88 (Dense)	(None,	4096)	16781312
dropout_52 (Dropout)	(None,	4096)	0
dense_89 (Dense)	(None,	4)	16388
Total naname: 46 769 000			

Total params: 46,768,900 Trainable params: 46,766,148 Non-trainable params: 2,752

[5 points] Train Model

racy: 0.2718 - val_loss: 1.4285 - val_categorical_accuracy: 0.2600

Epoch 2/100

```
Epoch 3/100
racy: 0.2476 - val_loss: 1.4257 - val_categorical_accuracy: 0.2600
Epoch 4/100
racy: 0.2718 - val_loss: 1.4125 - val_categorical_accuracy: 0.2800
Epoch 5/100
racy: 0.2573 - val_loss: 1.4218 - val_categorical_accuracy: 0.2800
racy: 0.2087 - val_loss: 1.4867 - val_categorical_accuracy: 0.2600
Epoch 7/100
racy: 0.2282 - val_loss: 1.4934 - val_categorical_accuracy: 0.2600
Epoch 8/100
racy: 0.2816 - val_loss: 1.5868 - val_categorical_accuracy: 0.2400
Epoch 9/100
racy: 0.1942 - val_loss: 1.5387 - val_categorical_accuracy: 0.2800
Epoch 10/100
racy: 0.3010 - val_loss: 1.5172 - val_categorical_accuracy: 0.3600
Epoch 11/100
racy: 0.2571 - val_loss: 1.5545 - val_categorical_accuracy: 0.3400
Epoch 12/100
racy: 0.1942 - val_loss: 1.5722 - val_categorical_accuracy: 0.3000
Epoch 13/100
racy: 0.2952 - val loss: 1.7581 - val categorical accuracy: 0.2600
Epoch 14/100
racy: 0.2524 - val_loss: 1.7039 - val_categorical_accuracy: 0.3000
Epoch 15/100
racy: 0.2621 - val loss: 1.7320 - val categorical accuracy: 0.3200
Epoch 16/100
racy: 0.2718 - val loss: 1.6356 - val categorical accuracy: 0.3000
Epoch 17/100
racy: 0.3107 - val_loss: 1.6825 - val_categorical_accuracy: 0.3000
racy: 0.3010 - val_loss: 1.6258 - val_categorical_accuracy: 0.3400
Epoch 19/100
racy: 0.3143 - val_loss: 1.7134 - val_categorical_accuracy: 0.2400
Epoch 20/100
racy: 0.2087 - val_loss: 1.6353 - val_categorical_accuracy: 0.2800
Epoch 21/100
racy: 0.2427 - val_loss: 1.6709 - val_categorical_accuracy: 0.2800
Epoch 22/100
racy: 0.3010 - val_loss: 1.6204 - val_categorical_accuracy: 0.3200
```

```
Epoch 23/100
racy: 0.2670 - val_loss: 1.5241 - val_categorical_accuracy: 0.3000
Epoch 24/100
racy: 0.2864 - val_loss: 1.6931 - val_categorical_accuracy: 0.2400
Epoch 25/100
racy: 0.2427 - val_loss: 1.4648 - val_categorical_accuracy: 0.4000
Epoch 26/100
racy: 0.2184 - val_loss: 1.4986 - val_categorical_accuracy: 0.3400
Epoch 27/100
racy: 0.2864 - val_loss: 1.6133 - val_categorical_accuracy: 0.2800
Epoch 28/100
racy: 0.2573 - val_loss: 1.5099 - val_categorical_accuracy: 0.3200
Epoch 29/100
racy: 0.2427 - val_loss: 1.5298 - val_categorical_accuracy: 0.3400
Epoch 30/100
racy: 0.1748 - val_loss: 1.5871 - val_categorical_accuracy: 0.3000
Epoch 31/100
racy: 0.2136 - val_loss: 1.6541 - val_categorical_accuracy: 0.2600
Epoch 32/100
racy: 0.3252 - val_loss: 1.7945 - val_categorical_accuracy: 0.1600
Epoch 33/100
racy: 0.2913 - val loss: 1.6282 - val categorical accuracy: 0.2400
Epoch 34/100
racy: 0.2816 - val_loss: 1.4641 - val_categorical_accuracy: 0.3600
Epoch 35/100
racy: 0.2379 - val loss: 1.5833 - val categorical accuracy: 0.2800
Epoch 36/100
racy: 0.2864 - val loss: 1.6305 - val categorical accuracy: 0.3400
Epoch 37/100
racy: 0.2767 - val_loss: 1.7364 - val_categorical_accuracy: 0.2400
racy: 0.2864 - val_loss: 1.4907 - val_categorical_accuracy: 0.3000
Epoch 39/100
racy: 0.2864 - val_loss: 1.5621 - val_categorical_accuracy: 0.2400
Epoch 40/100
racy: 0.2718 - val_loss: 1.4995 - val_categorical_accuracy: 0.2400
Epoch 41/100
racy: 0.3010 - val_loss: 1.7151 - val_categorical_accuracy: 0.2600
Epoch 42/100
racy: 0.2961 - val_loss: 1.4888 - val_categorical_accuracy: 0.3200
```

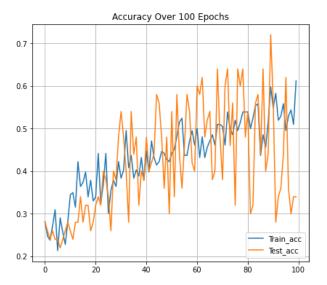
```
Epoch 43/100
racy: 0.2621 - val_loss: 1.6893 - val_categorical_accuracy: 0.2600
Epoch 44/100
racy: 0.2282 - val_loss: 1.5662 - val_categorical_accuracy: 0.3000
Epoch 45/100
racy: 0.2767 - val_loss: 1.5912 - val_categorical_accuracy: 0.3000
racy: 0.2718 - val_loss: 1.6003 - val_categorical_accuracy: 0.3000
Epoch 47/100
racy: 0.2670 - val_loss: 1.7495 - val_categorical_accuracy: 0.2800
Epoch 48/100
racy: 0.2476 - val_loss: 1.5963 - val_categorical_accuracy: 0.3200
Epoch 49/100
racy: 0.2767 - val_loss: 1.5506 - val_categorical_accuracy: 0.2400
Epoch 50/100
racy: 0.2427 - val_loss: 1.5835 - val_categorical_accuracy: 0.2800
Epoch 51/100
racy: 0.2427 - val_loss: 1.4519 - val_categorical_accuracy: 0.3400
Epoch 52/100
racy: 0.2379 - val_loss: 1.6366 - val_categorical_accuracy: 0.2800
Epoch 53/100
racy: 0.2330 - val loss: 1.5327 - val categorical accuracy: 0.3000
Epoch 54/100
racy: 0.2718 - val_loss: 1.6341 - val_categorical_accuracy: 0.3000
Epoch 55/100
racy: 0.1990 - val loss: 1.3422 - val categorical accuracy: 0.4400
Epoch 56/100
racy: 0.3447 - val loss: 1.6218 - val categorical accuracy: 0.2800
Epoch 57/100
racy: 0.2136 - val_loss: 1.5937 - val_categorical_accuracy: 0.3800
racy: 0.2476 - val_loss: 1.5012 - val_categorical_accuracy: 0.2800
Epoch 59/100
racy: 0.2767 - val_loss: 1.5073 - val_categorical_accuracy: 0.2800
Epoch 60/100
racy: 0.2330 - val_loss: 1.4351 - val_categorical_accuracy: 0.3800
Epoch 61/100
racy: 0.2621 - val_loss: 1.3189 - val_categorical_accuracy: 0.4400
Epoch 62/100
racy: 0.2670 - val_loss: 1.3600 - val_categorical_accuracy: 0.3400
```

Epoch 63/100

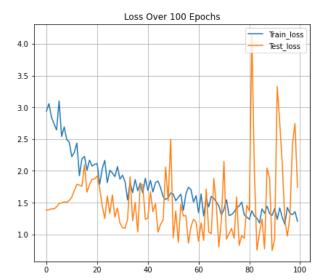
```
racy: 0.2476 - val_loss: 1.4634 - val_categorical_accuracy: 0.2800
Epoch 64/100
racy: 0.2330 - val loss: 1.3874 - val categorical accuracy: 0.3800
Epoch 65/100
racy: 0.2379 - val_loss: 1.5295 - val_categorical_accuracy: 0.2600
Epoch 66/100
racy: 0.2961 - val_loss: 1.5572 - val_categorical_accuracy: 0.3000
Epoch 67/100
racy: 0.2670 - val_loss: 1.3838 - val_categorical_accuracy: 0.4000
Epoch 68/100
racy: 0.3544 - val_loss: 1.5708 - val_categorical_accuracy: 0.3000
Epoch 69/100
racy: 0.3350 - val_loss: 1.4388 - val_categorical_accuracy: 0.3200
racy: 0.2816 - val loss: 1.4986 - val categorical accuracy: 0.2600
Epoch 71/100
racy: 0.3010 - val_loss: 1.6267 - val_categorical_accuracy: 0.3200
Epoch 72/100
0.2573
```

[5 points] Plot Accuracy and Loss During Training

```
In [70]:
          import matplotlib.pyplot as plt
          fig, (ax1, ax2) = plt.subplots(1, 2)
          fig.set figheight(6)
          fig.set figwidth(15)
          ax1.plot(res.history['categorical_accuracy'])
          ax1.plot(res.history['val_categorical_accuracy'])
          ax1.set title('Accuracy Over ' + str(NUM EPOCHS) + ' Epochs')
          ax1.legend(['Train acc', 'Test acc'], loc='lower right')
          ax1.grid(True)
          ax2.set_title('Loss Over ' + str(NUM_EPOCHS) + ' Epochs')
          ax2.plot(res.history['loss'])
          ax2.plot(res.history['val loss'])
          ax2.legend(['Train_loss', 'Test_loss'], loc='upper right')
          ax2.grid(True)
          plt.show()
```



Test accuracy: 0.5277777910232544



Testing Model